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Ontology-based personalized performance evaluation and dietary recommendation for weightlifting

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for obtaining a Doctoral Degree in Sports Science according to the
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“If everything was perfect, you would never learn and you would never grow”

-Beyoncé

Dedication

*To the memory of my father, Somtob Tumnark, who met his demise during my study.
If I could give you one thing in life, I would give you the ability to see yourself
through my eyes, only then would you realize how much you mean to me.

I wish you were here with me to see this process through to its completion.
As you look down from heaven, I hope you are proud of your little girl.

I will always carry you inside my heart; from now until we meet again.*

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TABLE OF CONTENTS

Table of contents.....	XI
List of Tables.....	XV
List of Figures.....	XVII
List of Equations.....	XXIII
Abstract.....	XXV
Resumo.....	XXVII
List of Abbreviations.....	XXIX
List of Publications.....	XXXIII
Chapter 1: General Introduction.....	1
1.1 Scope of thesis.....	5
1.2 Research questions and methodology.....	6
1.3 State of art.....	7
1.4 Thesis structure.....	22
Chapter 2: Power Output Patterns of Young Weightlifters during Snatch.....	23
2.1 Muscle power.....	26
2.2 Literature review of power output in Olympic weightlifters	29
2.3 Time series data mining.....	30
2.4 Materials and methods.....	35
2.5 Results.....	38
2.6 Discussion.....	43
2.7 Using LCSS technique to improve the power of discrimination power output pattern in weightlifters.....	47
2.8 Conclusion.....	53

Chapter 3: Ontology-Based Personalized Dietary Recommendation for Weightlifting.....	55
3.1 Relevant research on food recommendation system.....	59
3.2 Nutrition background.....	60
3.3 Ontology background.....	64
3.4 System design.....	65
3.5 Conclusions and future work.....	83
Chapter 4: Modeling Weightlifting “Training-Diet-Competition” Cycle with Domain and Task Ontologies.....	85
4.1 Ontology development methodology.....	90
4.2 Establishing the domain scope and analyzing problem scenarios.....	96
4.3 Modeling and design of the weightlifting domain ontology.....	102
4.4 Engineering the task ontology.....	111
4.5 Analysis of Semantic Rules.....	114
4.6 Evaluation of the knowledge representation.....	119
4.7 Conclusions.....	121
Chapter 5: Modeling Weightlifting TDC-cycle following a Modular and Scalable Approach.....	123
5.1A Generic, Flexible and Modular Weightlifting TDC Cycle Ontology-based Knowledge Representation	126
5.2 The Refactored Task Ontology.....	138
5.3 The Refactored Set of Axioms.....	142
5.4 Conclusions.....	153
Chapter 6: Modeling Weightlifting TDC-cycle by Mapping it to an Upper Ontology.....	155
6.1 The TDC-cycle Upper Ontology	158

6.2 The Refactored Third-Iterated Training Ontology.....	160
6.3 The Refactored Third-Iterated Nutrition Ontology.....	162
6.4 The Refactored Third-Iterated Biomechanics Ontology.....	164
6.5 Conclusions.....	166
Chapter 7: General Discussion and Conclusions.....	167
7.1 Conclusions.....	171
7.2 Limitations.....	173
7.3 Future work	174
References.....	175
Appendix.....	XXXV
Appendix A Ethical Approval.....	XXXVII
Appendix B Written Consent form.....	XXXVIII
Appendix C Nutrition Status of Thai National Team Weightlifters.....	XXXXIX
Appendix D Thai-based Sport Knowledge Questionnaire.....	XLIII
Appendix E Used tools for modeling the ontologies.....	XLIV
Appendix F Enlarge version of figures.....	LV

LIST OF TABLES

Table 1.1	Gap analysis among existing frameworks based on ontology support, scope, and intended use.....	21
Table 2.1	Power output and the description of related barbell kinematic variables in each phase of the snatch lift.....	41
Table 3.1	Activity factor for a general activity.....	74
Table 3.2	The metabolic equivalent for weightlifting.....	75
Table 3.3	Summary of the recommendations for daily nutrient intake and nutrient timing for weightlifters.....	76
Table 3.4	An example of suggested food group intakes in servings (per day) by calories requirements.....	76
Table 3.5	An example of suggested food group intakes in servings (per meal) by calories requirements.....	77
Table 3.6	The percentage of each meal.....	77
Table 3.7	An example of the food items nutrients database from INNUMAL-Nutrient software.....	77
Table 3.8	An example of the menus nutrients database from INNUMAL-Nutrient software.....	78
Table 3.9	An example of possible scenarios and queries.....	79
Table 4.1	Data properties of each concept presented on the domain ontology.....	107
Table 4.2	Definition of Concepts attributes in the Task Ontology.....	112

LIST OF FIGURES

Figure 1.1	Phases of the snatch movement.....	8
Figure 1.2	Deterministic model for the snatch integrating both barbell-related and weightlifter-related variables.....	12
Figure 1.3	Flowchart of the modeling procedure proposed by Bisi et al. (2011), consisting of the skeletal structure and muscles behavior sub models.....	14
Figure 2.1	Distance computation between two-time series with Euclidean.....	34
Figure 2.2	An example of dendrogram on the content of proteins.....	35
Figure 2.3	Variance explained by principal components for relative power output in sagittal plane.....	40
Figure 2.4	Dendrogram of the hierarchical cluster based on Euclidean distance presenting the classification of relative power output during snatch (from lift-off to catch phase) of young novice weightlifters.....	40
Figure 2.5a	Comparison pattern of relative power output time series between the lifter K and other lifters	41
Figure 2.5b	Comparison pattern of relative power output time series between individual lifters.....	41
Figure 2.6	Comparison pattern of barbell velocity time series between lifter K and other lifters.....	42
Figure 2.7	Comparison pattern of barbell acceleration time series between lifter K and other lifters.....	42
Figure 2.8	Comparison pattern of vertical barbell displacement time series between lifter K and other lifters.....	43
Figure 2.9	Comparison pattern of horizontal barbell displacement time series between lifter K and other lifters.....	43

Figure 2.10	Dendrogram of the LCSS distance presenting the classification of relative power output during snatch (from lift-off to catch phase) of young novice weightlifters.....	49
Figure 2.11	An individual relative power output pattern in cluster I (Left side) and cluster II (Right side).....	49
Figure 2.12	Comparison pattern of relative power output time series between cluster I (2.12 a) and II (2.12b)	50
Figure 2.13	Comparison pattern of barbell's velocity time series between cluster I and cluster II group.....	51
Figure 2.14	Comparison pattern of barbell's acceleration time series between cluster I and cluster II group.....	51
Figure 2.15	Comparison pattern of vertical barbell's displacement time series between cluster I and cluster II group.....	51
Figure 2.16	Comparison pattern of horizontal barbell's displacement time series between cluster I and cluster II group.....	52
Figure 3.1	General nutrition recommendations during different yearly training phases for strength and power athletes.....	61
Figure 3.2	Knowledge base framework for food and nutrition recommendation engine in sports.....	65
Figure 3.3	Ontology main concepts.....	66
Figure 3.4	Concepts, classes, and sub-classes of an ontology.....	67
Figure 3.5	Object type properties.....	69
Figure 3.6	Data type properties.....	69
Figure 3.7	Individual form.....	71
Figure 3.8	The user application for insertion of all the personal athlete data.....	80
Figure 3.9	The user application for insertion of training goals and food preferences... <td>80</td>	80
Figure 3.10	Choose your meal for today interface.....	81

Figure 3.11	An example of recommended results of menus for 1 day.....	82
Figure 4.1	Ontology versus Taxonomy.....	87
Figure 4.2	The problem solving for improving weightlifting ability.....	97
Figure 4.3	Weightlifting TDC-cycle OWL-and Rule-based Knowledge-based System	101
Figure 4.4	Methodology for building ontologies: its steps, key modeling, and design artefacts.....	102
Figure 4.5	Fragment of the TDC-Cycle hierarchy of classes.....	104
Figure 4.6	Class hierarchy of <i>ExerciseProperty</i>	105
Figure 4.7	Biomechanics-related classes.....	105
Figure 4.8	Classes or concepts used to model nutrition-related knowledge.....	106
Figure 4.9	Nutrition-related classes.....	106
Figure 4.10	Nine controlled vocabulary concepts.....	108
Figure 4.11	Constituent instances of <i>NutritionPortion</i> concept.....	109
Figure 4.12	Fragment of individuals or facts inserted in the fact base.....	109
Figure 4.13	A fragment of object properties among concepts on TDC-Ontology.....	110
Figure 4.14	An individual and its associated asserted data and object properties....	110
Figure 4.15	Some individuals and their associated object properties.....	111
Figure 4.16	Snatch, its six phases, and all associated exercise property analysis instances.....	120
Figure 4.17	Rule based evaluation of Transition and Turnover phase of Snatch.....	121
Figure 4.18	Result of the <i>topResources</i> query.....	121
Figure 5.1	The Refactored TDC-Cycle classes and relations on iteration 1.....	128
Figure 5.2	Fragment of the TDC-Cycle taxonomy on iteration 2.....	129
Figure 5.3	The Training Domain class hierarchy.....	131

Figure 5.4	Description of class <i>TrainingSequencePositionSnatch</i> using OWL axioms	131
Figure 5.5	Description of class <i>TrainingSnatch</i> using OWL axiom.....	131
Figure 5.6	The individuals that form static perspective (body movement) in <i>TrainingExercise</i> class	132
Figure 5.7	Training domain object properties.....	133
Figure 5.8	Biomechanics ontology class hierarchy.....	134
Figure 5.9	Object properties of biomechanics ontology.....	134
Figure 5.10	The BioMechResult class description.....	134
Figure 5.11	A measurement artefact as an instance BioMechResult class.....	134
Figure 5.12	Nutrition domain class hierarchy.....	136
Figure 5.13	Object properties of the nutrition	136
Figure 5.14	Definition of the NutritionDietaryProtocol.....	136
Figure 5.15	Set of individuals composing a meal domain.....	136
Figure 5.16	The Stakeholder domain class hierarchy.....	137
Figure 5.17	The Stakeholder domain object properties.....	137
Figure 5.18	The whole weightlifting TDC-cycle ontology.....	138
Figure 5.19	Definition of <i>TrainingReference</i> class using OWL axioms.....	139
Figure 5.20	Example of an inferred data property, <i>hasEvaluation</i> , as ‘inherited’ by the task domain ontology.....	140
Figure 5.21	The description of the <i>TaskDomain</i> class.....	141
Figure 5.22	Two identified training sessions, <i>TD1A1</i> and <i>TD1A2</i> , by running the OWL reasoner on the <i>TrainingDay</i> class	141
Figure 5.23	Description of <i>TD1A1</i> , an individual of <i>TrainingDay</i> class.....	141

Figure 5.24	Fragment of individuals or facts created to populate the new fact base.	141
Figure 5.25	Concepts, properties and their interactions in the modeling and design of rhythmic execution rule.....	143
Figure 5.26	Output info generated after executing the SWRL rule designated as <i>ExerciseOK</i>	146
Figure 5.27	Qualitative and quantitative evaluation of a movement by running one of the above movement rules.....	147
Figure 5.28	Qualitative evaluation of a lifting movement.....	148
Figure 5.29	Tabular form with results of the <i>TotalNutrients</i> SWRL query-based rule execution	152
Figure 5.30	Tabular form with results of the <i>NutritionEvaluationVitaminAMin</i> SWRL query-based rule execution	153
Figure 6.1	The upper ontology modeled around abstract concepts of actor, environment and process/task.....	158
Figure 6.2	Third-iterated training domain ontology refactored around the TDC-cycle upper ontology.....	161
Figure 6.3	Third-iterated nutrition domain ontology refactored around the TDC-cycle upper ontology.....	163
Figure 6.4	Third-iterated biomechanics domain ontology refactored around the TDC-cycle upper ontology.....	165

LIST OF EQUATIONS

Equation 1 $TEN = (RMR \times GAF) + EEE + TEF$	
EEE = 0.0175 x METs x body weight x duration of activity	
TEF = 10% ((RMR x GAF) + EEE).....	72
Equation 2 $RMR = 500 + 22 (LMB)$	73
Equation 3 $RMR = 66.47 + 13.75 (\text{weight}) + 5 (\text{height}) - 6.76 (\text{age})$	73
Equation 4 $RMR = 655.1 + 9.56 (\text{weight}) + 1.85 (\text{height}) - 4.68 (\text{age})$	73

ABSTRACT

Studies in weightlifting have been characterized by unclear results and information paucity, mainly due to the lack of information sharing between athletes, coaches, biomechanists, physiologists and nutritionists. Becoming successful in weightlifting performance requires a unique physiological and biomechanics profile based on a distinctive combination of muscular strength, muscular power, flexibility, and lifting technique. An effective training which is carefully designed and monitored, is needed for accomplishment of consistent high performance. While it takes years of dedicated training, diet is also critical as optimal nutrition is essential for peak performance. Nutritional misinformation can do as much harm to ambitious athletes as good nutrition can help. In spite of several studies on nutrition guidelines for weightlifting training and competition as well as on design and implementation of weightlifting training programs, to the best of authors' knowledge, there is no attempt to semantically model the whole "*training-diet-competition*" cycle by integrating training, biomechanics, and nutrition domains.

This study aims to conceive and design an ontology-enriched knowledge model to guide and support the implementation of "*Recommender system of workout and nutrition for weightlifters*". In doing so, it will propose: (i) understanding the weightlifting training system, from both qualitative and quantitative perspectives, following a modular ontology modeling, (ii) understanding the weightlifting diet following a modular ontology modeling, (iii) semantically integrating weightlifting and nutrition ontologies to mainly promote nutrition and weightlifting snatch exercises interoperability, (iv) extending modular ontology scope by mining rules while analyzing open data from the literature, and (v) devising reasoning capability toward an automated weightlifting "*training-diet-competition*" cycle supported by previously mined rules

To support the above claims, two main artefacts were generated such as: (i) a weightlifting nutritional knowledge questionnaire to assess Thai weightlifting coaches' and athletes' knowledge regarding the weightlifting "*training-diet-competition*" cycle and (ii) a dual ontology-oriented weightlifting-nutrition knowledge model extended with mined rules and designed following a standard ontology development methodology.

Keywords: ontology, nutrition, weightlifting, biomechanics, semantics, reasoning

RESUMO

Estudos em halterofilismo ou levantamento do peso têm sido caracterizadas por resultados dúbios e escassez de informação devidos à falta de partilha de informação entre os vários intervenientes, tais como atletas, treinadores, biomecânicos, fisiologistas e nutricionistas. Tornar-se bem sucedido no desempenho do levantamento do peso requer um perfil fisiológico e biomecânico particular, baseado numa combinação única de força muscular, potência muscular, flexibilidade e técnica de levantamento. Para a obtenção de um alto desempenho consistente é necessário um treino eficiente, cuidadosamente planeado e monitorizado. Embora sejam necessários anos de treino dedicado, a dieta é também um fator crítico, pois a nutrição ideal é essencial para o máximo desempenho. A falta ou a errada informação nutricional pode causar tanto dano a atletas ambiciosos, quanto uma boa nutrição pode ajudar. Apesar de vários estudos sobre as orientações nutricionais para treino e competição de levantamento do peso, bem como no desenho e implementação de programas de treino de levantamento do peso, tanto quanto é do conhecimento dos autores, nunca houve tentativas de modelar semanticamente todo o ciclo de “treino-dieta-competição”, integrando os domínios biomecânico, treino e nutricional.

Este estudo visa conceber e desenhar um modelo de conhecimento baseado em ontologias para orientar e apoiar a implementação de um “*Sistema de recomendação de treino e nutrição para atletas do halterofilismo*”. Ao fazê-lo, proporá: (i) compreender o sistema de treino de levantamento do peso, tanto qualitativo quanto quantitativo, seguindo uma modelação modular baseada em ontologias, (ii) entender a dieta de levantamento do peso seguindo uma modelação modular baseada em ontologias, (iii) integrar semanticamente ontologias de levantamento do peso e nutrição, principalmente para promover a interoperabilidade do ponto de vista da nutrição e do exercício de levantamento do peso, (iv) ampliar o âmbito da ontologia modular por meio de regras baseadas em lógica a partir da análise de dados disponíveis na literatura e (v) desenvolver capacidade de raciocínio tendo em vista um ciclo automatizado de “*treino-dieta-competição*” apoiado por regras de lógica previamente definidas

Para suportar os objetivos acima, dois artefactos principais foram criados: (i) um questionário de conhecimento nutricional para o levantamento do peso que visa avaliar o conhecimento dos treinadores e atletas tailandeses sobre o ciclo “*treino-dieta-competição*” e (ii) uma abordagem ontológica a um modelo de conhecimento nutricional e de levantamento do peso expandido com regras de lógica e desenvolvido seguindo uma metodologia padrão de desenvolvimento de ontologias.

PALAVRAS-CHAVE: ontologia, nutrição, levantamento de peso, biomecânico, semântica, raciocínio lógico

LIST OF ABBREVIATIONS

1RM	1-repetition maximum
A	Axiom
AAS	Anabolic androgenic steroids
ADA	The American Dietetic Association
ANOVA	Analysis of variance
API	Application programming interface
ASCM	The American College of Sports Medicine
ATP	Adenosine Triphosphate
ATP-PC	Adenosine Triphosphate-Phosphocreatine
BBC	The British Broadcasting Corporation
CA	Concepts and Attributes
CaseLP	Complex Applications Specification Environment based on Logic Programming
CHO	Carbohydrate
CLEPE	Conceptual LEvel Programming Environment
CPCC	Cophenetic correlation coefficient
CV	Controlled vocabulary
DLL	Dynamic linked library
EEE	Exercise energy expenditure
EI	Energy intake
EMG	Electromyography
FB	Fact base
FFM	Fat free mass
FMA	Foundational Model of Anatomy
FOODS	Food-Oriented Ontology-Driven System
FRS	Food Recommendation System
GAF	General activity factor
GRFs	Ground reaction forces
GTA	Groupware Task Analysis
HCA	Hierarchical Cluster Analysis
HuPSOON	Human Physiology Simulation Ontology
IDRA	Intelligent Diet Recommendation Agent
IOC	The International Olympic Committee

JNI	Java native interface
JS	Jump Squat
KB	Knowledge Base
KBE	Knowledge-based engineering
kcal	Kilocalorie
LBM	Lean body mass
LCSS	Longest Common Subsequence Distance
MCI	Mass Casualties Incidents
METs	Metabolic equivalents
MIREOT	Minimum Information to Reference an External Ontology Term
mph	Miles per hour
MyCF	My Corporis Fabrica
NCS	Nutrition Counseling System for Food Menu Planning
NFL	Normalized fiber length
OPB	Ontology of Physics for Biology
OSMMI	Ontology of the Musculo-skeletal System of the Lower Limbs
OWL	Web Ontology Language
OZONE	Zoomable Ontology Navigator
PA	Pennation angle
PC	Power Clean
PCs	Principal Components
PCA	Principal Component Analysis
PCSA	Physiological cross-sectional area
PHP	Parametric Human Project
PRO	Protein
PSM	Problem-solving method
R	Relationships
RMR	Resting metabolic rate
S	Squat
SHADE	Semantic Healthcare Assistant for Diet and Exercise
SQWRL	Semantic Query-Enhanced Web Rule Language
SUMO	Suggested Upper Merged Ontology
SWRL	Semantic Web Rule Language
TA	Terminologia Anatomica
TDC-cycle	Training-Diet-Competition Cycle

TEF	Thermic effect of food
TEN	Total energy needed
TOVE	Toronto Virtual Enterprise
V_{CM}	System's center of mass velocity
VO_2	Oxygen uptake
VPH	Virtual Physiological Human
WWW.	World Wide Web
XML	eXtensible Markup Language

LIST OF PUBLICATIONS

This doctoral thesis is based on the following scientific materials:

Journals

- Tumnark, P., Cardoso, P., Conceição, F., & Cabral, J. (2018). *Modeling Weightlifting “Training-Diet-Competition” Cycle following a Modular and Scalable Approach*. Submitted to The International Journal of Metadata, Semantics and Ontologies.
- Tumnark, P., Cardoso, P., Conceição, F., & Cabral, J. (2018). *Ontology-Assisted Weightlifting Knowledge Base: Nutrition Approach*. Submitted to ECTI Transactions on Computer and Information Technology.

Conferences

- Tumnark, P., Abreu, M., Macedo, M., Cardoso, P., Cabral, J. & Conceição, F. (2018). Modeling Weightlifting “Training-Diet-Competition” Cycle with Domain and Task Ontologies. In *Proceedings of the 10th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, Volume 2: KEOD*, ISBN 978-989-758-330-8, pages 207-214. DOI: 10.5220/0006929402070214.
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- Tumnark P., Oliveira V., Santibutr N., Cardoso, P., Cabral J., Conceição, F., & Vilas-Boas, J.P. (2014). Daily Menu Assistance System: A case study for Thai weightlifters. *Journal of Strength & Conditioning Research*, 28 (S1): Abstract.
- Tumnark, P., Phuchaiwattananon, O., Kerdchantuk, S., Conceição, F., & Vilas-Boas, J.P. (2014). Nutrition Status of Thai National Team Weightlifters. *Journal of Strength & Conditioning Research*, 28 (S1): Abstract.
- Tumnark, P., Pitaksathienkul, C., Chainok, P., Conceição, F., & Vilas Boas, J.P. (2014). Biomechanical Analysis of the Snatch in Novice Weightlifters: A case study. *Journal of Strength & Conditioning Research*, 28 (S1): Abstract.

CHAPTER 1

General Introduction

In Thailand, weightlifting is the most successful Olympic sport along with boxing. It is one of the only two sports in which Thailand has won gold, with three weightlifting gold medals in the last three Olympic Games. Becoming successful in weightlifting performance requires a unique physiological and biomechanics profile based on a distinctive combination of muscular strength, muscular power, flexibility, and lifting technique. An effective training which is carefully designed and monitored, is needed for accomplishment of consistent high performance. While it takes years of dedicated training, diet is also critical as optimal nutrition is essential for peak performance. This thesis develops a methodology supported by a computerized model; Ontology-Based Personalized Performance Evaluation and Dietary Recommendation for Weightlifting which will serve as a tool to help coach in prescribing and monitoring training and nutrition status of weightlifters. The current chapter presents the scope of this thesis, the research questions and the methodology proposed to answer them, and the structure of this thesis.

Introduction

Weightlifting (also known as Olympic weightlifting) is a distinguished sport often for training sport performance professionals because it requires fine motor coordination, great kinesthetic awareness, quickness, explosive ability, and greater technical perfection of movement pattern (Cioroslan, 1997). It consists of two competitive movements: the snatch, and the clean and jerk. The ability to perform as a weightlifter is impacted by several performance-related characteristics: (i) a unique physiological and biomechanics profile based on a distinctive combination of muscular strength, muscular power, and flexibility, and (ii) lifting techniques that generate great muscle power during the lift and transfer this power effectively to the barbell (Enoka, 1979; Garhammer, 1985, 1991; Gourgoulis et al., 2000; Isaka et al., 1996; Stone et al., 1998). A successful lifter will be able to sustain adequate power output long enough to lift the maximum weight with correct technique. Sustaining power output to efficiently overcome resistance involves two major factors: (i) the ability to sustain muscle energy production, and (ii) the ability to apply that muscle energy efficiently to overcome resistance. Improving the former requires both a well-designed training program and nutrition plan, whereas improving the latter requires the assistance of a sport biomechanist or a well-educated coach. They can help identify defective performance, prescribe measures to correct the identified deficiencies and finally implement the prescribed corrective procedures (Lamb, 1995).

For the last three decades, considerable studies have been conducted to improve weightlifters' performance (Akkus, 2012; Campos et al., 2006; Chiu et al., 2010; Enoka, 1988; Garhammer, 1980; Garhammer, 1981, 1985, 1991, 1993, 2001; Garhammer & Gregor, 1992; Garhammer & Takano, 2008; Gourgoulis et al., 2000; Gourgoulis et al., 2002; Gourgoulis et al., 2009; Gourgoulis et al., 2004; Hadi et al., 2012; Hakkinen, 1984; Harbili, 2012; Harbili & Alptekin, 2014; Ho et al., 2011; Hori et al., 2006; Isaka et al., 1996; Kipp et al., 2012; Musser et al., 2014; Nelson & Burdett, 1978; Okada et al., 2008; Winchester et al., 2009; Yavuz et al., 2015). They focused on training methodology, weightlifting biomechanics, nutrition, muscle architecture, and energy expenditure. Weightlifting biomechanics studies have been mainly focused on methodological issues. These include motion analysis methods, measurement reliability of biomechanics parameters, mechanical work, and power output at world championship level and during competition. The objective was to obtain data about performance characteristics of the world's best weightlifters while they are competing. Data such as barbell kinematics, body segment orientations and power

output in the top physical condition and under maximal competitive pressure may help to better understand the movement or skill of lifting techniques. Researchers have assigned four broad classes of variables to the biomechanics of the snatch: (i) barbell movement, (ii) body movement, (iii) mechanical work and (iv) the power output. Although many studies have been investigated key variables which play a role in successful outcome of a snatch lift, few of them have integrated both barbell- and weightlifter-related data in their analyses. Moreover, Beardsley (2016) presents an extensive and updated Olympic weightlifting literature review, pointing out that studies in weightlifting have been characterized by unclear results and paucity of information regarding biomechanical analysis and training methodology. This point was also supported by the fact that nearly stagnant progress at international level has been registered since 1997 across all weight categories in snatch competitions. Ho et al. (2014) pointed out that such stagnant progress may be explained by the absence of reliable scientific support for weightlifting movement. Furthermore, a limited number of literature was also found in the field of nutrition. Researchers have been analyzing the actual dietary practices of Olympic weightlifters for the last four decades to figure out the benefits of nutrition related to exercise performance. It is often claimed in the weightlifting sport literature that the dietary habits of weightlifters may not yield the desired training gains and/or health benefits due to the emphasis placed on high protein consumption (with high fat) at the expense of adequate carbohydrate ingestion (Cabral et al., 2006; Chen et al., 1989; Grandjean, 1989; Heinemann & Zerbes, 1989; Van Erp-Baart et al., 1989). However, there were inconsistencies among existing studies relating diet quality to physical activity/exercise level and they justify such discrepancy to a relatively crude and imprecise self-reported measures of physical activity, unreliable dietary assessments, and/or small sample size (Capling et al, 2017).

Enhancing the understanding of the mechanics of successful lift, requires collaborative contributions of several stakeholders such as coach, nutritionist, biomechanist and physiologist as well as the aid of technical advances in motion analysis, data acquisition, and methods of analysis. Currently, there are still a lack of knowledge sharing between these stakeholders. The knowledge owned by these experts are not captures, classified or integrated into an information system for decision-making. Therefore, the studies in weightlifting have been characterized by unclear results and paucity of information regarding an integrated biomechanical analysis, training methodology, and nutrition analysis. Ontology is an alternative, among many

techniques, that has been widely accepted as a useful method to simulate human proficiency in narrowly defined domain during the problem solving stage, by integrating descriptive, procedural, and reasoning knowledges (Chau, 2007). An ontology-driven weightlifting knowledge model can be seen as a solution for promoting a better understanding of the weightlifting domain as a whole. It can unify concepts and terminologies among weightlifting stakeholders, while partially helping obviate the paucity and inconsistencies of existing results. However, the weightlifting knowledge model should be scalable to easily integrate further related domain of weightlifting, and also used to support the implementation of weightlifting recommender systems. In spite of several studies on nutrition guidelines for weightlifting training and competition as well as on design and implementation of weightlifting training programs, to the best of authors' knowledge, there is no attempt to semantically model the whole "*training-diet-competition*" cycle by integrating training, biomechanics, and nutrition domains.

This study aims to conceive and design an ontology-enriched knowledge model to guide and support the implementation of "*Recommender system of workout and nutrition for weightlifters*". In doing so, it will propose: (i) understanding the weightlifting training system, from both qualitative and quantitative perspectives, following a modular ontology modeling, (ii) understanding the weightlifting diet following a modular ontology modeling, (iii) semantically integrating weightlifting and nutrition ontologies to mainly promote nutrition and weightlifting snatch exercises interoperability, (iv) extending modular ontology scope by mining rules while analyzing open data from the literature, and (v) devising reasoning capability toward an automated weightlifting "*training-diet-competition*" cycle supported by previously mined rules. To support the above claims, two main artefacts were generated such as: (i) a weightlifting nutritional knowledge questionnaire to assess Thai weightlifting coaches' and athletes' knowledge regarding the weightlifting "*training-diet-competition*" cycle and (ii) a dual ontology-oriented weightlifting-nutrition knowledge model extended with mined rules and designed following a standard ontology development methodology.

This chapter presents an overview of the research, problems, and the structure of thesis. In accordance, the remainder of this chapter is organized as follows: Section 1.1 describes scope of thesis; Section 1.2 presents the research questions and the methodology proposed to answer them; Section 1.3 describes state of art; and Section 1.4 presents the structure of this thesis.

1.1 Scope of Thesis

The scope of this thesis focuses on building a knowledge framework for Olympic weightlifting, bringing together related fields such as training methodology, weightlifting biomechanics, and nutrition while modeling the synergy among them. In so doing, terminology, semantics, and used concepts are unified among researchers, coaches, nutritionists, and athletes to partially obviate the recognized limitations and inconsistencies and so, leading to a research environment which promotes better understanding and more conclusive results. To make this goal achievable under the PhD time constraint, the weightlifting spectrum is narrowed to snatch-only movement.

1.2 Research Questions and Methodology

The weightlifting literature is full of experiments and analyzes related to biomechanics, dietary, and training methodologies and so, we believe that before more inconclusive experimental results, a knowledge framework should be in place to support individualized and holistic approach to snatch analysis, while obviating the above mentioned limitations and inconsistencies. For this reason, this thesis tries to answer to the following questions:

- (i) How can each of the main weightlifting research domains of biomechanics, nutrition, and training methodology be modeled?
- (ii) Which computer-based technology can be explored to model each involved domain related to weightlifting research and practice?
- (iii) How to semantically model the whole weightlifting "*training-diet-competition*" cycle?

To answer them, the following methodology was approached:

- (i) Conceiving and designing the weightlifting training following a modular ontology modeling.
- (ii) Conceiving and designing the weightlifting biomechanics following a modular ontology modeling.
- (iii) Conceiving and designing the weightlifting dietary following a modular ontology modeling.

- (iv) Semantically integrating training, biomechanics, and dietary ontologies to mainly promote nutrition and weightlifting snatch exercises interoperability.
- (v) Extending each modular ontology scope by mining rules while analyzing open data from the literature on collected training and nutritional data to improve modularity, flexibility and scalability.
- (vi) Devising reasoning capability toward an automated weightlifting “*training-diet-competition*” cycle supported by previously mined rules.

1.3 State of Art

This section presents fundamental concepts and technical foundation related to weightlifting including the sport of weightlifting, biomechanics of weightlifting, and nutrition status of weightlifters. It also presents related works that used semantic web technologies to develop biomechanics and food recommendation systems.

1.3.1 The Sport of Weightlifting

Since 1972 two overhead lift competitions have been promoted in the sport of weightlifting, the snatch and the clean and jerk. The sport is often referred to as Olympic (style) weightlifting since it was contested in the Olympic Games (Komi, 2003). Weightlifting is defined as the sport in which athletes attempt to lift the most weight in the snatch and the clean and jerk. In competition, the weightlifter has 3 attempts in the snatch followed by 3 attempts in the clean and jerk. The heaviest successful attempt in each event is added together to determine the final classification. The recognized body weight classed are: men ≤ 56 kg, ≤ 62 kg, ≤ 69 kg, ≤ 77 kg, ≤ 85 kg, ≤ 94 kg, ≤ 105 kg; and women ≤ 48 kg, ≤ 53 kg, ≤ 58 kg, ≤ 63 kg, ≤ 69 kg, ≤ 75 kg, and > 75 kg.

A series of snatch movements starts with the barbell on the floor, and by applying proper technique, the lifter finishes with the barbell over the head in either the squat or split position. Squat snatch is characterized by the lifter lifting the bar as high as possible and pulls himself/herself under it in the squat position. In the split snatch, the lifter “split” his/her legs, placing one foot in front of them and one behind, allowing lifter to receive the bar lower as in the squat snatch (Akkus, 2012; Baumann et al., 1988; Gourgoulis et al., 2000). Snatch technique has been broken down into specifics phases and positions. Although the definition of the phases and positions is clearly

established, they are inconsistent across the literature (Akkus, 2012; Bartonietz, 1996; Campos et al., 2006; Gourgoulis et al., 2000; Ho et al., 2014; Storey & Smith, 2012). In this study, the snatch is divided into 5 phases and 6 positions (Figure 1.1) according to the change in direction of the knee angle and the height of the barbell as suggested by Bartonietz (1996) and Ho et al. (2014).

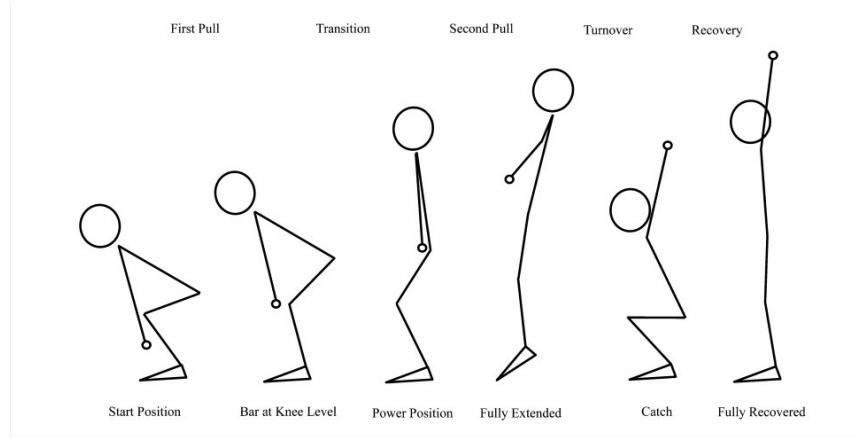


Figure 1.1 Phases of snatch movement (Bartonietz, 1996; Ho et al., 2012).

- (i) **Start position** is defined by the position where the middle of the foot is aligned (i.e., inline) with the stationary barbell, hips and knees flexed, and the back kept “neutral”.

The first pull involves initiating the movement of the barbell off the ground. Although the back is maintained (or held) neutral, extension predominantly at the knee and, to a lesser extent, at the hip contributes to overcoming the barbell’s inertia. This phase is completed upon the barbell reaching knee level.

- (ii) **Bar at the knee level** is defined by the position where barbell reach the knee level.

The transition phase subsequently begins with shifting from knee extension to flexion to adopt the power position.

- (iii) **Power position** is defined by the position where the shoulders, hips, and heels are inline with the bar reaching the height of the hips, which is required to develop vertical force through the legs in the second pull.

When the second pull begins, a coordinated rapid hip and knee extension, with plantar flexion, results in the position with the lower limb joints reaching full extension and effectively generate and transfer power to the bar to displace it over the head.

- (iv) **Fully extended** is defined by the position where the lower limb joints reaching full extension. At this point, toward the end of the second pull phase, the bar reaches the peak velocity before the peak displacement.

In the turnover phase, the weightlifter subsequently moves the body rapidly in a downward direction and pulls himself under the bar to adopt the catch position.

- (v) **Catch position** is defined by the position where the arms being kept extended and the weightlifter attaining a position identical to the bottom of an overhead squat.

In the recovery phase, the weight is rested in the extended arms before an overhead squat is performed and completes the lift.

- (vi) **Fully recovered** is defined by the position where the weightlifter completes the lift by standing in a fully recovered position.

1.3.2 Biomechanics of Weightlifting

In competition, the main objective of every weightlifter is trying to lift the weights near or above those of personal best lifts. To achieve that goal, lifters must be able to adopt their body position and the coordination of joint displacements at the different phases of the lifts precisely throughout the movement. This is to ensure that the force the lifter applies to the barbell will be transmitted efficiently to move the load upwards during the snatch (Garhammer, 1980; Garhammer, 1985; Ho et al., 2014). Moreover, the ability to optimize barbell displacement of weightlifters to their individual physical characteristic is also crucial (Campos et al., 2006; Wang & Pylypko, 2009). Although many research has been investigated the biomechanical features associated with technique and performance of snatch lifting, the identification of optimal technique and how does it contribute to the performance is still unclear. Ho et al. (2014) point out that this is due to the fact that errors in the technique during the lifting can be overcome by compensatory movements and a successful lift can still be achieved. This point causes a gap between the weightlifter's actual performance and what the weightlifter could

potentially lift. To narrow this gap, the identification of what determines success for each individual lifter is needed in order to better understand the interaction of various factors (e.g., which ones lead to efficient technique and which ones limit the performance) (Hoover et al., 2006; Isaka et al., 1996). The authors suggested that technique analysis of weightlifters should be classified as qualitative, quantitative, and predictive.

Qualitative Analysis: Based on the coaches' experience and observation

Coaches use the illustration of precise positions at each phase of movement (as presented in the Figure 1.1) combined with their accumulation of experience through observation to develop their ability to pinpoint the errors in the lifter's technique. For example, Jones et al. (2010) presents an extensive biomechanical analysis of the Olympic snatch movement. The major objective was to determine the correct bar path, the amount of time spent in each phase of the exercise, and/or the specific joint angles during those phases. More importantly, they split snatch movement in positions and phases as described earlier and then presented a checklist as a tool to evaluate the success of subjects in performing the Olympic snatch. Such a checklist provides detailed evaluation of an athlete's strengths and weaknesses. Coaches can use it to design effective training programs tailored to athlete's specific needs. The study of Winchester et al. (2009) supported this approach and proved that it can help athletes to improve their snatch performance. The possible strategy behind this approach is that the athletes use a more kinesthetic approach to learn efficient techniques, rather than depending on visualizing textbook (Takano, 1993).

Quantitative Analysis: Based on the scientific measurement

The use of quantitative technical analysis during snatch lifting allows sport scientists and coaches to identify defective technique, prescribe measures to correct the identified deficiencies, and implement the prescribed corrective procedures for weightlifters. This process requires a cooperation among coach, weightlifter, and scientist to establish a common focus when observing the movement (Lees, 2002; Ho et al., 2014). Kinematic and kinetic data are often used as feedback to athletes. These data can be obtained from the following instruments:

- (i) video cameras setup which offer two-dimensional kinematic data; this method has been used to explore snatch technique during competitions;

- (ii) motion analysis systems using multiple infrared cameras which offer three-dimensional kinematics data; this method provides a highly accurate angular displacement of all joints in the body as well as the bar;
- (iii) force platforms which offer kinetic data; this method has been used to investigated the movement of the center of mass, mechanical work, power, and internal joint kinetics (when combined it with motion analysis);
- (iv) surface electromyography (sEMG) which offers information such as pattern of force production by muscle and the relationship between mechanical work and metabolism;
- (v) isokinetic dynamometry which offers information about dynamic muscle contractions;
- (vi) ultrasound which offers information related to muscle architecture.

By reviewing classical approaches to biomechanical analysis in weightlifting, Ho et al. (2014) proposed a deterministic model for the snatch (Figure 1.2). It involves both barbell- and weightlifter-related variables to promote a more individualized and holistic approach to snatch analysis. The key contributing factors to determine the success of weightlifters are a complex interaction of several variables. Therefore, several area of focus have been established in the literature such as studies dealing with barbell movement (Anderson et al., 2008; Bartonietz, 1996; Baumann et al., 1988; Chiu et al., 2010; Garhammer, 1985; Gourgoulis et al., 2002; Gourgoulis et al., 2004). They classified barbell trajectory, identified optimal lifting techniques, and estimated barbell kinematic parameters. Studies regarding body movement have explored net joint moment, joint angular velocities, and joint angles (Enoka, 1988; Gourgoulis et al., 2000b; Gourgoulis et al., 2002; Gourgoulis et al., 2009; Gourgoulis et al., 2004; Stone et al., 2006; Wang & Pylypko, 2009). Studies related to the relationship between mechanical work and metabolism have investigated EMG amplitude (Bisi et al., 2011; Brandon et al., 2013; Buchanan et al., 2005; Yavuz et al., 2015). Studies concerning power output have measured ground reaction force and total work done on the barbell (Cormie et al., 2007; Hori et al., 2007; Kawamori et al., 2005; Enoka, 1988; Kipp et al., 2013; Kipp et al., 2012).

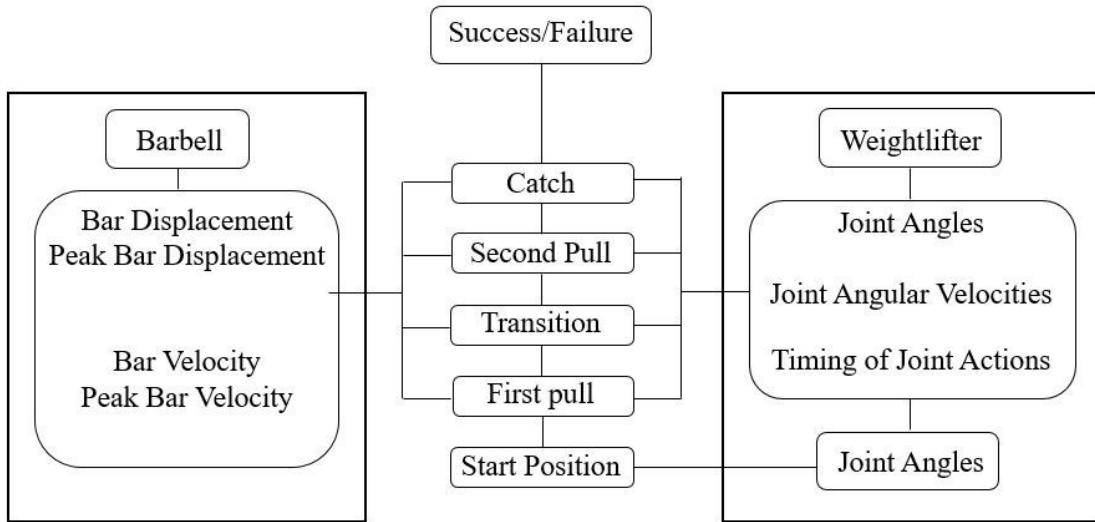


Figure 1.2 Deterministic model for the snatch integrating both barbell-related and weightlifter-related variables (Adapted from Ho et al. (2014)).

Lifters use a wide range of technique and patterns of movement. So far, it is unclear which one is the optimal, as the patterns are affected by both the lifted load and individual anthropometry (Anderson et al., 2008; Musser et al., 2014; Nejadian et al., 2008). Gourgoulis et al. (2009) found no significant difference between successful and unsuccessful lifts in the angular displacement and velocity data of the lower-limb joints, the trajectory and vertical linear velocity of the barbell, or the generated work and power output during the first and second pulls of the lift. Consequently, the general movement pattern of the limbs and the barbell was not modified in unsuccessful lifts in relation to the successful ones. However, significant differences were found in the direction of the barbell's resultant acceleration vector, suggesting that proper direction of force application onto the barbell is crucial for a successful performance in snatch lifts. Thus, the authors suggested that coaches should pay particular attention to the applied force onto the barbell from the first pull. Beardsley (2016) pointed out that the best way to train Olympic weightlifters is a contentious issue. Many existing frameworks and principles of weightlifting training are based on Bulgarian and Russian methods. The adoption of these two methods was justified due to the number of gold medals won by the two countries in the 1980' Olympic Games. However, some studies (Fair, 1988; Franke & Berendonk, 1997; Storey & Smith, 2012) associated the possibility of such success to the extreme use of anabolic androgenic steroids (AAS) compared with other national teams. Many studies (Garhammer, 1992; Storey, 2012) contrast the Russian and Bulgarian frameworks. The former involves a detailed planning and complicate periodization. The training plan is characterized by a wide

variety of exercise with high volume at lower relative loads. However, the latter is comprised of much less planning and periodization. This training plan is described by fewer exercises, mainly in the competition lifts. Training is performed at high volume and high relative loads.

The relationship between mechanical work and metabolism has been studied for several years, but it is still not well understood (Bisi et al., 2011; Brandon et al., 2013; Buchanan et al., 2005; Yavuz et al., 2015). The paper's main finding pointed the integration of a model for the muscle energy expenditure into musculoskeletal models (Bisi et al., 2011). Being able to measure energy expenditure will merge nutrition with biomechanics and training methodology. It will be crucial to recommend the amount of macronutrients intake during training and competition periods, mainly to avoid athletic fatigue or staleness (McArdle et al., 2010). To achieve more accurate estimates of several biomechanics parameters associated with Olympic weightlifting while using existing motion analysis systems, Beardsley (2016) suggested incorporating the three main aspects of muscle architecture: normalized fiber length (NFL), pennation angle (PA), and physiological cross-sectional area (PCSA). Including muscle architecture is important because the muscle determines the force production capacity, contraction velocity, and optimal function. Together, these three main factors can be used to describe any given muscle or individual muscle regions in terms of (i) architectural patterns or arrangement of muscle fascicles within a muscle, (ii) combination and variability of these three factors, (iii) how they can be measured, and (iv) how each specific type of training intervention, resting, increasing age, and surgical procedures can alter these factors (Albracht et al., 2008; Fukutani & Kurihara, 2015; Lieber & Friden, 2000, 2001; Noorkoiv et al., 2010; Stenroth et al., 2016; Wakahara et al., 2013). Muscular characteristics of strength-trained athletes has been studied to identify training-specific muscle adaptations and it allowed researchers to differentiate between athletes (Tesch & Karlsson, 1985; Tesch et al., 1984, Fry et al., 2003). Those studies include both genetics and non-genetic factors as well as training methods, especially the various types of resistance exercise (Fry et al., 2003). The main objective was to determine the relationship among muscle fiber subtypes, contractile protein expression, and physical performances of weightlifters. Several studies integrate a model for muscle energy consumption with conventional Hill-type model for muscle contraction (Bhargava et al., 2004; Bisi et al., 2011; Buchanan et al., 2005). To ensure the reliability of the biomechanics measurements, electromyography (EMG) has been used to measure and explore EMG amplitude within a muscle (Bisi et al.,

2011; Brandon et al., 2013; Buchanan et al., 2005; Yavuz et al., 2015). EMG amplitude has been explored in the transverse abdominis, spinae, vastus lateralis, trunk muscle, gluteus medius, deltoid and/or biceps across different phases of training exercises. Figure 1.3 shows the flowchart of the modeling procedure proposed by Bisi et al. (2011), with subject-specific model parameters calibrated by comparing joint moment predictions of the model with joint moments estimated by inverse dynamics.

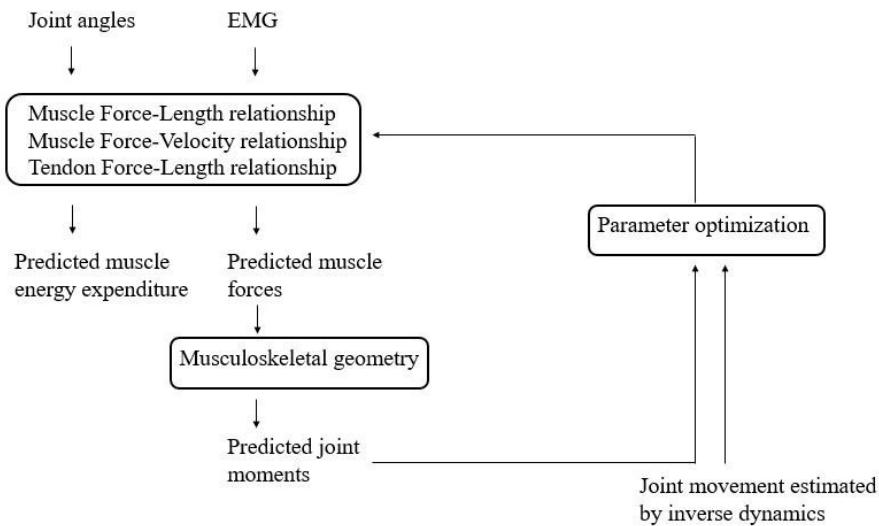


Figure 1.3 Flowchart of the modeling procedure proposed by Bisi et al. (2011), consisting of the skeletal structure and muscles behavior sub models.

Although most of the EMG-driven models address generic human movement, Brandon et al. (2011) work specifically assessed the reliability of a novel analysis system for Olympic weightlifting, comparing surface electromyography (sEMG) synchronized with electrogoniometry and a barbell position transducer. There was good reliability in all three variables measured: normalized sEMG amplitude of vastus lateralis, knee joint motion from electrogoniometry, and mean power from barbell displacement data during the concentric phase of the barbell squat exercise. Therefore, the authors concluded that the system used is relatively inexpensive and simple to use, which, combined with the good reliability, enables a useful monitoring tool of strength training, able to detect meaningful changes in muscle activation or performance.

Power has been considered to be important for athletic performance because it is one indication of the ability to produce force quickly. While some researchers have found the correlations between the ability to produce high power outputs and specific measures of athletic performance (e.g. Sleivert et al. 2004), some have reported dissimilar findings (e.g. Harris et al. 2008a). In contrast, most investigations assessing

the correlation between muscular power output and playing ability level have reported significant relationships (e.g. Baker et al. 2001; Baker et al. 2002; Baker et al. 2008). Indeed, some researchers have found that power outputs are very good discriminators of which level athletes are currently competing at (e.g. Baker et al. 2008). In weightlifting, most of the many studies regarding mechanical power outputs during weightlifting exercise are related to external power outputs which focus on the effects of manipulating the load and the subsequent effects on maximal power outputs, obtained from either barbell kinematic data, ground reaction force (GRF) data, or a combination of both (Cormie et al., 2007; Hori et al., 2007; Kawamori et al., 2005). Only a few (Enoka, 1988; Kipp et al., 2013; Kipp et al., 2012) studied internal power outputs due to the expensive price of the equipment needed to acquire the data necessary to calculate the internal joint power, and also to alleviate required information, processing, effort, and time overheads. While the external power outputs data provide important information which is easy to acquire, they do not provide an insight into the used power production of the individual joint. Furthermore, although the internal power outputs data provide more information, they are not practical to use. Many instruments are widely utilized in literature to measure the gains in power output such as force platforms and position transducers (e.g., linear position transducer, video camera). While the former is often considered to be the preferred method as it directly measures the force applied to the ground through the feet, the validity of the latter has been questioned, given that the force values must be estimated (Cormie et al., 2007; Hori et al., 2007). Although the previous studies agree that linear position transducer measurements may not be directly comparable to force plate measurements, they still can be effectively used in the practical setting. Given the cost-effective means of data collection, this is especially true when the same method is used to monitor athletes' progress over time (Cormie et al., 2007; Cronin et al., 2004, Hori et al., 2007).

1.3.3 Nutrition Status of Weightlifters

Besides providing the energy for training, competition, and recovery, in the case of weightlifting and other strength-power sports, nutrition also promotes training adaptations, including skeletal muscle hypertrophy (Slater & Phillips, 2011). A summary of the reported dietary intake of adult strength-power athletes in training (Chen et al., 1989; Hassapidou, 2001; Storey & Smith, 2012), regarding to macronutrient consumption, showed that weightlifters consume a greater number of daily servings of protein-rich sources when compared with other athletes. As a result, the protein intake of male weightlifters has been reported to range between 1.6 g/kg/day and 3.2 g/kg/day, which is higher when compared with the recommended 1.6–2.0 g/kg/day for resistance training athletes. Furthermore, weightlifters derive approximately 40–44% of their daily energy intake from dietary fat, which is also well above the acceptable range for health and athletic performance of 20–35%. This is probably a consequence of their greater intake of protein-rich animal products. Conversely, the reported carbohydrate intakes in weightlifters of 2.9–6.1 g/kg/day are insufficient according to the current recommended levels of 7–12 g/kg/day for athletic individuals (Rodriguez et al., 2009; Slater & Phillips, 2011). Combined, these reports suggest that the dietary habits of male weightlifters may not yield the desired training gains and/or health benefits, due to the emphasis placed on protein consumption (with high fat) at the expense of adequate carbohydrate ingestion.

1.3.4 Semantics-related Works

This section presents several related works that use semantic web techniques in similar situations and domains. It focuses on biomechanics, food/nutrition or health-related fields using ontology and SWRL rules approaches.

A) *Ontology related to Biomechanics*

A survey of ontology-based work regarding to health-related fields is presented by Ullah & Khan (2015) but none of the described ontology address biomechanics. The main focus was on knowledge construction and representation by first identifying three main classes of medical ontologies: generic, specific, and Mass Casualties Incidents (MCI). Furthermore, they investigated the suitability of such ontologies for use in MCI which is one of the newly proposed security protocol to measure and handle all kinds of situation on disaster locations due to flood, earthquakes or plane crash. Rosse &

Mejino (2003) proposed Foundational Model of Anatomy (FMA) as a reference ontology in biomedical informatics for correlating different views of anatomy, aligning existing and emerging ontologies in bioinformatics ontologies, and providing a structure-based template for representing biological functions. FMA is based on the terminology and structure of the Terminologia Anatomica (TA), a structured vocabulary designating the anatomical entities that comprise the human body. Mogk et al. (2013) presented the Parametric Human Project (PHP) that is assisted by an evolvable ontological framework, supporting knowledge regarding human anatomy and biomechanics, and the relationship between form and function. Such framework incorporates sufficient granularity to support the assembly of a "complete" human model that enables multi-purpose, multi-scale modeling and simulation. It is assisted by existing anatomical and biomedical frameworks such as Ontology of Physics for Biology (OPB) and My Corporis Fabrica (MyCF). OPB was used to extend existing ontologies for biological entities (e.g., molecules, cells, and organs), with physical properties such as energies, volumes, and flow rates. Basically, OPB is a computational ontology designed by Cook et al. (2013) to declaratively represent the formal structure of systems dynamics theory and thermodynamics, as they relate to biological processes. Mainly, it is used in the annotation and representations of biophysical knowledge encoded in repositories of physics-based bio-simulation models. OPB was first described by two classes, the *Physical entity* and *Physical property* and later extended with the *Physical dependency taxonomy* of classes to represent rules by which physical properties of physical entities change during occurrences of physical processes. MyCF was built on FMA while extends it with topological, geometrical, and functional aspects of individualized anatomy. In PHP, MyCF is used to store multiple instances of the same anatomical entity and so, representing general variability in human anatomy based on the number of instances that exist in the database. Rabattu et al. (2015) describes MyCF Embryo assisted by 3D models and an ontology to enable a declarative description of different embryological models that capture the complexity of human developmental anatomy. The proposed ontology describes the compositions of organs and structures while integrating a procedural description of their 3D representations, temporal deformation and relations with respect to their developments. Dicko et al. (2013) presented and discussed a biomechanical simulation ready-model through the integration of an anatomical ontology with specific data. Receiving user-defined functional descriptors, anatomical entities such as bones and muscles are generated according to the ontological knowledge. It also generates physical model based on reference geometry.

and mechanical parameters assisted by user-defined functional descriptors. Additionally, they detailed an example of a musculoskeletal simulation of knee flexion and hip flexion and abduction, based on rigid bones and the Hill muscle model, with subject-specific 3D meshes non-rigidly attached to the simulated bones. Anderson et al. (2008) described a new ontology aimed towards the neuromuscular simulation field to promote collaboration and knowledge sharing between partners in different subdomains. The reusable knowledge infrastructure or ontology is extended to handle model specific data, simulation setup, results and discussions/conclusions. Gündel et al. (2013) presented, HuPSON, a human physiology simulation ontology as a basis for shared semantics and interoperability of simulations, models, algorithms, and other resources in the Virtual Physiological Human (VPH) domain. It is based on Basic Formal Ontology while adhering to the Minimum Information to Reference an External Ontology Term (MIREOT) principles. Dao et al. (2009) designed OSMMI, an extensible ontology to help understanding the impact of pathologies of the musculoskeletal system on the gait in biomechanics. OSMMI ontology focuses on the lower limbs of the human body and consists of 14 classes and their 10 relations. Classes are *Nervous system, Ligament, Muscle, Tendon, Cartilage, Bone, Limb, Posture, Support of load, Diarthrosis Joint, Movement, Articular, Contact, Contact of environment* and *Gait* while relations are *inform, command, attach, compose, act, influence, form, support, create, and characterize*. Turcin et al. (2013) described ways how OSMMI ontology can be mapped to data warehouse models and steps in decision support system creation. In so doing, they present a generic 7 steps data mining algorithm, data warehouse where measures are organized, collected, and represented as facts which are hold in fact tables, as well as issues regarding gait disorder based on knee injuries.

To the authors' knowledge only few of existing ontologies are oriented to biomechanics field but with the main focus on clinical settings, such as rehabilitation, orthopedics, and surgery. They are too generic and so, requiring further extensions to describe details demanded by biomechanics of weightlifting.

B) Ontology related to food recommendation

The attempt to implement and develop a knowledge-driven information system which is capable of generating consistent healthy diet plans based on users' existing health and medical conditions (e.g., diabetic, losing weight, and chronic kidney disease) is not recent. There is a large number of projects and publications concentrating on this topic. The research work by Snae & Bruckner (2008) presented Food-Oriented

Ontology-Driven System (FOODS), a counseling system for food or menu planning in a restaurant. The ontology contains specifications of ingredients, substances, nutrition facts, recommended daily intakes for different regions, dishes, and menus. This expert system assists in finding the appropriate dish for the consumers based on their individual nutrition profiles. FOODS comprises of a food ontology, an expert system using the ontology and some knowledge about cooking methods and prices. Its user interface is suitable for both novices and experts in computers and diets. Protégé is used as the tool for setting up the ontology in OWL with the combination of bottom-up and top-down approaches. Fudholi et al. (2009) designed and developed the daily menu assistance using ontology concept. It includes the knowledge of the domain concept and its relationships based on semantic web application, with users entering their required personal data to calculate the energy expenditure. Then, the system calculates the data and gives an appropriate menu from database. The drawbacks of these systems are lacking the indicators of nutrient balance, energy requirement, and caloric ratios related to the meal or menu chosen. Many researchers developed a personalized food recommendation system more specifically for diabetics. The objectives are to help them controlling blood glucose level and to prevent the complications. Such as, Chang-Shing et al. (2008) proposed Intelligent Diet Recommendation Agent (IDRA) by using fuzzy set based inference mechanism to recommend diet menu for dinner. The system calculated and recommended menu by analyzing whole day taken meal with users entering their food eaten. Then the system adjusted how many calories and nutrients is needed or lack for dinner. The limitation of IDRA is the lack in defining relationships between food items and diabetes (e.g., which food item is recommended or not for diabetes) and counseling only the remaining calories for dinner intake, instead of all daily meals. Suksom et al. (2010) implemented a rule-based personalized food recommender system. The objective is to assist users who have a special nutrition need (e.g., diabetics) in daily diet selections based on some nutrition guidelines. The main components of the system are user personal profiles, food and nutrition databases, and knowledge base. The developed food and nutrition ontology is integrated with rules and stored in the knowledge base. The system utilizes the knowledge base in providing recommendations based on nutrition requirements of each user. However, the systems have limitations similar to those of FOODS, which were mentioned before. Phanich et al. (2010) proposed Food Recommendation System (FRS) by using food clustering analysis (i.e., Self-Organizing Map and K-mean clustering) to help diabetics select foods. They recommended the proper substituted foods in the context of

nutrition and food characteristic based on the similarity of eight significant nutrients. Food items are grouped together in various classifications based on their different nutrient values definition. Therefore, in order to use this system effectively, users should have some nutrition knowledge before using it. Exercise or physical activity which is considered to be an important factor to calculate the energy requirement is completely ignored. This is the limitation of all systems that were mentioned above. Therefore, some researchers tried to add “exercise or physical activity” as a factor to calculate energy requirement to their systems in order to make them more accurate. For example, Usthasopha et al. (2010) presented a new nutrition counseling system for food menu planning (NCS). It was designed and implemented by combining two technologies, K-means clustering and expert system in order to assist users to find appropriate food menu based on gender, height, weight, and exercise activity to meet their energy requirement. However, this system is not proper for users with chronic diseases or professional athletes. Faiz et al. (2014) developed Semantic Healthcare Assistant for Diet and Exercise (SHADE) by integrating ontology semantically (based on person, food, disease, and exercise domain). It generates recommendations as inferences based on data and rules using Pellet reasoner. SHADE recommends diet and exercise suggestion for diabetics. The recommendations are dynamic as they are based on recent blood glucose level, taken meal, and performed activities. However, this system is a prototype application, initially as a case study, for only type 2 diabetics.

Only few researchers were interested to develop food recommending system for professionals and amateur athletes. For example, Minnea et al. (2011) proposed recommender system of workout and nutrition for runners by integrating web crawling and ontology. The system is a mixture between experts' knowledge and a social dimension in generating the nutrition and workout plan. The system provides information to users regarding the workout (training program) and treatment recommend in case of injury alongside diet plan that best suits them, based on their profile information, food preferences, and goals. However, the user's target group for this system is beginners, to assist them keeping the performers in shape.

1.3.5 Conclusions

The following Table 1.1 presents a gap analysis among the most important recent research frameworks compared to our envisioned solution.

Table 1.1 Gap analysis among existing frameworks based on ontology support, scope, and intended use.

References	Ontology	Nutrition	Weightlifting	Biomechanics
FOODS (Snae & Bruckner, 2008)	✓	✓		
IDRA (Chang-Shing et al., 2008)	✓	✓		
Protégé, SWRL and SQWRL in Fuzzy Ontology-Based Menu Recommendation (Fudholi et al., 2009)	✓	✓		
FRS (Phanich et al., 2010)	✓	✓		
Food and Nutrition Recommender System (Suksom et al., 2010)	✓	✓		
Nutrition Counseling System and Food Menu Planning (Usthasopha et al., 2010)	✓	✓		
The Runner (Donciu et al., 2011)	✓	✓		
SHADE (Faiz et al., 2014)	✓	✓		
FOODS-Diabetes Edition (Boulos et al., 2015)	✓	✓		
Parametric Human Project (Mogk et al., 2013)	✓			✓
OSMMI ontology (Dao et al., 2009)	✓			✓
Ontology for Gait Analysis (Turcin et al., 2013)	✓			✓

We conclude that an ontology-driven weightlifting knowledge model may be the right solution for promoting a better understanding of the weightlifting domain as a whole, since it can unify concepts and terminologies among weightlifting stakeholders, and at the same time obviate the paucity and inconsistencies of existing results. The weightlifting knowledge model should be scalable to easily integrate further related domain of weightlifting, and also used to support the implementation of weightlifting Recommender Systems. By developing it in the form of ontology and presented as a separate component in the architecture of the recommender systems, it also leverages flexibility, adaptability, and easy upgradability to the latter.

1.4 Thesis Structure

This thesis is organized as follows:

- *Chapter 2* describes the use of integrated PCA and HCA method as an exploratory tool to find and/or understand possible similarities and hidden patterns among lifters with different skills.
- *Chapter 3* describes the design and implementation of an ontology-based personalized dietary recommendation for weightlifting. The implemented system was used as an exploratory tool to partially understand the weightlifting TDC-cycle, mainly regarding the nutrition and training domains.
- *Chapter 4* presents and discusses the first-iterated Weightlifting TDC-cycle ontology rule- and knowledge-based system. It describes the ontology-driven approach used to model each identified domains (i.e., weightlifting, training, and nutrition), the analysis and design of each individual ontology, as well as the integration of individual ontologies.
- *Chapter 5* presents and discusses the second-iterated Weightlifting TDC-cycle ontology, refactored toward improved modularity, flexibility and scalability.
- *Chapter 6* presents and discusses the third-iterated Weightlifting TDC-cycle ontology, refactored toward improved flexibility and scalability, comparatively to the second iterated version.
- *Chapter 7* concludes this thesis by presenting the conclusions of our research and the limitations found during the development of our weightlifting knowledge model, as well as suggestion regarding the future work towards fulfilling the aforementioned limitations.
- Next a *list of references* is presented.
- *Appendix* presents A) Ethical Approval; B) Written consent form; C) Nutrition status of Thai national team weightlifters; D) The drafted questionnaire template used to collect knowledge regarding sport nutrition of Thai weightlifters; E) Used tools for modeling the ontologies.

CHAPTER 2

Power Output Patterns of Young Weightlifters during Snatch

In order to provide biomechanical answer to the previously introduced main problem statement of this thesis (i.e., “*How can each of the main weightlifting research domains of biomechanics, nutrition, and training methodology be modeled?*”), experiments need to be conducted to investigate and define the biomechanical profile of weightlifter. The main interest is directed to “Power output” as an indicator to assess performance changes and provide feedback of training program. This current chapter proposes the use of integrated PCA and HCA method as an exploratory tool to find and/or understand possible similarities and hidden patterns of power output during snatch among young weightlifters with different skills. The chapter starts with the definition and the importance of muscle power, the methods of measuring the power output, the literature review of power output in Olympic weightlifters, and time series data mining. Then, it continues with the objectives, methods, results, and discussion. Lastly, the use of LCSS technique is presented to improve the power of the discrimination power output pattern in weightlifters.

Introduction

Power is a measure of how much work can be performed in a given period of time and it can be calculated as a product of force and velocity (Hedrick, 1993). In the Olympic weightlifting, as a sport activity which completed in a very short period of time, the success of a weightlifter's attempt is largely affected by the athlete's power output capacity (Hori et al., 2007). Therefore, improving power-generating ability of the muscle is one of the main goals for weightlifting training program. Moreover, monitoring and tracking the power output profile is useful for coaches and athletes to assess performance changes, provide feedback of training program, and detect fatigue or/and injuries. Therefore, much experimental research has been conducted to understand how power should be assessed and developed over the last two decades (Cormie et al., 2007; Enoka, 1988; Garhammer, 1980; Garhammer, 1985, 1991, 1993; Hori et al., 2007; Kawamori et al., 2005; Kipp et al., 2013; Kipp et al., 2012; Stone et al., 2003). Three common methods have been used to measure power output in the literature as following: (i) a position transducer is used as an equipment combined with inverse dynamic approach to calculate velocity and force from displacement-time data, (ii) a force platform is used to obtain force data along with the forward dynamic approach to calculate velocity from force-time data, and (iii) both a force platform synchronized with a position transducer are used to obtain velocity and force data. Theoretically, the most logical and valid methodology would be the values obtained from a force platform. However, no matter which method is utilized, the researchers are likely to report these data as the peak power or average power between 2 time points by using standard data analysis techniques. Although these statistical approaches are able to summarize and represent the individual biomechanics of a group in a single pattern (as an average behavior with deviations as possible errors; standard deviation band), they reduce the data severely. They may discard much important information (Donoghue et al., 2008) and, in particular, do not allow further insight into the pattern of power production of an individual athlete over time due to the fact that information is lost during the process of averaging (Hasson & Heffernan, 2011). Based on the importance of power output measurement and the relative absence of studies on the power output patterns of weightlifters, the purpose of this study was to apply PCA (Principle Component Analysis) combined with the HCA (Hierarchical Cluster Analysis) to a power output time series, attempting to

explore four questions: (i) What is the relative power output pattern of each young novice weightlifter during snatch?; (ii) Can the young weightlifters be grouped based on a similarity to one or more patterns?; (iii) Can these groupings be explained?; (iv) Is there any techniques better than PCA combined with the HCA to discriminate the power pattern of weightlifters?

The remainder of this chapter is organized as follows: Section 2.1 describes the definition, the importance of muscle power and the methods of measuring the power output; Section 2.2 presents the literature review of power output in Olympic weightlifters; Section 2.3 presents time series data mining; Section 2.4 describes materials and methods; Section 2.5 presents results; Section 2.6 presents discussion; Section 2.7 explains the use of LCSS technique to improve the power of discrimination power output pattern in weightlifters; and Section 2.8 ends with some conclusions.

2.1 Muscle Power

2.1.1 The definition of Muscle Power

Power, by definition, is a measure of how much work can be performed in a given period of time and it can be calculated as a product of force (N; Newton) and velocity (m/s). So, power can be expressed as a value in N·m/s but it is widely reported as Watts (W) (Hedrick, 1993). In order to understand this topic well, the term of “muscle power” must be defined (e.g., what exactly is being investigated). As explained by Beardsley (2016), the most common outcome measure reported by studies as “muscle power” can be considered into three levels:

- (i) It is either a concentric or an eccentric action that the muscle itself performs. Putting it differently, it is a linear system in which a tensile (pulling) force is generated by the contractile machinery, subsequent to a neural signal;
- (ii) The muscle force acts on a bone, which is fixed to another bone at either one or both ends in the form of a joint. This joint means that there is a pivot and consequently a rotational system in which a perpendicular force acts on the moment arm to produce a moment/torque. If this moment acts on the joint and is not countered by an equal and opposite moment, then the moment produces a rotation of the joint and the rate at which it turns can be measured as an angular velocity. The product of the joint moment and the angular velocity is the joint power (internal power output);

- (iii) Two or more joints act together in concert to produce a dynamic, compound movement (e.g., a leg press or a bench press) and then, there is a linear movement produced by the extremely coordinated interactions of the joints. The output of this linear system, which is sometimes called system power/external power to differentiate it from individual joint powers/internal power, can be measured simply as the force produced multiplied by its linear velocity.

Therefore, internal power is defined as the product of the joint torque and the angular velocity whereas external power refers to the aggregate of multiple joint powers resulting in, such as a combination of hip, knee, and ankle power.

2.1.2 The Importance of Power

The concept of power seems to be so intuitive in weightlifting—a sport which requires explosiveness and the application of maximal strength in the shortest time possible (Newton & Jenkins, 2013). This explosiveness in sport is also termed “speed-strength” which is defined as “any capacity that contains both a force (strength) and speed component to muscular action” (Young, 1993). As proposed by Newton and Dugan (2002), factors contributing to a lifter’s power capacity include maximum strength, high load speed strength, low load speed strength, rate of force development, skill performance, and power endurance. For this reason, the success of a weightlifter’s attempt is largely affected by power-generating ability of the muscle (Hori et al., 2007). Therefore, research has been directed to the topic of how power can be assessed, developed, and monitored in order to assess performance changes and provide feedback to athletes and coaches.

The correlation between the ability to produce high power and athletic performance remains unclear. While Sleivert et al. (2004) presented significant correlation between sprint start performance and power measured during concentric jump squats, Harris et al. (2008) reported very different results. On the contrary, the correlation between muscular power output and playing ability level have revealed significant relationships. As reported by Baker and Newton (2002), professional rugby league players showed significantly higher power output than high school players during weighted jump squat with 20 kg weight. Young et al. (2005) also reported that in professional football players, starters showed higher power output than non-starters during weighted jump squat with 40 kg weight and CMJ without external load. Therefore, it is suggested that power outputs can be used as an indicator to discriminate the level of the athletes.

2.1.3 Methods of Measuring the Power Output

A) Direct Measurement

Many instruments are widely utilized in literature to measure the gains in power output such as position transducers (e.g., linear position transducer, video camera) and force platforms. The power output is commonly measured by using one of the following methods:

- (i) using a position transducer, velocity and force are calculated from displacement-time data, while the resulting power generated to barbell is obtained using inverse dynamic approach (Baker et al, 2001);
- (ii) using a force platform, velocity is calculated from force-time data, while the resulting power in the system (barbell + body) is measured using the forward dynamic approach (Kawamori et al., 2005);
- (iii) using a position transducer, velocity and force are calculated from displacement-time data, while the resulting power in the system (barbell + body) is obtained through the inverse dynamic approach (Stone, O'Bryant, et al., 2003);
- (iv) using a force platform synchronized with a position transducer, force data obtained from the force platform is multiplied by the velocity data read from the position transducer as the resulting power in the system (barbell + body) (Young et al., 2005).

The power output calculated using these methods is classified as an external or system power. To calculate joint or internal power, a motion analysis system is needed to collect joint position data throughout the movement. Angular velocities and accelerations are derived from angular position data and they are used to calculate joint torques. The product of joint torque and angular velocities is equal to the joint power (Noffal & Lynn, 2012).

B) Indirect Measurement

Although the most logical and valid methodology to measure power output values is obtained directly from force platforms or position transducers, the access to those instruments is limited due to the expensive price of such equipment. Therefore,

coaches have been searching for alternative testing methods that can be easily performed in a practical setting. Previous research has showed the relationship between power output and measures of explosive strength such as weighted jump squats (Stone, O'Bryant, et al., 2003), bench press (Cronin et al., 2000), and throwing performance (Stone, Sanborn, et al., 2003). Vertical jump has also reported to measure and refer to this as a field-test approach for estimating power output and weightlifting ability (e.g., squat, snatch, and clean and jerk) (Carlock et al., 2004).

2.2 Literature Review of Power Output in Olympic Weightlifters

Most of the many studies regarding mechanical power outputs during weightlifting exercise are related to external power outputs which focus on the effects of manipulating the load and the subsequent effects on maximal power outputs, obtained from either barbell kinematic data, ground reaction force (GRF) data, or a combination of both (Cormie et al., 2007; Hori et al., 2007; Kawamori et al., 2005). Only a few (Enoka, 1988; Kipp et al., 2013; Kipp et al., 2012) studied internal power outputs due to the expensive price of the equipment needed to acquire the data necessary to calculate the internal joint power, and also to alleviate required information, processing, effort, and time overheads. While the external power outputs data provide important information which is easy to acquire, they do not provide an insight into the used power production of the individual joint. Furthermore, although the internal power outputs data provide more information, they are not practical to use. Consequently, Kipp et al (2013) tried to find correlations between internal and external power outputs during weightlifting exercise. Their findings supported the use of the traditional work-energy method to make inferences about joint/internal power outputs from system/external power outputs during the clean at loads of 85% of 1-repetition maximum (1RM) and the impulse-momentum method to make inferences about the sum of all joint/internal power outputs from system/external power outputs at loads of 75 and 85% of 1RM. The work-energy method calculates the power output by summing the total amount of potential and kinetic energies up to the point of maximum vertical barbell velocity and divides this sum by the time taken to reach this point. The impulse-momentum method calculates power output as the product between the vertical velocity of the barbell-lifter system and the vertical component of the GRF vector.

No matter which method is utilized, the researchers are likely to report these data as the peak power or average power between 2 time points by using standard data

analysis techniques (i.e., determination of mean, standard deviation, etc.). They also focus on the best performance of an athlete in a particular phase (i.e., power output during the first pull phase or the second pull phase) (Akkus, 2012; Gourgoulis et al., 2000; Hadi et al., 2012; Okada et al., 2008). Although these statistical approaches are able to summarize and represent the individual biomechanics of a group in a single pattern as an average behavior with deviations as possible errors (e.g. standard deviation band), they reduce the data severely. They may discard very important information (Donoghue et al., 2008) and, in particular, they do not allow further insight into the pattern of power production of an individual athlete over time because that information is lost during the process of averaging (Hasson & Heffernan, 2011).

Because the investigation of the power output pattern (timing and temporal structure) may provide additional information for weightlifting training design, time-series data analysis techniques are needed to detect altered movement patterns or to differentiate the power output patterns of individual lifters. One of the statistical approaches which is suggested to be a powerful tool to solve these kind of problems is multivariate statistical analysis. It offers the capacity to eliminate collinearity and to facilitate analysis, presenting only the essential structures hidden in the data (Dona et al., 2009). Among these multivariate statistical techniques, a method commonly used to identify and quantify movement techniques in sports is Principal Component Analysis (PCA) (Hotelling, 1933). PCA is a pattern recognition method used to extract feature from the large datasets (e.g., time-series data) or to classify and determine group differences. It is widely used in sport analysis (Dona et al., 2009; Kipp & Harris, 2015; Troje, 2002; Troje et al., 2005). Moreover, PCA can be combined with classification procedures such as cluster analysis (e.g., Hierarchical Cluster Analysis (HCA)) where PCA is defined as an unsupervised feature extraction technique (Webb, 2002), for instance to classify movement patterns of athletes with different skill levels (Schorer et al., 2007; Watelain et al., 2000).

2.3 Time Series Data Mining

The term “time series” can be defined as a sequence $X = (x_1, x_2, \dots, x_m)$ of observed data over time, where m is the number of observations. By tracking a time series of data/phenomenon/movement and recognizing differences in patterns of data, important information can be produced. Typical characteristics of time series data are high-dimensionality and feature correlation, combined with the measurement-induced

noised which make the classic data mining algorithms analysis ineffective and inefficient for time series. As a results, time series data mining has received attention in the past two decades. Many approaches have been used for recognizing patterns and mining of time series data which can be classified into three categories: (i) *unsupervised learning* when a given pattern is assigned to an unknown class (e.g., clustering; hierarchical clustering), (ii) *supervised learning*, when a given pattern is assigned to one of the pre-defined classes, using labeled data to build a model or guide the pattern classification (e.g., classification; k-nearest neighbors), and (iii) *semi-supervised learning*, when a given pattern is assigned to one of the pre-defined classes, using both labeled and unlabeled data (e.g., semi-supervised classification; 1-NN) (Jessica Lin). However, when dealing with high-dimensional data, the computational cost of using those methods often prevents the method from being applied. Therefore, dimension reduction are carried out as a pre-processing step. Typically, this is accomplished by applying PCA. In this study, in the first session PCA and HCA are applied as “unsupervised classification” method to study the data structure, look for similarities between relative power output patterns among athletes, and evaluate whether clusters exist in a dataset.

2.3.1 Principle Component Analysis (PCA)

PCA (Hotelling, 1933) is probably the most popular multivariate statistical technique which is used by almost all scientific disciplines. The goals of PCA are to extract the most important information from the data table, compress the size of the data set by keeping only the important information, simplify the description of the data set, and analyze the structure of the observations and the variables. To achieve these goals, PCA must be able to compute new variables called principal components which are obtained as linear combinations of the original variables. The first principal component is required to have the largest possible variance (i.e., this component should explain or extract the largest part of the inertia of the data table). The second component is computed under the constraint of being orthogonal to the first component and to have the largest possible inertia. The other components are computed likewise. The values of these new variables for the observations are called factor scores. These factors scores can be interpreted geometrically as the projections of the observations onto the principal components (Abdi & Williams, 2010). While one can use the results of the PCA for the analysis of various data sets or for data reduction only, the results of PCA

can also be combined with classification procedures such as cluster analysis as described by Webb (2002), where PCA is defined as an unsupervised feature extraction technique for further analysis.

PCA were used in sport biomechanics first time by Troje et al. (2002) to analyze the perception of gait in human. The authors showed that the whole body movement of gait contains information that allows human observers or computer classification algorithms to distinguish, for example, between male and female, young and old, happy or sad, relaxed or nervous walkers. Since then, there were many studies following their approach by using it to further investigate the perception of human movement and developing classification or identification algorithms in gait (Chang & Troje, 2009; Troje et al., 2005; Westhoff & Troje, 2007). Only few investigators have applied this method to sports: (i) Dona et al. (2009) applied functional PCA method to distinguish knee kinematic and kinetic differences of competitors at differing levels of expertise in race walking, (ii) Kipp et al. (2012) used PCA to identify multi-joint lower extremity kinematic and kinetic synergies in weightlifting, and (iii) Kipp and Harris (2015) applied the same approach to determine the patterns of barbell's acceleration during the snatch in weightlifting competition.

2.3.2 Hierarchical Cluster Analysis (HCA)

Cluster analysis was developed to identify pattern in high-dimensional datasets. A dataset subjected to cluster analysis typically consists of a collection of objects of interest which are measured on several characteristic dimensions. In order to identify shared patterns between objects, a common metric among the different characteristics needs to be defined. Consequently, the identified metric might afford an estimation of the degree of (dis)similarity between the objects. Cluster analysis uses similarity information to quantitatively group objects into clusters in an iterative step-wise manner. Among the other clustering techniques, HCA (Ward, 1963) is the most popular. It is achieved by using an appropriate metric of samples distance (e.g., Euclidean distance) and linkage criterion among groups. This method begins with many clusters as there are observations, with each observation forming a separate cluster. The algorithm then merges nearest neighbors according to their predefined distance metric, resulting in combination of clusters. The process of combination continues by reducing the number of clusters at each step until all observations are clustered into a single group. The distance between observations are typically

displayed as a simple graphical view of the observation grouping called dendrogram (Blashfield & Aldenderfer, 1978; Kaufman & Rousseeuw, 2008; Rein et al., 2010).

Cluster analysis approaches have been adopted by many researchers for studying in various sports movement. For example, Schorer, et al (2007) investigated movement pattern of five handball players. The objective was to analyze the movement patterns of handball players during throwing to different sections of a goal. Shoulder, elbow, wrist, and hip displacement of throwing side were recorded and analyzed. A two-stage strategy was adapted with a single linkage cluster analysis as the first stage to identify outliers, followed by a cluster analysis using the Ward-algorithm. A group of three major clusters were indicated based on the skill level of the participants. Moreover, by investigating the sub-grouping within clusters, they found that the player with the greatest skill exhibited the greatest levels of movement pattern variability compared with the novice player which used very few movement patterns. Ball and Best (2007) also applied cluster analysis to study force plate data recorded during golf swing. A combination of hierarchical and nonhierarchical cluster analysis method was used to analyze the movement of the center of pressure among 62 participants during swing. The results showed that weight transfer in participants can be distinguished according to two different strategies. The first one was involved in continuous movement of the center of pressure in the forward direction during and after club-ball contact, whereas the second one was involved in the reverse direction during club-ball contact.

2.3.3 Longest Common Subsequence Distance (LCSS)

Although Euclidean distance is most widely used to measure distance among time series due to its simplicity to perform and get the results, it presents several drawbacks, including: (i) it compares only time series of the same length, (ii) it does not handle outlier or noise, and (iii) it has no ability to manage time axis gap (Cassisi et al, 2012) (Figure 2.1a). Euclidean involves in matching a giving point from a time series with the point from another one that occurs at the same time. However, the results from a two-time series with the same shapes that do not occur concurrently on time axis may have high Euclidean distance, which is considered illogical and it can lead to a wrong interpretation.

LCSS distance (Vlachos et al., 2002) is a time stretching distance developed to solve those problems. It matches two-time series together by allowing a given point from one-time series to match with one or several points from the other. Moreover, it allows

them to stretch, without rearranging the sequence of the elements. That is, LCSS can keep some elements unmatched by allowing one point of a time series to be matched with one or zero point of the other (Figure 2.1b). This feature made LCSS distance more resilient to noise than Euclidean distance.

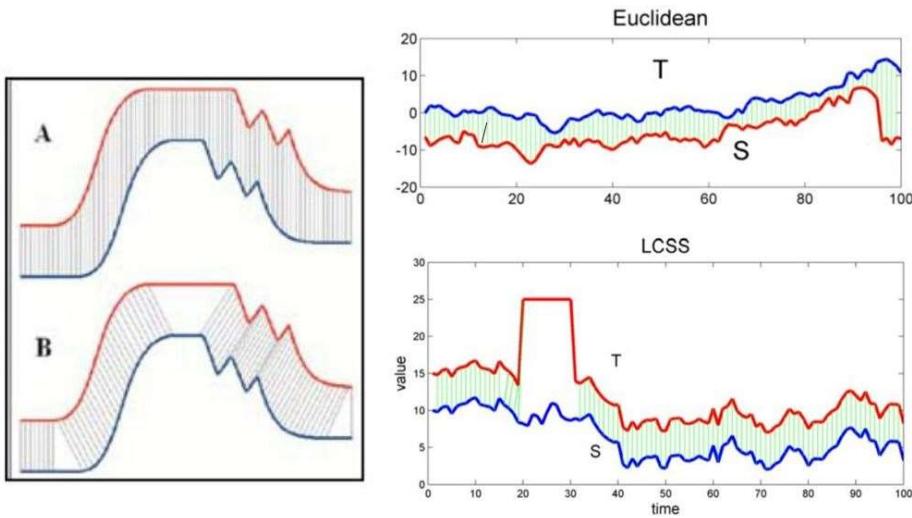


Figure 2.1a, and 2.1b Distance computation between two time series with Euclidean (A) and LCSS (B) (Cassisi et al., 2012)

2.3.4 Interpretation Variables

Many methods have been suggested for the evaluation of the statistic significant of the cluster (e.g., Fisher test), but no satisfactory solution have been found due to the very different structure of clusters found in practical problem. In reality, the significance of a cluster is based on the possibility of interpretation. Interpretation means that the author uses external information to explain the results of each cluster suggested by dendrogram. Frequently, the real problem suggests that some categories exist, therefore, the interpretation step is to compare the number and the composition of the clusters with these categories.

The dendrogram on one interpretation variable does not present mathematical difficulties. The abscissa is the interpretation variable and the ordinate is the similarity. In figure 2.2, is an example of the interpretation variable of the content of proteins. By cutting the dendrogram at similarity of 0.35, three clusters and a singleton are obtained.

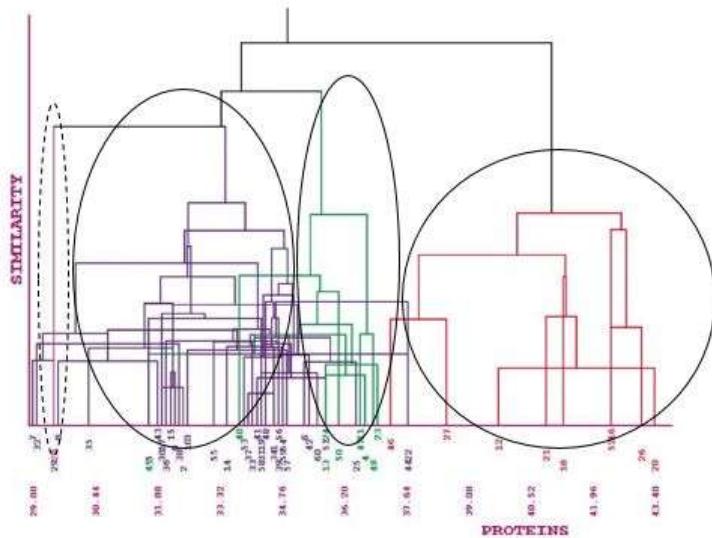


Figure 2.2 An example of dendrogram on the content of proteins

2.4 Materials and Methods

2.4.1 Experimental Approach to the Problem

The rationale of this study was that each lifter has a unique movement pattern which can be modified by training, injury, disease or disability. Some changes are easy to detect from traditional exercise data analysis (e.g., joint torque, joint angle). However, others are challenging. As such, PCA combined with HCA as an advanced human movement analysis technique was applied to a relative power output time series aimed at recognizing differences in patterns of movement. We hypothesized that (i) the analysis would extract and identify the power output pattern of each weightlifter, (ii) power output patterns can be used as a variable to group lifters based on their similarity, and (iii) by adding other biomechanical characteristics (e.g., barbell kinematic variables), we can explain the technical difference among lifters who exhibit a different pattern. To identify the relative power output patterns, we measured the kinematic characteristics of each weightlifter and barbell while they lifted 80% of their respective 1RM. PCA combined with HCA was used to extract the relative power output time-series pattern, while automated clustering was applied to group lifters based on the similarity of their relative power output patterns. The description of the related barbell kinematic variables in each phase of the lift (e.g., barbell velocity, barbell acceleration, and barbell displacement) were added as explanatory variables to the model (relative power output pattern) which could help to explain why individual athletes exhibit different patterns.

2.4.2 Subjects

Seventeen young novice weightlifters (6 boys, 11 girls) participated in this study ($\text{mean} \pm \text{SD}$; age 15.06 ± 1.78 years old; height 158.89 ± 10.72 cm; body mass 58.77 ± 11.83 kg; 1 RM snatch: 46.88 ± 12.05 kg; relative 1RM snatch: 0.8 ± 0.15 kg/kg). All lifters were actively engaged in resistance training programs that involved weightlifting exercises and were members of a school-level weightlifter team. Prior to the experiment, all weightlifters were briefed on the scope of the study and signed informed consent forms approved by the ethical committee of the Faculty of Sport, University of Porto (See in Appendix A and B). All participants reported that they were free of musculoskeletal injury at the time of the study.

2.4.3 Procedures

A brief warm-up was performed prior to beginning data collection. Then, the lifters performed 2–3 repetitions at 50, 65, and 80% of their self-reported 1RM for the snatch. Approximately 2–3 minutes of rest was allowed between each trial. Only data from the final set at 80% of 1RM were considered for further analysis in this study. This load limit was selected because the weightlifting technique stabilizes only at loads $\geq 80\%$, which can be used as a proxy for competitive weightlifting performance (Lukashev, 1982).

Six video cameras (Smart DX, BTS Bioengineering, Italy) were set up around the lifting stage to capture the three-dimensional *motion* of the subject and the movement of the barbell at 100 Hz. Sixteen reflective markers were placed on the lifter's body and two reflective markers were placed at the right and left edge of the barbell axis. GRF data were synchronically collected using two force platforms (Kistler, Switzerland) at 400 Hz.

The kinematic characteristics of each lifter and barbell were determined by the following steps. First, a human model was created and selected anatomical points were digitized manually with the aid of tracking software (Smart tracking, BTS Bioengineering). The points were: base of great toe, ankle, knee, hip, shoulder, elbow, wrist, and barbell. Second, the snatch motion data were associated with the defined model (Smart analyzer, BTS Bioengineering). Third, the raw position-time data were smoothed using a 4th order low-pass Butterworth digital filter with a cut-off frequency of 4 Hz. Fourth, the kinematic variables of the “barbell + lifter” system were computed

(system center of mass position and velocity). Finally, derived biomechanical quantities such as power ($\text{GRF}^*\text{V}_{\text{CM}}$) were computed based on the impulse-momentum method (Hori et al., 2007; Kipp et al., 2013). This method calculated the mechanical power output as the product between the vertical velocity of the barbell + lifter system and the vertical component of the GRF vector. We used this method to calculate the external power output because the correlation of the external power output calculated from this method and the internal power output are more robust over a greater range of loads than any other method. This method captures the power production of the entire lower extremity and the entire lift-barbell system, whereas other methods capture only the mechanical power generated to the barbell (Kipp et al., 2013).

The relative power output (power per total weight i.e., body weight + bar weight) and barbell kinematic variables (e.g., barbell velocity, barbell acceleration, and barbell displacement) were computed as a means of inter-subject comparison (Garhammer, 1981; Hoover et al., 2006; Isaka et al., 1996). However, at the end of this stage, only relative power output time-series data were stored for further processing.

2.4.4 Data Processing for PCA combined with HCA

As a pre-processing step, all relative power time-series were differentially rescaled in time so that the duration of each of the sub-phases became the same among all individuals. Interpolating the time series with cubic splines, *the first pull* on all lifters expanded to 82 points, *the transition* to 18 points, *the second pull* to 11 points, *the turnover* to 27 points, and *the catch* to 194 points. This means that we lost the precise timing information, but we could compare the power evolution on each sub-phase among lifters.

The data processing step was performed by applying PCA combined with HCA on the relative power output time-series (from first phase to catch phase). It consisted of a two-step process. First, the rescaled relative power time-series data were arranged in one 17×336 (snatch lifts \times time points) data matrix that was used as the input to PCA (Hotelling, 1933). The PCA operated to reduce the dimensionality of data and produced a set of eigenvectors and eigenvalues. In order to determine how many meaningful components should be retained for interpretation, we follow “Proportion of variance accounted for” criteria. Based on this criteria, the chosen factors should

explain at least 85% of the variance of the original data (SAS Institute Inc., 2000). Secondly, HCA was used based on the Euclidean distance of the calculated coefficient matrix for automated clustering to identify the inter-individual differences in the relative power output patterns between lifters.

The results of this analysis (PCA+HCA) can be presented as a tree diagram (dendrogram) where each line represents the similarity or the distance between lifters. The length of the vertical lines measures the separation between the merged clusters. It is common practice to “cut” the dendrogram at the similarity corresponding to the longest branches, to obtain “significant” clusters (Forina et al., 2002). Then, the cophenetic correlation coefficient (CPCC) (Sokal & Rohlf, 1962) was computed to measure how well the cluster tree generated by the clustering algorithms (Euclidean distance) reflected the original data. The closer the value of CPCC is to 1, the more accurately the clustering solution reflects the original data (Saraçlı et al., 2013).

2.5 Results

Descriptive data related to power output are presented in Table 2.1. The mean relative peak power output was 4.91 ± 3.17 W/kg, with the subject K showing the greatest value (15.5 W/kg). The mean total relative power output was 98.13 ± 29.84 W/kg, with subjects Q, B, O, and K showing higher value compared to the mean of the group.

PCA was used to extract the relative power output time series with the first-six principal components accounting for 85.56% of the variance in all relative power output profiles (Figure 2.3). Once the six primary principal components were extracted, they were used as the inputs for HCA, which revealed the relationships among lifters. The projection of the dendrogram on the relative power output time series shown in Figure 2.4 revealed that based on the similarity of power patterns, the lifter K showed a significant difference compared with the other lifters (CPCC = 0.9436). Consequently, it can be observed that young novice weightlifters in our study had two different patterns underlying the relative power output time series (Figures 2.5a, 2.5b). The first pattern was performed by the lifter K and was characterized by a very high power output spike during the transition pull phase and another regular power output spike during the catch phase. The second pattern was performed by the rest of lifters and it is related to two regular power output spikes during transition to the second pull phase and another one during the turnover phase. Although, the lifter P showed the spike during the first pull phase, it was not big enough to be detected.

Table 2.1 Power output and the description of related barbell kinematic variables in each phase of the snatch lift.

Subject	Body	Lifted	Relative Peak	Total Relative Power Output (W/kg)	Barbell's Velocity	Max Bar	Max Bar	Max Bar	Drop
	Weight (kg)	Load (kg)	Power Output (W/kg)		1 st to 2 nd pull (%)	Acceleration (m/s ²)	Height (m)	Subject's height (%)	
									Distance (m)
A	29.8	25	6.67	96.13	+35.60	6.90	1.12	84	0.23
B	46.3	32	7.43	144.37	+28.50	8.67	1.23	85	0.24
C	58.7	39	3.12	71.80	+31.56	10.78	1.33	82	0.28
D	65.8	40	2.44	57.93	+48.70	5.51	1.42	87	0.27
E	67.6	43	2.78	85.79	+40.70	10.87	1.42	88	0.31
F	47.7	40	5.40	86.87	+38.16	4.84	1.21	81	0.19
G	62.9	38	4.09	106.65	-8.59	11.15	1.38	84	0.20
H	66.9	49	1.83	56.25	+19.11	12.73	1.23	79	0.22
I	68.8	52	4.92	99.68	-2.74	13.07	1.51	84	0.32
J	69.4	64	4.78	106.40	+34.44	7.30	1.37	78	0.20
K	46.1	50	15.5	126.95	+42.21	6.90	1.08	76	0.12
L	49.0	38	1.77	73.39	+21.38	2.66	1.28	83	0.24
M	54.6	42	3.46	71.68	-5.54	15.36	1.21	78	0.09
N	54.8	57	4.56	82.02	+11.25	7.60	1.24	81	0.21
O	68.5	60	4.81	127.09	+28.60	4.0	1.42	85	0.26
P	69.0	70	6.16	112.54	+26.15	8.11	1.37	83	0.25
Q	73.2	58	3.69	162.72	-14.86	13.75	1.18	75	0.07
Mean	58.77	46.88	4.91	98.13	22.03	8.84	1.29	81.94	0.22
SD	11.83	12.05	3.17	29.84	19.45	3.65	0.12	3.72	0.07

Relative peak power = Peak power output/total weight (body weight + barbell), Total relative power output = Total power output time series/total weight (body weight + barbell), Barbell's velocity 1st to 2nd pull = Barbell's velocity during transition phase (which increase/decrease from the end of 1st pull to 2nd pull phase), Max bar acceleration = Maximum barbell acceleration during the 2nd pull phase. Max bar height = Maximum bar height during the pull phase, Max bar height/Subject's height = (Maximum barbell height/the subject's height) *100, Drop distance = Distance travelled at peak vertical displacement to the point of stability in the catch position.

Barbell kinematic variables are shown in Figure 2.6-2.9 to explain the technical difference between lifters who exhibited such a different relative power output pattern (lifter K and other lifters (mean \pm SD)). More description of related barbell kinematic variables in each phase of the lift are presented in Table 2.1. The results showed that the mean of barbell velocity increase during transition phase was $22.03 \pm 19.45\%$, i.e.,

only 4 lifters (Q, M, G, I) lost barbell velocity from first to second pull. The mean of maximum barbell acceleration during second pull was $8.84 \pm 3.65 \text{ m/s}^2$ and 7 lifters (C, E, G, H, I, Q, M), showing a maximum barbell acceleration higher than the mean of the group. The mean of maximum barbell height was $1.29 \pm 0.12 \text{ m}$ ($81.94 \pm 3.72\%$ of subject's height) and lifters Q and K showed the lowest maximum barbell height. The mean of drop distance was $0.22 \pm 0.07 \text{ m}$, lifters Q, M and K showed the lowest drop distance value compared to the mean of the group.

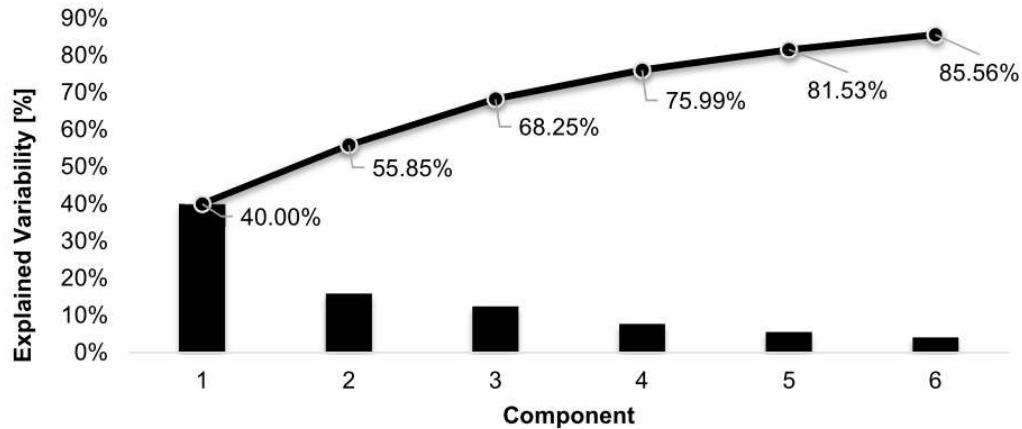


Figure 2.3 Variance explained by principal components for relative power output in sagittal plane. Each bar represents the variance explained by the corresponding PC (Principal Component); the line above each bar shows the cumulative percentage.

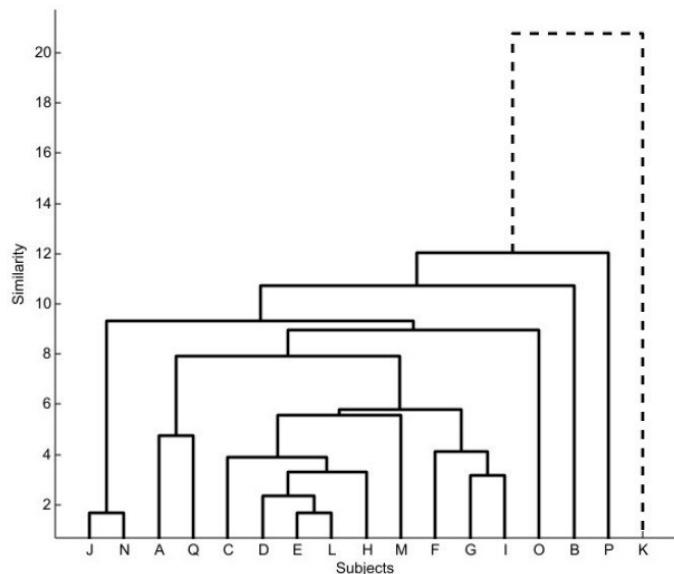


Figure 2.4 Dendrogram of the hierarchical cluster based on Euclidean distance presenting the classification of relative power output during snatch (from lift-off to catch phase) of young novice weightlifters.

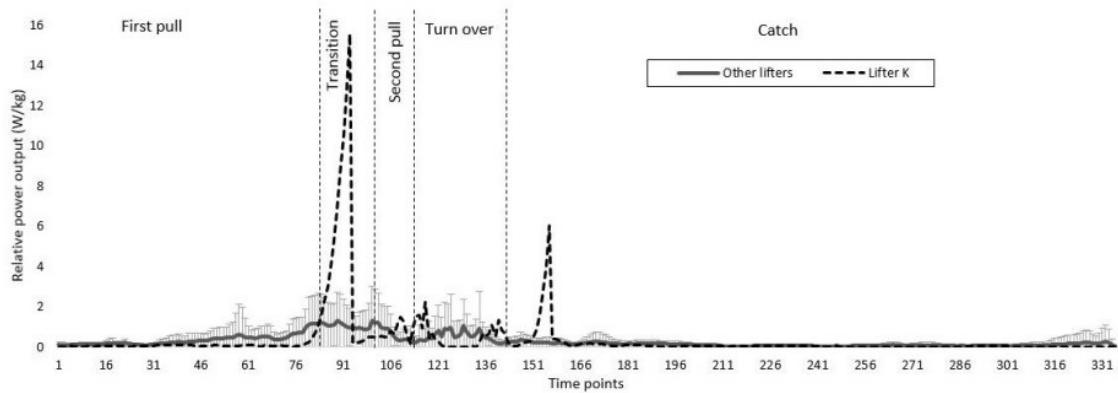


Figure 2.5a Comparison pattern of relative power output time series between the lifter K and other lifters (error bars shown mean \pm SD).

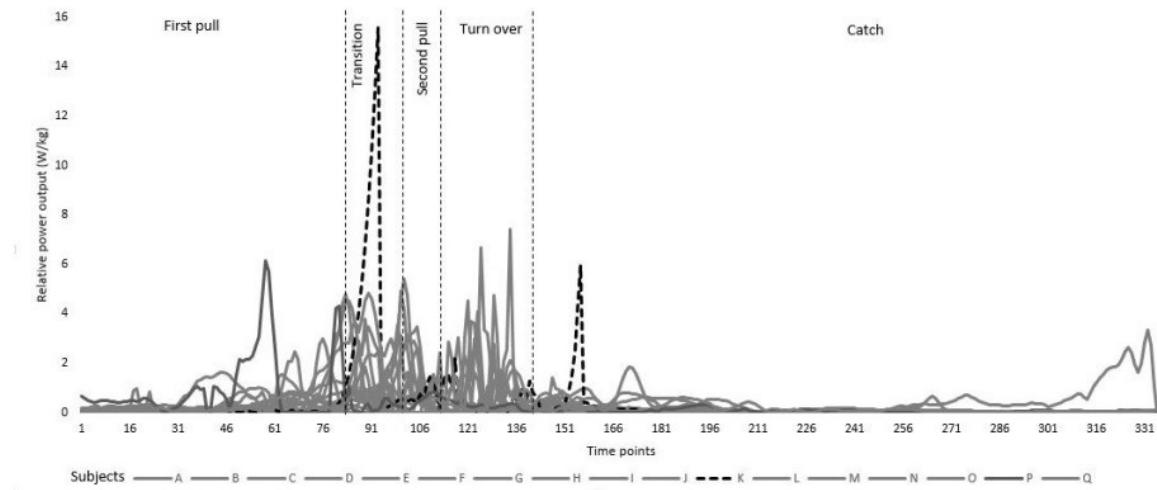


Figure 2.5b Comparison pattern of relative power output time series between individual lifters.

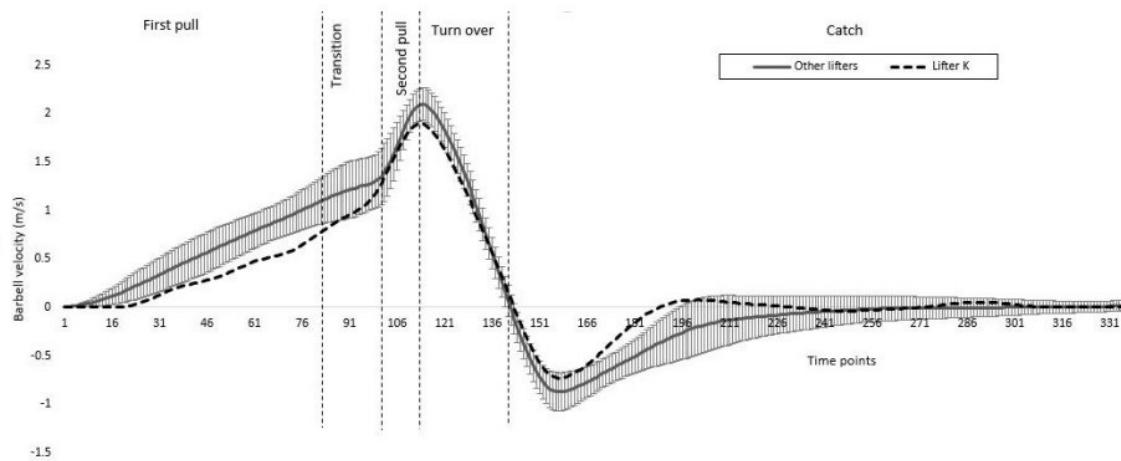


Figure 2.6 Comparison pattern of barbell velocity time series between lifter K and other lifters (mean \pm SD).

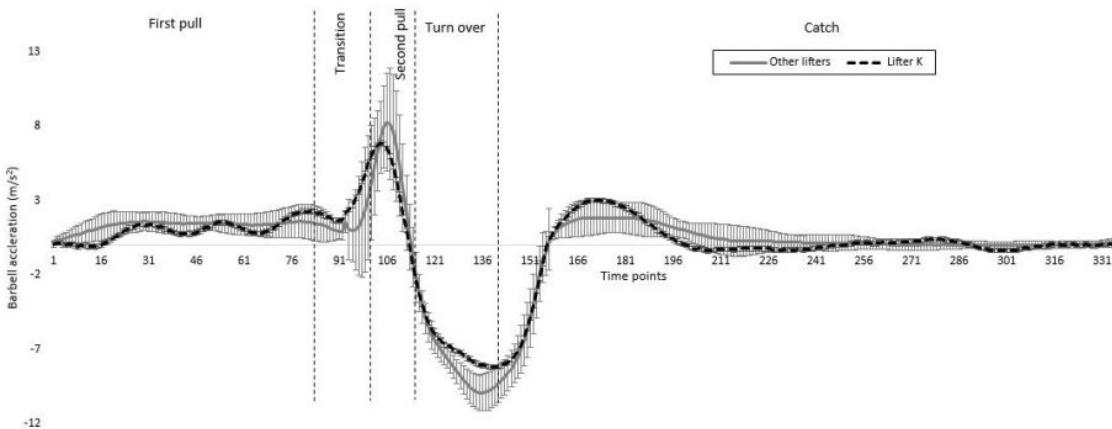


Figure 2.7 Comparison pattern of barbell acceleration time series between lifter K and other lifters (mean \pm SD).

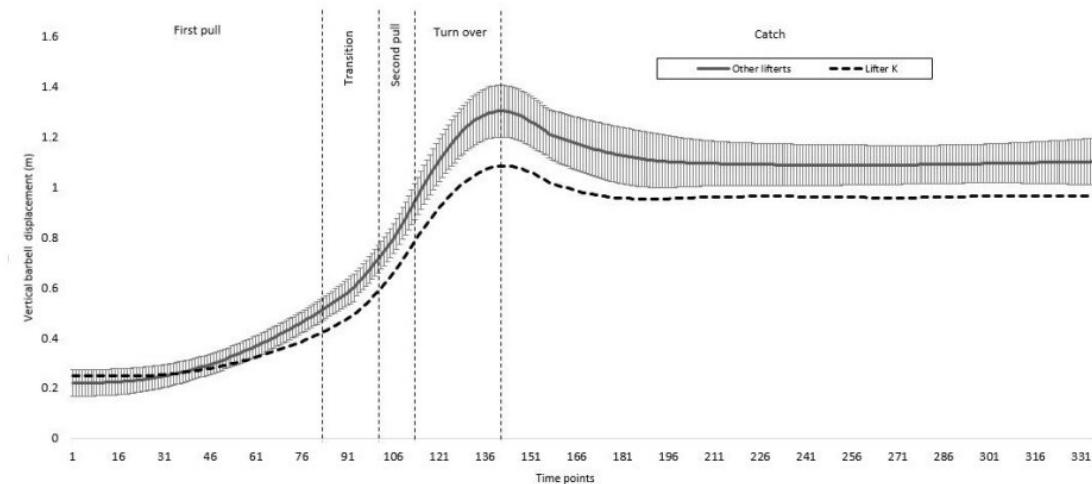


Figure 2.8 Comparison pattern of vertical barbell displacement time series between lifter K and other lifters (mean \pm SD).

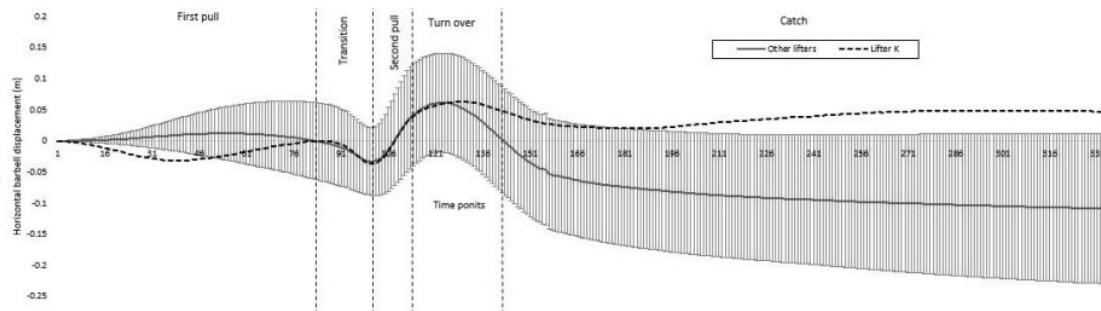


Figure 2.9 Comparison pattern of horizontal barbell displacement time series between lifter K and other lifters (mean \pm SD).

2.6 Discussion

The results of this study showed that by applying PCA combined with HCA to the relative power output time series, we were able to identify the power output pattern of each weightlifter, separate lifters who had a distinctly different pattern out of the group and group those who were similar. Moreover, by adding barbell kinematic variables as explanatory variables, we were able to speculate on the technical variation that may explain these differences.

The relative power output pattern of young novice weightlifters in this study can be identified according to two different patterns. The first pattern was performed by the

lifter K (i.e., high peak during transition phase and regular peak during catch phase) and the second pattern was performed by the rest of the group (i.e., regular peak during transition and turnover phase) (Figure 2.5). This finding is different from previous research (Garhammer, 1980; Garhammer, 1991; Gourgoulis et al., 2000) which reported the performance of adult elite weightlifters. The previous research results showed that the majority of power production of weightlifters during snatch is related to the pulling movement component, with the mechanical power presented in the second pull phase being significantly higher than that in the first pull phase. Gourgoulis et al (2004) found that the average relative power output was significantly lower for adolescent weightlifters during both the first and second pull phases compared to adult weightlifters. The difference can be explained by the fact that the explosive power output in the second pull is a result of flexion of the knee during the transition phase. Such knee flexion should be performed rapidly enough to allow the storage of elastic energy and elicit a stretch reflex immediately following the concentric contraction of the knee and hip joint extensor muscles. The adolescents showed significantly less bending in the knee joint during the transition phase and less angular extension velocity of the knee during the second pull phase. These characteristics indicate their lower ability to utilize the stored elastic energy compared to the adults. Therefore, the results of adults might not be a valid comparison in this study because our subjects were young weightlifters with different levels of maturity. Our finding was also different to that of Gourgoulis et al (2004) in some points, i.e., our study reported the power output pattern along the snatch movement in which peak power appeared during the transition phase, whereas Gourgoulis reported only the power output during the first pull and the second pull phase, while it seemed that the peak power happened in the second pull. This difference is perhaps due to:

- (i) *The different level of athletes* as subjects in the previous study were national-level weightlifters with relative 1RM 1.50 kg/kg, while our subjects were school-level weightlifters with relative 1RM 0.8 kg/kg;
- (ii) *The different method of calculating external mechanical power output* as in the previous study is used the work-energy method which only calculates mechanical power generated to the barbell (the ability to import power to an external object). Therefore, it excludes power produced by the lifter-barbell system or the lifter alone (Gourgoulis et al., 2004; Hori et al., 2007), while our

study used the impulse-momentum method which calculated mechanical power from GRF and velocity data of the lifter-barbell system (reflects the mechanics of the entire system). Most of researches (Garhammer, 1980; Garhammer, 1991; Gourgoulis et al., 2000; Gourgoulis et al., 2004) used the work-energy method because there is no equipment required (e.g., force plate). However, we used another method because it is more suitable for our subjects. Since our subjects were young novice weightlifters, most of the mechanical power they generated were to lift their own center of mass more than lift the barbell.

Improved performance in weightlifting can result from increased strength and improved technique (Garhammer, 1980) and both of these changes would increase the power output value. Therefore, in this study, we attempted to use barbell kinematic variables as explanatory variables to help explain the technical difference between lifters who exhibited different relative power output patterns. The pattern of the barbell's vertical linear velocity is important for assessing the lifting technique (Baumann et al., 1988; Garhammer, 1985; Isaka et al., 1996). A lifter with a good, effective technique is one who can pull the barbell smoothly during the transition phase without a notable dip in the velocity. On the other hand, decreasing the barbell's velocity before the second pull (appearing as two velocity peaks) indicates an ineffective technique because the lifter is required to produce more force than necessary in order to reaccelerate the barbell during the second pull phase (Baumann et al., 1988). In this study, the lifter K displayed a steady increase in the barbell's velocity from the first pull to the second pull phase up to a single velocity peak with no notable dip in the velocity profile (+42.21% in Table 2.1 and Figure 2.4), while 25% of the rest of the group, consisting of 4 lifters, lost barbell velocity during the transition phase.

The excessive magnitudes of the barbell's acceleration (Figure 2.7) which appeared during the second pull phase indicated a waste of force used to achieve greater barbell acceleration than needed. Instead, it should be transferred into lifting the barbell loads (Kipp & Harris, 2015). This is due to the fact that the goal of weightlifting is to lift the maximum weight, not to generate the maximum acceleration. In this study, 68% of the other lifters (11 athletes) showed higher magnitudes of barbell acceleration compared to the lifter K.

Regarding the pattern of the barbell's displacement (Figure 2.8), the lifter K showed the lowest peak vertical barbell displacement (1.08 m; 76% of subject's height) and lower travelled distance at peak vertical displacement to the point of stability in the catch position (drop distance; 0.12 m) compared to the other lifters. These results were consistent with the suggestion of Baumann et al (1988) that the maximum height of the barbell in the turnover phase should be around 70% of the lifter's height. This is considered as the sufficient maximum barbell displacement and the drop distance should be minimized to allow for a more upright position to be adopted in the catch position. These movements have been proven to help increase the technical efficiency of the snatch in elite weightlifters (Isaka et al., 1996).

The horizontal barbell's displacement during the lift is considered as a parameter that indicates "efficient lifting". Baumann et al (1988) reported that the horizontal barbell's displacement for the best weightlifter was smaller than for the poorest lifter in each weight category. In this study, by looking at the pattern of horizontal displacement, we can assume that the lifter K has a barbell horizontal movement pattern quite different from the others as he/she can manage to project his/her body upward, minimize horizontal movement, and keep the barbell close to the reference line (a vertical line drawn from the starting point of the barbell) throughout the lift. This finding was supported by Akkus (2012) who suggested that successful lifts are not dependent on a specific trajectory pattern but they are more a result of power output. The greater the power output, the more consistent the horizontal barbell displacement pattern.

In conclusion, PCA was applied combined with HCA to the relative power output time series of young novice weightlifters and considering those results together with a description of related barbell kinematic variables in each phase of the lift. It could therefore be argued that the pattern of relative power output of each lifter reflects their underlying technical element. Specifically, in our study, the lifter K tended to attain his/her peak power higher and earlier in the transition phase and later in the turn over phase, he/she seemed to be the lifter with a better technique compared to the rest of the group. Therefore, it is suggested that power output pattern can be used as an index for technical evaluation to assess performance changes and provide feedback for coaches and athletes rather than relying on the average power production. However, more research is needed to establish a certain pattern which can be used to distinguish between lifters of different skill levels.

Our study should be considered in light of few limitations. First, the load that subjects performed in this study was 80% of 1RM. This load was chosen to avoid injury and damage to both subjects and equipment. The fact that the subjects were young novice weightlifters meant that when they were asked to perform the lifts on force plates with several markers attached to their body, they tended to be nervous about the task and failed to lift at their maximum weight. Nevertheless, using the impulse-momentum method to calculate the external power output proved that inferences can be made about the internal joint power at loads of 75 and 85% of the 1RM. Second, subjects who participated in this study were young novice, school-level weightlifters, as reflected in the load they lifted during the experiment. The range of performance levels of the lifters was fairly narrow. As a result, the application of PCA combined with HCA could only detect a single outlier in the group. This was probably because by using PCA, it was necessary to determine how many and which principal components should be extracted or retained. Most studies retain only a few of the first of several PCs with the largest explained variance while rejecting the smaller ones. This may lead to the loss of useful hidden information. As Jolliffe (1982) pointed out, the principal components with small eigenvalues can be as important as those with a large variance. Therefore, it is possible that other studies may try to use other statistical techniques with greater sensitivity to detect differences in relative power output time-series in weightlifting.

2.7 Using LCSS Technique to Improve the Power of Discrimination Power Output Pattern in Weightlifters

As above results showed, PCA combined with Euclidean-assisted HCA was not powerful enough to clearly differentiate the relative power output pattern of young weightlifters. Therefore, in this paragraph we aim to improve the results from the previous one by using a more robust and efficient similarity measuring algorithm for finding similarity between time series. This technique is called the Longest Common Subsequence (LCSS).

2.7.1 Data Processing: LCSS Technique as HCA's Distance Metric

Relative power output time-series data were the same as those from the previous paragraph in the topic titled as "*Procedure*". Then, those time series were appropriately compared following a three-step-based approach supported by similarity computation methods. Firstly, all data sets were time normalized to 100% of the pull phase of the

snatch (i.e., from the time the barbell lost contact with the platform to the time the barbell is stabilized over the head) to facilitate between-subjects' comparisons as the duration of the pull phase varied slightly from one subject to another. Secondly, 16-bit quantization was applied to all datasets for reducing digital noise. Lastly, Longest Common Subsequence (LCSS) technique was used for evaluating the similarity among the above normalized time series datasets.

2.7.2 Results and Discussion

The LCSS technique was used to measure the similarity of relative power output time series. The projection of dendrogram in Figure 2.10 revealed that based on the similarity of power patterns, 17 samples were classified into two main clusters. Cluster I consists of 9 subjects which are F, K, M, A, C, I, N, D, L and cluster II consists of 8 subjects which are H, O, G, J, Q, P, B, E (Figure 2.11). Although both patterns were characterized by a high relative power output spike during the transition, second pull, and turn over phase, they were difference from each other. The curve of the former group has gradually increased from the first pull until reached its peak at the transition phase. Then, it went down immediately before reaching another peak in the second pull phase, whereas the latter group showed the curve spike and wave during first pull until catch phase (Figure 2.12).

To explain the differences between those two power output patterns, barbell kinematic variables must be taken into account. When comparing the pattern displayed by barbell's velocity and barbell's acceleration through the phases of snatch (Figure 2.13, 2.14), it showed that subjects in cluster I can better maintain the barbell's acceleration with no notable dip, whereas subjects in cluster II showed the decreasing of barbell's acceleration during the transition phase. When considering the vertical barbell's displacement (Figure 2.15), subjects in cluster I showed lower average peak barbell's displacement compare to subjects in cluster II (1.27 ± 0.13 VS 1.32 ± 0.09 m and $81.8 \pm 0.03\%$ VS $82.1 \pm 0.04\%$ of lifter's height), whereas the average travelled distance at peak vertical displacement to the point of stability in the catch position (i.e., drop distance) of both group are quite the same (0.21 ± 0.06 VS 0.21 ± 0.07 m).

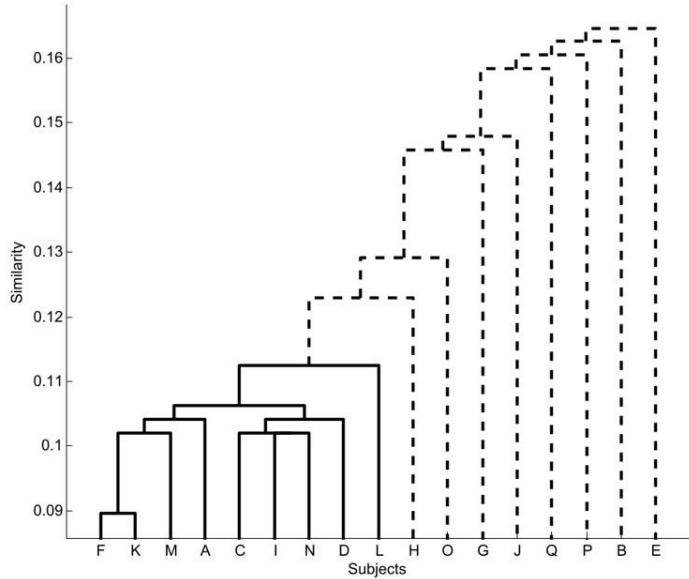


Figure 2.10 Dendrogram of the LCSS distance presenting the classification of relative power output during snatch (from lift-off to catch phase) of young novice weightlifters.

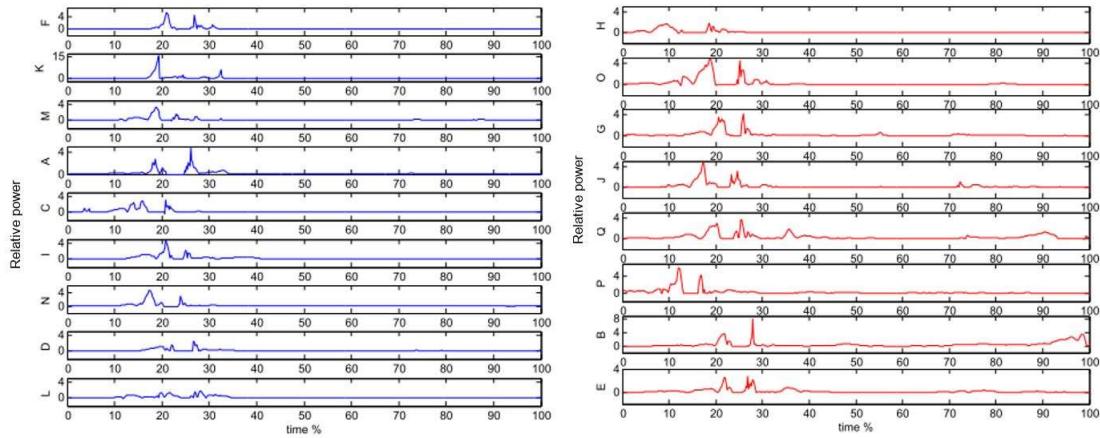


Figure 2.11 An individual relative power output pattern in cluster I (Left side) and cluster II (Right side).

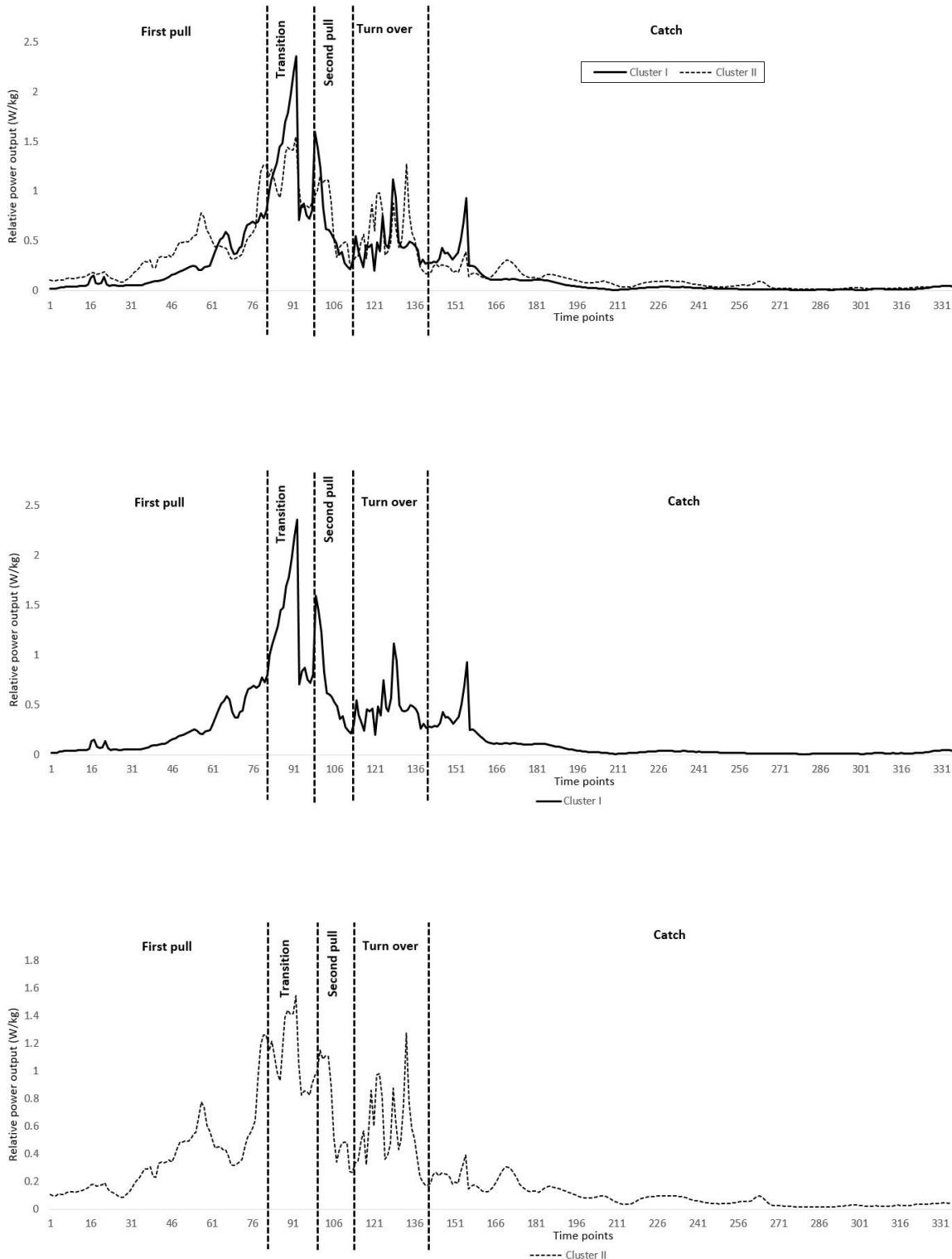


Figure 2.12 Comparison pattern of relative power output time series between cluster I (2.12 a) and II (2.12b).

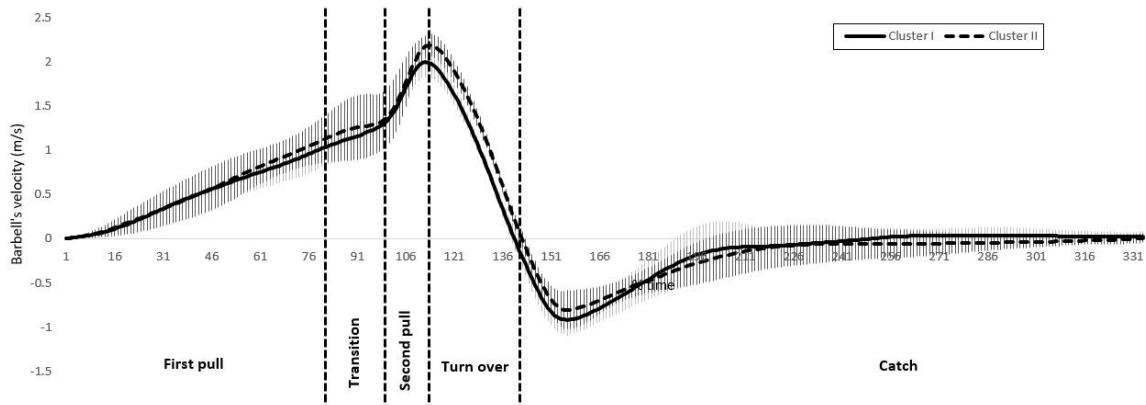


Figure 2.13 Comparison pattern of barbell's velocity time series between cluster I and cluster II group ($\text{mean} \pm \text{SD}$).

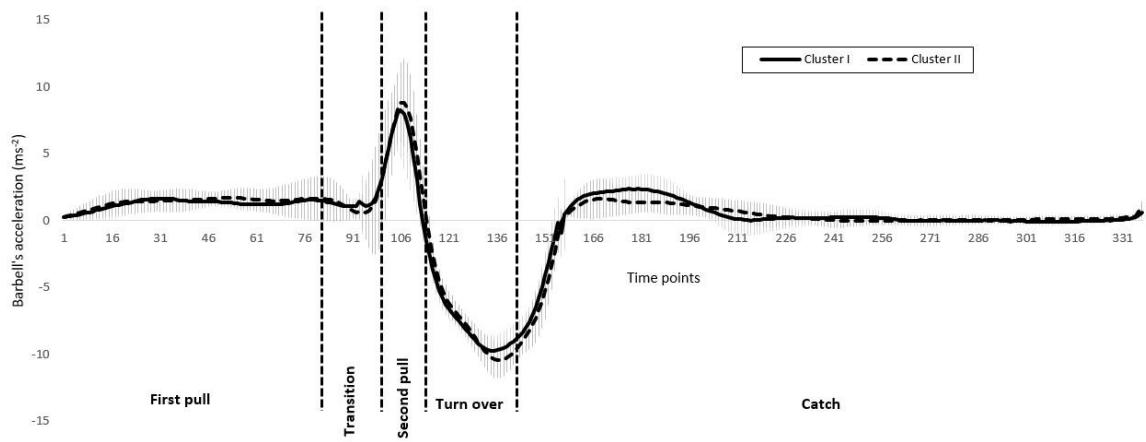


Figure 2.14 Comparison pattern of barbell's acceleration time series between cluster I and cluster II group ($\text{mean} \pm \text{SD}$).

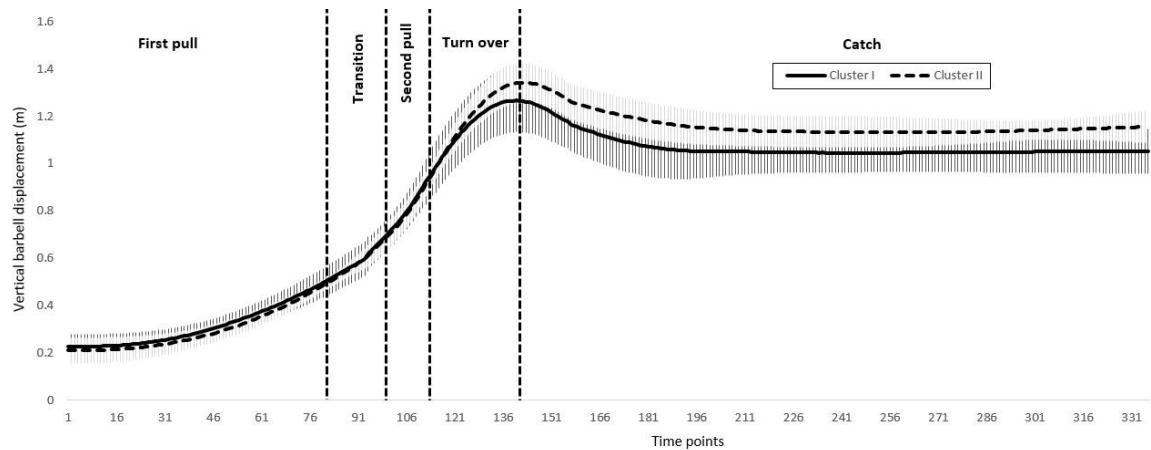


Figure 2.15 Comparison pattern of vertical barbell's displacement time series between cluster I and cluster II group ($\text{mean} \pm \text{SD}$).

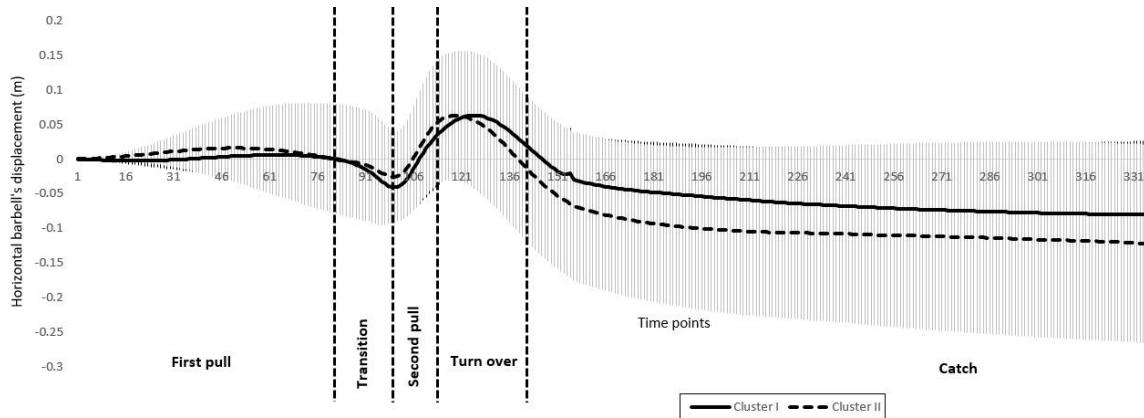


Figure 2.16 Comparison pattern of horizontal barbell's displacement time series between cluster I and cluster II group ($\text{mean} \pm \text{SD}$).

For horizontal barbell's displacement (Figure 2.16), subjects in cluster I showed more consistent average horizontal displacement of the barbell pattern than subjects in cluster II. From the results of these barbell kinematic variables, they indicate that subjects in cluster I have higher ability to provide power output in an efficient manner than subjects in cluster II. Therefore, it can be determined that subjects in cluster I are more skillful than subjects in cluster II. Consequently, we can conclude that the analysis of LCSS was sensitive enough to discriminate different power output patterns of weightlifters with different skillful. Moreover, this technique provided more relevant information to that of standard technique for the analysis of power output time series derived from young weightlifters performing snatch. As found in the result of relative power output values (Table 2.1), even though subject D and H displayed values quite similar (57.93 VS 56.25 W/kg), LCSS analysis classified them into a different cluster due to the similarity of power output pattern, which is identical to the case of subject K and O. This finding supports the idea that only looking on the relative power output values is not enough to determine the lifter's skillful/performance. Thus, considering relative power output values together with their patterns for the whole movement is one way to help coach and lifters to determine correctly the performance of lifters.

In conclusion, by using LCSS technique, we were able to distinguish different patterns of power output among those lifters of different skill levels into two clusters, as lifters which are more skillful ($n=9$) and less skillful ($n=8$). The advantage of using LCSS over PCA combined with HCA are: (i) it is more resilient to noise, (ii) information is not lost during the process, and (iii) there is no need for interpolating the time-series before using LCSS technique.

2.8 Conclusions

The integrated PCA and HCA algorithm was implemented in Matlab by first extracting features while reducing the dimensionality of the collected weightlifting data, followed by the reconstruction of original data from the chosen principal components to obtain the residual data, and only then clustering together the features on the residual data. While trying to answer the four questions of section 2.4, it became obvious that PCA and HCA are an arbitrary method and it should only be used for exploring similarities and hidden patterns among lifters with different skills. Firstly, the choice of the HCA's distance metric was not trivial and it should always be tested. Secondly, both PCA and HCA standard methods offered by Matlab can be corrupted with extreme values (i.e., outliers), if they are not previously removed from the collected data. Thirdly, our experiment suffers from the missing data problem as we discarded very important information regarding lifter's body movement variables, which offer a better and consistent model of the lifting execution. Furthermore, our experiment purposely deviated a little from related works with some pointed disadvantages, as it targeted novice lifters instead of high-performance ones, the maximum power output was found in transition phase instead of in the second pull phase, and lifters performed with barbell weights at 80% of their self-reported 1RM instead of barbell weights closer to their 1 RM.

For more conclusive answers, more robust classification method (e.g., artificial neural networks) should be applied, as tried by the existing weightlifting literature, but unfortunately also with inconclusive results.

CHAPTER 3

Ontology-Based Personalized Dietary Recommendation for Weightlifting

After exploring the importance of muscle power in the previous chapter, we continue to answer one more question of this thesis “*Which computer-based technology can be explored to model each involved domain related to weightlifting research and practice?*”

To answer this question, in term of nutrition domain, we design and implement an ontology-based personalized dietary recommendation for weightlifting. The used methodology is based on conceiving and designing the weightlifting training and weightlifting dietary following a modular ontology. It requires tool including Protégé as an open-source platform which allows users to build an ontology in OWL and Pellet as a reasoner. This implemented system was used as an exploratory tool to partially understand the weightlifting TDC-cycle, mainly the nutrition and training domains. Subsequently, this chapter presents relevant research on food recommendation system, nutrition and ontology background. Then, it describes the system design and finishes with suggestions for future work.

Introduction

Sport nutrition is considered as a new area of study involving the application of nutritional principles to enhance sports performance. The nutritional requirements of athlete are different in different sports. They will be influenced by many factors such as body mass and amount and intensity of training load. For weightlifters, the main nutrition goal is to obtain the adequate energy and necessary nutrients for fueling of resistance training, recovery from this training, and promotion of training adaptations. Those adaptations include muscle growth and optimal body composition. Although it is widely recognized that a well-planned nutrition program can significantly enhance athletic performance, many research reported that weightlifters did not achieve optimal dietary practice. For example, the protein intake of male weightlifters is reported to range between 1.6 g/kg/day and 3.2 g/kg/day (Chen et al., 1989; Hassapidou, 2001; Storey & Smith, 2012), which is higher than the recommendation. Furthermore, weightlifters derive approximately 40–44% of their daily energy intake from dietary fat (Chen et al., 1989; Grandjean, 1989), which is also well above the acceptable range for health and athletic performance of 20–35%. This is probably a consequence of their greater intake of protein-rich animal products. Conversely, the reported carbohydrate intakes in weightlifters of 2.9–6.1 g/kg/day (Cabral et al., 2006; Van Erp-Baart et al., 1989) are insufficient according to the current recommended levels of 6–10 g/kg/day for athletic individuals. These results are in accordance with our preliminary study (See in Appendix C) which reported that a high proportion of Thai national team weightlifters were not in energy balance and so, failed to meet carbohydrate, protein, and micronutrient recommendations. The primary reason for such inadequate diets may come from the fact that some athletes lack of nutrition knowledge and express some nutritional misconceptions, so they are unable to make appropriate food choices. Traditional consultation and development of athletes' nutrition plans require sport nutritionists to perform a series of steps including (i) *nutrition assessment* to get to know the athlete and understand his/her situation and his/her objectives, (ii) *nutrition evaluation* to determine the athlete's calories and nutrients need, address the goal, and determine the athlete's nutrient timing needs for training and for competition day, (iii) *nutrition intervention* to create nutrition and hydration plan for all phases of training and completion cycle as well as provide a specific amount of nutrients recommendation, and (iv) *nutrition monitoring* to determine and measure the amount of progress from nutrition plan. These general

steps involve many type of information: athlete's condition; anthropometric data, biochemical data, current dietary habits, type of sport; specific sport, training program and time line, nutrition requirements, special nutrient needs, nutrient restrictions, and food nutrition composition. A nutrition plan must to incorporate not only nutrition strategy but also strategies for hydration and recovery that an athlete can follow on a daily basis. It also includes design protocol for pre, during, and post workout nutrition to ensure adequate and timely carbohydrate and protein intake to enhance recovery from the training sessions. Therefore, to develop a specific nutrition plan for an individual, the sport nutritionist must be able to integrate the complex logical relationships between the athlete's metrics and the various concept from literature.

In this chapter, the designed and implemented ontology-based personalized dietary recommendation for weightlifting is described. The objective is to answer the previously introduced main problem statement of this thesis (i.e., "*Which computer-based technology can be explored to model each involved domain related to weightlifting research and practice?*"). We followed a methodology based on conceiving and designing the weightlifting training and weightlifting dietary approaching a modular ontology. It requires tool including Protégé as an open-source platform which allows users to build an ontology in OWL and Pellet as a reasoner. We also developed a Thai-based sport nutrition knowledge questionnaire (See in Appendix D) as a tool to evaluate nutrition knowledge of athletes. With this implemented system, we expect that it can help us to partially understand the weightlifting TDC-cycle, mainly concerning to the nutrition and training domains.

The remainder of this chapter is organized as follows: Section 3.1 describes relevant research on food recommendation system; Section 3.2 describes nutrition background; Section 3.3 presents ontology background; Section 3.4 presents system design; Section 3.5 presents conclusions and future work.

3.1 Relevant Research on Food Recommendation System

In this paragraph we shall briefly present some relevant research on Food Recommendation System. Fudholi et al (2009) designed and developed a daily menu assistance in the context of a health control system of a population. This project uses ontology to model a nutrition needs domain while implementing a rule-based inference engine. It is implemented as a semantic web application, where users enter abstinence foods and personal information to calculate several parameters while being presented with an appropriate menu from database. Cantais et al. (2005) designed a food ontology for diabetes control from a nutrition point of view to support health care of diabetes patients. The ontology was developed based on some referenced nutrition guides for diabetes patients. The food ontology consists of 177 classes, 53 properties, and 632 instances. Thirteen major classes of food types were defined including unprocessed aliments, major miscellaneous categories, and food types determined by the main ingredient. Some of the defined properties include nutrition elements such as fat, fiber, and carbohydrate. Also for diabetes control, Hong et al (2008) implemented web-based expert system for nutrition counseling and management, also based on ontologies. This system uses food, dish and menu database which are fundamental data to assess the nutrient analysis. Clients can search food composition and conditional food based on nutrient name and amount. The system is able to organize food according to Korean menus, and it is able to read nutrient composition of each food, dish, and menu. The Food-Oriented Ontology-Driven System (FOODS) (Snae & Bruckner, 2008) is another ontology-based expert system of a counseling system for food or menu planning. It uses a food-oriented ontology to implement a system which has two user interfaces, one for who cooks and another for costumers or users that want advice for their meals. Suksom et al. (2010) implemented a rule-based system for a personalized food recommender system, aimed to assist users in daily diet selections. It is based on some nutrition guidelines ontology and focused on personalization of recommendation results by adding user's health status information that may affect their nutrition needs.

Our work adopted some food ontology design schemes from these references. However, comparing to those works, our work was focus only in weightlifting athletes. We extended the personalized food ontology defined in previous studies by adding information related to athletes' training program that may affect their nutrition needs, while unifying the food and sport ontologies. Our recommendations are based on sport nutrition guidelines, which were transformed into rule-based knowledge.

3.2 Nutrition Background

3.2.1 Fuel utilization and energy systems in weightlifting

To set the structure of subsequent nutritional recommendation for weightlifters, a brief overview of energy system and fuel utilization should be explained. Chemical energy is released when the body break down macronutrients (i.e., carbohydrate, fat, and protein). Then, that energy is converted into Adenosine Triphosphate (ATP) which is the form of energy that can be utilized by the body. ATP is considered as the “cellular currency” for muscle contraction. Without adequate supplies of ATP, muscular contraction and training adaptations from resistance training will not occur. For weightlifting competition, the main energy provider is the phosphagen system. This energy system supplies for a very high intensity exercise lasting up to 8 to 10 seconds. The phosphagen system is the quickest way to resynthesize ATP. Creatine phosphate (CP), which is stored in skeletal muscles, donates a phosphate to Adenosine Diphosphate (ADP) to produce ATP. No carbohydrate or fat is used in this process because the regeneration of ATP comes only from stored CP. The entire process can occur without the presence of oxygen which makes it an anaerobic system. However, in the weightlifting training, especially with the high volumes, a lifter may also rely on the fast glycolytic system. This energy system supplies for a moderate to very high intensity exercise lasting from 6 seconds up to about 30 seconds, and up to 2 minutes for moderate to high intensity exercise. It is considered as the second-fastest way to resynthesize ATP. The energy source for the regeneration of ATP comes from blood glucose (from food) and muscle glycogen (the stored form of glucose in the body). This process is also an anaerobic system (Bompa & Buzzichelli, 2015; Rodriguez et al., 2009; Slater & Phillips, 2011; Stellingwerff et al., 2011).

3.2.2 Guideline for macronutrients, micronutrients, and supplementation intake

The first nutritional priority for all athletes is to meet their energy needs. Energy intake supports optimal body function, determines the capacity of macro-and micronutrient, and assists in manipulating body composition (Rodriguez et al., 2009). A small energy deficit between energy intake and output can cause body fat loss at the beginning. However, long term energy deficit induces a loss of muscle mass and thus, loss of strength and endurance injury, and illness. Ultimately, leading to a decrease of training/competition performance. To avoid this problem, athletes should concentrate

on maintaining an energy balance to suit their energy expenditure. For weightlifters, it is challenging to meet their energy needs due to their high body weight and high-volume intense training. According to Scala et al. (1987), energy expenditures of elite weightlifters can be as high as 600-1,000 kcal/hour or >3,000 kcal/week during the preparation phase. However, it will be lower during tapering. Most of energy expenditure happens during recovery which depends on the volume of training. The complete recovery can take as much as 24 to 48 hours (Burleson et al., 1998; Melby et al., 1993; Schuenke et al., 2002). Nevertheless, even in the same type of sport, the energy requirement for each athlete is different. It depends on body size, physique, event, training load, and training volume on the periodized training and competition cycle (as an example in Figure 3.1).

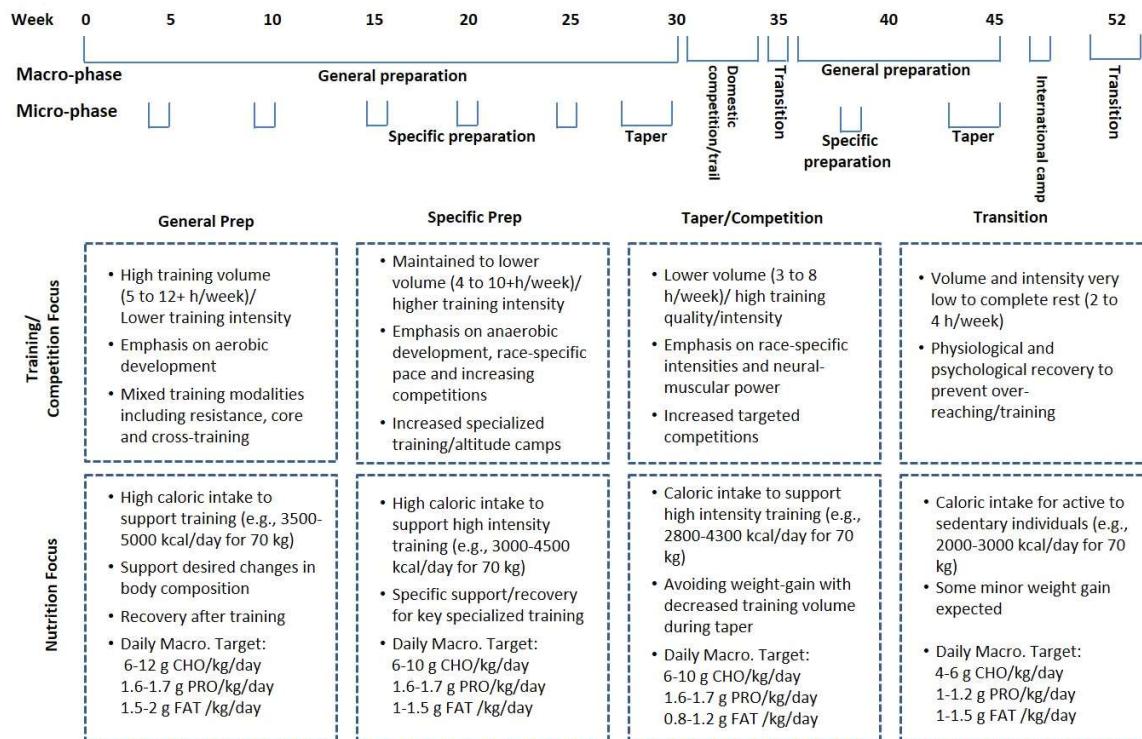


Figure 3.1 General nutrition recommendations during different yearly training phases for strength and power athletes. Nutrition recommendations for a 70-kg strength and power sport athlete (Slater & Phillips, 2011; Stellingwerff et al., 2011).

The following paragraphs are the guideline for carbohydrate, protein, fat intake.

The guideline for strength/power athletes proposes a range of daily carbohydrate intakes between 6 and 12 g/kg body mass per day (depending on individual training volume and intensity) (Slater & Phillips, 2011; Stellingwerff et al., 2011). Although the recommendations for carbohydrate feeding before exercise are widely accepted for endurance exercise to enhance work capacity (Hargreaves et al., 2004), a specific recommendation for an optimum rate or timing for strength-power athletes before and during any training session cannot be determined due to the inconsistency of the results. A beneficial role of acute carbohydrate ingestion has been reported in some studies (Haff et al., 2001; Haff et al., 1999; Lambert et al., 1991) to increased total work capacity at a rate of 1g/kg body mass before resistance exercise and 0.5 g/kg body mass during exercise. However, the others did not find any benefit (Haff et al., 2000; Kulik et al., 2008). To optimize glycogen recovery, it is generally recommended to ingest carbohydrate immediately after exercise at a rate of 1 to 1.2 g/kg body mass (Burke et al., 2004). However, for strength and power athletes, the combination of carbohydrate and protein ingestion acutely after resistance training results in more favorable recovery outcome, including restoration of muscle glycogen stores and muscle protein metabolism, than either carbohydrate or protein alone (Miller et al., 2003). A rate of 0.8 g/kg/h carbohydrate plus 0.4 g/kg/h protein is recommended for the acute recovery period (Slater & Phillips, 2011). It results in a similar muscle glycogen resynthesize over 5 hours as 1.2 g/kg/h carbohydrate alone after intermittent exercise (Van Loon et al., 2000) and it may reduce muscle damage which often seen in strength trained athletes (Cockburn et al., 2010).

Strength and power athletes have been educated to consume high protein diet for many years. Therefore, the majority of athletes easily achieved the protein needs recommendation even if the amount is approximately twice compared with the current recommendations for sedentary or as much as 1.6 -1.7 g protein/kg body mass/day (Slater & Phillips, 2011). Exceeding protein intake guidelines were often found in strength and power athletes as reported by Chen et al. (1989) and Heinemann & Zerbes (1989) that the protein intake of weightlifters were as high as 3.0 g/kg/day. There is no evidence that these high daily protein intakes can provide any more benefits regarding to the response of training or increase the gains in muscle mass and strength (Thomas et al., 2016). Furthermore, there is evidence supporting that the

dietary protein requirement for experienced resistance-trained athletes is reduced. It is because an intense period of resistance training reduces protein turnover and improves net protein retention (Hartman et al., 2006). The requirement of protein intake can be elevated as high as 2.0 g/kg/h in case of energy restriction or when sudden inactivity occurs (e.g., injury). When it is spread over the day, it may have an advantage of preventing fat free mass (FFM) loss (Rodriguez et al., 2007). Rather than the amount of protein, the attention for strength and power athletes should be directed to the daily distribution of protein intake as it relates to training and the source of dietary protein (Tang & Phillips, 2009). Consequently, the current guidelines focus instead on total protein intake over the day as the traditional guidelines. They highlight that the muscle adaptation can be maximized by ingestion protein at rate 0.3 g/kg immediately after key exercise session and every 3 to 5 hours over multiple meals (Moore et al., 2009; Phillips, 2014). In addition to optimal protein sources, it is well documented that high-quality proteins are effective for maintenance, repair, and synthesis of muscle proteins (Tipton et al., 2007).

For weightlifters, the optimum daily fat intake should be 20-35% of total energy intake (Thomas et al., 2016). For athletes who want to reduce body fat or lose body weight, a fat intake of 0.5-1.0g/kg body mass per day is suggested and the focus should be on increasing sources of unsaturated or essential fatty acids (Kreider et al., 2010).

To maintain fluid balance and prevent hypo-hydration, the recommendations suggest the ingestion fluid at a rate of 0.5-2 l/hour, every 5-20 minutes, with small amount of 150-200 ml each time. Furthermore, it should be increased in hot and humid environments (Kerksick et al., 2008; Kreider et al., 2010). During recovery from exercise, rehydration should include replacement of both water and salt lost in sweat, especially when the exercise takes place for more than two hours and sweat losses are high (Shirreffs & Sawka, 2011). Any event lasting longer than one hour, which results in fatigue, will benefit from carbohydrate intake at a rate of 20-60 g/h. The use of sports drink with 4-8% carbohydrate content allows carbohydrate and fluid need to be met simultaneously in most situations.

Supplement usage rate is reported to be high in sports such as bodybuilders, weightlifters, track, and field athletes (Brill & Keane, 1994; Burke et al., 1991; Froiland et al., 2004). While multi-vitamin and mineral supplements are highly used by all athletes, other products such as protein powders, specific amino acid supplements,

caffeine, and creatine monohydrate appear to be popular among strength-trained athletes (Nieper, 2005; Sheppard et al., 2000; Slater & Phillips, 2011). This is due to the fact that these kind of supplements are the only supplement that has been reported to be “Apparently effective and generally safe” to enhance skeletal muscle hypertrophy and functional capacity in response to resistance training (Kreider et al., 2010; Trakman et al., 2016).

3.3 Ontology Background

For this study we need a knowledge based framework and for that, a unified ontology of nutrition and sports was designed and implemented for exploratory purpose. Ontology in the computers science field is a data model that describes concepts (classes) in a specific domain alongside their relationships. Ontology was successfully used to share concepts across applications and exchange information. It exchanges information based on semantics rather than using syntax (Noy & McGuinness, 2001). While programming with object-oriented, we center around methods on classes, and we make design decisions based on the operational properties of classes, in ontology we make the decisions based on the structural properties of a class.

There are four main elements of ontology, concepts or classes, individuals, properties, and relationships which together make it a knowledge base. Classes are collections of objects, sets or abstract groups, describing concepts in the ontology specific domain. They can contain both a subclass that describes more specific concepts and an individual. An example of a class would be a food class that would contain various subclasses like food type and food group. Individuals are the basic components of ontology. The individuals may be concrete concepts like a specific menu or an ingredient or an abstract one like numbers. Properties are related to individuals or class, as they are something that define or explain them. There are two types of properties: *data type* used to assign a valor to a property or class, (e.g., a menu *hasEnergy* 150 kcal) or *object type* through which an object can be attributed to other (e.g., menu A *hasIngredient* b). The last of the main elements of ontology are the relationships that consist in all relations between classes and individuals. So, ontology is the exact description of things and the relationship between them.

The recommender engine interprets the ontology data in OWL (Web Ontology Language) format that is a standard ontology language designed for processing web

information. OWL is written in XML and so, it can be exchanged between different computers and different applications. The expert engine performs questions on the ontology data to get back the nutrition/food data saved there, as well as inferring on athlete information and preferences to give the menu recommendations for each specific case. The application for insertion of the data is developed in Java and it works with Jess API for the interaction with the ontology. Later on Chapter 4, the ontology concept will be more deeply described.

3.4 System Design

The unified Sports and Nutrition ontology was developed in Protégé (Protégé, 2013), a free and open-source platform which allows users to build an ontology in OWL. Protégé also enabled the use of SWRL rules (Horrocks et al., 2004), SWQRL queries, PELLET (Clark et al., 2004), and a reasoner in this project. Figure 3.2 presents a knowledge base framework for food and nutrition recommendations engine in sports. Used tools for modeling the ontologies will be more deeply described in Appendix E.

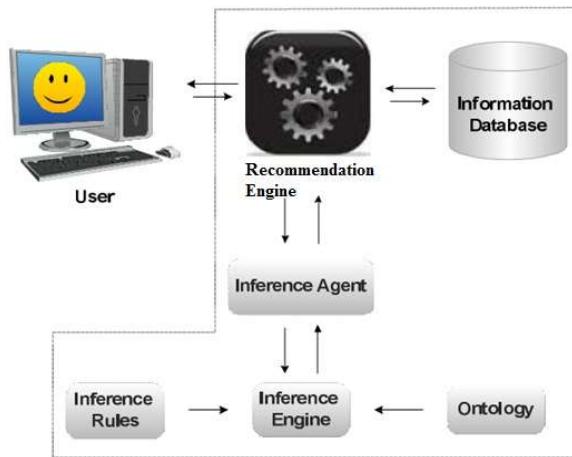


Figure 3.2 Knowledge base framework for food and nutrition recommendation engine in sports
(Adapted from Fudholi et al., 2009).

3.4.1 Ontology Development

A) Modeling Concept

The development of the ontology involved defining the four main elements of ontology, i.e., the classes or concepts, the individuals, the properties, and all the relationships. In this case, we decided to start with only one specific sport which is the weightlifting.

We used a top-down approach by starting with the definition of the most general concepts in the domain and then, subsequently, the specialization of those concepts. Such ontology was modeled around the four main concepts which are Athlete, Food, Nutrition, and Sports (Figure 3.3). It consists of 120 classes, 950 individuals, and 25 properties.

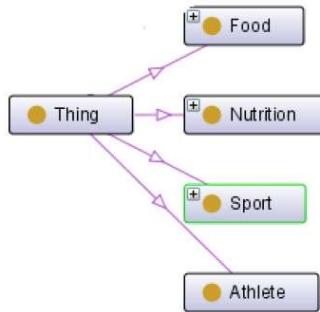


Figure 3.3 Ontology main concepts.

The Athlete Concept: The athlete class represents the concept of the athlete profile with the athlete information saved in a database, providing all the necessary information about the required personal data such as *Name, Age, Gender, Height, Weight, and Number of training hours*.

The Food Concept: The food class is the root of this model and represents the concept of the food which consists of multiple subclasses such as *Food Group, Food Type, Process Type, and Type of Meals*.

The Nutrition Concept: The nutrition concept represents all the nutrition needs of an athlete and all the nutrients present in an ingredient/food item.

The Sports Concept: The sport concept represents athletes' characteristic which affect their nutrition needs.

B) Modeling Classes and Subclasses

Classes are collections of objects, sets or abstract groups describing concepts in the ontology specific domain. They can contain both a subclass that describes more specific concepts and an individual. We have our main classes as the main concepts which are mentioned above (e.g., *Athlete* concept, *Food* concept, *Nutrition* concept,

and *Sport* concept). An example of subclass in *Food* Concept will be explained in detail as follows (Figure 3.4)

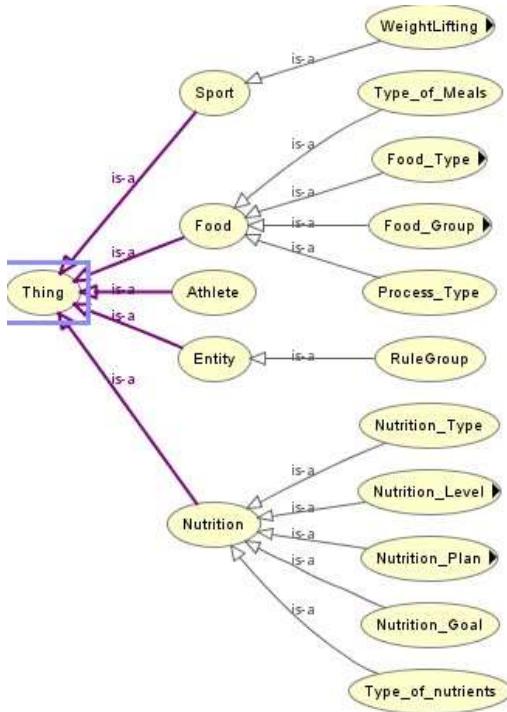


Figure 3.4 Concepts, classes, and sub-classes of an ontology.

The *Food* concept consists of 4 subclasses:

Food Group – This subclass is divided into 5 groups and each group will be divided into smaller sub-classes for more specific type of food. For example:

Group 1: Grain food consists of *Whole grain* (*individual: wheat, brown-rice, oat, etc.*), *Refined grain* (*individual: white flour, white bread, white rice, etc.*), etc.

Group 2: Vegetables, Beans, and Fruits consist of *Vegetables* (*individuals: cabbage, tomato, cucumber, etc.*), *Beans* (*individuals: lentil, green bean, black bean, etc.*), and *High sugar fruits* (*individuals: lychees, figs, mango, etc.*) and *Low sugar fruits* (*individuals: cranberries, raspberries, blackberries, etc.*), etc.

Group 3: Meat and nuts consist of *Seafood* alongside the following subclasses of *Fish* (*Individuals: sardines, salmons, catfish, trout, etc.*); *Mollusk* (*individuals: oysters, scallops, mussels, squid, octopus, etc.*); *Crustaceans* (*individuals: shrimps, crabs, lobsters, etc.*); *Other Seafood* (*individuals: jelly fish, frogs, etc.*);

Poultry (*individuals*: chicken, duck, Turkey, etc.); *Non-Poultry* (*individuals*: pork, beef, lamb, etc.); and *Nut* (*individuals*: almonds, walnuts, peanuts), etc.

Group 4: Dairy Product consists of *Cheese* (*individuals*: soft, hard), *Milk* (*individuals*: whole fat, low fat, non-fat), *Yogurt* (full fat, low-fat, non-fat), etc.

Group 5: Fats, Oils, and Sweets consist of *Fats* (*individuals*: salad dressing, mayonnaise, butter, margarines, etc.), *Oil* (*individuals*: canola oil, olive oil, soybean oil, etc.), *Sweets* (*individuals*: candy, soft drinks, jams, jellies, etc.), etc.

Food Menu – This subclass represents the different type of food items according to the following three categories: *main dish*, *dessert* and *snack*, or *beverage*. For example;

Main dish such as spicy basil chicken, pork steak, barbecue shrimp, etc.

Dessert and snack such as chocolate, cake, cookie, ice cream, etc.

Beverage such as tea, soft drink, juice, etc.

Process Type – This subclass represents how the food item is cooked (e.g., grill, roasted, stir-fry, fry, or smoked).

Type of Meals – This subclass represents the food item advised time of ingestion. (e.g., breakfast, lunch, dinner, before workout, during workout, after workout). All food items can have more than one type.

The *Nutrition* concept consists of 4 subclasses:

Nutrient Type – Macronutrients are presented in all ingredients or food items (e.g., Egg consists of carbohydrate, protein and fat).

Nutrition Level – It represented the level of nutrients per ingredient or food item (e.g., Rice: high carbohydrates or Egg: high protein).

Nutrition Goal – The amount of nutrients that meet an individual's requirement (e.g., carbohydrate 300 g/day or protein 120 g/day).

Nutrition Plan – A special plan in which an individual athlete needs (e.g., to maintain weight/increase muscle or decrease weight/maintain muscle).

The *Sport* concept has 1 subclass:

Periodization of training – The systematic planning of athletes training consists of general preparation phase, specific preparation phase, competition phase, and transition phase. The athletes' energy needs are different according to the different phase of training.

C) Modeling Properties

Properties are related to individuals or classes, as they are something that defines or explains them. Individuals can have two types of properties: either the data type, which is used to assign a value to a property or class or the object type, which is used to attribute one object to another one. The object type and data type properties for nutrition and food knowledge based are listed as follows (See Figure 3.5 and 3.6):

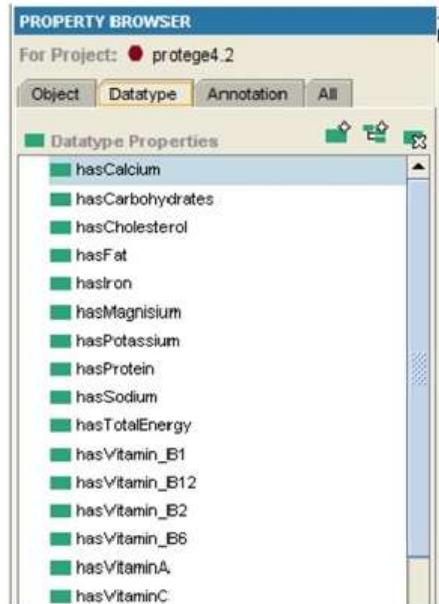
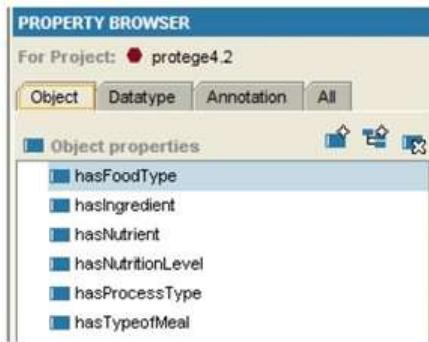


Figure 3.5 Object type properties.

Figure 3.6 Data type properties.

Object type properties:

hasProcessType: This property attributes a specific type of food processing to a menu. So, it can be assured that every menu item has a food process.

Domain: *Beverages, Dessert_snack, Main_dish*

Range: *Process_Type*

Example: *Spicy_basil_chickenhasProcessTypeStir_fry*

hasIngredient: This property attributes a specific ingredient to a menu. So, it can be assured that all menus have ingredients (one or more).

Domain: *Beverages, Dessert_snack, Main_dish*

Range: *Food_Group*

Example: *Spicy_basil_chickenhasIngredientChicken*

hasNutrient: This property attributes a specific nutrient to a menu or ingredient. So, it can be assured that all menus or ingredient have specific nutrients (one or more).

Domain: *Beverages, Dessert_snack, Main_dish*

Range: *Type_of_nutrients*

Example: *Spicy_basil_chickenhasNutrientProtein*

hasNutritionLevel: This property attributes a specific nutrition level to a menu or ingredient. So, it can be assured that all menus and ingredient have nutrition levels.

Domain: *Beverages, Dessert_snack, Main_dish*

Range: *Nutrition_Level*

Example: *Spicy_basil_chickenhasNutritionLevelLowFat*

hasTypeofMeal: This property attributes a type of meal to a menu. So, it can be assured that all menus have meal types.

Domain: *Beverages, Dessert_snack, Main_dish*

Range: *Type_of_Meal*

Example: *Spicy_basil_chickenhasTypeofMealLunch*

Data type properties:

Figure 3.6 presents data type properties. All these properties have the same domain and range as follows:

Domain: *Beverages, Dessert_snack, Food_Group, Main_dish, Type_of: nutrients*

Range: *Float*

Example: *ChickenhasProtein = 30.0g*

D) Modeling Individuals

Individuals are the basic components of an ontology. The individuals may be concrete concepts like a specific menu, an ingredient, or an abstract one like numbers of calories in a menu. Since the number of individuals are very large (e.g., all menus, ingredients, etc.), only some examples will be presented. All the lowest subclasses have at least one individual. For example:

Individuals of type of processing: baking, boiling, smocking, frying, stir-frying, roasting, etc.

Individuals of beverages: apple juice, Coca-Cola, coffee, tea, ice-tea, etc.

Individuals of type of meal: breakfast, lunch, dinner, before workout, during workout, after workout.

Individuals of nutrient: carbohydrate, protein, fat, calcium, etc.

Individuals Form (Figure 3.7) is the form in Protégé which is used to enter individual data items within a data class. It contains the data-entry field for each property which will be attached to a class. Data entry field can be texts, integers, cardinality, etc. Therefore, this form is used to enter all properties to food and ingredients that is attached to them.

The screenshot shows the Protégé FORM EDITOR interface. The left panel, titled 'FORM BROWSER', displays a tree view of ontology classes under 'For Project: protege4.2'. Classes listed include owl:Thing, Athlete, Food, Food_Group, Food_Type, Process_Type, Type_of_Meals, Nutrition, owl:NamedIndividual, p2:Entity, p3:Entity, Sport, and swrla:Entity. The 'Food_Group' class is currently selected and highlighted in green. The right panel, titled 'FORM EDITOR', shows the individual form for the 'Food_Group' class. The 'Display Slot:' dropdown is set to ':NAME'. Below it, there are six data entry fields arranged in two rows of three. Each field has a 'Value' and 'Type' column. The fields are labeled: 'hasCalcium', 'hasPotassium', 'hasVitamin_B2'; 'hasCarbohydrates', 'hasProtein', 'hasVitamin_B6'; and 'hasCholesterol', 'hasSodium', 'hasVitaminA'. Each field includes a delete button ('X') and a plus sign ('+') for adding more values.

Figure 3.7 Individual form

3.4.2 Menus Calculation

The classic energy balance equation states that if energy intake (total kilocalories consumed) equals energy expenditure (total kilocalories expended), then weight is maintained. That maintenance of body weight and body composition over time requires not only that energy intake equal energy expenditure but also that intakes of protein, carbohydrate, fat equal their oxidation rates. People who meet these criteria are in energy balance.

A) Estimate Total Energy Expenditure

Energy expenditure is one side of the energy balance equation. Any alteration in energy expenditure can result in weight gain or loss if energy intake and consumption are held constant. In this chapter, the predicting energy expenditure based on age, gender, and anthropometric measurements are used to estimate energy expenditure of an athlete. To avoid confusion with other terms, we use term “Total energy needed (TEN)” to refer to the value obtained from equation 1 or predicting energy expenditure based on age, gender, and anthropometric measurements.

In this study, TEN was calculated by the factorial method (equation 1). TEN comprises the Resting metabolic rate (RMR), Thermic effect of food (TEF), and Energy expended in physical activity which includes activities of daily living calculated by General activity factor (GAF) and planned exercise events calculated by Exercise energy expenditure (EEE). RMR was calculated by either the Cunningham or Harris-Benedict equation. Once a values of RMR has been obtained, TEN can be estimated by a variety of factorial methods which depend on the type and intensity of activity. In this study, both GAF and EEE were estimated. While the former represents energy expended for everyday activities (e.g., walking, driving, watching TV, and going to the class), the latter is the activity expended in planned or purposeful activity (e.g., running, swimming, and weight training) for a scheduled amount of time and at a specific level of intensity. Those factors were calculated as indicate below:

$$\text{TEN} = (\text{RMR} \times \text{GAF}) + \text{EEE}^* + \text{TEF}^{**} \quad (\text{Equation 1})$$

*EEE (in kcal) = 0.0175 x value of METs ($\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) x body weight (kg) x duration of activity (min)

**TEF = 10% ((RMR x GAF) + EEE)

Resting Metabolic Rate (RMR): RMR is the energy required to maintain systems of the body plus thermoregulation regulation at rest. The RMR accounts for 60-80% of total daily energy expenditure in most sedentary healthy adults (Manore et al., 2009). In athletes, this percentage varies depending on the intensity of the activities. Thompson et al. (1993) found that RMR represented only 38-47% of total energy expenditure in male endurance athletes while Beidleman et al (1995) reported RMR may represent <20% of total energy expenditure in ultramarathon in women. It is well documented that RMR is mainly influenced by age, gender, and fat free mass (FFM) which generally explain about 80% of the variability of RMR (Bogardus et al., 1986). RMR prediction equations have been developed from different laboratories using populations differing in age, gender, and level of activity. It is best to use the RMR equation most representative of the studied population. The Cunningham (Equation 2) and Harris-Benedict equation (Equation 3) are the best equations to predict RMR in both active men and women (Thompson & Manore, 1996). While the former requires the measurement of lean body mass (LBM), the latter is easier to use when LBM cannot be directly measured.

The Cunningham Equation (Cunningham, 1980):

$$\text{RMR} = 500 + 22 \text{ (LBM)} \quad (\text{Equation 2})$$

The Harris – Benedict Equation (Harris&Benedict, 1918):

Males: $\text{RMR} = 66.47 + 13.75 \text{ (weight in kg)} + 5 \text{ (height in cm)} - 6.76 \text{ (age in years)}$

(Equation 3)

Females: $\text{RMR} = 655.1 + 9.56 \text{ (weight in kg)} + 1.85 \text{ (height in cm)} - 4.68 \text{ (age in years)}$

(Equation 4)

Thermic Effect of Food (TEF): TEF represents the increase in energy expenditure above RMR that results from the consumption of food and beverage throughout the day. TEF includes the energy cost of food, digestion, absorption, transport, metabolism, and storage within the body. It is generally accounts for 6-10% of total daily energy needed, but vary from 4-15%, depending on size of the meal and its composition (e.g., percentage of kilocalories from protein, fat, carbohydrate, alcohol) (Manore et al., 2009).

General Activity Factor (GAF): To obtain GAF, the general activity factor will be determined for the time the athlete is not participating in specific activities and then multiply this factor by the predicted RMR. GAF can be as low as 10-20 % of RMR for a sedentary person and as high as more than 100% of RMR for a very active person. Although many researches establish unique activity factors for their research setting, factor of 1.2-1.6 are commonly used with sedentary people and those who have light activity. This factor can be applied to either the whole day or a weighted activity factor.

Table 3.1 Activity factor for a general activity.

Level of activity	Activity factor
Sedentary or confined to bed	1.2
Very light activity	Men 1.3 Women 1.3
Light activity	Men 1.6 Women 1.5
Moderate activity	Men 1.7 Women 1.6
Heavy activity	Men 2.1 Women 1.9
Exceptional activity	Men 2.4 Women 2.2

A *sedentary person* refers to a person who has minimum movement during the day. Most activities mainly involve with sitting or lying, watching television or reading.

A *very light activity person* refers to a person who has activities involved with seated and standing activities, painting trades, driving, laboratory work, typing, sewing, ironing, cooking, playing cards, playing musical instrument.

A *light activity person* refers to a person who has activities involved walking on a level surface at 2.5-3 mph, garage work, electric trades, carpentry, restaurant trades, house cleaning, child care, golf, table tennis.

A *moderate activity person* refers to a person who has activities involved with walking on a level surface at 3-4 mph, carrying a load, cycling, skiing, tennis, dancing.

A *heavy activity person* refers to a person who has activities involved with walking with a load uphill, tree felling, a heavy manual digging, basketball, climbing, football, soccer.

Exercise Energy Expenditure (EEE): To obtain EEE, the amount of energy expended in the specific activities is determined by using the standardized and comprehensive list of energy cost values for a wide variety of activities published by Ainsworth et al. (2000) which is reported in metabolic equivalents (METs). An example of METs for weightlifting activities is presented in Table 3.2. MET is a unit of measurement that represents work rate or oxygen uptake (VO_2). One MET is equal to a VO_2 of $3.5 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ which can be converted to $\text{kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ equal $0.0175 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$. Therefore, EEE was calculated according to the following steps. Firstly, multiply the value of METs ($\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) by 0.0175 to convert it to $\text{kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ and then, multiply the value (from previous step) by the kilogram body weight of the individual and the number of minutes spent in the activity.

Table 3.2 The metabolic equivalent for weightlifting (Ainsworth et al., 2000).

Type of activity	METs
Weight lifting, power lifting or body building, vigorous	6.0
Weight lifting, power lifting or body building, light or moderate effort	3.0

Other Input Variables: The system provides three options for athletes to select from, regarding the weight management or weight goal (i.e., lose weight, maintain weight or gain weight). If an athlete selects “lose weight”, the system will calculate energy recommendation less than TEN for 500 kilocalories/day. If an athlete selects “maintain weight”, it will calculate energy recommendation equal TEN, and if an athlete selects “gain weight”, it will calculate energy recommendation more than TEN for 500 kilocalories/day.

The Recommended Amount and Percentage of Nutrients Per Day: According to sport nutrition guidelines from ADA, ASCM, IOC, and sport-specific nutrition guidelines for strength and power sports (Rodriguez et al., 2009; Slater & Phillips, 2011), it can be summarized using recommendations for daily nutrient intake and nutrient timing for weightlifters, as shown in Table 3.3. Because weightlifters usually need high energy intakes to meet their high-volume intense training, the suggested balanced diet servings need to be adjusted in to several meals (e.g., breakfast, lunch, dinner, before workout, during workout, and after workout). Table 3.4 and 3.5 show the modified

intake servings suggested from each food group by calories requirements for weightlifters.

In this study, the proposed system calculates energy recommendation per meal by dividing the TEN by the number of meals. Normally, weightlifters have their training 2 times a day; morning and afternoon session. Therefore, they will eat 5-7 meals a day, i.e., before morning training session, during training, breakfast (within 30 min after training), lunch, before afternoon training session, during training, and dinner (within 30 min after training). Since it is not possible to get a perfect value of energy for each menu or combined menus, we need to determine a margin of energy per meal. For example, an athlete's demanding energy intake of 711 kcal for breakfast, it is possible that there is no menu perfectly matching that value on the list. The margin was determined as TEN_MIN (for each meal) = $50 - (TEN * \%Meal)$, TEN_MAX (for each meal) = $50 + (TEN * \%Meal)$. In this way, the athlete will receive recommended menus which have an energy between 661-761 kcal. Table 3.6 presents the percentage of each meal according to nutrient recommendations and nutrient timing.

Table 3.3 Summary of the recommendations for daily nutrient intake and nutrient timing for weightlifters.

Nutrient Recommendations

Carbohydrate: 6 to 10 g/kg per day for general training needs and 8 to 12 g/kg per day for athletes who perform multiple training sessions per day

Protein: 1.6 to 1.7 g/kg per day for general training needs and it can be elevated as high as 2.0 g/kg/h in case of energy restriction, illness, and injuries.

Fat: 20-35% of total energy intake for general training needs, 0.5-1.0g/kg body mass per day for athletes who want to reduce body fat or lose body weight; mainly from unsaturated or essential fatty acids sources.

Table 3.4 An example of suggested food group intakes in servings (per day) by calories requirements.

Food group	Calorie			
	2500 kcal	2800 kcal	3000 kcal	3300 kcal
Grains	11	14	14	15
Protein foods	8	9	9	9
Dairy	1	1	1	2
Vegetable	4	4	4	5
Fruits	6	6	6	8
Oil/Nut/Seed	8.5	9.5	10.5	11
Sugar	13	14	15	17

Table 3.5 An example of suggested food group intakes in servings (per meal) by calories requirements.

Food group	2500 kcal			2800 kcal			3000 kcal			3300 kcal		
	Before workout	During workout	Main meal	Before workout	During workout	Main meal	Before workout	During workout	Main meal	Before workout	During workout	Main meal
Grains	2		9	3.5		10.5	3.5		10.5	3		12
Protein foods	1		8	1		8	1		8	1		8
Dairy			1			1			1			2
Vegetable			4			4			4			5
Fruits	2		4	1.5		4.5	1.5		4.5	3.5		4.5
Oil			8.5			10.5			10.5			11
Sugar		10	3		10	3	2	10	3	2	10	4

*1 day = 2 before workout meals, 2 during workout meals and 3 main meals

Table 3.6 The percentage of each meal.

Meal	Percent of Total Energy	Percent of Total Carbohydrate	Percent of Total Protein	Percent of Total Fat
Before morning training session	10%	15%	Not defined	Not defined
During training	5%	6-8%	Not defined	Not defined
Breakfast	23%	Not defined	30%	30%
Lunch	23%	Not defined	30%	30%
Before afternoon training session	10%	15%	Not defined	Not defined
During training	5%	6-8%	Not defined	Not defined
Dinner	23%	Not defined	30%	30%

Table 3.7 An example of the food items nutrients database from INNUMAL-Nutrient software.

Food (100 g)	Nutrient								
	Calories (kcal)	Carbohydrate (g)	Protein (g)	Fat (g)	Vitamin A (RE)	Vitamin C (mg)	...	Iron (mg)	Zinc (mg)
Rice	133	30.3	2.3	0.3	0	-	...	0.3	0.44
Pork	116	0	21.8	3.2	-	0	...	1	1
Egg	155	1.6	12.8	10.8	368	-	...	3.1	1.1
Cabbage	23	3.6	1.9	0.2	192	51	...	1.3	0.5
Mango	80	18.8	0.9	0.2	26	9.18	...	0.2	0.1

Table 3.8 An example of the menus nutrients database from INNUMAL-Nutrient software.

Food	Nutrient							zinc
	Calories (kcal)	Carbohydrate (g)	Protein (g)	Fat (g)	Vitamin A	...		
	Fried Noodles with Prawns (250 g)	592.5	59.5	19.25	30.75	63.08	...	5
	Rice with Stewed Pork Leg (250 g)	407.5	50.75	18	14.75	-	...	2
	Fried Rice with Pork (250 g)	377.5	41.75	14.75	16.75	-	...	1.5
	Creamy Coconut Tapioca (1 piece)	42.11	6.95	0.41	0.77	0.13	...	0.17
	Deep Fried Dough Strick (1 piece)	67.35	0.66	14.22	3.97	-	...	-

Daily Menu Calculation: A menu is defined according to the food composition that is consumed by an athlete during one meal. The calculation of calories and nutrients in each menu is done by means of INMUCAL-Nutrient Software, Institute of Nutrition, Mahidol University, Thailand (*Manual of INMUCAL-Nutrients*, 2009) (Figure 3.7, 3.8). While most macronutrients (carbohydrate, protein, fat) could be found in this software's database, some micronutrients for local food items may not be present. The data which is not covered by the software was sourced from Thai Food Composition Table of Nutrition Division, Department of Health, Ministry of Public Health of Thailand (Sinwat, 2001). Adequacy of each nutrient intake is determined based on sport-specific nutrition guidelines for strength and power sports (e.g., weightlifting) which are available in the following two references: Rogozkin (2000), Slater & Phillips (2011) and the 2003 Dietary Reference Intake of Thai People ("Dietary Reference Intake (DRI)", 2006).

B) Rule Engine

The rules were developed using SWRL Protégé editor, and all tested from the SQWRL tab which runs a Protégé application that allows the query of the ontology inside Protégé execution environment. The rules were defined using nutrition and sports knowledge to determine the athlete's calories and nutrients need according to athlete's profile and training phase. The more restrictions the athlete put, the less food menus will be recommended. All those rules were written in SWRL, a language that allows the definition of rules as well as querying the ontology via Java. Therefore, we can get

the menus in our application with the specific rules constrains. Table 3.9 presents some examples of possible scenarios and queries.

Table 3.9 An example of possible scenarios and queries.

Scenarios for energy needs	Queries
User A is a male weightlifter with 25 yrs; he has 63 kg, 162 cm, muscle mass 54.8 kg; his general activity is considered very light; he trains 2 time a day (each time is 60 min); his training phase is general preparation phase; he likes to eat beef; he wants a main dish for lunch.	If (gender = male, age = 25, weightgoal = 63, mmass= 54.3 and generalacti = very light and train=general and duration =120 and athletefav = beef and menu = mdish and time = lunch) Then recommendedmenu = (hasEnergy(620 <= energy <= 720) and hasBeef)
User B is a female weightlifter with 26 yrs; she has 97 kg, 165 cm, muscle mass 72.7 kg; her general activity is considered very light; she trains 2 time a day (each time is 60 min); her training phase is specific preparation phase; her weight goal is 94 kg; she likes to eat pork; she wants a main dish for dinner.	If (gender = female, age = 26, weightgoal = (94-97), mmass = 72.7 and generalacti = very light and train = specific and duration =120 and athletefav = pork and menu = mdish and time = dinner) Then recommendedmenu = (hasEnergy(651 <= energy <= 750) and hasPork and low_fat)

3.4.3 Expert Recommender Engine Application

A) Main Page Interface: Personal, Training Profile, and Food Preferences

The Java application was developed in a way that an athlete as a main user can add all the data needed and then received the specific menus; all the data can be saved in a database for future usage and update. The application works with the Jess API (Smith & Friedman-Hill, 2013) which is a rule engine fully compatible with OWL and SWRL. The main page interface is a personal profile where the athlete adds his/her information (Figure 3.8). To give menu recommendations as demanded by the athlete, various variables must be added both in training and food preferences' parts. In the training part: data about age, gender, weight, height, level of activity, duration of training, training phase, and weight goal are necessary to estimate the energy needs to achieve the goal. Athletes can also choose the favorite and non-favorite menus or ingredients, so the system will avoid the non-favorite and will choose between the menus with the favorite ingredients. More options are allowed to be chosen from, such as the process type of cooking preferences (e.g., steaming, baked, grill etc.) or the

number of beverage needed (Figure 3.9). After the submission of the personal profile, training, and food preferences interfaces, all filled information are transformed in a SQWRL query that will question the ontology, producing all the recommendations results following the rules as previously saved in the ontology-assisted knowledge base.

The screenshot shows a 'Personal Profile' form with the following fields:

- Name: [text input]
- Age: [text input]
- Gender: Male [dropdown menu]
- Weight: [text input] kg
- Height: [text input] cm
- Level of general activity: Sedentary [dropdown menu]
- Number of training hours: [text input]
- Training Phase: General Preparation [dropdown menu]
- Use Scale
- Skip Food Preferences
- Weight Variation: Maintain Weight [dropdown menu]

At the bottom is an 'Ok' button.

Figure 3.8 The user application for insertion of all the personal athlete data.

The screenshot shows a 'Food Preferences' form with the following fields:

- Non-Favorite Ingredients: [dropdown menu] None [dropdown menu] None
- Favorite Ingredients: [dropdown menu] None [dropdown menu] None
- Favorite Process Type: [dropdown menu] None
- Non-Favorite Process Type: [dropdown menu] None
- Number of Beverages: [dropdown menu] None
- Beverage: [dropdown menu] None

At the bottom is a 'Submit' button.

Figure 3.9 The user application for insertion of training goals and food preferences.

B) Results Interface: Select Your Meals

In this page, the athlete has 7 meals to consider. Each meal has 3 options to select from (i.e., first item, second item, or third item). It depends on the total energy needed for each meal and the energy and nutrients content of each recommended food item. For example, when athlete selects the first item for breakfast, the system will check if

the energy content of that selected food item is in the range of the total energy needed. If only one food item can fulfill the total energy needed, no other food items will be available for selection. However, if it does not fulfill the total energy needed, the athlete will be able to select the second and the third food items to achieve the energy goal (Figure 3.10).

	First Item	Second Item	Third Item
Breakfast	Klong_krang_krob_kem	None	None
Before Training	Cookie_chocolate_chip	None	None
During Training	Energy Drink 33cl		
After Training	None	None	None
Lunch	Guay-Tew-Rad-Na-Moo_Fried_rice_noodle...	Pad-Tua-Falyao-Sai-Moo_Sauté_green_veal...	Last-Nuea-E-san_Beef_cooked_northeastern...
Before Training	Kanom_Toa_Kearw	Pancake	None
During Training	Energy Drink 33cl		
After Training	Lui_Chups	None	None
Dinner	Yum-Moo-Yor_Sour_steamerd_pork_sausage...	Khao_ghat_Moo_Sai_Khai_Fried_rice_with_p...	None

	First Item	Second Item	Third Item
Breakfast	Cheesecake	Bread_rice_bean_filled	None
Before Training	Computt_salad_baked	None	None
During Training	Energy Drink 33cl		
After Training	Bread_chocolate_top	None	None
Lunch	Khao-Moo-Daeng_Rice_with_roasted_red_p...	Pta-Insee-Tod_Mackerel_spanish_salad_drie...	None
Before Training	Snack_crisspy_rice_bour_baked_fried	None	None
During Training	Energi Drink 33cl		
After Training	Cake_fruit	None	None
Dinner	Ho-mok-Pia-chon-Sai-Bai-Yor_Fish_with_c...	Tom-Kha-Kai	Ho-mok-Pia-chon-Sai-Bai-Yor_Fish_with_cury...

Figure 3.10 Choose your meal for today interface.

C) Results Interface: Report Dietary Recommendation

All information about the athlete can be seen in this page, including personal profile, training profile, an estimate total energy and macronutrients requirement, and dietary recommendation (Figure 3.11).

User Profile

Name:	Joao	Weight:	69	kg
Gender:	Male	Height:	168	cm.
Age:	16	Activity Factor:	Light	



Training Profile

Training Duration:	120	minute
Training Intensity:	Moderate (5.0)	METs
Training Phase:	General Preparation	
Weight Goal:	Maintain Weight	

Energy and Macronutrient Recommendation

TEN =	3,579	Kcal	Carbohydrate	546	g
			Protein	117	g
			Fat	103	g

Dietary Recommendation for 1 day

Before Training 6.00-6.15 A.M.	Sandwich with jam 2X, Apple 1X, Orange juice 1X
During Training Every 10 to 20 min	Sport drink 1X
Breakfast 8.00-8.30 A.M.	Rice with roasted pork loin with garlic and pepper 1X, Kale fried in oyster source 1X, Skim milk 1X
Lunch 12.00-12.30 P.M.	Rice with green curry with chicken 1X, Stir Fried Fish with Chinese Celery 1X, Banana 1X
Before Training 3.00-3.30 A.M.	Raisin bread 1X, Mango 0.5X, Juice 1X
During Training Every 10 to 20 min	Sport drink 1X
Dinner 7.00-7.30 A.M.	Rice with wing bean shrimp salad 1X, Stewed beef spicy soup 1X, Guava 1X

Figure 3.11 An example of recommended results of menus for 1 day.

3.5 Conclusions and Future Work

This chapter described the developed personalized food and nutrition recommendation system for weightlifting by using a rule-based knowledge framework. In doing so, a unified ontology of nutrition and sports was designed and implemented using Protégé. The four main concepts of ontology are including; Athlete, Food, Nutrition, and Sport. Under each concept, related sub-concepts and instances were asserted. Each domain knowledge was modeled according to the gathering data from literatures and interviewing experts in nutrition field. SWRL and SQWRL were used to create semantic rules. This implemented system is able to calculate the athlete's calories and nutrients needed based on the individual profile and recommend specific menus according to the training phase and weight goal. However, populating the fact base of such ontology-based system was a labored task due to the huge dimension of *Food Concept*. Therefore, requiring a lot of effort and time to insert individual data items in order to cover all available menus items.

Observations or results captured while using this system will be applied during modeling, design and implementation of the weightlifting TDC cycle knowledge base, which will be iteratively improved through the next chapters. For instance, some of the above defined and instantiated individuals can be used to populate the fact base of the new weightlifting ontology, while some of the above SWRL rules will be refactored, extended and pruned to tackle specific weightlifting TDC-cycle problems. Future work should be directed to the real-time data gathering through sensors and automatically updating database without user intervention. Following these approaches, the recommendation will be more precise and accurate and it will also allow the use of alerts when some parameter is not input correctly. To be able to communicate with the sensor via Java application, a DLL (dynamic linked library) should be created in C++ because Java doesn't allow user to directly communicate with hardware. For the communication between the DLL and Java, JNI (java native interface), a framework that specifies a communication protocol between Java code and external library's, should be considered.

CHAPTER 4

Modeling Weightlifting “Training-Diet-Competition” Cycle with Domain and Task Ontologies

This chapter is an extension of the previous chapters and it aims to promote a complete and better understanding of the proposed weightlifting rule- and knowledge-based system.

This chapter tries to answer the research questions of how to semantically model the whole weightlifting “*training-diet-competition*” cycle by conceiving and designing each individual ontology (i.e., training, biomechanics, and dietary) and semantically integrating them to mainly promote biomechanics, nutrition and weightlifting snatch exercises interoperability. It presents and discusses the lightweight, first-iterated weightlifting Training-Diet-Competition cycle (TDC-cycle) Ontology.

Introduction

Although ontology and its design methodology were shortly introduced during the exploratory Chapter 3, both definition will be extended over here to promote a better and clear understanding of the proposed weightlifting rule- knowledge-based system, as presented below in the Figure 4.3. Observations from exploratory chapter 2 and 3 were applied, while extended with main stakeholders' ideas collected during interviews to draw the competence questions presented in section 4.2.

Philosophically, ontology is the study of being, kinds and structures of objects. It includes properties, events, processes, and relations in every area of reality. It also deals with all questions about entities, and concerns how they are hierarchically classified according to similarities and differences. From an artificial intelligence perspective, ontology is the outcome of analysis and modeling that makes use of the concepts of modularity and connection. It translates into an explicit and structured framework of concepts and semantics, with the capacity to present novel relationships. Hence, ontology is viewed as a data model describing concepts in a specific domain. This data model is presented as classes along with classes' relationship. It conceptualizes the domain by explicitly defining all primitives, concepts, and constraints. It is represented by a formal language that can be processed by computers. Ontology was successfully used to share concepts across applications and exchange information based on semantics rather than using syntax.

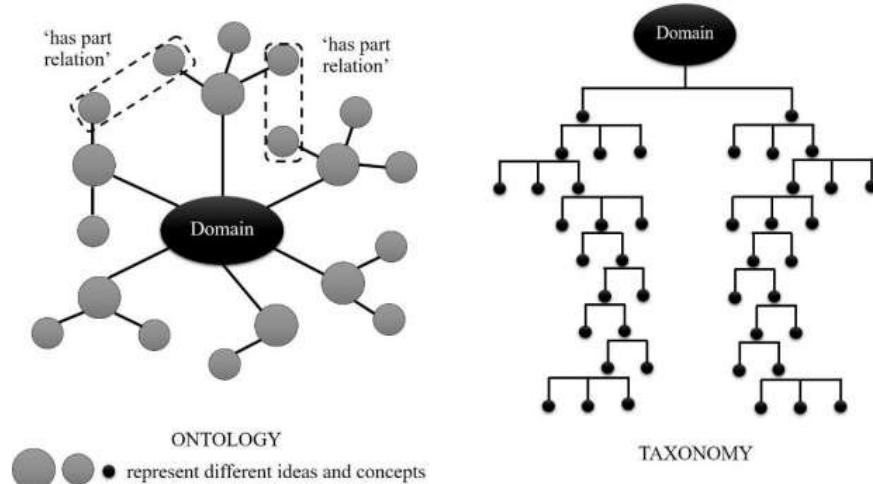


Figure 4.1 Ontology versus Taxonomy (Jashapara, 2011).

Another way to understand the meaning of ontology is by direct comparison to object-orientation where the focus is on classes' methods and decisions assisted by operational properties of classes, while in ontology decisions are based on the structural properties of classes. Ontology can also be compared to taxonomy (see Figure 4.1). While the former includes cardinality and restrictions, the latter is limited to "is a" kind of relationship. In other words, it organizes controlled vocabulary terms into a tree-like structure, being the controlled vocabulary the list of authorized keywords used to describe individuals of a taxonomy or ontology.

The main elements of an ontology are classes, individuals, properties, and relationships. An ontology together with a set of individual instances of classes constitutes a knowledge base. It is stored as entities and the relationships between them. Classes are collections of objects, sets or abstract groups, describing concepts in specific domain. They can contain both a subclass describing more specific concepts and an individual. An example of a class would be a *Food* class that would contain various subclasses like *food type* and *food group*. Individuals may be concrete concepts like *a specific menu* or *an ingredient* or an abstract concept like *food preference*. Properties are related to individuals or classes, as they are something that defines or explains them. Individuals can have two types of properties: either a data type, which is used to assign a value to a property or class, (e.g., a menu *hasEnergy* 150kcal)) or the object type, which is used to attribute one object to another one (e.g., menu A *hasIngredient* b). Relationships are unlimited not only in quantitative terms but also in complexity. They made modularity become a necessary demand for ontology modeling. Modularity allows researchers to model a given domain in many different ways. For example, a domain can consist of objects that relate to each other, possess attributes, participate in processes, may have one or more states or situations defining values of its attributes, react to events triggering the change of its state, and contain other objects. However, by using a logical description based on their properties to describe ontologies, the following relations must be presented: (i) relation between classes, (ii) relation between individuals or classes instances, and (iii) the relations between classes and individuals.

Ontologies have been used for: (i) expressing domain-general terms in a top-level framework, (ii) knowledge sharing, for communication in multi-agent systems, (iii) natural language understanding, (iv) making document navigation easier, browsing

and search, (v) consistency checking, (vi) configuration support, (vii) interoperability of tools and data, (viii) system engineering support, among many others. In system engineering, ontology has been used to identify system requirements and constraints, as well as to define relationships among components and subsystems that compose a system. Additionally, it can be used to support reuse-by-design of modules among different software systems.

There are different types of ontologies which are defined by Obitko (2001) as following:

- (i) *Workplace Ontologies* which specify boundary conditions characterizing and justifying problem solving behavior in the workplace.
- (ii) *Task Ontologies* which establish a vocabulary for describing a problem-solving structure of all existing tasks. They are independent from the domain by assigning roles to each object and the relations between them. Perez (1999) describe the reasoning process of a knowledge-based system in an implementation- and domain-independent manner. They usually are characterized by (i) inference steps required to achieve the goal of a task, (ii) control structures over the defined steps, and (iii) knowledge roles to specify the role that domain knowledge plays in each inference step.
- (iii) *Domain Ontologies* which can be either task-dependent or task-independent. The former requires some specific domain knowledge in order to be able to solve a task whereas the latter describes the structure and behavior of an object or theories and principles that govern a domain.

In addition, Prestes et al. (2013) presented another classification for different kinds of ontologies based on the level of generality. Examples include top-level/upper, application, core, domain, and task ontologies. *Top-level ontologies* are independent of a particular problem or domain. They are used to describe very general concepts like space, time, matter, object, event, action. *Application ontologies* are strictly related to a specific application. They are used to describe concepts of a particular domain and task. *Core ontologies* are viewed as mid-level ontologies (i.e., between top-level ontologies and domain ontologies). They specify generic concepts and relationships in a large domain by reusing upper ontology concepts complemented with new ones specific to domains and tasks.

The remainder of this chapter is organized as follows: Section 4.1 describes the methodology used for modeling and designing performance-oriented domains,

including task ontologies; Section 4.2 describes in detail domain scope and problem scenarios of the weightlifting TDC cycle and briefly presents a proposed TDC Competency Questions Engine; Section 4.3 presents the building of the whole domain ontology by individually describing each ontology subset and relationships between classes, following the proposed approach; Section 4.4 describes the building of task ontology, including the set of semantic rules that relate facts to infer new knowledge; Section 4.5 evaluates the ontology-based knowledge representation; Section 4.6 ends with some conclusions.

4.1 Ontology Development Methodology

Several generation of methodologies for building ontologies has been reported. Among them the following ones are enumerated:

- (i) *First generation* with main focus on the ontology modeling and development process while ignoring issues such as maintenance and reuse (Ribeiro et al., 2006). It is mainly represented by methodologies applied in TOVE (Grüninger & Fox, 1995) and ENTERPRISE (Uschold & Tate, 1998), both consisting of the following steps: (i) identification of the ontology purpose, (ii) domain knowledge acquisition, formally coding of the domain knowledge, and (iii) ontology evaluation. In TOVE a set of competence questions identified during the first step is compared against the formally expressed ontology.
- (ii) *Second generation* with main focus on performing specification, conceptualization, integration, and implementation as often as required, during the ontology lifetime. It is mainly represented by the methodology described in the first version of Methontology (Lopez et al., 1997) which uses translators to generate the ontology from a set of intermediate representations.
- (iii) *Third generation* with main focus on reusability and configuration management as activities of the development process. It is best represented by On-To-Knowledge (Sure, 2003) which focused on content-driven knowledge management through evolving ontologies. On-To-Knowledge leverages the use of ontologies for various tasks of information integration tasks and mediation.

(iv) *Fourth generation* with main focus on strengthening modularity and reuse of engineering design ontologies to better deal with the complexity of knowledge that is required to be brought together to support the design of knowledge-based decision-making system. It is mainly represented by the novel knowledge-based engineering (KBE) framework which adopts best practices from previous ontology development methods along with a model-driven architecture style to implement platform-independent knowledge-enabled product design systems, e.g., within the aerospace industry (Sanya & Shehab, 2014). Another representative of this generation is the middle-out approach suggested by Obrst et al. (2012), mixing aspects of top-down and bottom-up analyzes. Bottom-up and top-down analyzes require understanding the semantics of the underlying data sources which are to be integrated and the end-users who will actually use the resulting ontology-informed, semantically integrated set of data sources, respectively.

The NeOn methodology (Berges et al., 2016) follows a completely different approach for ontology engineering than previous ones as it does not prescribe a rigid workflow. Instead it suggests a variety of pathways for developing ontologies. Basically, it is a scenario-based methodology for building ontologies and ontology networks through collaborative aspects of ontology development and reuse. Scenarios consist of several processes or activities that can be combined in flexible ways to achieve the expected goal.

In this study, ontological modeling and designing the weightlifting TDC cycle demands collaborative contributions of several stakeholders such as athletes, coaches, nutritionist, biomechanist, knowledge engineer, and device designer to better construct concepts into a domain ontology and process/task ontology, representing declarative and procedural knowledge, respectively. These two kind of knowledge must be complemented with facts or instances, as well as inference knowledge to build the weightlifting TDC cycle knowledge base.

The first proposal for ontologically modeling the weightlifting TDC cycle, which is described next in this chapter, drives its main focus toward avoidance of complexity, memory exhaustion, ontology load time, and performance degradation than on modularity at domain-level and scalability issues, as dictated by fourth generation methodologies. Therefore, it consists of only one domain ontology and one task

ontology. The domain ontology contains several areas of domain knowledge (i.e., training, nutrition, and biomechanics knowledge) of the weightlifting TDC cycle, which include qualitative and quantitative values. The task ontology describes the problem-solving structures of all existing tasks. Additionally, the number and complexity of axioms are well-balanced to reduce computation time, as the ontology became easier while helping the reasoner to perform faster. In so doing, reasoning tasks are solvable in polynomial time with respect to the size of the whole input ontology (i.e., ontology itself plus its individuals). Hence, based on the guidelines proposed by Chi et al. (2015), the following steps are proposed to ontologically model and design the first version of the weightlifting TDC cycle:

- (i) *Establishing the domain scope and analyzing the problem scenarios* for each individual domain of the TDC cycle to identify tasks and task knowledge needed for problem solving with respect to each individual domain knowledge.
- (ii) *Modeling each individual domain as a subset of the domain ontology* by gathering data from literatures and interviewing domain experts. It will be guided by a controlled vocabulary, including common terms for the purpose of reference and communication. It will basically produce a hierarchical taxonomy complemented with identification of concept to properties and concept to instance relationships.
- (iii) *Modeling each individual task ontology as a subset of the task ontology* by describing and implementing identified problem solving broken into subtasks and steps to perform a task. Each task ontology subset comes with asserted and inferred properties where the latter corresponds to at least one axiom for implementing the reasoning process.
- (iv) *Developing semantic rules* through logical and non-logical axioms collected from known facts to infer implicit knowledge. These axioms will be used to build the inference mechanism used to solve TDC issues, as well as to closely integrate each individual and modular ontology subsets previously built.

Although the foundation for sport ontology was first addressed in earlier 1970 through published studies conducted first by Huizinga and later by Ellen Gerber (Morgan, 1976), there are only few ontologies targeting sport domain. Rigorous and appropriate manner about thinking in sport started with these two controversial essays of Huizinga

and Ellen Gerber. Huizinga's essay which is the precursor of Gerber's essay, "*Arguments on the Reality of Sport*", established a pre-ontological experience of sport phenomenon by following an ontic approach (i.e., based only on factual observations). The ontological shift was leveraged by Gerber's essay criticizing Huizinga's negative rendering of play/sport following an ontological perspective (i.e., moving from factual observations to constitutive elements and criteria used for concepts it formulates).

Few found examples about sport ontologies are:

- (i) SmartWeb system (Oberle et al., 2007) was designed around a simple lightweight Sport Event domain ontology for publishing data about competitive sports events. The Sport Event ontology is originated in a specific BBC use case and it models football events of varying granularity (tournaments, matches, and match events such as goal shots) as well as persons, places, and some more abstract entities like result tables. The Sport Event ontology promotes interoperability with more general ontologies such as Smart SUMO DOLCE and SUMO while featuring a large set of instances that primarily model facts of the Football World Cups 1930–2006.
- (ii) Muthulakshmi (2015) presents an ontology for sport training through e-learning which is based on a query template for storage and retrieval of sports information. It has a basic concept of sports ontology complemented with physiological variable measured before and after events, as well as with physical activity. The dataset of BBC 2012 with the information about the events, venue, schedule, and the performance of the athlete was enhanced with physiological variable to better improve the performance of the e-learner system.
- (iii) CaseLP (Zini & Sterling, 1999) is a declarative logical framework for prototyping agent-based applications which proposes an approach to add explicit ontologies in multi-agent systems based on logic programming. A domain ontology from sport results and an agent level ontology are exploited in CaseLP to perform semantic checks of agent architectural descriptions, to check agent behavioral rules used by an agent to provide its services, and as a knowledge repository to be exploited during agent execution. This ontology of sports models concepts such as sport, competition, competitors as well as relationships that relate these concepts.

- (iv) Miksch & Hammermuller (1999) represent the sport workout as time-oriented skeletal plans using Asbru. Asbru is a machine-readable language to represent and to annotate guidelines based on the task-specific ontology. Skeletal plans are plan schemata at various levels of detail that capture the essence of the procedure that can be instantiated and refined dynamically over significant periods of time and in highly dynamic environments. To automatically transfer various interactions between different workout exercises to the current situation of an individual athlete, they address issues such as the transfer of available knowledge, individual adaptation, and effective evaluation of intended effects after the planned exercises.
- (v) Nwe Ni Aung & Naing (2011) present information retrieval from Sports Domain Ontology using First-Order Logic rules and retrieve relevant semantic relationships between concepts from it. Contrary to most of existing ontology-based information retrieval systems which use concepts mapping, they use semantic relationships between ontology of concepts to retrieve more relevant and correct results.
- (vi) Zhai & Zhou (2010) present a sport ontology addressing fine-grained granularity and wide coverage of information for semantic retrieval for sports information in WWW. They use SPARQL query language to realize the intelligent retrieval at semantic level according to the relations of “synonymy of”, “kind of” and “part of” between sports concepts.

Although not uniquely associated to sport domain, a task ontology is fundamental in modeling, design, and implementation of smart ontology-based systems addressing the planning of a sport workout as demonstrated by Miksch & Hammermuller (1999). Task ontologies have been described in several studies such as the following ones:

- (i) Mitsuru et al. (1998) investigate the property of problem solving knowledge, design its ontology and then illustrate the design principle of a Conceptual LLevel Programming Environment (CLEPE) as an implemented system based on Task ontology.
- (ii) Yuan & Liu (2012) propose an abstract task ontology model that models temporal relationships among tasks into relation in task ontology model while can also be instantiated to task ontologies for tasks in different domains. The

knowledge about a specific task is modeled in its task ontology and retrieved by an ontology reasoning component supporting a domain independent dialogue manager.

- (iii) Rajpathak et al. (2001) discuss ontology as a reference model describing entities which exist in a universe of discourse and their properties and they also present a generic task ontology for scheduling problems which is both domain and application independent. They describe main concepts and axioms in their scheduling task ontology, while briefly comparing it to other task ontology proposals.
- (iv) Smith & Becker (1997) discuss the use of ontologies as a basis for structuring and simplifying the process of constructing customized domain-specific task scheduling solutions. By studying commonality and variability in scheduling system their proposed scheduling ontology (named OZONE) defines a reusable and extensible base of concepts for describing and representing scheduling problems, domains and constraints. In so doing, the OZONE ontology provides a framework for analyzing the information requirements of a given target domain, and a structural foundation for constructing an appropriate domain model.
- (v) Veer et al. (2002) present Task World Ontology derived from the conceptual framework of Groupware Task Analysis (GTA) to describe the way we look at the task world during task analysis. GTA is a task analysis method and its main focus goes toward group users or organizations and their activities according to a sequential temporal relation. GTA's task model contains three different aspects of the task world, including agents, work, and situation.
- (vi) Benjamins & Pierret-Golbreich (1996) present an architecture for problem-solving method (PSM) consisting of three interrelated parts: functional specification, requirements, and operational specification. They also identify two gaps around PSM mainly between a PSM and the domain knowledge it uses as well as between PSM and the goal that it is supposed to achieve. Then, they present two types of assumptions based on an architecture of PSM to bridge the two gaps: one is used to strengthen a PSM, and another one to weaken the goal to be achieved in a particular domain.

- (vii) Chandrasekaran & Josephson (1997) describe method ontology as task and method-dependent and then they identify two dimensions (i) Knowledge about the objective realities in the domain of interest, (ii) Knowledge about problem-solving on which such content theories might lie to make the problem-solving knowledge sharable and reusable.
- (viii) Chi et al. (2015) integrate multiple knowledge domains such as chronic kidney disease, food nutrient composition, and problem solving method to implement a chronic disease dietary consultation system. The system consists of three major design components: a domain ontology, a task ontology, and semantic rules. They describe the task ontology in terms of conceptual structure as well as in terms of problem solving knowledge while separating asserted properties from inferred properties with the latter described through the use of SWRL and SQWRL.

To the best of authors' knowledge supported by a literature review, there is no ontology exploring the interoperability among nutrition, weightlifting training, and biomechanics domains.

4.2 Establishing the Domain Scope and Analyzing Problem Scenarios

Managing training and competition performance of weightlifters is a very challenging problem due to the interplay among multiple sources of unobserved heterogeneity at athletes' profile, competition, training model, dietary protocol, research, resource, or year level. It involves several knowledge sources, spreading into several information dimensions such as biomechanics, coaching and training as well as nutrition dietary (see Figure 4.2). Nutritional knowledge, for example, includes the definition of dietary protocol, energy expenditure estimation, energy balance, as well as food composition in terms of macronutrients and micronutrients. Dietary protocol as a concept, includes recommended food intake according to athletes' preferences and restrictions at specific training and competition instants. Coaching and training knowledge supports a qualitative analysis technique which includes a controlled vocabulary consisting of common terms to alleviate semantic differences between training methods (e.g., Russian and Bulgarian models), lifting exercises and their phases concepts, as well as barbell and body kinematics and kinetics. The coaching and training dimension is mostly represented by descriptive terms or abstract values regarding lifting exercises'

performance which can be mapped to ground values measured in real-time by biomechanics analysis systems or energy expenditure measurement devices. Biomechanics knowledge supports a quantitative analysis approach based on ground values and it includes a controlled vocabulary consisting of sub-concepts (e.g., acquisition method, calibration method, and analysis method) and concepts like lifting analysis, resource, and muscle activity.

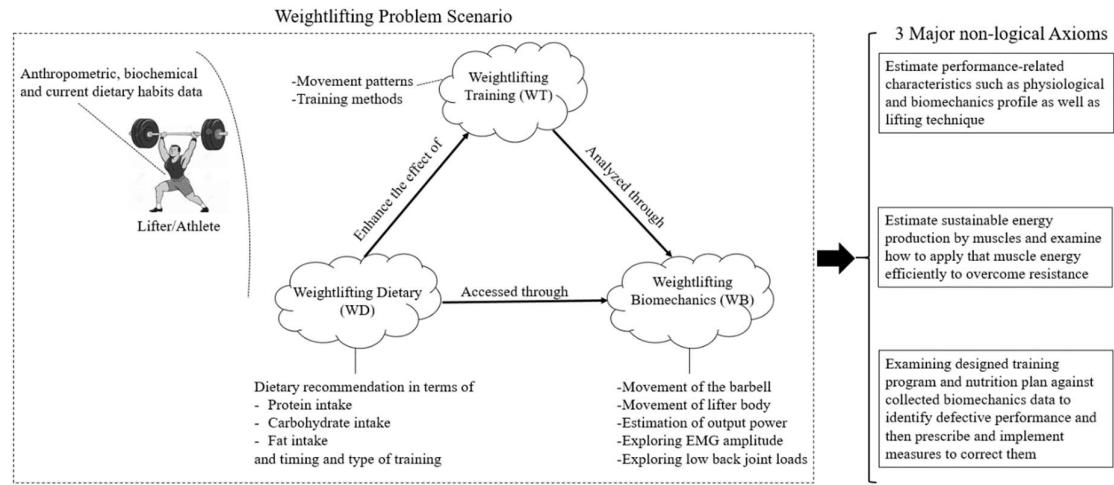


Figure 4.2 The problem solving for improving weightlifting ability.

To compound the problem, such multiple-dimensional information space is still sensitive to:

- (i) *Device or resource internal knowledge* consisting of inner working of devices and the process by which data are transferred, processed, and analyzed. It is required to obtain high data quality, discriminating between error and noise-free measurement data (George et al., 2014).
- (ii) *Integration of training metrics other than performance* such as weight cutting, as weightlifters need to maintain their ideal bodyweight category and so, facing certain amount of dieting before competition (Laputin, 1982)
- (iii) *Years of dedicated training* (5 to 10) for an athlete to reach full potential with heavier athletes taking longer than lighter athletes (Laputin, 1982)
- (iv) *Nervous systems* as weaker athletes require more volume at lower intensity than stronger ones (Laputin, 1982)

- (v) *Athletes' choices about effort and risk-taking* in a tournament setting which encourages to take more risks towards outstanding performance (Christos & Mario, 2008)
- (vi) '*Choking under pressure*' phenomenon which suggests athletes may perform badly under pressure, even though motivation and effort may be high (Christos & Mario, 2008)

Furthermore, the device internal knowledge will be a must in insuring a proper biomechanics laboratory's set up which will leverage a near noise-free collected signal, mainly due environmentally-based sources of error (e.g., electrical interference, thermal or chemical noise) while preventing sport biomechanist of being another source of measurement error. Such knowledge will dictate, in some way, the involvement of embedded system engineers as another stakeholder in the modeling of weightlifting TDC cycle as they know the design and function of devices (e.g., signal sampling, flow, amplification, and processing as well as device calibration), as well as how to interpret devices' technical information such as linearity, hysteresis, cross-talk, natural frequency, and maximum frequency ratio.

To implement the problem scenarios analysis for the management of weightlifting training and competition performance, we firstly tackle individually each information dimension of the TDC cycle and only then formalize the problem solving according to the following two sets of non-logical axioms, required to estimate and/or measure performance and energy production, as well as to examine and monitor the designed and prescribed training and nutrition programs to each individual athlete:

4.2.1 Assessment and Monitoring of Nutrition Features

Several prediction equations and method of analyzes will be required to estimate and measure the energy expenditure which depends on muscular activation and muscle contraction. Both anthropometric and metabolic measurements having been carried out because physical activities are usually classified in terms of their mutually dependent biomechanical and metabolic aspects, as well as their intensities and durations. Therefore, not only body composition should be assessed but also other potential sources of change in energy expenditure during lifting activities through activation levels of major muscles groups. By assessing the activation patterns and energy expenditures while lifting, the prescribed energy intake is examined to

determine the energy balance status and then accordingly adjusted (i.e., in terms of macronutrients and micronutrients) for a more suitable dietary intake. For accurate measurement of energy expenditure and outcome assessment, accelerometer-, electromyography-, heart rate-, calorimetric-, spectrometric-, or stadiometric-based devices have been used to collected data related to diverse energy expenditure components which are later processed using analysis or optimization methods such as artificial neural networks, ANOVA, and many other statistical methods. Meng & Kim (2012) grouped existing physical activity measurements into three categories: subjective methods (e.g., questionnaires, activity diaries, and interviews), objective methods (e.g., physiological measurements and motion sensors), and criterion methods (e.g., calorimetry and doubly labeled water). Several approaches for above methods are described in the following studies: (Bisi et al., 2011; Cen et al., 2011; Dickin et al., 2017; Gerrior et al., 2006; Grüninger & Fox, 1995; Haskell & Kiernan, 2000; Hay et al., 2008; Levine, 2005; Ogata et al., 2016; Thomas et al., 2016; Tikkanen et al., 2014)

4.2.2 Assessment and Monitoring of Biomechanics Features

To maintain consistence in each lift while enhancing performance, weightlifting biomechanics have been analyzed following qualitative, quantitative, and predictive approaches, as well as combinations of them. Quantitative approaches within Olympic weightlifting biomechanics have been toward kinetics and kinematics of barbell and weightlifter body, mainly trying to classify barbell trajectory, identify optimal lifting technique, explore low back joint loads, quantify barbell parameters (e.g., barbell velocity, barbell acceleration, barbell displacement, and barbell lift duration), joint kinematic, joint angular velocities, and joint angular displacement, and the effect of the loads. Furthermore, EMG has been explored to leverage accurate and reliable measurement while several other studies focus on measuring relationships among the above quantified parameter, such as: (i) measuring relationships of force, velocity, and power exerted in a specific movement pattern, (ii) correlating force, or torque, velocity for groups of muscles, (iii) correlating internal and external mechanical power output and internal mechanical joint power output across different loads, and (iv) correlating skill and load to joint-power. In so doing, it requires several devices such as goniometers, motion capture systems, force plates, EMG-based sensors, and accelerometers, as well as several and different method of analysis based on artificial

neural network, intra-repetition analysis, analysis of variance, dynamic equations of motions, genetic algorithm, and 3D kinematic analysis. Additionally, some studies described simulated kinematics based on mathematical modeling and optimization of snatch technique using several models for: joint moments, anthropometric data, barbell trajectory, weightlifter multi-body on sagittal plane, muscle activations, muscle geometry, barbell kinematics, and weightlifter biomechanical at various positions. Approaches regarding above mentioned methods can be found in the following studies: (Beardsley, 2016; Enoka, 1988; Ho et al., 2014; Kipp et al., 2013; Nejadian & Rostami, 2007; Rahmati & Mallakzadeh, 2014; Ross et al., 2017; Wang & Buchanan, 2002; Zhai & Zhou, 2010)

The choice or design of the proper research methodology based on the above variety of equations and analysis methods will be inevitable and should be mainly supported by accuracy and statistical power associated to each of them. Alternatively, new research should be designed to maximize statistical power of some promising identified approaches (e.g., by enlarging sample size, effect size, and level of statistical significance), as well as integrating some of them (e.g., merging objective in the lab assessment with qualitative in the field assessment).

Having already defined the motivation for addressing issues related to the weightlifting TDC cycle, the following general competence questions (i.e., typical consultation questions) were formulated to be answered by the ontology and so, limiting the ontology scope:

- (i) Did the athlete properly lift the barbell?
- (ii) Did the athlete's body move accordingly during exercises phases?
- (iii) Was the athlete well-served in terms of macronutrients and micronutrients according to the training protocol specificity?
- (iv) Did the rhythmic execution reflect an efficient snatch technique?

The rhythmic execution, should be understood as the definition presented by Ho et al. (2014) and Szabo (2012), i.e., the coordination movement of the weightlifter-barbell system for an efficient and effective lift.

Figure 4.3 shows the proposed TDC Competency Questions Engine Architecture with its main building blocks, stakeholders and perspectives. Each actor plays a

fundamental role in the assessment task. The Reasoning and Knowledge Base layer encompass three non-overlapping sublayers. The four perspectives are defined as follows:

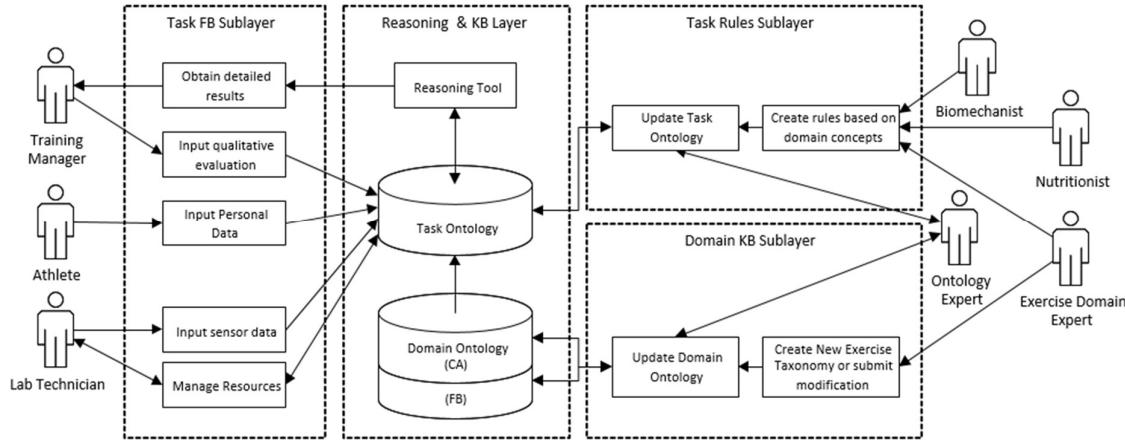


Figure 4.3 Weightlifting TDC-cycle OWL- and Rule-Knowledge-based System.

- **Task Fact Base (FB)** encloses task related instances. The Athlete creates his profile by inserting relevant personal data. The Training Manager and Lab Technician are in charge of updating the knowledge base with training data, respectively, providing qualitative and quantitative assessments.
- **Reasoning and Knowledge Base (KB)** is composed of all available knowledge over which the reasoning is performed. The **Task FB** input is used as a trigger to start the inference process, which is based on SWRL rules. The output of this process is given as a series of axioms, representing detailed results with practical, human readable data.
- **Task Rules** comprises all SWRL rules created to infer knowledge from training related instances. These rules may be created or updated by several experts from different domains such as Nutrition, Biomechanics, and Physiology.
- **Domain Knowledge Base** refers to the application-independent axioms, which can be updated to better cope with improvements in the understanding of applicable fields.

Knowledge bases (KB) are implemented as ontologies, which were divided into assertion axioms (i.e., *Fact base; FB*) and terminological axioms (i.e., *Concepts and*

Attributes; CA) to illustrate the interaction of both areas in the global architecture. Each *KB* and respective rules were created using Protégé and its plug-ins. Given the modularity of this approach and the flexibility of knowledge insertion and revision, this architecture favors extensibility without compromising the overall adopted structure.

4.3 Modeling and Design of the Weightlifting Domain Ontology

For the overall design and development process, the methodology outlined in the work of Chi et al. (2015), briefly described above in Section 4.2.2 and illustrated by Figure 4.4, was followed.

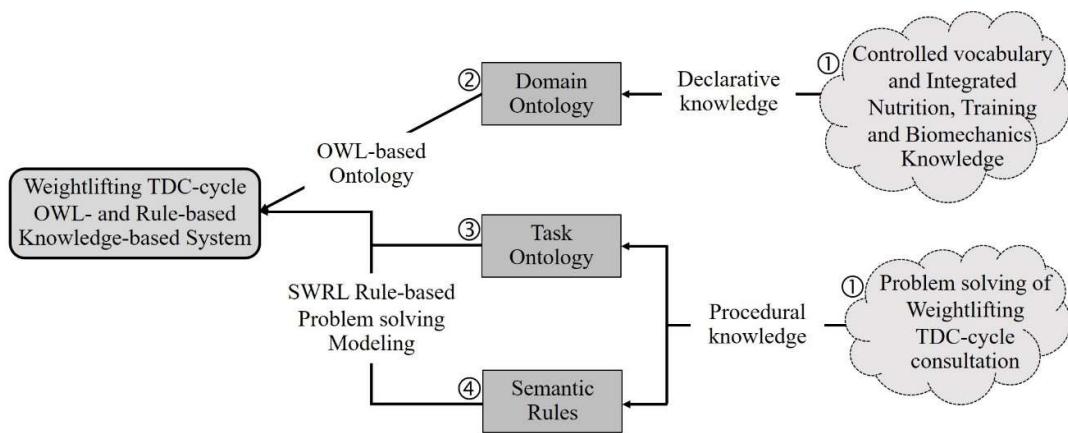


Figure 4.4 Methodology for building ontologies: its steps, key modeling, and design artefacts (Adapted from Chi et al., 2015).

To obtain a deep understanding of aspects and concrete entities comprising the weightlifting TDC cycle, repetitive collaboration meetings were organized between athletes, coaches, and multidisciplinary researchers as biomechanist and nutritionist of Porto University along with electronics and software engineers of University of Minho. The following design artefacts express ontologies in the weightlifting TDC-cycle knowledge-based system i.e., the TDC-Ontology = (*CA*, *CV*, *FB*, *R*, *A*):

- (i) *CA* is a series of concepts set and attributes set related to concepts, representing both domain and task ontologies;
- (ii) *CV* is a controlled vocabulary, consisting of a list of authorized common keywords used to describe individuals of *CA* on the fact base (*FB*);

- (iii) FB complements the CA structure with set of individuals that are instantiations for the concepts from CA and both aim for a common understanding of the domain for ontological sharing and reuse;
- (iv) R represents relationships between classes, mainly object properties of “*has-a*” type, which are used on SWRL rules specified in A to enable problem solving;
- (v) A is a set of axioms to facilitate reasoning about individuals on FB and it aims for solving specific weightlifting TDC-cycle problems, previously formulated through competency questions.

A) Concepts and Attributes (CA)

Different concepts in the TDC-Ontology have been divided into four main knowledge sets, namely, training, biomechanics, nutrition, and problem solving, complemented with an athlete profile concept as nearly all observation and measurement are around athlete's activities. The first three sets correspond to domain ontology which identifies general concepts and their relations in the field of weightlifting, while the fourth one is part of the task ontology. Figure 4.5 shows a partial conceptual model of the domain ontology with concepts organized in a taxonomic ‘*is-a*’ hierarchy.

- *Training- or coaching-related ontology subset* refers to classes modeling exercises performed by athlete, with each exercise consisting of several phases or sub-exercises. Basically, these concepts are used to promote a qualitative weightlifting analysis and are mainly represented by abstract values regarding observable lifting performance by a coach.
- *Biomechanics-related ontology subset* is used to leverage a quantitative weightlifting analysis and are represented by the *ExerciseProperty* concept which main purpose is complementing qualitative lifting performance values with biomechanics ground values measured during a lifting exercise phase, using biomechanics equipment. Figure 4.6 presents several subclasses of the *ExerciseProperty* concept, where each instance has associated data properties measuring the read values (e.g., barbell position).

Another view of the involved classes can be seen in Figure 4.7 In this perspective, irrelevant classes were removed, and all relations are of type *hasSubclass*.

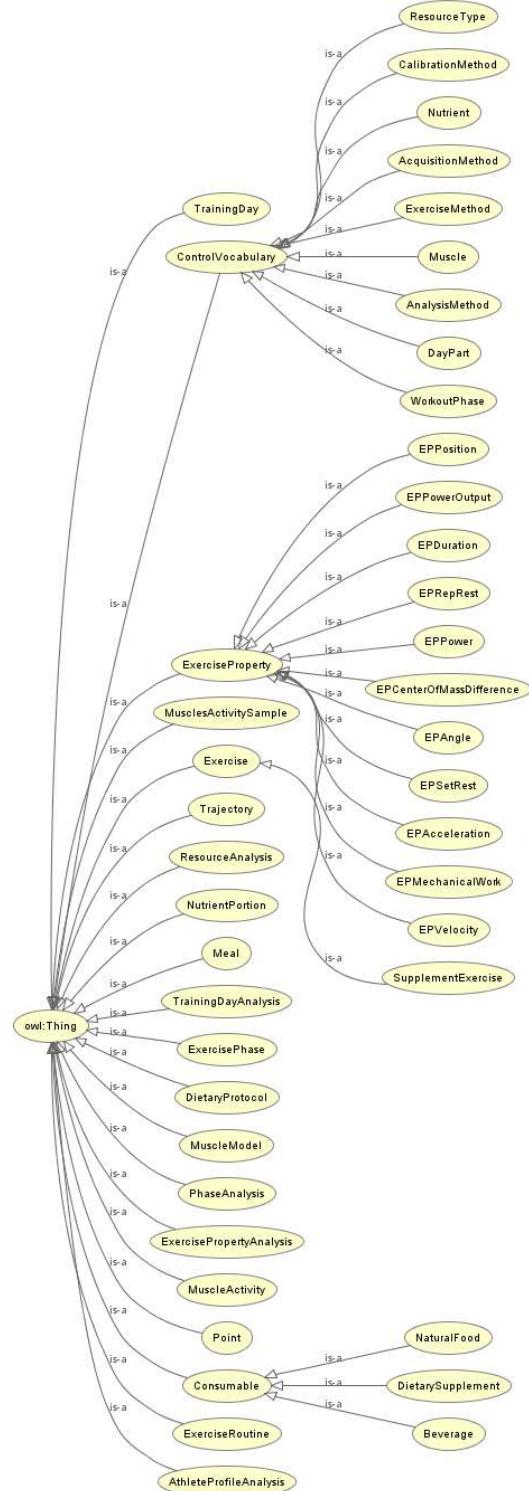


Figure 4.5 Fragment of the TDC-Cycle hierarchy of classes.

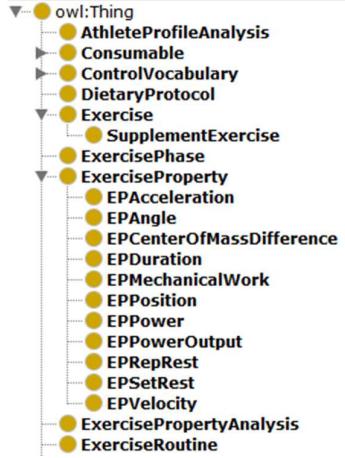


Figure 4.6 Class hierarchy of *ExerciseProperty*.

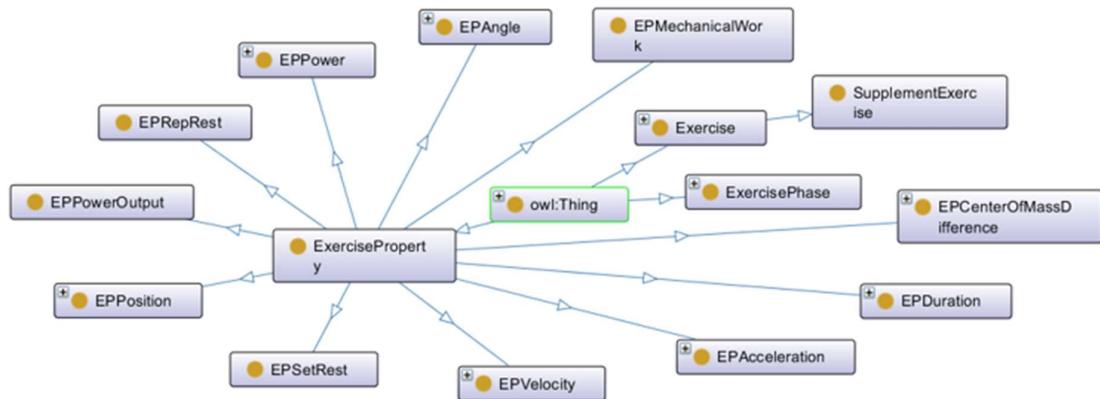


Figure 4.7 Biomechanics-related classes.

- *Nutrition-related ontology subset* is also used to leverage a quantitative weightlifting analysis and it is modeled by the following subclasses (see Figure 4.8). The *DietaryProtocol* related to each workout period, the respective *NutrientPortions*, and the *Consumable* having nutrients. Nutritional ground values are measured for a lifting exercise, using a combination of energy expenditure measurement equipment, prediction equations, and methods of analysis.

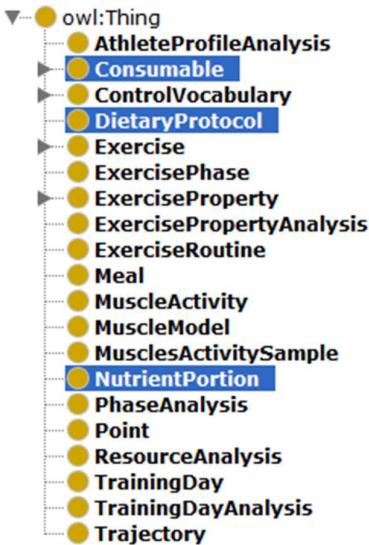


Figure 4.8 Classes or concepts used to model nutrition-related knowledge.

The *DietaryProtocol* concept prescribes the receipt of nutrient portions for a specified workout phase, the *NutrientPortions* concept identifies a specific nutrient and its amount in terms of macro- and micro-nutrients and the *Consumable* concept represents the food and drink that are sources of nutrients. Analogously to the displayed perspective on Figure 4.8, nutrition related classes are also shown on Figure 4.9 with *hasSubclass* relations.

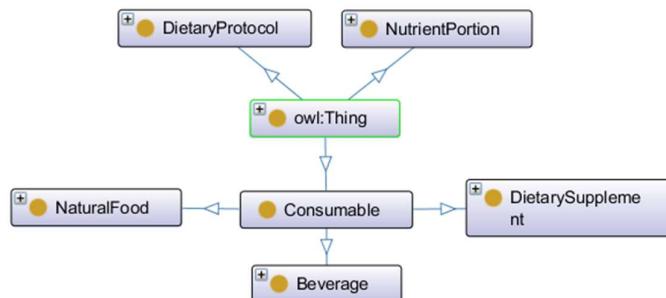


Figure 4.9 Nutrition-related classes.

Table 4.1 Data properties of each concept presented on the domain ontology.

Concept	Property	Type	Range	Description
Consumable	HasNutrientPortion*	Asserted	NutrientPortion	
	hasCalories	Asserted	(double)	
Control Vocabulary				
Acquisition Method	hasAccuracy	Asserted	(double)	
	hasIntrusionLevel	Asserted	(int)	
Analysis Method	hasAccuracy	Asserted	(double)	
Calibration Method	hasAccuracy	Asserted	(double)	
Nutrient	hasName	Asserted	(string)	
Dietary Protocol	hasAthlete*	Asserted	AthleteProfile Analysis	
	hasAthletePreference*	Asserted	Consumable	
	hasAthleteRestriction*	Asserted	Consumable	
	hasNutrientPortion*	Asserted	NutrientPortion	
	hasWorkoutPhase*	Asserted	WorkoutPhase	
ExerciseProperty	hasMax	Asserted	(double)	
	hasMin	Asserted	(double)	
	hasName	Asserted	(string)	
NutrientPortion	hasNutrient*	Asserted	Nutrient	
	hasValue	Asserted	(double)	

*indicates an object property

B) The Controlled Vocabulary (CV)

Horizontal to concepts defined in CA, there is a list of authorized keywords, used across both domain and task ontology. As shown in Figure 4.10, the list contains nine subclasses and under each of them, authorized keywords are used to provide reference and indexing for communication with other concepts and instances.

- *WorkoutPhase* concept defines periods for which a dietary protocol is prescribed which is instantiated as authorized keywords *Preworkout*, *Duringworkout*, and *Postworkout*.
- *DayPart* concept represents day time prescribed for weightlifting training and dietary intake. It is instantiated as authorized keywords *Morning*, *Afternoon*, and *Evening*.

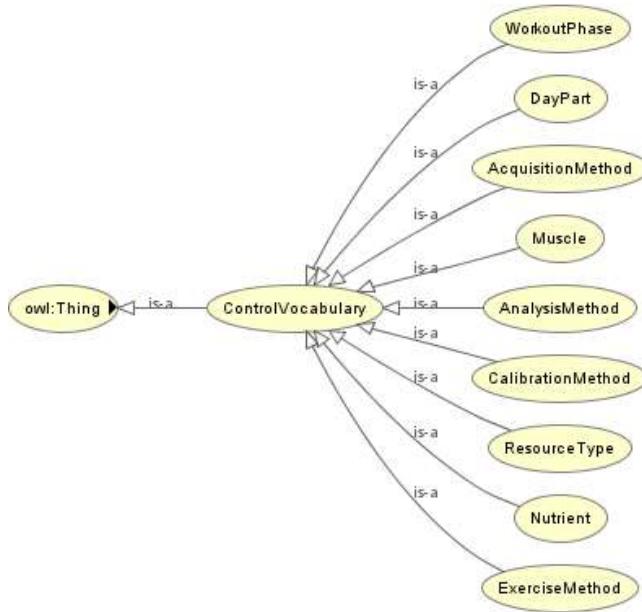


Figure 4.10 Nine controlled vocabulary concepts.

- *AcquisitionMethod* concept establishes methods used to collect quantitative ground values, e.g., heart rate monitor, motion analysis, electromyography, or force measurement.
- *Muscle* concept defines muscles where activity should be measured, e.g., quadriceps femoris muscle.
- *AnalysisMethod* concept establishes analysis methods used for the assessment of energy expenditure and biomechanics features from several kinds of collected data such as kinetics, kinematics, and physiological.
- *CalibrationMethod* concept establishes some known methods for proper calibration of biomechanics equipment (e.g., for force plates: a method for calibrating the vertical force axis is to apply a dead weight of known value) which is instantiated as authorized keywords *OnePointCal*, *TwoPointCal*, and *CurveFittingCal*.
- *ResourceType* concept defines resource types used for quantitative measurement of barbell kinematics/kinetics and body kinematics/kinetics (e.g., video cameras, infrared cameras, force platform, position transducer), body composition, and energy expenditure as well as training resource (e.g., barbell and weight plates).

- *Nutrient* concept includes groups of macro- and micro-nutrients, as standard vocabulary used in energy expenditure assessment and dietary intake to promote optimal health and performance across different scenarios of weightlifting training.
 - *ExerciseMethod* concept classifies weightlifting training methods under Bulgarian or Russian frameworks and principles.

C) The Fact Base as a set of individuals (FB)

Concepts in the domain ontology are further elaborated and terminal concepts are described in terms of instances. These individuals belonging to the ontology will act as the foundations of the knowledge base supporting the problem solving activity. The fact base is populated by a collection of facts generated through the elaboration of domain ontology concepts, i.e., terminal concepts are described in terms of instances. These instances contain measured nutritional and biomechanics ground values as well as observable training-related abstract values collected by coaches which are mapped to corresponding ground values. As an example, Figure 4.11 shows the *NutritionPortion* concept filled with its constituent instances. See Figure 4.12 for more individuals or facts.

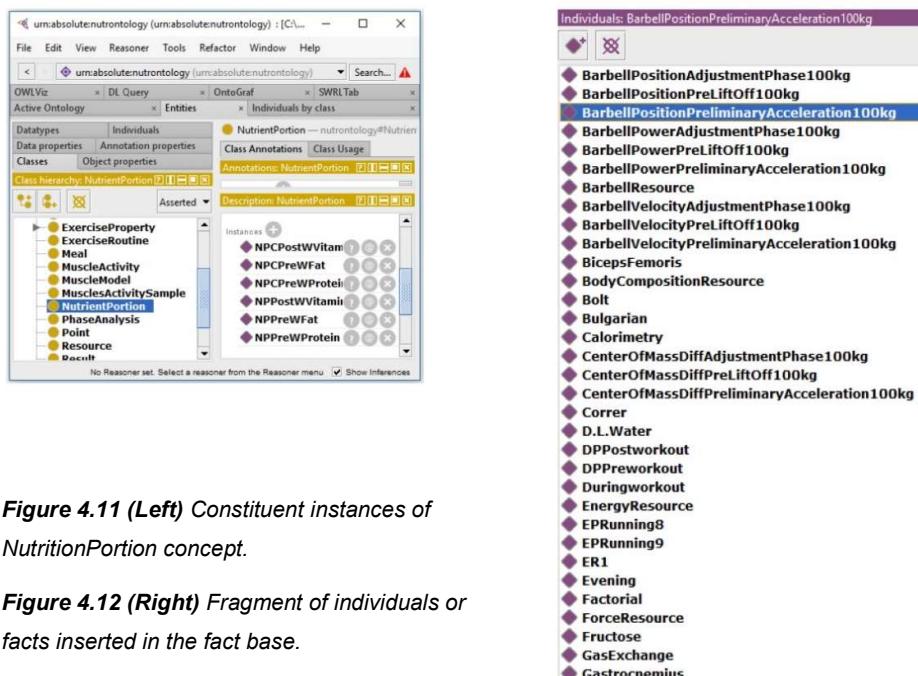


Figure 4.11 (Left) Constituent instances of NutritionPortion concept.

Figure 4.12 (Right) Fragment of individuals or facts inserted in the fact base.

D) Relationships between classes (R)

Excluding the data properties presented in Table 4.1, the remaining relationships (i.e., among classes) are constructed as object properties given in Figure 4.13, while Figure 4.14 shows an individual of *ExercisePhase* concept and its associated asserted data and object properties.

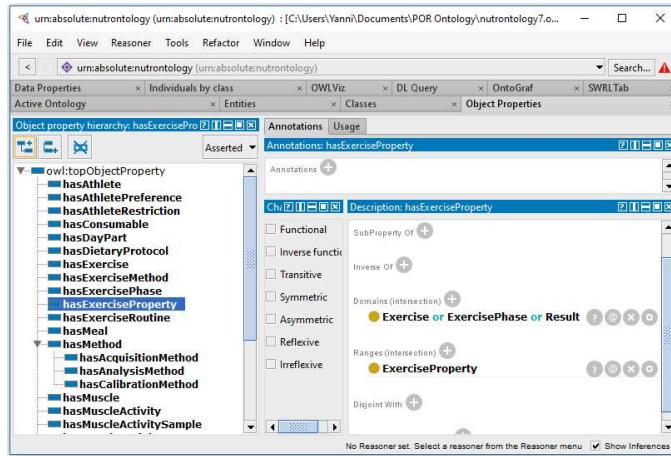


Figure 4.13 A fragment of object properties among concepts on TDC-Ontology.

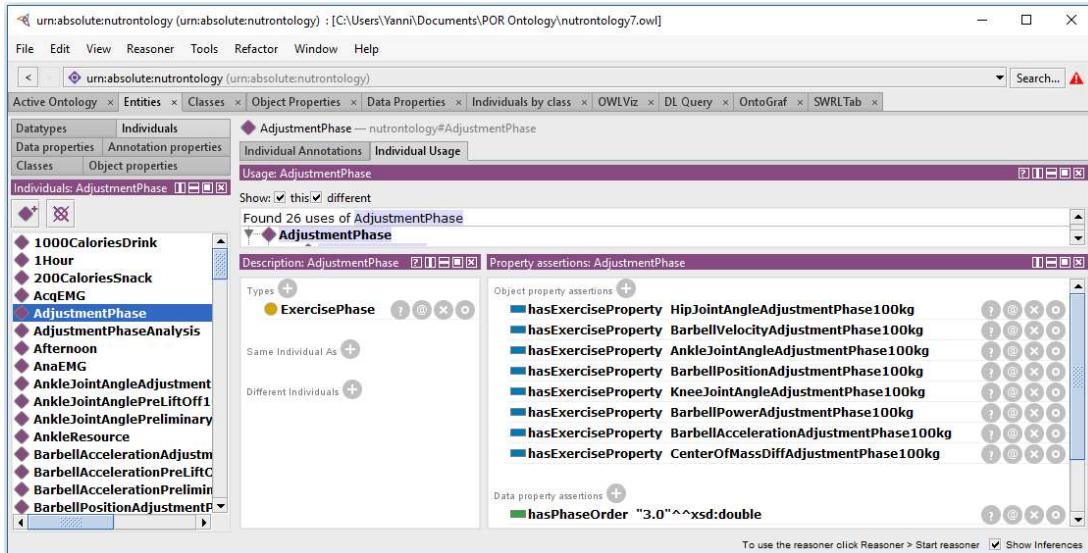


Figure 4.14 An individual and its associated asserted data and object properties.

Figure 4.15 displays some individuals that represent the analysis of a phase of the Snatch exercise. The *Snatch* exercise individual is related to 5 phases (6 positions) by the object property *hasExercisePhase* and, for the *Liftoff* position (first pull phase), there are some *ExerciseProperty* individuals where each is related to a *Result*

individual that belongs to an individual of the *PhaseAnalysis* concept, called *LiftoffAnalysis*.

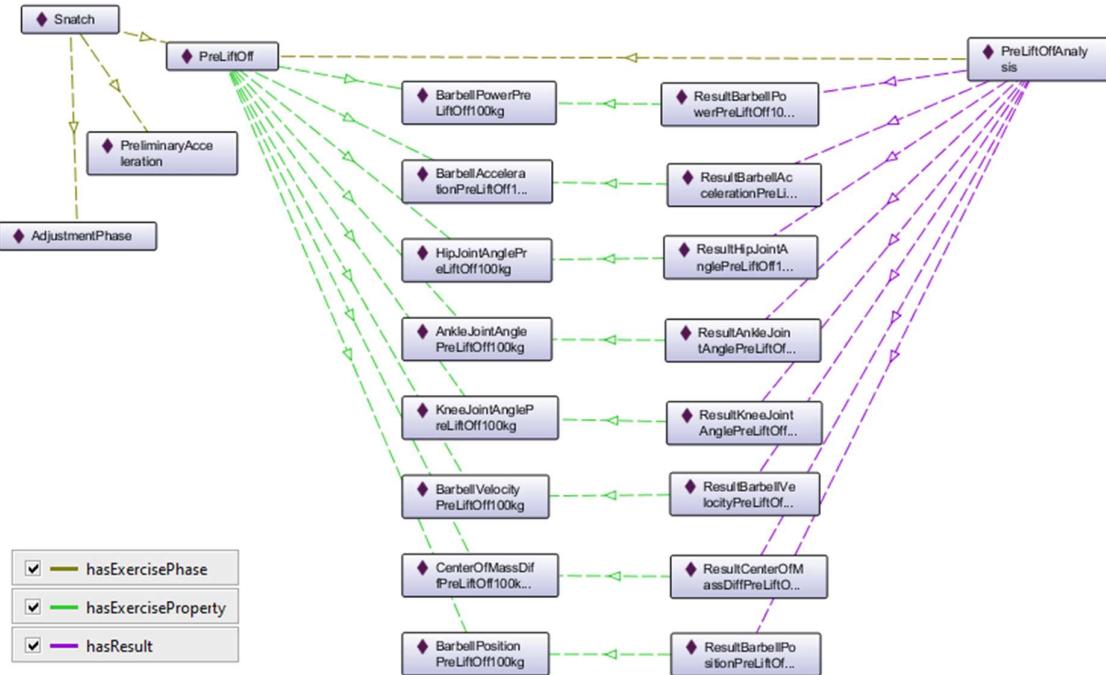


Figure 4.15 Some individuals and their associated object properties.

4.4 Engineering the Task Ontology

To solve specific weightlifting TDC-cycle problems as previously formulated through competency questions, the task ontology uses the conceptual structure of the domain ontology expressing the semantic knowledge of biomechanics, nutrition, and training dimensions of the TDC-cycle, while defining other concepts' constituent properties to describe the problem solving structure. Basically, (i) property values of known facts or unknown knowledge are defined to separate asserted properties from inferred ones (see Table 4.2), (ii) the corresponding domain and range of properties are asserted, and then, (iii) SWRL rules supported by SQWRL are created for reasoning about individuals on *FB* and so, addressing the insufficient expressivity of ontologies in properties association and operation required by the formulated competency questions.

Generically, the problem solving structure consists of two main groups, i.e., nutrition analysis and training analysis (i.e., addressed both in terms of qualitative and quantitative analysis, being the latter achieved through biomechanics analysis) according to Figure 4.2 and also the aforementioned competency questions.

Table 4.2 Definition of Concepts attributes in the Task Ontology.

Concept	Property	Type	Range	Description
AthleteProfile Analysis	hasMuscleModel*	Asserted	MuscleModel	
	hasTrainingDay*	Asserted	TrainingDay	
	hasAge	Asserted	(double)	
	hasEEE	Inferred	(double)	Exercise Energy Expenditure
	hasGAF	Asserted	(double)	General Activity Factor
	hasGender	Asserted	{"Female", "Male"}	
	hasHeight	Asserted	(double)	
	hasWeight	Asserted	(double)	
	hasName	Asserted	(string)	
PhaseAnalysis	hasExercisePhase*	Asserted	ExercisePhase	
	hasMuscleActivity Sample*	Asserted	MuscleActivity Sample	
	hasResource*	Asserted	Resource Analysis	
	hasResult*	Asserted	ExerciseProperty Analysis	
	hasEnergyExpenditure Measurement	Asserted	(double)	
	hasEvaluation	Inferred	(string)	
	hasProblem	Inferred	(string)	
	isCompensated	Asserted	(boolean)	Indicates if a phase is considered well executed qualitatively (coaching) despite of what is measured quantitatively (biomechanics)

Concept	Property	Type	Range	Description
Resource Analysis	hasAccuracy	Inferred	(double)	
	hasAcquisition Method*	Asserted	Acquisition Method	
	hasAnalysisMethod*	Asserted	AnalysisMethod	
	hasCalibration Method*	Asserted	Calibration Method	
	hasResourceType*	Asserted	ResourceType	
	hasName	Asserted	(string)	
ExerciseProperty Analysis	hasExerciseProperty*	Asserted	Exercise Property	
	hasEvaluation	Inferred/ Asserted	(string)	
	hasValue	Asserted	(double)	
TrainingDay Analysis	hasPhaseAnalysis*	Asserted	PhaseAnalysis	
	hasTrainingDay*	Asserted	TrainingDay	
	hasDietaryMargin	Asserted	(double)	
	hasDietaryProblem	Inferred	(string)	
	hasEEE	Inferred	(double)	Exercise Energy Expenditure
	hasEnergyDifference	Inferred	(double)	
	hasEnergyIntake	Inferred	(double)	
	hasRMR	Inferred	(double)	Resting Metabolic Rate
	hasTEN	Inferred	(double)	Total Energy Needed

*indicates an object property

Therefore, some concepts that constitute the problem solving structure are:

- *AthleteProfileAnalysis* concept contains 9 properties, being 8 asserted properties (age, gender, name, weight, height, training day, muscle model, and general activity factor) and 1 inferred from rule *EEE* (Exercise Energy Expenditure).
- *PhaseAnalysis* concept contains 8 properties. 6 are asserted properties and 2 are inferred properties, which are used for the evaluation of an exercise's phase. (see rule *analyze*)

- *ResourceAnalysis* concept contains 5 asserted properties (name, type, acquisition method, calibration method, and analysis method) and 1 inferred property that represents the accuracy of the resource and it is inferred using rule *topResources*.
- *ExercisePropertyAnalysis* concept contains 2 asserted properties (name and exercise property) and another property that is either asserted or inferred, to represent the evaluation of the result. When inferred, this evaluation maps to rules *evaluateMax*, *evaluateMin*, and *evaluateMinMax*.
- *TrainingDayAnalysis* concept contains 9 properties, where 3 are asserted (phase analysis, training day, and dietary margin) and 6 are inferred. The EEE is inferred by rule *EEE*. TEN and RMR are inferred by rules *TENmale* or *TENfemale*. The energy intake is inferred by rule *EI* while the difference between consumed and needed energy is mapped to Rule *balance*. 1 property used to report dietary problems of the training day, which is inferred from rules *evaluateNutrientsMax* and *evaluateNutrientsMin*.

Three of these concepts are combined to form a complete biomechanics and nutrition analysis chain, being the core of the problem solving structure. Starting with the *ExercisePropertyAnalysis*, this concept analyzes the individual biomechanics characteristics of an exercise which are mapped to the *ExerciseProperty* concept. Then, *PhaseAnalysis* focuses on several phases of each exercise and provides a broader analysis of the biomechanics of an exercise. Lastly, *TrainingDayAnalysis* encompasses the analysis of nutrition for a full training day of multiple exercises.

4.5 Analysis of Semantic Rules

All the 11 inferred properties of the Task Ontology require semantic rules that relate facts and, thus, are able to infer new knowledge. In order to answer all the competency questions, SWRL-based rules and SQWRL queries were used. SWRL rules operate over the instances of the ontology and are expressed as a chain of atoms that, if all hold true, a consequence is produced. SQWRL queries work similarly to the SWRL rules but are used for retrieving knowledge from the ontology instead of creating it. Also, query's result needs to be manually added to the ontology. Overall, 9 rules and 3 queries were created and these can be separated into three broad categories: Biomechanics/Coaching, Nutrition, and Resource reliability.

A) Biomechanics/Coaching rules

(i) **evaluateMinMax** used for the evaluation of an exercise and it starts by evaluating if each of its properties are within a considered favorable range. It verifies whether the value of an exercise property's result is within the specified range, and in case of being true, it causes the result to receive a positive evaluation denoted by the word "OK". Breaking down the rule, it starts by obtaining an *ExercisePropertyAnalysis* individual called *r* (1) and its value (2) using the *r*'s *hasValue* data property. Then it obtains, through the *hasExerciseProperty* object property, the *ExerciseProperty* individual *p* (3) and, like before, its min and max values (4-5) are retrieved using the *hasMin* and *hasMax* data properties, respectively. After obtaining all the necessary values, the rule then checks if the result's value is within the exercise property's range (6-7) and it asserts *r*'s evaluation as "OK" (8).

Rule: evaluateMinMax	
ExercisePropertyAnalysis(?r)	(1)
^ hasValue(?r, ?v)	(2)
^ hasExerciseProperty(?r, ?p)	(3)
^ hasMin(?p, ?min)	(4)
^ hasMax(?p, ?max)	(5)
^ swrlb:greaterThanOrEqual(?v, ?min)	(6)
^ swrlb:lessThanOrEqual(?v, ?max)	(7)
-> hasEvaluation(?r, "OK")	(8)

(ii) **evaluateMin** is used to evaluate if the value of the result is below the minimum. It uses the *ExerciseProperty*'s name to be easily identifiable, as this evaluation will be later used for the overall examination of the exercise.

Rule: evaluateMin

```

ExercisePropertyAnalysis(?r)
  ^ hasExerciseProperty(?r, ?p)
  ^ hasValue(?r, ?v)
  ^ hasMin(?p, ?min)
  ^ swrlb:lessThan(?v, ?min)
  ^ hasName(?p, ?n)
  ^ swrlb:stringConcat(?s, ?n,
    " is below minimum")
-> hasEvaluation(?r, ?s)

```

(iii) evaluateMax is similar to the previous rule, and it is only used to evaluate if the value is above the maximum.

Rule: evaluateMax

```

ExercisePropertyAnalysis(?r)
  ^ hasExerciseProperty(?r, ?p)
  ^ hasValue(?r, ?v)
  ^ hasMax(?p, ?max)
  ^ swrlb:greaterThan(?v, ?max)
  ^ hasName(?p, ?n)
  ^ swrlb:stringConcat(?s, ?n,
    " is above maximum")
-> hasEvaluation(?r, ?s)

```

(iv) analyze examines if the exercise was not properly executed by checking if there are any unsuccessful results and so, reporting all associated problems.

Rule: analyze

```

PhaseAnalysis(?a)
  ^ hasResult(?a, ?r)
  ^ hasEvaluation(?r, ?s)
  ^ swrlb:notEqual(?s, "OK")
  ^ isCompensated(?a, ?c)
  ^ swrlb:equal(?c, false)
->hasEvaluation(?a, "Failed") ^
  hasProblem(?a, ?s)

```

B) Nutrition rules

- (i) **EEE** calculates the Exercise Energy Expenditure based on the formula EEE = METs * 0.0175 * Weight * Duration.

Rule: EEE

```
TrainingDayAnalysis(?tda)
^ hasPhaseAnalysis(?tda, ?pa)
^ hasResult(?pa, ?r)
^ hasExercisePhase(?pa, ?ep)
^ EPDuration(?p)
^ hasExerciseProperty(?r, ?p)
^ hasValue(?r, ?d)
^ hasTrainingDay(?tda, ?td)
^ hasAthlete(?td, ?a)
^ hasWeight(?a, ?w)
^ hasExerciseRoutine(?td, ?er)
^ hasExercise(?er, ?e)
^ hasExercisePhase(?e, ?ep)
^ hasMET(?e, ?m)
^ swrlb:multiply(?v0, "0.0175"^^xsd:float, ?m)
^ swrlb:multiply(?v1, ?v0, ?d) ^ swrlb:multiply(?v2,
?v1, ?w) ° sqwrl:makeBag(?b, ?v2)
° sqwrl:makeBag(?b, ?v2)
^ sqwrl:groupBy(?b, ?tda)
° sqwrl:sum(?s, ?b)
-> sqwrl:select(?tda, ?s)
```

- (ii) **femaleTEN** calculates the Resting Metabolic Rate (RMR) and the amount of energy needed (TEN) by an athlete, in this case, a female athlete.

Rule: femaleTEN

```
TrainingDayAnalysis(?tda)
^ hasTrainingDay(?tda, ?td)
^ hasAthlete(?td, ?a)
^ hasGender(?a, "Female")
^ hasWeight(?a, ?w)
^ hasHeight(?a, ?h)
^ hasAge(?a, ?age)
^ hasGAF(?a, ?g)
^ hasEEE(?tda, ?eee)
^ swrlb:multiply(?ww, 9.56, ?w)
^ swrlb:multiply(?hh, 1.85, ?h)
^ swrlb:multiply(?aa, 4.68, ?age)
^ swrlb:add(?r1, 655.1, ?ww)
^ swrlb:add(?r2, ?r1, ?hh)
^ swrlb:subtract(?rmr, ?r2, ?aa)
^ swrlb:multiply(?rmr2, ?rmr, ?g)
^ swrlb:add(?ten, ?rmr2, ?eee)
-> hasRMR(?tda, ?rmr) ^ hasTEN(?tda,
?ten)
```

- (iii) **EI** is used to calculate the necessary energy intake for a training day, based on the meals consumption for that day.

Rule: EI

```

TrainingDayAnalysis(?tda)
^ hasTrainingDay(?tda, ?td)
^ hasMeal(?td, ?m)
^ hasConsumable(?m, ?c)
^ hasCalories(?c, ?cal)
° sqwrl:makeBag(?b, ?cal)
^ sqwrl:groupBy(?b, ?td)
° sqwrl:sum(?s, ?b)
-> sqwrl:select(?td, ?s)
```

- (iv) **balance** compares the energy intake with the amount of energy needed to calculate the energy difference.

Rule: balance

```

TrainingDayAnalysis(?tda)
^ hasEnergyIntake(?tda,?i)
^ hasTEN(?tda,?e)
^ swrlb:subtract(?r,?i,?e)
->hasEnergyDifference(?tda,?r)
```

- (v) **evaluateNutrientsMin** evaluates the athlete's nutrients intake for each workout phase. In this case, it evaluates if the intake is below the recommended level and reports a problem.

Rule: evaluateNutrientsMin

```

TrainingDayAnalysis(?tda)
^ hasDietaryMargin(?tda, ?dm)
^ hasTrainingDay(?tda, ?td)
^ hasMeal(?td, ?m)
^ hasWorkoutPhase(?m, ?wp)
^ hasName(?wp, ?wpn)
^ hasConsumable(?m, ?c)
^ hasNutrientPortion(?c, ?cnp)
^ hasNutrient(?cnp, ?n)
^ hasName(?n, ?nn)
^ hasValue(?cnp, ?cv)
^ hasDietaryProtocol(?td, ?dp)
^ hasWorkoutPhase(?dp, ?wp)
^ hasNutrientPortion(?dp, ?np)
^ hasNutrient(?np, ?n)
^ hasValue(?np, ?v)
^ swrlb:multiply(?r1, ?v, ?dm)
^ swrlb:subtract(?r2, ?v, ?r1)
^ swrlb:lessThan(?cv, ?r2)
^ swrlb:stringConcat(?s1, ?wpn, " nutrient intake is
below recommended level ")
^ swrlb:stringConcat(?s2, ?s1, ?nn)
^ swrlb:stringConcat(?s3, ?s2, " should be: ")
^ swrlb:stringConcat(?s4, ?s3, ?v)
^ swrlb:stringConcat(?s5, ?s4, " but it is: ")
```

```

^ swrlb:stringConcat(?s6, ?s5, ?cv)
^ swrlb:stringConcat(?s7, ?s6, ")")
-> hasDietaryProblem(?tda, ?s7)

```

C) Resource Reliability rule

- (i) ***topResources*** retrieves all the resources for each type in descending order of accuracy.

Rule: <i>topResources</i> <hr/> ResourceAnalysis(?res) <hr/> ^ hasResourceType(?res, ?rt) <hr/> ^ hasMethod(?res, ?m) <hr/> ^ hasAccuracy(?m, ?ac) <ul style="list-style-type: none"> ◦ sqwrl:makeBag(?b, ?ac) ◦ sqwrl:groupBy(?b, ?rt, ?res) ◦ sqwrl:max(?max, ?b) -> sqwrl:select(?rt, ?res, ?max)
--

4.6 Evaluation of the Knowledge Representation

The implemented rule based inference is only possible when the *FB* is duly populated. SWRL rules generate results only when the conditions specified in the antecedent (body) hold. This is true when the domain instances exist and are correctly classified.

Open data sources were analyzed to gather these instances. Different literature pieces were used to cross-check the legitimacy of the acquired information.

The knowledge representation can be evaluated from different perspectives:

- *Consistency*, which performs a semantic evaluation on the asserted instances, among other logical checks. The semantic assessment feature applied on object or data property based relations is the most used in the KB. This is true due to the absence of axioms, specifically asserted for the computation of class subsumption hierarchies.
- *Applicability*, being the inference results the main focus of this point. The competency questions were objectified in the form of SWRL rules. This process has no specific formula and the interpretation of those questions is crucial to

perform an adequate translation to a logical description. Nevertheless, it is an iterative process which may suffer improvements at any time. The following section will evaluate the reasoning results.

To illustrate the reasoning process, a simple test case was inserted in Protégé. The athlete had to perform a full Snatch lift, while monitoring numerous biomechanical variables. To accomplish that, six instances of *PhaseAnalysis* were created along with several phase related sensor results. These values, which are *ExercisePropertyAnalysis* instances (see Figure 4.16), were linked to the analysis instance via the *hasResult* object property.

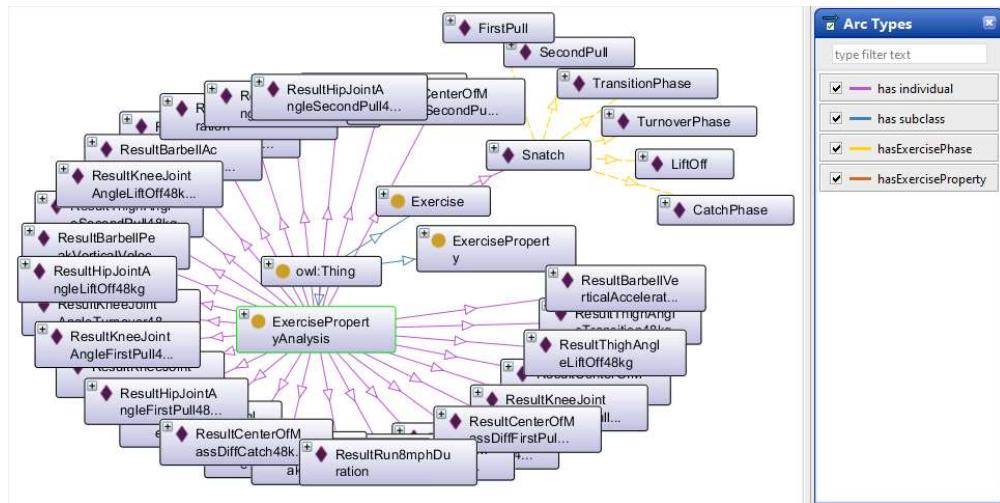


Figure 4.16 Snatch, its six phases and all associated exercise property analysis instances.

Upon comparison of the results with exercise ranges (domain knowledge), Pellet, which was the chosen reasoner, inferred the existence of 2 values out of bounds in the third phase of the exercise. Since there were problems to be reported and the exercise was not declared as compensated by the *Training Manager*, the evaluation shows a failure message, as can be seen in Figure 4.17. Each problem is described in natural language instead of description logics. On the right side of the same figure is the analysis of the fifth phase, which generated no problems, since it was manually reported as being compensated by the *Training Manager*.

Queries were tested using the SQWRL Tab plug-in of Protégé. The developed resource-related query evaluates the accuracy of every resource based on its analysis, acquisition and calibration methods. Figure 4.18 presents the obtained results for each resource in a descending order of accuracy.

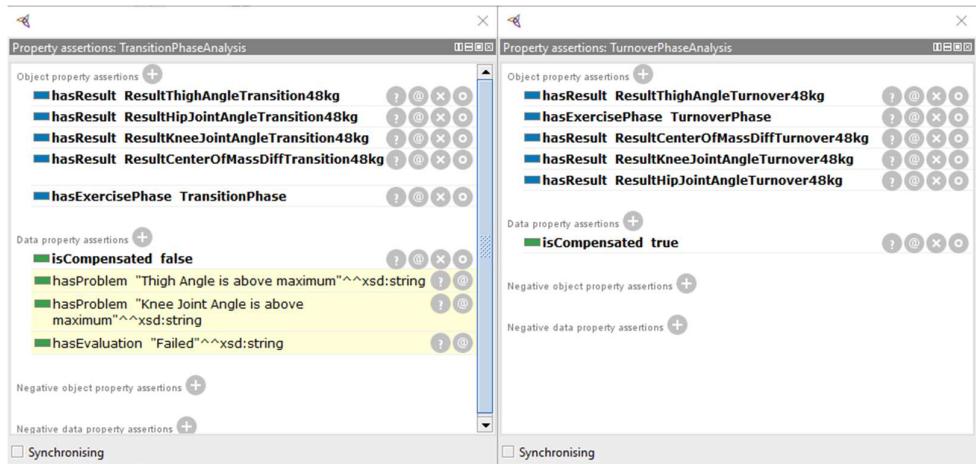


Figure 4.17 Rule based evaluation of Transition phase and Turnover phase of Snatch.

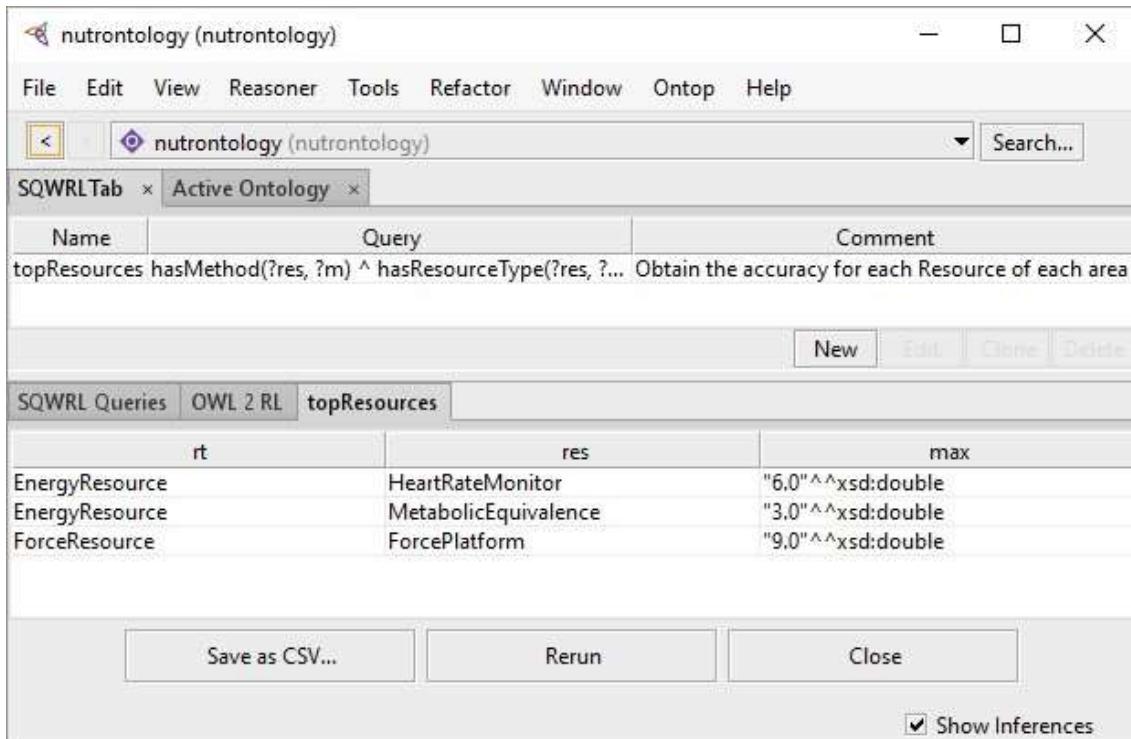


Figure 4.18 Result of the topResources query.

4.7 Conclusions

This study demonstrated the use of OWL and SWRL to semantically model the whole weightlifting TDC-cycle, bringing together related knowledge subdomains such as training methodology, weightlifting biomechanics, dietary, muscle's architecture and energy expenditure while modeling the synergy among them. Nutritional, biomechanics, and coaching/training facts were combined with SWRL rules representing rhythmic execution and energy balance to infer athlete's lifting

performance. Moreover, these rules can be used to trigger and classify any qualitative-quantitative lifting mismatch as corner cases which will deserve deeper and future quantitative analysis, both regarding nutritional and biomechanics perspectives.

Each KB and respective rules in TDC Competency Questions Engine Architecture were created using only Protégé and its plug-ins, resulting into: 43 classes, 57 properties, and 29 relationships. Overall, 9 SWRL rules and 3 SQWRL queries were created and these can be separated into three broad categories: Biomechanics/Coaching (e.g., *evaluateMinMax*, *evaluateMin*, *evaluateMax*, and *analyze*), Nutrition (e.g., *EEE*, *EI*, *femaleTEN*, *balance*, and *evaluateNutrinetsMin*), and Resource reliability (e.g., *topResources*).

In spite of the mentioned applicability of the proposed weightlifting TDC-cycle OWL knowledge-based system, few drawbacks have been identified to be later tackled in the next iterated TDC-ontology:

- (i) Re-design the TDC-Ontology to address domain-level modularity, as well as being more scalable, while applying fully fourth generation methodologies.
- (ii) Devise the integration of new concepts and properties which will ease the modeling of corner cases (i.e., qualitative-quantitative lifting mismatch).
- (iii) Enable energy expenditure to be evaluated using different non-logical axioms based on prediction equations (e.g., EEE) as well as on analysis and optimization methods which take into account muscular activation and muscle contraction, for more accurate measurement.
- (iv) Iteratively tune rhythmic execution SWRL rules according to identified corner cases, biomechanics analysis, and optimization approaches, as well as to reference top performance athletes, both in terms of rhythm and anthropometric features.
- (v) Re-design the TDC-Ontology around existing ontologies to leverage easy management, updating and sharing of the TDC-Cycle information. Possible ontologies candidates are OPA, OPE, SHCOntology, and Kinect-Ontology (Diaz Rodriguez et al., 2013), only to name a few.

Furthermore, more tests should be made based not only on open data presented and discussed in the existing literature but also lively collected during weightlifting training at Porto University.

CHAPTER 5

Modeling Weightlifting TDC-cycle following a Modular and Scalable Approach

This chapter presents and discusses the second-iterated Weightlifting TDC-cycle ontology, refactored toward improved modularity, flexibility and scalability. The deeper focus is on qualitative semantics rules to leverage better rhythm understanding based on drafted heuristics and procedural rules. The rhythmic execution SWRL rules are iteratively tuned according to identified corner cases, biomechanics analysis, and optimization approaches, as well as to reference top performance athletes, both in terms of rhythm and anthropometric features. A two-level analysis technique is proposed for the integration of observed and measured data to enhance the understanding of weightlifting performance and consequently a better explanation for observed mismatched lifting rhythm. The refactoring process followed during modeling and design of the second-iterated TDC Cycle Ontology is described. Then, the new refactored task ontology is presented. Lastly, the new refactored semantic rules or axioms are proposed, which provides the context for this chapter.

Introduction

The previous chapter presented the first-iterated weightlifting TDC-cycle ontology. The domain ontology was modeled only briefly and minimally. Each identified information dimension of biomechanics, coaching and training, and dietary nutrition was modeled as subdomains. The objectives were to seize some more insight about weightlifting TDC cycle and to speed up the reasoner performance. In this chapter, however, the second-iterated model for weightlifting TDC cycle is, contrary to the previous one, much more flexible, modular, and scalable through much more elaborated and extended ontologies, at each of the above identified domain levels. Putting it differently, each information dimension is declaratively extended and modeled by its own ontology. Then, it is accordingly interrelated with the other ones through object properties and well-designed heuristics and procedural rules.

Furthermore, the main focus is on qualitative semantics rules to leverage better rhythm understanding based on drafted heuristics and procedural rules. The rhythmic execution SWRL rules are iteratively tuned according to identified corner cases, biomechanics analysis, and optimization approaches, as well as to reference top performance athletes, both in terms of rhythm and anthropometric features. The method proposed in this chapter consists in a two-level analysis technique: the lower-level statistical analysis and the higher-level semantic analysis. The main focus of this chapter goes to semantics analysis. The statistical analysis, data, devices, and optimization methods are extracted and identified from literature review to be later transformed to semantics artefacts (i.e., data properties and rhythmic execution SWRL rules). We believe that such a two level-analysis is crucial for the integration of observed and measured data to enhance the understanding of weightlifting performance and consequently a better explanation for observed mismatched lifting rhythm.

The remainder of this chapter is organized as follows: Section 5.1 describes the refactoring process followed during modeling and design of the second-iterated TDC Cycle Ontology; Section 5.2 presents the new refactored task ontology; Section 5.3 describes the new refactored semantic rules or axioms; Section 5.4 presents some conclusions.

5.1. A Generic, Flexible, and Modular Weightlifting TDC Cycle Ontology-based Knowledge Representation

The design of new weightlifting TDC cycle declarative knowledge was driven through the following steps. Firstly, collecting new insights about weightlifting TDC cycle during modeling of the first-iterated ontology. Secondly, leveraging the concept of bring the problem to a broader context by partially (i.e., only at domain-level and not at design-level) approaching the automated scenario-based training (SBT) as proposed by Peeters et al. (2014). SBT is a practical training form in high-risk professions during which learners engage in interactive role-playing exercises, called ‘scenarios’. Scenarios are usually staged within a simulated environment. Therefore, the previous weightlifting TDC cycle declarative knowledge was refactored in a similar way to the domain ontology proposed for SBT, but excluding the scenario generator and the associated system or design ontology. Additionally, another main focus was toward the extended ontologies for each dimension of weightlifting TDC cycle and existing interoperability among them. This feature helped us to identify and define corner cases under the mismatching of two binomials: coaching-biomechanics (e.g., mismatched lifting rhythm) and planned energy intake-expenditure (e.g., energy imbalance) for a given training day or session. Such corner cases are characterized by both qualitative (e.g., coach and nutritionist observations) and quantitative (biomechanics measurement and nutrition assessment), which are expressed by well-designed heuristics and procedural rules.

Before the refactoring of the previously constructed domain ontology starts, it was reviewed by the indicated domains’ experts and stakeholders (as presented in the right side of Figure 4.3). This is to ensure that the required knowledge to reason about the problem scenarios of the weightlifting TDC cycle are fully covered. This process was achieved by the two following steps. Firstly, the previous domain ontology was evaluated for consistency and applicability by both advisors from UMinho and UP as well as software engineering (UMinho). This review session led to the identification of the four drawbacks which was presented at the end of chapter 4 (on page 122):

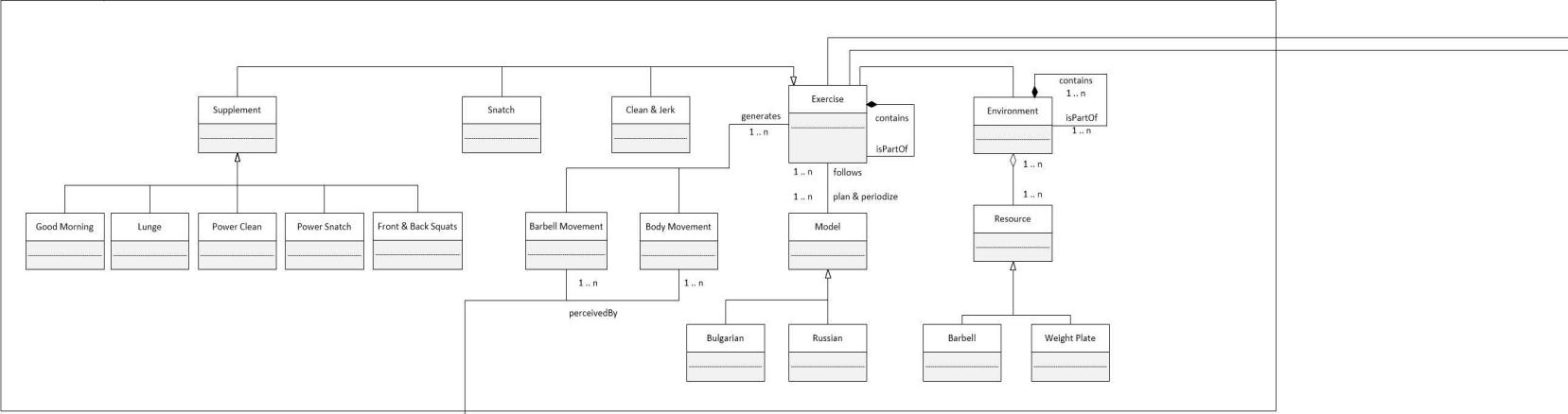
- (i) weak modularity and scalability,
- (ii) missing corner cases modeling,
- (iii) inaccurate measurement of energy expenditure and,
- (iv) inaccurate modeling of rhythmic execution.

Secondly, the previous domain ontology was evaluated for completeness by several Thai weightlifters and coaches as well as a physiologist from Kasetsart University (Thailand), ontology experts from Jilin University (China), both advisors as a biomechanist and software engineering (Portugal). As a result, this second review session suggested (i) addition of some concepts (e.g., anthropometric features) to more clearly differentiate qualitative from quantitative parameters, (ii) loose-coupling those parameters through axioms which model the coaching-biomechanics and energy intake-expenditure binomials, and (iii) improvement of modularity and scalability. These suggestions led to the adjustment of the previous domain ontology at the *Task Rules Sublayer* (Figure 4.3).

The following paragraphs describe the refactored *TDC-Ontology*, starting with each individual ontology on training, biomechanics, nutrition, and stakeholder domains, while enumerating and commenting changes suggested during the evaluation process. Figure 5.1 generically and partially represents the refactored *TDC-Ontology* = (CA, CV, FB, R, A) as its focus is mainly on sets CA and R, but it is also extended in term of the sets A and FB.

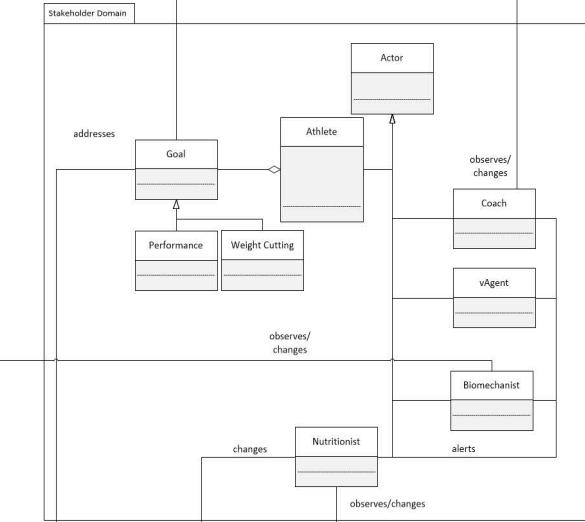
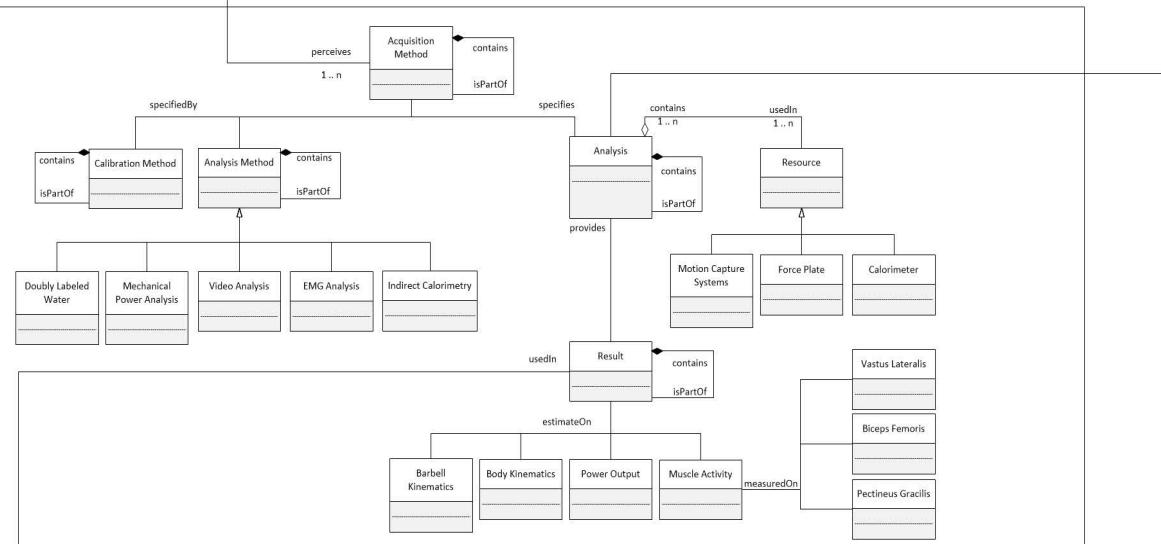
Figure 5.2 partially shows only the implemented TDC-Cycle taxonomy of the new refactored ontology (i.e., representing a class hierarchy based only on *is-a* kind of relations).

Layer 1: Training Domain

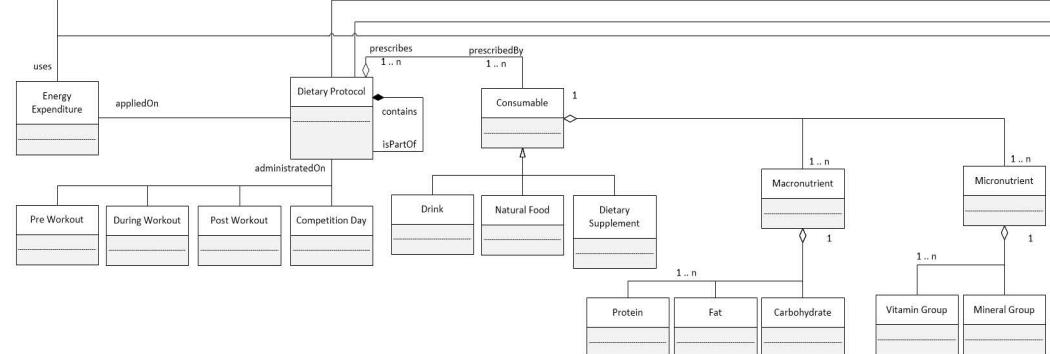


hasAthleteGoal

Layer 2: Biomechanics Domain



Layer 3: Nutrition Domain



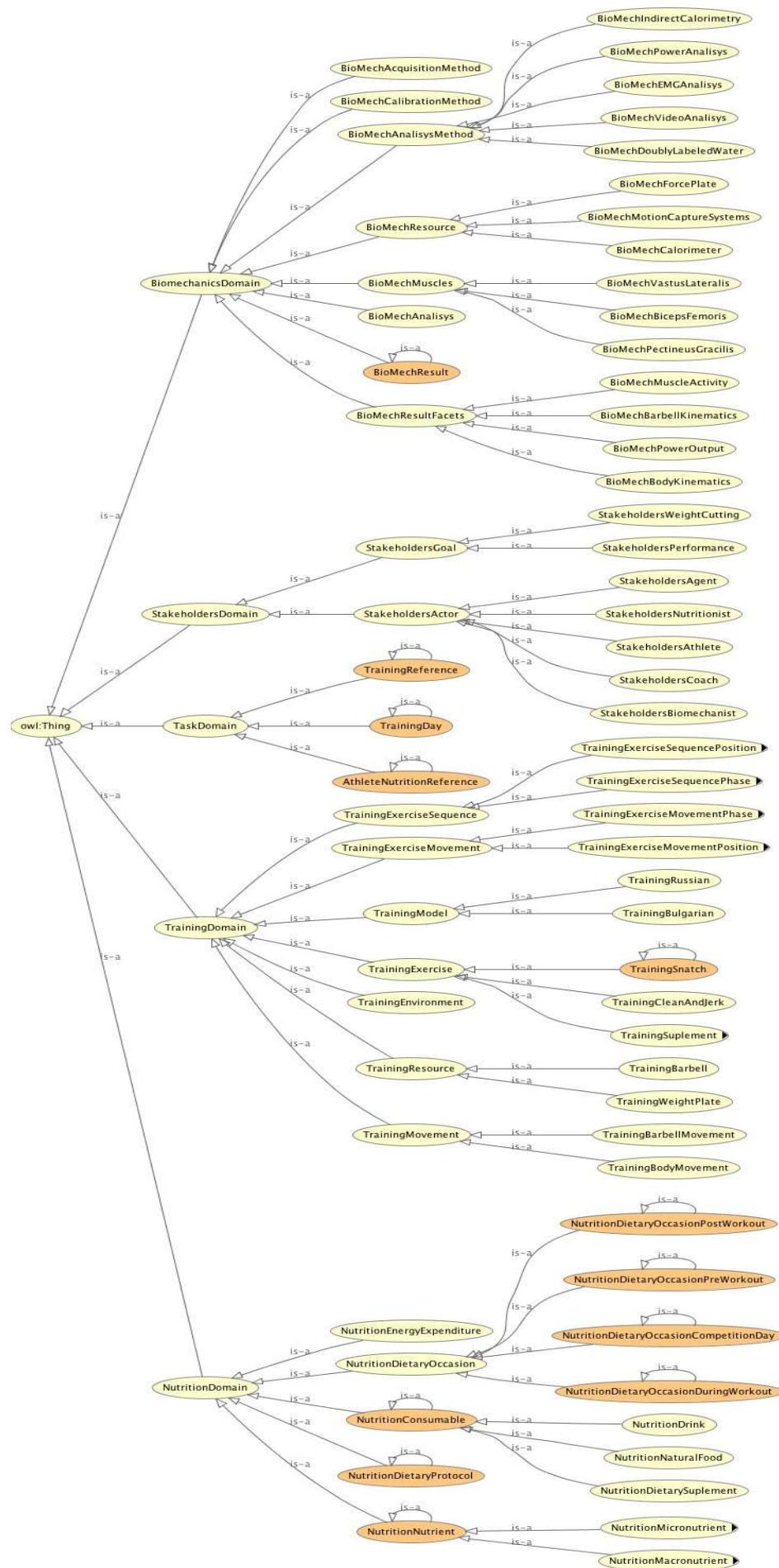


Figure 5.2 Fragment of the TDC-Cycle taxonomy on iteration 2. (Enlage version in Appendix)

5.1.1 The Training or Coaching Domain

In the *training domain* ontology (Layer 1 of Figure 5.1), the central concept is the *Exercise* which is composed by several smaller or more specific analysis or steps. It is expressed by means of *isPartOf* arrow and *contains* diamond. Exercises are performed in an *Environment* (e.g., a Gym), which is composed by one or more *Resources* or equipment (e.g., like barbell and/or weight plates). An environment has specific configuration or *Setting* expressed as a set of attributes (e.g., humidity and temperature). These setting can challenge not only an athlete capability to appropriately perform the proposed exercise but it also affects the energy expenditure, when exercising in such environment. It should be noted that the *Environment* concept was modeled based on the work of Ermolayev et al. (2008). The environment setting is expressed as a set of data properties, while exercises target specific athlete's goals and dietary programs are represented through relationships *hasAthleteGoal* and *changes* (i.e., change of *DietaryPlan*), respectively. Accordingly, the *FB* artefact of the TDC-Ontology is extended with some instances of *Exercise* concept, through three subclasses. They are, namely, *Supplement*, *Snatch* and *Clean&Jerk*. The instances of *Supplement* subclass are *GoodMorning*, *Lunge*, *PowerClean*, *PowerSnatch*, and *Front&Back Squats*. All exercises follow a model which is expressed by the concept of *Model*. In this case, exercises consist of two instances (i.e., *Bulgarian* and *Russian*) and two relationships (i.e., *follows* and *plan&periodize*). While performing an exercise, several kinematics and kinetics attributes of the barbell and the athlete's body are generated through qualitatively observation of coaches as well as quantitatively measurement using sport biomechanics technology. These relationships are represented by relationships *observes* and a hidden one related to the *Result* concept, respectively.

The following Figure 5.3 depicts the OWL implementation, using Protégé, of the training domain class hierarchy. For practical reasons, it should be noted that each name inside its associated domain/class are preceded by the domain name, (e.g., *TrainingEnvironment* and *TrainingExercise* are classes from the training domain). The *TrainingExerciseMovement* class and its sub-classes are added to create terminology for positions and phases of an exercise (as explained earlier in section 1.3.1). Based on these concepts, the class *TrainingExerciseSequence* specifies the set of phases and positions for a kind of exercise (Figure 5.4). As our main exercise is snatch, *TrainingSnatch* is defined by both *TrainingSequencePositionSnatch* and *TrainingSequencePhaseSnatch* classes (Figure 5.5).

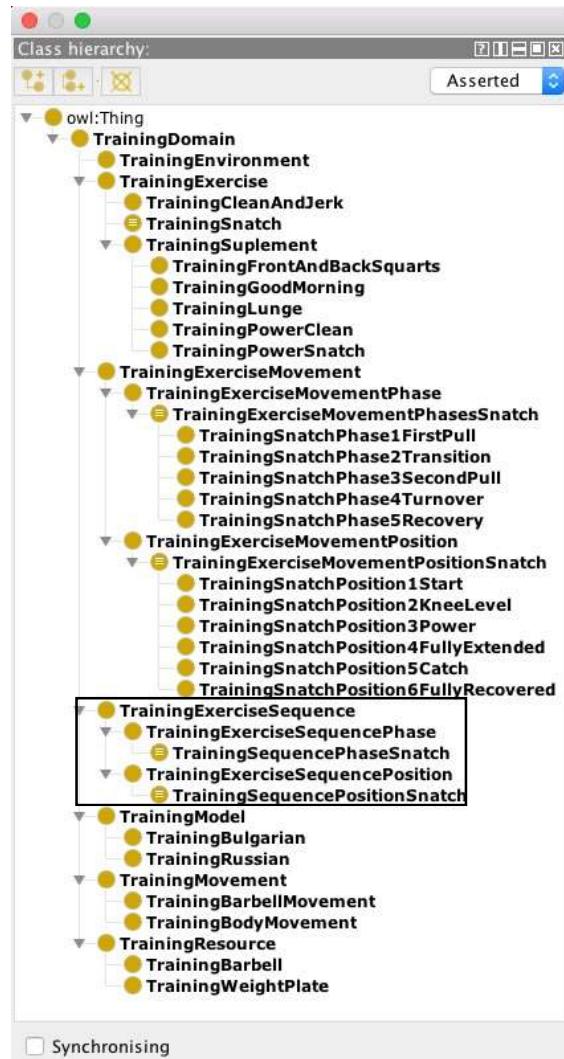


Figure 5.3 The Training Domain class hierarchy.

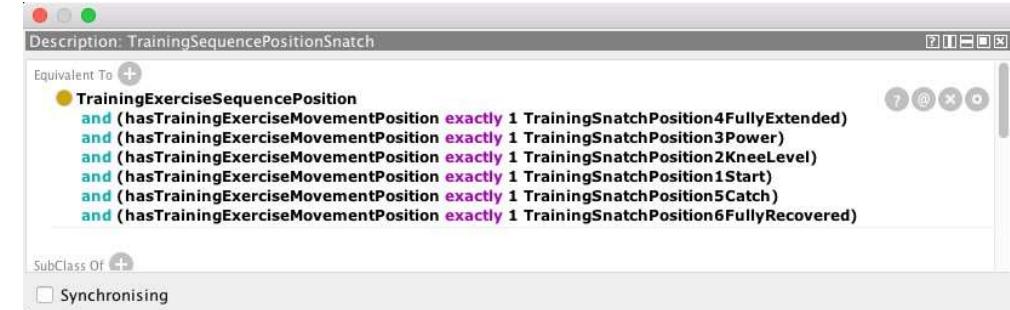


Figure 5.4 Description of class TrainingSequencePositionSnatch using OWL axioms.

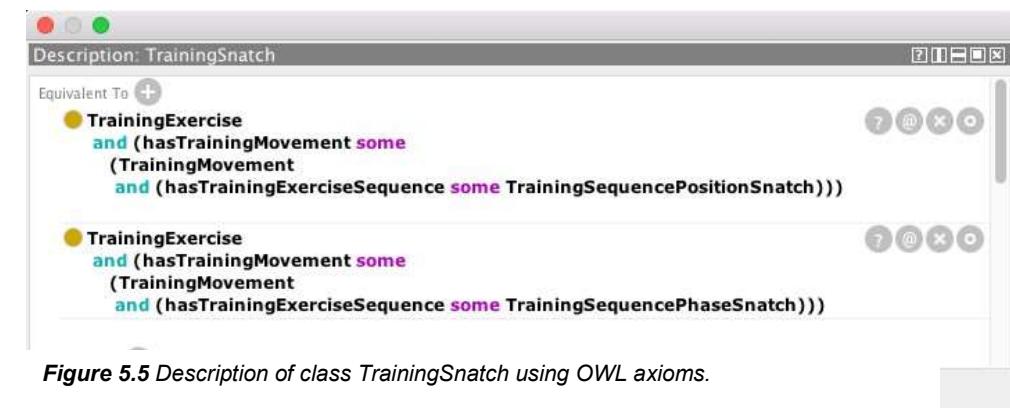


Figure 5.5 Description of class TrainingSnatch using OWL axioms.

According to the concept of snatch movement, at least one of those sequences, position or phase, must be presented. In fact, when assessing an exercise, it is done according to static perspective (positions; considered on athlete's body) or dynamic perspective (phases; considered on barbell). To quantify the movement, it requires a joined role of coaches and biomechanics measurements. Therefore, based on these collected static (body movement) and dynamic data (barbell movement), alongside the support of OWL rules, it is possible to assess the quality of the movement in terms of positions and rhythm, as suggested by Lenjannejadian & Rostami (2008), Lin et al (2015), and Szabo (2012).

Figure 5.6 shows a set of individuals which represent static perspective or body movement in the *TrainingExercise* class. These individual include several object properties related to movement (Figure 5.7). The important aspect of this implementation is the binding between the training domain and the biomechanics domain. In this example, it can be seen that a position (e.g. power position) is related to a set of biomechanical individuals (e.g. center of mass, knee joint angle, etc.). Each biomechanical individuals asserts a quantitative value, given by a measurement device.

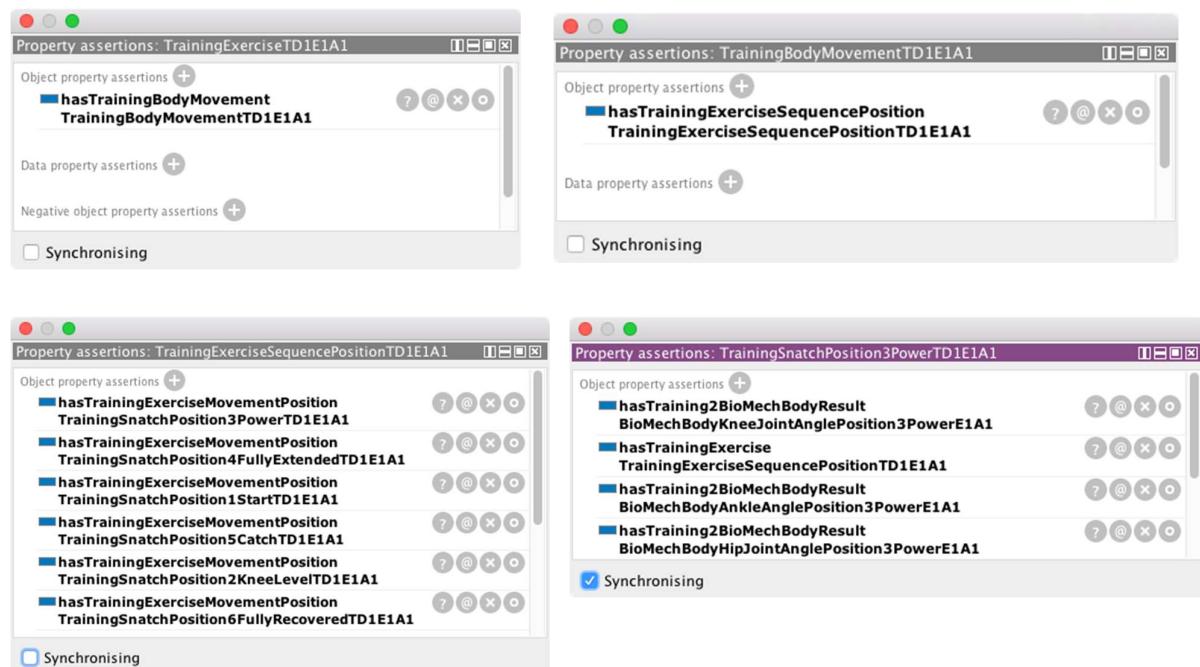


Figure 5.6 The individuals that form static perspective (body movement) in *TrainingExercise* class.

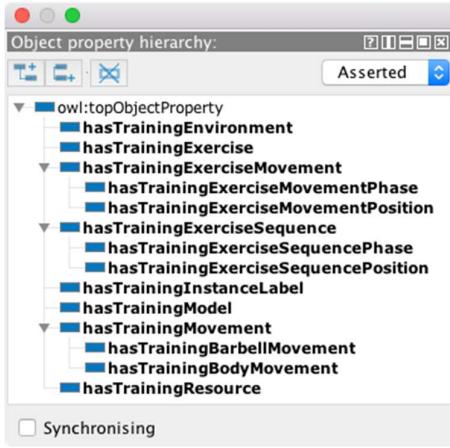


Figure 5.7 Training domain object properties.

5.1.2 The Biomechanics Domain

In the *biomechanics domain* ontology (Layer 2 of Figure 5.1), the central concept is the *Analysis* which is composed by several smaller or more specific analysis or steps. It is expressed by means of *isPartOf* arrow and *contains* diamond. Several *resources* with specific configuration or *Setting*, which are used during the analyzes, are expressed by data properties. There are several instances of biomechanics resources such as 2D/3D motion analysis systems, force platforms, EMG-based sensors, linear position transductor, accelerometers or calorimeter. They are expressed by the '*is-a*' relationship as indicated by the arrow. During analysis, several results are produced and expressed by the relationship *provides*. These results can be proposedly used for energy expenditure estimation and/or qualitative-quantitative comparative analysis. For the latter, the set of axioms (i.e., the artefact of the set A) in the TDC-Ontology is accordingly extended to evaluate the rhythmic execution. The *Result* concept is also a composite and it can be estimated on barbell and body kinematics/kinetics, power output, muscle activities, and so on. For example, the barbell kinematics can be represented through a set of sequential xy-coordinates using a kind of flow data property; muscle activities can be measured on major muscles groups such as Vastus Lateralis, Biceps Femoris, Pectineus Gracilis and many more. An analysis is qualified or driven through the *specify* relationship with an acquisition method, represented by the composite concept of *AcquisitionMethod*. This concept is internally described by a set of annotation properties to add static knowledge to the TDC-ontology, transmitting important information to the stakeholder domain individuals (e.g., athletes, coaches, nutritionist, biomechanist). Such kind of annotation properties can be valuable even to

electronics engineers. In case the devices are wrongly calibrated or improperly calibrated, they can try to understand and fix those errors. Individually, each acquisition method is specified by two other fully annotated composite concepts of *CalibrationMethod* and *AnalysisMethod*. Subclasses of the latter concept are *DoublyLabeledWater*, *MechanicalPowerAnalysis*, *VideoAnalysis*, *EMGAnalysis*, *IndirectCalorimetry*, only to mention a few.

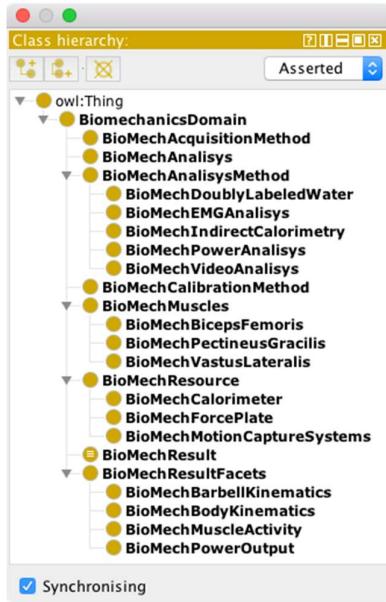


Figure 5.8 Biomechanics ontology class hierarchy.

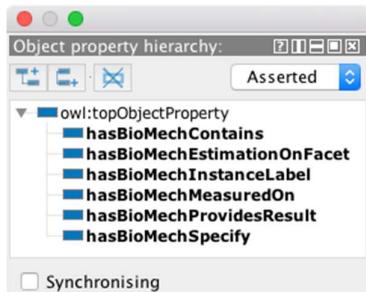


Figure 5.9 Object properties of biomechanics ontology.

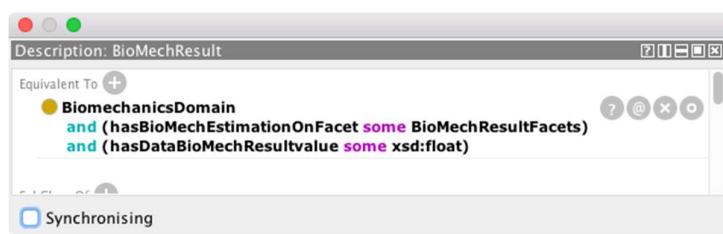


Figure 5.10 The BioMechResult class description.



Figure 5.11 A measurement artefact as an instance of BioMechResult class.

Figure 5.8 presents the implemented class hierarchy of the biomechanics domain after being designed using the Protégé environment. Regarding the original drafted class diagram of Figure 5.1, two classes, *BioMechResultFacets* and *BioMechMuscles*, were introduced, just for clarification purpose. The first one includes several results facets that a biomechanical result can be assigned to while the latter groups a set of muscles. In Figure 5.9 is presented the objects relationships, or properties in ontology parlance, of the biomechanics domain. Any other relations involving classes in other domains,

such as nutrition and training, is implemented in the whole TDC-Cycle ontology that wraps together the four individual domain ontologies, including the stakeholder domain.

Figure 5.10 and 5.11 presents the definition of the *BioMechResult* concept/class and an individual of such class, respectively.

5.1.3 The Nutrition Domain

In the *nutrition domain* ontology (Layer 3 of Figure 5.1), the central concept is the *DietaryProtocol*. It is also a composite which relates to the *Consumable* concept through *prescribes* and its inverse (i.e., *prescribedby*) relationships. Each dietary protocol can prescribe several consumables from different food categories as expressed by the following subclasses of *Drink*, *NaturalFood* and *DietarySupplement*. Individually, each consumable contains a certain amount of macro- and micro-nutrients. Micronutrients consist of three key nutrients expressed by the concepts of *Protein*, *Fat* and *Carbohydrate*, alongside the multiple cardinality relationship of *contains*. Micronutrients contain two groups of nutrients represented through *VitaminGroup* and *MineralGroup* concepts. Traditionally, a dietary protocol is administrated on several pre-workout, during-workout, post-workout, or competition day, accordingly to an established timing sequence. The energy expenditure analysis is applied on each dietary protocol after its administration and at the end of the above four stages of pre-workout, during-workout, post-workout, or competition day. It uses collected metabolic rate measurements as performed by using both technologically and analytically approaches. Analytical technique for determination of energy-expenditure is achieved based on specific configuration or *Setting* given by a set of data property (e.g., age, gender, weight, height, GAF, SAF and METs).

The implemented class hierarchy of the nutrition domain is presented in Figure 5.12, with its associated object properties (Figure 5.13). While the *NutritionDietaryOccasion* class was created to group the meals/nutrient prescription occasions, the *NutritionDietaryProtocol* class was implemented to model both meals and nutrients prescriptions (Figure 5.14, 5.15). A meal (i.e., an individual of *NutritionDietaryProtocol* class) has consumables which is given by the *hasNutritionDPPrescribesConsumable* relationship. Each consumable has nutrients (i.e., *hasNutritionNutrient*) in which each nutrient has a nutritional value (i.e., *hasNutritionNutrientValue*).

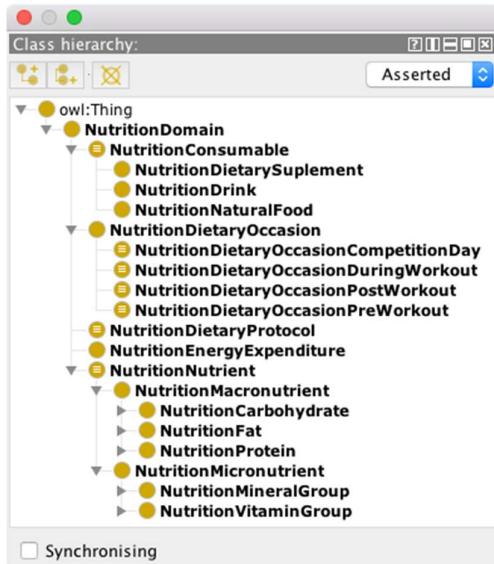


Figure 5.12 Nutrition domain class hierarchy.

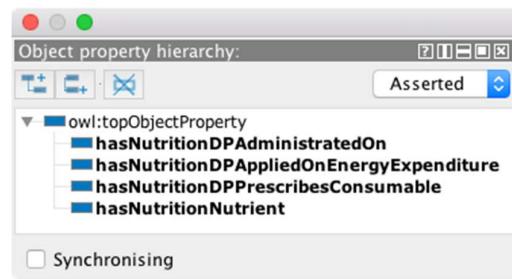


Figure 5.13 Object properties of the nutrition domain.

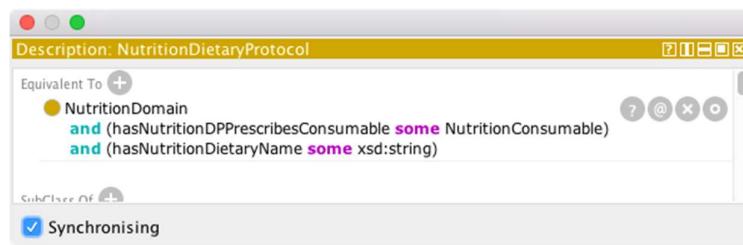


Figure 5.14 Definition of the NutritionDietaryProtocol class.

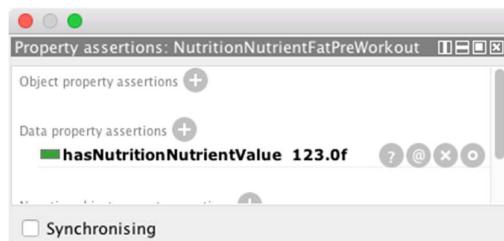
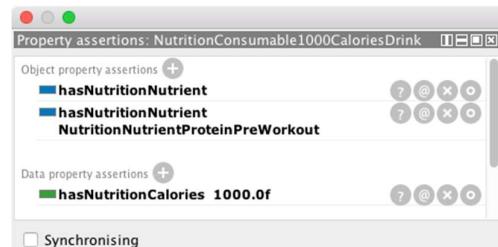
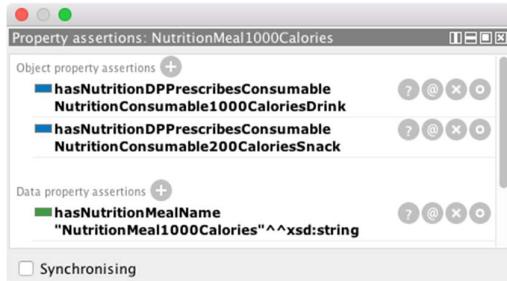


Figure 5.15 Set of individuals composing a meal domain.

5.1.4 The Stakeholder Domain

All three layers, as described above, demand for information provided by key involved stakeholders in the weightlifting sports. In the *stakeholder domain*, the central concept is the *Actor*. It is described by a set of data properties (e.g., name and role). The *Actor* concept is composed by five subclasses, namely, *vAgent* (*virtual agent*), *Coach*, *Athlete*, *Nutritionist* and *Biomechanist* through the ‘*is-a*’ relationship. Key role of a virtual agent, if implemented, will be alerting coaches and other stakeholders for the occurrences of abnormal observations/measurements. The main concern is the corner cases (e.g., unbalanced rhythm and nutrition) according to designed SWRL rules. Furthermore, a coach is also notified or alerted of any abnormal observations or measurements by biomechanist and nutritionist. The *Coach* concept is related to the training ontology through the concept *Exercise* and relationship *observe&change*. This is because a coach can prescribe, change, and qualitatively assess some exercises attributes. Similar kind of *observe&change* relationships relate *Biomechanist* and *Nutritionist* concepts to biomechanics and nutrition ontologies through *Analysis* and *DietaryProtocol* concepts, respectively. Additionally, the nutritionist prescribes a particular dietary protocol to an athlete. The *Athlete* concept has several set of data properties. Anthropometric (Khaled, 2013) and metabolic features as well as the rhythmic execution of a top performance athlete are grouped as a reference athlete. A goal is set by coaches and nutritionists during the prescription of an exercise and dietary protocols, respectively. Therefore, possible subclasses of the *Goal* concept are given by the concepts of *Performance* and *WeightCutting*.

The implemented stakeholder domain class hierarchy and its domain object properties are presented in Figure 5.16 and 5.17, respectively.



Figure 5.17 The Stakeholder domain object properties.

Figure 5.16 The Stakeholder domain class hierarchy.

5.2. The Refactored Task Ontology

With all individual domain ontologies already designed, the whole weightlifting TDC-cycle ontology wraps them all together while being extended by integrating the task domain ontology (Figure 5.18).

As mentioned previously on Chapter 4, the task domain is extended with concepts required to establish relation between individual domains of nutrition, biomechanics and training in order to later infer about energy expenditure and rhythm quality from both qualitative and quantitative perspectives.

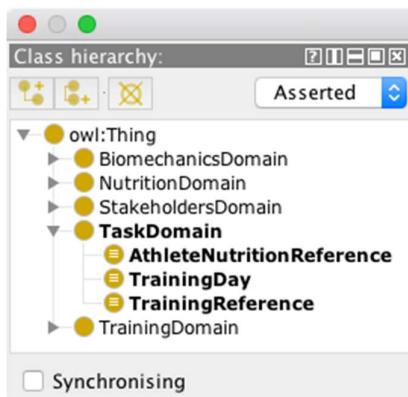


Figure 5.18 The whole weightlifting TDC-cycle ontology.

Compared to the previous task domain ontology which consists of *AthleteProfileAnalysis*, *PhaseAnalysis*, *ResourceAnalysis*, *ExercisePropertyAnalysis* and *TrainingDay Analysis* concepts, the new task domain was refactored around more generic concepts of *AthleteNutritionReference*, *TrainingDay*, and *TrainingReference*, as shown in Figure 5.18. It hosts individuals of nutrition, biomechanics and training domains, required for SWRL reasoning about energy expenditure and rhythm quality. Thus, *TrainingDay*, *AthleteNutritionReference*, and *TrainingReference* are classes hosting individuals representing an athlete's training days, prescribed nutrients to an athlete, and a top reference athlete data, respectively. It is worth noting that the *TrainingReference* class contains not only anthropometric features but also quantitative rhythmic execution parameters (e.g., barbell/body kinematics and barbell trajectory on each snatch phase). The former was created to ensure that the athletes are comparable in the same weight class. In other words, *TrainingReference* class contains individuals like a passive actor (i.e., an athlete reference) as well as

individuals regarding snatch exercises, as correctly performed by the associated reference athlete. The definition of the *TrainingReference* class is presented in Figure 5.19.

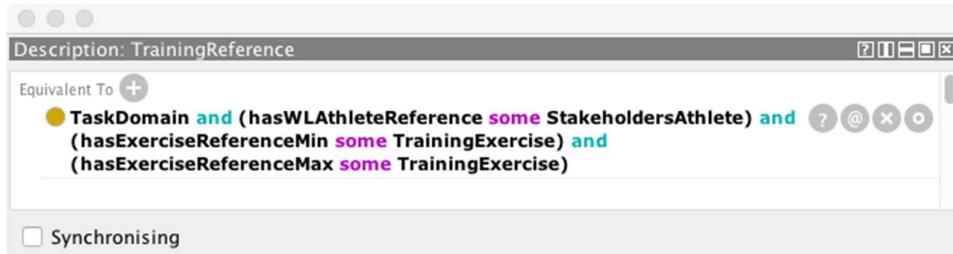


Figure 5.19 Definition of *TrainingReference* class using OWL axioms.

Unlike the previous version, the first-iterated version where the task domain ontology had their own data properties, in this version all data properties are “inherited” from the various domains (i.e., through the *TrainingReference*, *AthleteNutritionReference* and *TrainingDay*). For example, the *TrainingReference* class in Figure 5.19 is a wrapper for a set of two *TrainingExercise*. It represents the range of parameters for a successful rhythmic execution, according to a top reference athlete. Therefore, the task domain ontology implicitly uses the data properties of *TrainingExercise* class individuals (as given in the above Figure 5.6). The same approach applies for data properties of *AthleteNutritionReference* class individuals (Figure 5.15).

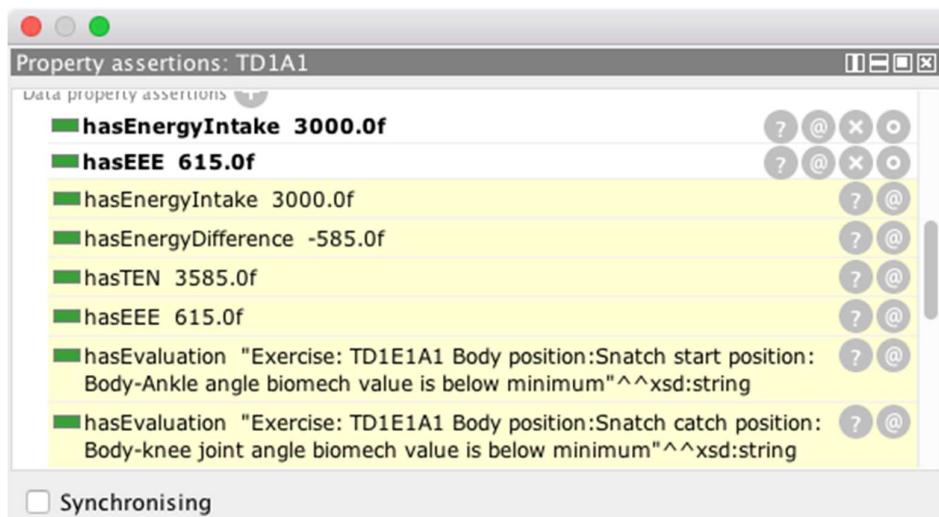


Figure 5.20 Example of an inferred data property, *hasEvaluation*, as ‘inherited’ by the task domain ontology

Figure 5.20 exhibits the setting of the inferred *hasEvaluation* data property in a *TrainingDay*'s individual after the execution of one of the drafted SWRL rules in the following paragraph 5.3. It should be mentioned that each inferred data property is related to a SWRL rule and composed by chaining the concept in which such property belongs to other individuals. In doing so, it is easier to reason about energy expenditure and rhythm execution quality.



Figure 5.21 The Description of the TrainingDay Concept.

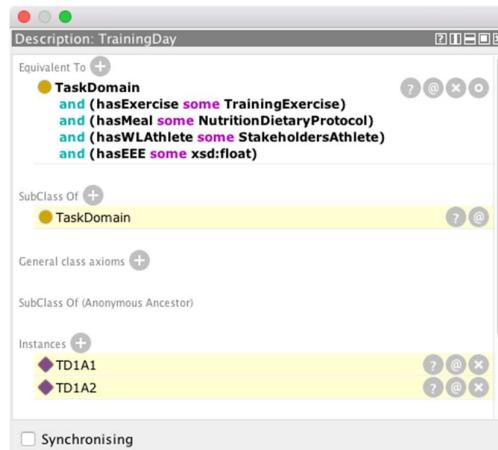


Figure 5.22 Two identified training sessions, TD1A1 and TD1A2, by running the OWL reasoner on the TrainingDay class.

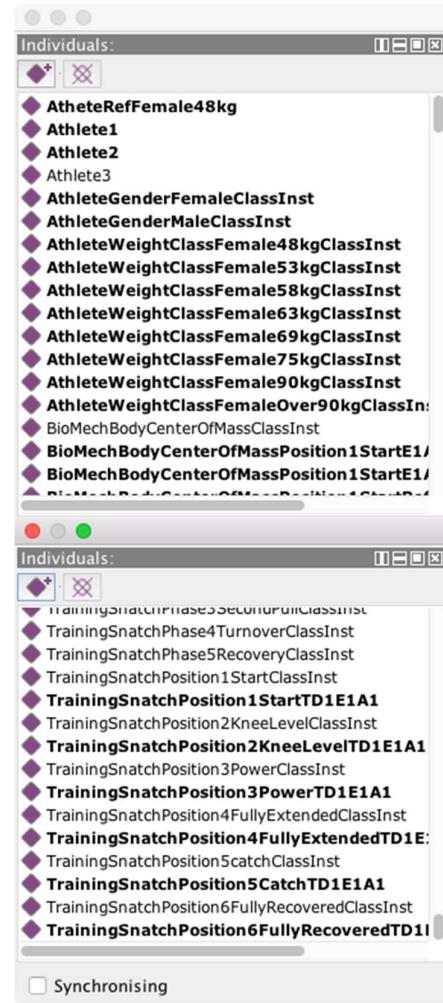


Figure 5.24 Fragment of individuals or facts created to populate the new fact base.



Figure 5.23 Description of TD1A1, an individual of TrainingDay class.

Figure 5.21 presents the description of the *TrainingDay* concept as an integrator class for all domains and it is composed by some exercises, performed by an athlete, and the meals taken during that day. In fact, the individuals of such class became the foundation for most of drafted SWRL rules. One can see that there is no reference to the biomechanics features as they are implicit to the exercise as shown below in Figure 5.22. In this example, by executing the reasoner, two different individuals of training sessions *TD1A1* and *TD1A2* were identified. *TD1A1* is described in Figure 5.23.

Figure 5.24 exhibits some individuals of concepts in the *CA* set (i.e., they are instantiations for the concepts from *CA*). They are created to populate the fact base and so, updating the knowledge base with quantitative values (ground values) as well as qualitative values (abstract values). While the former can be measured and collected using biomechanics devices, the latter are asserted by coaches and nutritionists through direct observation. Furthermore, these two actors can map some of their abstract or observed values to specific ground values. For instance, when assessing the rhythmic execution quality of a given athlete, comparatively to his/her related top reference athletes.

5.3 The Refactored Set of Axioms

Having the *FB* already populated, then each inferred data property must be related to a SWRL rule, relating individuals' asserted data properties to create new knowledge, for instance, about energy expenditure and rhythm execution quality. Next, some of the drafted SWRL rules and queries are described and they are based on the following points:

- (i) Data properties related to the task domain ontology can be of four types (1) quantitative or ground value, (2) qualitative or abstract value, (3) abstract value mapped to ground value, and (4) processed values which are outputs of mathematical models for biomechanical/nutritional activities (e.g., lifting trajectory or formulas for energy-expenditure) or statistical analysis which is given through artificial neural networks, dedicated regression equations, and so on (see Ammar et al., 2018; Knight et al., 2005; Kowsar et al., 2016; Staudenmayer et al., 2009; Velloso et al., 2013).
- (ii) SWRL rules are drafted according to the written observations and comments in the conclusions and discussions paragraphs of papers in the literature review.

The following SWRL rules are divided into two main parts. The first part (rules A-F) which is related to rhythmic execution are implemented based on training movements and the respective biomechanics data as presented in Figure 5.25. To model the rhythmic execution as envisioned by Ho et al. (2014), we believe that body movements must be mapped on exercise positions while barbell captured on exercise phases. For each exercise perspective, position and phase, a set of biomechanics data is collected. The second part (rules G-L) which relates to energy balance between intake and expenditure. Energy and nutrients intake data are obtained from menus in which nutritionist prescribed for an athlete in a given training day, whereas energy and nutrients expenditure data are obtained from estimated energy expenditure equations and the nutrients reference values.

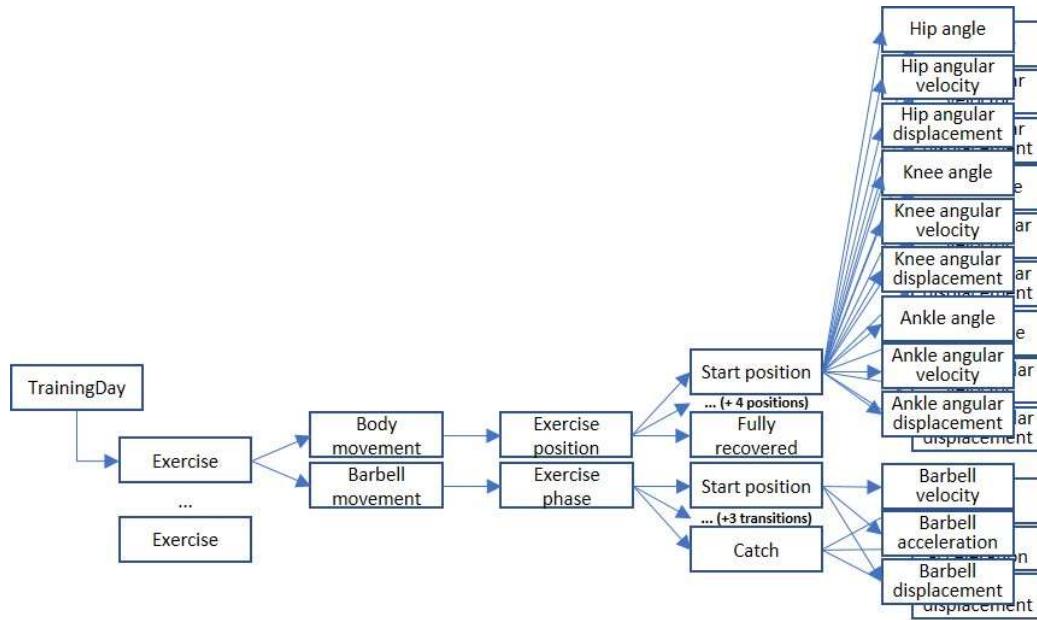


Figure 5.25 Concepts, properties and their interactions in the modeling and design of rhythmic execution rule.

A) SWRL rule: *AthleteExerciseEvaluation-BodyPosMin/Max*

The *AthleteExerciseEvaluation-BodyPosMin* SWRL rule evaluates alongside its pair rule *AthleteExerciseEvaluation-BodyPosMax*, if an exercise was well-performed by an athlete according to the static (based on the exercise's positions) perspective. Due to the carefully implemented ontology, either static or dynamic perspectives are inferred and/or asserted using a similar set of rules.

As a template for the set of rules, the rule *AthleteExerciseEvaluation-BodyPosMin* evaluates if the quantitative data collected for the athlete's movement positions are below a minimum, regarding a reference athlete.

Rule: AthleteExerciseEvaluation-BodyPosMin

```

TrainingDay(?td)
  ^ hasWLAthlete(?td, ?at) ^ hasWLAthleteWeightClass(?at, ?awc) ^          (1)
hasWLAthleteGender (?at, ?ag)
  ^ hasExercise(?td, ?te) ^ hasWLTechImprovement (?te,?tei) ^
hasTrainingExerciseName (?te, ?tenm) ^ hasTrainingInstanceLabel(?te,           (2)
?tel)
  ^ hasTrainingBodyMovement (?te, ?bm)                                         (3)
  ^ hasTrainingExerciseSequencePosition (?bm, ?es)                           (4)
  ^ hasTrainingExerciseMovement (?es, ?mp) ^
hasTrainingInstanceLabel (?mp, ?mpl) ^                                         (5)
hasTrainingInstanceLabelString (?mp, ?mps)

  ^ hasTraining2BioMechBodyResult (?mp, ?br) ^
hasBioMechInstanceLabel (?br, ?brl) ^ hasBioMechStringValue (?br,             (6)
?brs) ^ hasDataBioMechResultvalue (?br, ?brv)
  ^ TrainingReference(?tr) ^ hasWLAthlete(?tr, ?atr) ^
hasWLAthleteWeightClass (?atr, ?awc)                                         (7)
  ^ hasWLAthleteGender (?atr, ?ag)
  ^ hasExerciseMin(?tr, ?ter) ^ hasTrainingInstanceLabel (?ter, ?tel)        (8)
  ^ hasTrainingBodyMovement (?ter, ?bmr)                                       (9)
  ^ hasTrainingExerciseSequencePosition (?bmr, ?esr)                         (10)
  ^ hasTrainingExerciseMovement (?esr, ?mpr) ^
hasTrainingInstanceLabel (?mpr, ?mpl)                                         (11)
  ^ hasTraining2BioMechBodyResult (?mpr, ?brr) ^
hasBioMechInstanceLabel (?brr, ?brl) ^                                         (12)
hasDataBioMechResultvalue (?brr, ?brrv)
  ^ swrlb:lessThan(?brv, ?brrv) ^ swrlb:stringConcat(?str, "Exercise: "
", ?tenm " ", "Body position: ",?mps, ": ", ?brs, " is below           (13)
minimum")
-> hasEvaluation(?td, ?str) ^ hasResultIndividual(?te,
AthleteExerciseEvaluationNOTOKClassInst)                                     (14)

```

Lines (1) to (6) capture athlete results, by proceeding with the following SWRL rule chaining: (1) *TrainingDay* has an athlete, which has a weight class and a gender. The two parameters will be used later to match the respective reference athlete. It must be noted that since male and female's weight classes are not disjoint, the gender attribute must also be used. (2) A *TrainingDay* has also an exercise, and this has a name, and a reference label (*hasTrainingInstanceLabel*). All labels referenced in this rule were inferred by other OWL assertions axioms. The purpose of those label is only to support the rule implementation, and so, matching the respective individual in the reference athlete side. (3) An exercise has a body movement alongside a barbell movement, but for computing efficiency purposes, the latter is implemented by another SWRL set of rules. (4) A body movement has an exercise sequence position. (5) The exercise sequence position has several exercise movements. In case of snatch lifting, they

consist of start, knee level, power, fully extended, catch and fully recovered. (6) Each exercise movement has collected biomechanical ground values or processed values. Each of the ground/processed value will match the respective reference athlete for the comparable set of values, in terms of measuring the same body/barbell part with the same quantities or instrument (e.g. measuring the knee angles at the start position).

Lines (7) to (12) mimic the previous rules but with regard to the reference athlete. It proceeds with the following chaining: (7) The *TrainingReference* will match the athlete's weight class and gender, and so, selecting the reference athlete. (8) For the selected reference athlete, the minimum reference values will be selected for the appropriate exercise, e.g. snatch lifting. (9) As in the athlete side, an exercise has movements and, in this case, they are body movements. (10) The exercise sequence will match athlete's sequence. (11) The same goes for the exercise movements. (12) Each exercise movement, from the reference athlete, has associated biomechanics ground values or processed results.

Finally, the line (13) compares the athlete's attributes to the minimum attributes of the reference athlete, while the line (14) sets the inferred *hasEvaluation* data property in the *TrainingDay* individual, with the appropriate value. The other atom sets a property, in each exercise that will be used for rhythm assessment in the *ExerciseConflict* rule.

As mention earlier, the *AthleteExerciseEvaluation-BodyPosMax* SWRL rule is grouped with previous one to provide the upper bound of "valid" athlete's movement positions. The rule is similar to the previous one, but different in line (8) where *hasExerciseMax(?tr, ?ter)* is used instead to look for upper bound values in the reference athlete, in line (13) the function *swrlb:greaterThan(?brv, ?brrv)* checks the upper limits, and in the remaining atom at the same line which must be accordingly changed. Another related rule, *AthleteExerciseEvaluation-BodyPosOK*, verifies if the values are in-between these min and max references and if so, it sets a property in the exercise, stating that the body movement performed was OK. This property will be used in *theExerciseOK* rule.

B) SWRL rule: *AthleteExerciseEvaluation-BarbellPhaseMin/Max*

The other group of rules, implemented by *AthleteExerciseEvaluationBarbellPhaseMin* and *AthleteExerciseEvaluationBarbellPhaseMax* checks if the exercise was well

performed from the dynamic perspective, i.e., regarding the barbell's parameters during the exercise phases. The approach is the same as presented in *AthleteExerciseEvaluation-BodyPosMin* rule but replacing *hasTrainingBodyMovement* at line (3), (9) and *hasTrainingExerciseSequencePosition* at lines (4), (10) by *hasTrainingBarbellMovement* and *hasTrainingExerciseSequencePhase*, respectively. As in the body movement rules which presents *AthleteExerciseEvaluation-BodyPosOK*, for barbell movement, there is also a rule *AthleteExerciseEvaluation-BarbellPhaseOK*. The objective is to verify if the values of the barbell movements are in-between the min and max references and also in that case it sets a property in the exercise stating that the barbell movement was OK. This property will also be used in *theExerciseOK* rule.

C) SWRL rule: *BarbellTrajectory*

This rule is computationally intensive and complex due to the usage of array of points. The goal of this rule is to access if the movement in each phase is in accordance with a reference movement. If it is, the rule asserts an individual, *AthleteExerciseTrajectoryOKClassInst*, which will be later used by *ExerciseOK* rule to validate the overall exercise. It is similar to *AthleteExerciseEvaluation-BodyPosMin* rule, except that it is dealing with barbell movements at line (3), mapping the phases of an exercise at line (4) and with their movements at line (5). The measurements used by this rule, are points of a trajectory, in an ordered sequence (6). Lines (7) to (12) relate these values to the reference values, as in *AthleteExerciseEvaluation-BodyPosMin* rule. The difference is that, unlike the latter which compares with a lower threshold, this rule checks whether user points are inside the defined range for each point. A unique range value for all the trajectory points could be set, but for improving flexibility a tolerance was defined for each point. In line (12) the reference values and tolerance are obtained while at line (13) they are compared with the user data. If all points of all phases, are in the tolerance range of the reference then, a specific individual is asserted at line (14) to signal success.

Rule: <i>TrainingTrajectory</i>
TrainingDay(?td) ^ hasWLAthlete(?td, ?at) ^ hasWLAthleteWeightClass(?at, ?awc) ^ hasWLAthleteGender (?at, ?ag) (1)
^ hasExercise(?td, ?te) ^ hasWLTechImprovement (?te, ?tei) ^ hasExcerciseName(?te, ?tenm) ^ hasTrainingInstanceLabel(?te, ?tel) (2)
^ hasTrainingBarbellMovement (?te, ?bm) (3)
^ hasTrainingExerciseSequencePhase (?bm, ?es) (4)

```

^ hasTrainingExerciseMovement(?es, ?mp) ^ hasTrainingInstanceLabel(?mp,
?mpl) ^ hasTrainingInstanceLabelString(?mp, ?mps) (5)
^ hasTraining2BioMechBodyResult(?mp, ?br) ^ hasBioMechInstanceLabel(?br,
?brl) ^ hasBioMechSeqValue(?br, ?brs) ^ hasDataBioMechResultXvalue(?br,
?brvx) ^ hasDataBioMechResultYvalue(?br, ?brvy) (6)

^ TrainingReference(?tr) ^ hasWLAthlete(?tr, ?atr) ^
hasWLAthleteWeightClass(?atr, ?awc) (7)
^ hasWLAthleteGender (?atr, ?ag)

^ hasExerciseMin(?tr, ?ter) ^ hasTrainingInstanceLabel(?ter, ?tel) (8)
^ hasTrainingBarbellMovement (?ter, ?bmr) (9)
^ hasTrainingExerciseSequencePhase (?bmr, ?esr) (10)

^ hasTrainingExerciseMovement(?esr, ?mpr) ^
hasTrainingInstanceLabel(?mpr, ?mpl) (11)
^ hasTraining2BioMechBodyResult(?mpr, ?brr) ^
hasBioMechInstanceLabel(?brr, ?brl)
^ hasBioMechSeqValue(?brr, ?brs) ^ hasDataBioMechResultXvalue (?brr,
?brrvx) (12)
^ hasDataBioMechResultYvalue (?brr, ?brrvy) ^
hasDataBioMechResultvalueTolerance(?brr, ?brrvto)
^ swrlb:multiply(?tolx, ?brrvx, ? brrvto) ^ swrlb:multiply(?toly,
?brrvy, ? brrvto)
^ swrlb:subtract(?minx, ?brrvx, ?tolx) ^ swrlb:subtract(?miny, ?brrvy,
?toly) (13)
^ swrlb:add(?maxx, ?brrvx, ?tolx) ^ swrlb:add(?maxy, ?brrvy, ?toly)
^ swrlb:greaterThan(?brrvx, ?minx) ^ swrlb:lessThan(?brrvx, ?maxx)

^ swrlb:greaterThan(?brrvy, ?miny) ^ swrlb:lessThan(?brrvy, ?maxy)

-> hasResultInstance(?te, BarbelTrajectoryOKClassInst) (14)

```

D) SWRL rule: *TechniqueImprovement*

Both SWRL rules mentioned earlier aim to check if the exercise technique improves and if so, it invokes the following rule, *TechniqueImprovement*, for validation of such goal. It is known that the lifting technique depends on the load, so weightlifting literature (e.g., Szabo (2012)) suggested that the ideal weight for technique improvement should be on the range of 80-85%. Usually, this label is used to map a type of exercise, in this case, to a snatch lifting exercise.

Rule: *TechniqueImprovement*

```

TrainingDay(?td) ^ hasWLAthlete(?td, ?at) ^
hasWLAthleteWeightMax(?at, ?awm)
^ hasExercise(?td, ?te) ^ hasExcerciseWeight(?te, ?tew) ^
swrlb:multiply(?lowv, awm, 0.80)^ ^ swrlb:multiply(?hiv, awm,
0.85)^swrlb:greaterThan(?tew, ?lowv) ^ swrlb:lessThan(?tew, ?hiv)
-> hasWLTechImprovement (?te, "OK")

```

E) SWRL rule: *ExerciseOK*

The atom chaining of *ExerciseOK* rule starts at line (1) by scanning each exercise in a *TrainingDay* and checking at line (2) if both body/barbell movements and barbell trajectory are correct. If they are correct, at line (3) a property is asserted stating that the exercise was well performed.

```
Rule: ExerciseOK

TrainingDay(?td) ^ hasExercise(?td, ?te) ^ hasExerciseName(?te,
?tenm) ^ hasTrainingInstanceLabel(?te, ?tel) (1)
^hasResultIndividual( te, BarbelMovementOKClassInst) ^
hasResultIndividual( te, BodyMovementOKClassInst) ^
hasResultIndividual( te, BarbellTrajectoryOKClassInst) ^
swrlb:stringConcat(?str, "Exercise: ", ?tenm, "- well performed") (2)
-> hasEvaluation(?td, ?str) (3)
```

The following Figure 5.26 illustrates the execution of the *ExerciseOK* rule.

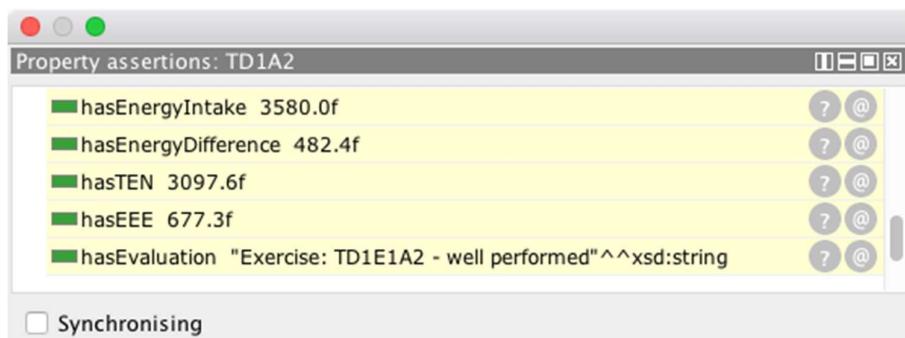


Figure 5.26 Output info generated after executing the SWRL rule designated as *ExerciseOK*.

F) SWRL rule: *ExerciseConflict*

What if in certain cases there is a mismatch between an executed exercise performance and its related reference performance, while the former is acceptable by the coach? This is considered as an interesting “corner case” where different properties interact together to compensate each other. The rule *ExerciseConflict*, allows for the identification of such cases. As the system also highlights the error, it is easy to find the properties that are compensating each other. The atom chaining of *ExerciseConflict* rule starts at line (1) by scanning each exercise in a *TrainingDay* and checking at line (2) if it is not correctly performed (i.e., if the *AthleteExercise*

EvaluationNOTOKClassInst was asserted by the movement rules). At line (3) is checked if the coach approved the exercise (i.e., if the *AthleteExerciseCoachEvaluationOKClassInst* was asserted by the coach). At line (4) a property is asserted, stating that the exercise was qualitatively accepted by the coach but not quantitatively, based on biomechanical measurement.

Rule: *ExerciseConflict*

```

TrainingDay(?td) ^ hasExercise(?td, ?te) ^ hasExerciseName(?te, ?tenm)
^ hasTrainingInstanceLabel(?te, ?tel)                                     (1)

^ hasResultIndividual (?te, AthleteExerciseEvaluationNOTOKClassInst) ^   (2)
hasExerciseMovementCoachEvaluationOK( ?te,
AthleteExerciseCoachEvaluationOKClassInst) ^
swrlb:stringConcat(?str, "Exercise: ", ?tenm, "- validated by coach -
NOT BY THE SYSTEM ")

-> hasEvaluation(?td, ?str)                                              (4)

```

In Figure 5.27 two aspects have been checked. The individual *AthleteExerciseEvaluationNOTOKClassInst* asserted by the coach, and the individual *AthleteExercise EvaluationNOTOKClassInst* inferred by the execution of one of the movement rules. Based on the information showed in Figure 5.28, previous rules make the reasoner infers that the exercise was “*validated by the coach*” (see Figure 5.28).

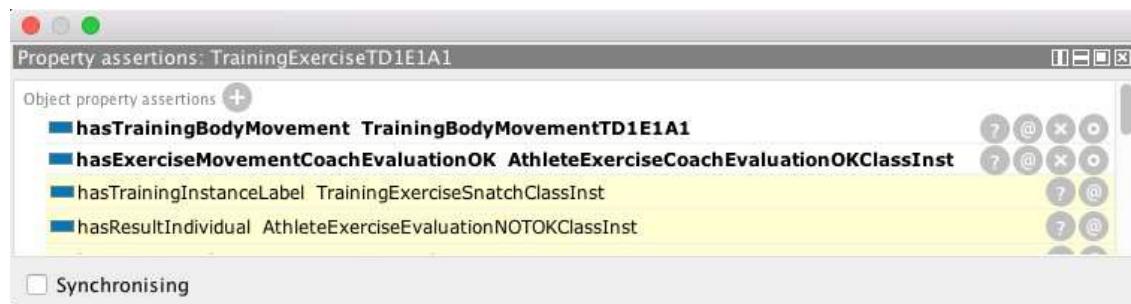


Figure 5.27 Qualitative and quantitative evaluation of a movement by running one of the above movement rules.



Figure 5.28 Qualitative evaluation of a lifting movement.

G) SWRL rule: *ExerciseEnergyExpenditure*

The *ExerciseEnergyExpenditure* rule is a SQWRL which uses the following analytical equation of energy expenditure, $EEE = 0.0175 * METs * Weight * Duration$, to calculate the expended energy for a training day. Its obtained result will be used in the TEN calculations and its atoms are chained as follows. At line (1) a *TrainingDay* has an associated athlete with his weight. At line (2) is expressed that such athlete performed a set of exercises, each exercise has its own duration and METs value. At line (3) the above EEE formula is applied using as inputs data properties retrieved using preceding atoms. At line (4) the result is outputted per each training day and used to assert the *HAS_EEE* data property in the respective *TrainingDay* individual.

Rule: <i>ExerciseEnergyExpenditure</i>	
TrainingDay(?td) ^ hasWLAthlete(?td, ?ta) ^ hasWeight(?ta, ?taw)	(1)
^ hasExercise(?td, ?te) ^ hasTrainingExerciseMET(?te, ?MET) ^	(2)
hasTrainingExerciseDuration	
(?te, ?ed)	
swrlb:multiply(?METw, "0.0175"^^xsd:float, ?MET) ^^	(3)
swrlb:multiply(?r1, ?ed, ?METw) ^ swrlb:multiply(?r2, ?r1,	
?taw) . sqwrl:makeBag(?b, ?r2)	
-> sqwrl:select(?td, ?EEE)	(4)

H) SWRL rule: *TENFemale/Male*

The *TENFemale* rule calculates the TEN (total energy needed) and RMR (resting metabolic rate) of an athlete, in this case, a female athlete, although the latter value is not used by now. The rule uses the same analytical equations as presented earlier in

page 72, 73. The chaining of its associated atoms starts at line (1) expressing that a *TrainingDay* has a *hasEEE* data property, as calculated earlier. At line (2), each training day also refers to an athlete from which is selected several attributes. At line (3) these attributes are used to calculate the RMR, while at line (4) the previous result is also retrieved to obtain the TEN. Finally, at line (5) both obtained results are used to assert *hasRMR* and *hasTEN* data properties of the involved *TrainingDay* individual. A *TENMale* rule is similarly drafted and implemented.

Rule: *TENFemale*

```

TrainingDay(?td) ^ hasEEE(?td, ?eee)                                     (1)
  ^ hasTrainingAthlete(?td, ?ta) ^ hasWLAthleteGender(?ta,
    AthleteGenderFemaleClassInst) ^ hasHeight(?ta, ?hgt) ^
    hasWeight(?ta, ?wgt) ^ hasAge(?ta, ?age) ^ hasGAF(?ta, ?gaf)          (2)
    ^ swrlb:multiply(?a1, "4.68"^^xsd:float, ?age) ^ swrlb:multiply(?h1,
      "1.85"^^xsd:float, ?hgt) ^ swrlb:multiply(?w1, "9.56"^^xsd:float,
      ?wgt) ^ swrlb:add(?r1, "655.1"^^xsd:float, ?w1)                      (3)
    ^ swrlb:add(?r2, ?r1, ?hgt) ^ swrlb:subtract(?rmr, ?r2, ?a1)
    ^ swrlb:multiply(?r3, ?rmr, ?gaf) ^ swrlb:add(?r4, ?eee, ?r3)           (4)
    ^ swrlb:multiply(?ten, "1.1"^^xsd:float, ?r4)
-> hasRMR(?td, ?rmr) ^ hasTEN(?td, ?ten)                                (5)

```

I) SWRL rule: *EnergyIntake*

The *EnergyIntake* rule is a SQWRL which calculates the energy intake for a training day, based on the meals consumption for that day. The chaining of its atoms starts at line (1) addressing each taken meal of a *TrainingDay*. At line (2) consumables are selected and from each of them it is individually selected the caloric value. At line (3) the result accumulatively added to those from other consumables from all other meals in that training day. Finally, at line (4) the results are outputted per each training day, while the *HAS_EI* data property in the respective *TrainingDay* individual is asserted.

Rule: *EnergyIntake*

```

TrainingDay(?td) ^ hasMeal(?td, ?m)                                         (1)
  ^ hasNutritionDPPrescribesConsumable(?m, ?mc) ^ hasNutritionCalories(?mc, ?cal) (2)
    . sqwrl:makeBag(?b, ?r1) . sqwrl:sum(?EI, ?b)                            (3)
-> sqwrl:select(?td, ?EI)                                                 (4)

```

J) SWRL rule: EnergyBalance

The *Balance* rule compares the energy intake as calculated by the *EnergyIntake* rule, with the amount of energy needed (i.e., the previously computed TEN value) to calculate the energy difference.

Rule: EnergyBalance

```
TrainingDay(?td) ^ hasEnergyIntake(?td, ?i) ^ hasTEN(?td, ?e) ^  
swrlb:subtract(?r, ?i, ?e)  
-> hasEnergyDifference(?td, ?r)
```

K) SWRL rule: TotalNutrients

The *TotalNutrients* rule is a SQWRL which sums all the nutrients for a given meal. Its chaining starts at line (1) by selecting the consumables for each meal in a training day. At line (2) is expressed that each consumable has a set of nutrients, with a name and value. At line (3) a set of these values is created, grouped by meal and training day, and added according to its grouping. Finally, at line (4) the results are provided in a tabular form, while they are used to assert or populate the data properties such as *HAS_VitaminA*, *HAS_Iron*, etc. in the respective meal individuals.

Rule: TotalNutrients

```
TrainingDay(?td) ^ hasMeal(?td, ?m) ^  
hasNutritionDPPrescribesConsumable(?m, ?mc) (1)  
^ hasNutritionNutrient(?mc, ?mn) ^ hasNutritionNutrientName(?mn, ?mnn)  
^ hasNutritionNutrientValue(?mn, ?mnv) (2)  
. sqwrl:makeBag(?b, ?mnv) ^ sqwrl:groupBy(?b, ?td, ?m, ?mnn) .  
sqwrl:sum(?NUT, ?b) swrlb:multiply(?r1, ?cal) (3)  
. sqwrl:makeBag(?b, ?r1) . sqwrl:sum(?EI, ?b)  
-> sqwrl:select(?td, ?m, ?mnn, ?NUT) ^  
sqwrl:columnNames("TrainingDay", "Meal", "NutritionNutrientName",  
"NutritionNutrientValue") (4)
```

The following Figure 5.29 presents the result of the execution of the *TotalNutrients* rule. Based on the results obtained from the execution of the *TotalNutrients* rule, several other rules were created to check if each result is in accordance with the respective athlete's nutritional profile. Below is presented the *NutritionEvaluation VitaminAMin* rule for the evaluation of the level of vitamin A in a consumed, meal according to a given athlete's nutritional profile. Similar rules were also created for the evaluation of Vitamin A, Vitamin C, etc.

SQWRL Queries	OWL 2 RL	TotalNutrients	
TrainingDay	Meal	NutritionNutrientName	NutritionNutrientValue
TD1A1	NutritionMeal1000Calories	Iron	"7.0"^^xsd:float
TD1A1	NutritionMeal1000Calories	VitaminC	"20.0"^^xsd:float
TD1A1	NutritionMealPostWMeal	VitaminA	"166.0"^^xsd:float

Save as CSV... Rerun Close

Figure 5.29 Tabular form with results of the TotalNutrients SWRL query-based rule execution.

L) SWRL rule: *NutritionEvaluationVitaminAMin*

The atom chaining of *NutritionEvaluationVitaminAMin* rule starts at line (1) by selecting the athlete and his/her intake meals for a given training day. At line (2) is expressed that each meal has its scheduled intake time or nutritional occasion (i.e., pre, post or during workout). At line (3) and line (4) are expressed that a meal has a total of vitamin A and an athlete has associated a nutritional reference values, respectively. At line (5) the respective occasion reference values must be chosen in order to compare them to meal values, while at line (6) is guaranteed that the nutrition element must be the same. At line (7) the comparison is performed and a string with the result is constructed in case of a problem. Finally, at line (8) a property is asserted in the meal individual. The following Figure 5.30 presents the result of the execution of the *NutritionEvaluationVitaminAMin* rule.

Rule: *NutritionEvaluationVitaminAMin*

TrainingDay(?td) ^ hasWLAthlete(?td, ?at) ^ hasMeal(?td, ?m) ^	(1)
hasNutritionMealName(?m, ?mn)	
^ hasNutritionDPAministratedOn(?m, ?ao) ^	(2)
hasNutritionProtocolName(?ao, ?aon)	
^ HAS_VITAMINA(?m, ?v)	(3)
^ AthleteNutritionReference(?ar) ^ hasWLAthleteReference(?ar, ?at)	(4)
^ hasNutritionDPAministratedOn(?ar, ?ao)	(5)
^ hasNutritionReferenceMin(?ar, ?nrm) ^	
hasNutritionDPPrescribesConsumable (? nrm, ?nrmc)	(6)
^hasNutritionNutrient(?nrmc, ?nnr) ^ VitaminA(?nnr) ^	
hasNutritionNutrientValue(?nnr, ?nnrv)	
^ swrlb:lessThan(?v, ?nnrv) ^ swrlb:stringConcat(?s1, "In meal ", ?mn,	
" (at occasion ", ?aon, ") VitaminA intake is below recommended	(7)
level")	
-> hasDietaryProblem(?td, ?s1)	(8)

Property assertions: TD1A2	
hasEnergyIntake 3580.0f	?
HAS_VITAMINA 166.0f	?
hasEnergyDifference 482.0f	?
hasTEN 3097.6f	?
hasEEE 677.3f	?
hasResult "VitaminA: Value BELOW the daily recommendation"^^xsd:string	?
hasEvaluation "Exercise: TD1E1A2 - well performed"^^xsd:string	?

Synchronising

Figure 5.30 Tabular form with results of the NutritionEvaluationVitaminAMin SWRL query-based rule execution.

5.4 Conclusions

This second-iterated TDC-ontology was mainly refactored toward better domain-level modularity, and scalability, while partially moving to fourth generation methodologies. More specifically, each information dimension was declaratively extended and modeled by its own ontology, expressed at different layers, and then interrelated among them by improved heuristics and procedural rules. Each layer was modeled around its designated composite central concept such as *Exercise*, *Analysis*, and *Dietary Protocol* at training, biomechanics, and nutrition layers, respectively. Furthermore, gender differentiation was leveraged according to existing weight classes, mainly because only 69 kg class is common between male and female weightlifters. Also, a new information dimension was modeled through the stakeholder domain. In so doing, any top reference athlete is instantiated as any regular athlete individual for easy and direct comparison of training features during rhythmic execution analysis. This will also enable rhythm comparison among low-performance athletes, which we hope it will help, to some extent, understanding the failing/mismatched pattern.

In spite of the mentioned better modularity and scalability of the proposed weightlifting TDC-cycle OWL knowledge-based system, few drawbacks have been identified to be later addressed in the next improved/iterated TDC-ontology:

- (i) Some concepts seem to be overlapped among the three domains, suggesting further refactoring of the declarative knowledge. For instance, the three central concept of each layer can all be modeled through a smaller declarative generic

task ontology. Notice that the task domain ontology as defined in this work is a very specific implementation, according to our problem solving structure.

- (ii) Also the *Environment* concept modeled at the training layer can be moved to the above declarative task ontology and then refactored around *Resource* and *Consumable* concepts presented at biomechanics and nutrition layers, respectively.
- (iii) Missing of annotation properties for describing statistical and mathematical models and only drafting the rules around the conclusion and discussion section of paper. Only then, the output of math/statistical methods are used to assert data properties ‘inherited’ by the task domain ontology.
- (iv) Conceptually mapping the rhythm rules is on an upper layer as they are based the correct execution of the athlete in terms of kinetics and kinematics.

However, after a considerable effort to populate the FB with all individuals required to exercises the prescribed rules, promising results and knowledge regarding the understanding of rhythmic execution were collected.

CHAPTER 6

Modeling Weightlifting TDC-cycle by Mapping it to an Upper Ontology

This chapter presents and discusses the third-iterated Weightlifting TDC-cycle ontology, refactored toward improved flexibility and scalability, comparatively to the second-iterated ontology.

The main focus is on modeling an abstract or generic upper ontology to decouple *task*, *actor*, and *environment* concepts from weightlifting domain specificities. An upper ontology will offer the advantage of being able to semantically model any other sports domains (e.g., swimming or long jumping). With this approach, it will simplify the semantic integration of previous domain ontologies of nutrition, training, biomechanics and stakeholder, by defining general and sharable concepts which are restricted in compositions by axioms applicable across all them. After modeling and designing the upper ontology, it will serve as a foundation of the previous four domain ontologies, as it will be mapped to them.

Introduction

According to Chapter 4 where the task ontology was modeled and designed in the first-iterated weightlifting TDC-cycle ontology and Chapter 5 where it was partially and implicitly embedded on each domain ontologies of the second-iterated TDC-cycle ontology, the main objective was strictly focused on weightlifting needs, leading, according to Arp et al., 2015, to non-sharable data and non-optimal use of resources. Notice that the notion of problem-solving method is presented not only at the whole architecture of weightlifting TDC-cycle, but also at a lower-level of each individual domain which composes it. Therefore, instead of only a specific-purpose task ontology for the weightlifting TDC-cycle problem-solving structure (as presented in the first two versions), here an abstract or generic upper ontology is also modeled, following similar approaches to those presented in Peeters et al. (2014) and Mizoguchi et al. (1995), to decouple *Task*, *Actor*, and *Environment* concepts from weightlifting needs. In doing so, such an upper ontology will be commonly used to semantically model any other sports domains (e.g., swimming or long jumping). More specifically, it will simplify the semantic integration of previous domain ontologies of nutrition, training, biomechanics, and stakeholder, by defining general and sharable concepts. These concepts are restricted in compositions by axioms applicable across all them. After modeling and designing the upper ontology, it will serve as a foundation of the previous four domain ontologies as it will be mapped to them.

The remainder of this chapter is organized as follows: Section 6.1 describes modeling and design of the abstract TDC-cycle upper ontology; Section 6.2, Section 6.3 and Section 6.4 present and discuss the third-iterated refactored training, nutrition and biomechanics domain ontologies, respectively; Section 6.5 shortly presents some conclusions.

6.1 The TDC-cycle Upper Ontology

The proposed upper-level ontology for the TDC-cycle was modeled around generic central concepts of *Actor*, *Process*, and *Environment* as presented in Figure 6.1. It will be applicable to a generic characterization of the previously identified domain ontologies of the TDC-cycle and later restricted through some axioms for consistency purpose.

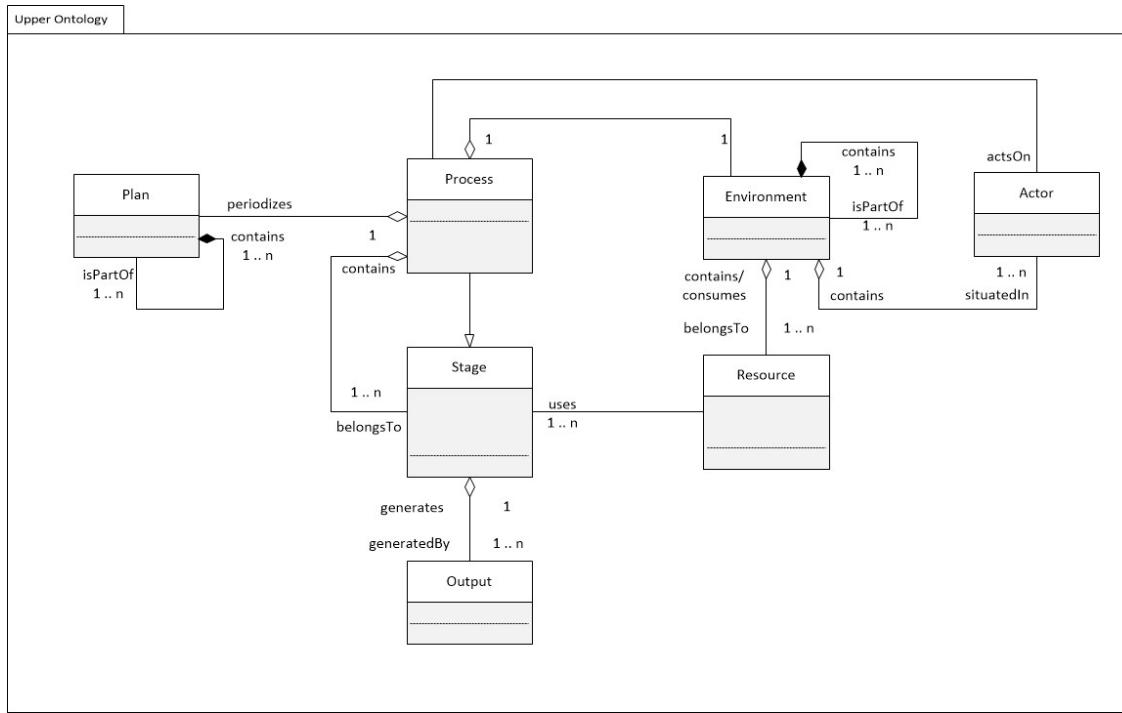


Figure 6.1. The upper ontology modeled around abstract concepts of Actor, Environment and Process/Task.

For modeling and designing of such an upper ontology for TDC-cycle, we postulate that any process has its own environment(s), while the process describes the problem solving structure associated to training execution/analysis (i.e., exercise and observation), nutrition analysis (i.e., quantitative energy expenditure) and biomechanics analysis (i.e., quantitative analysis of performed exercise). Furthermore, stakeholders such as coach, biomechanist, nutritionist, and athlete can act on their related processes of observations, analyzes, and exercising.

In fact, the concept of *Process* is a generalization of the central concepts of *Exercise*, *Analysis*, and *DietaryProtocol* as modeled in the second-iterated TDC-Ontology. Hence, it is expressed as a composite of plans and stages in which each stage will be

performed in an environment at a given scheduled time. Basically, the concept of *Plan*, offers a way to express the sequencing and timetable or schedule of each stage of a process, while the concept of *Stage* represents: (1) acquisition, processing, and result interpretation during a biomechanical analysis, (2) first pull, transition, second pull, turnover, catch, and recovery phases while exercising a snatch or (3) pre-workout, during-workout, post-workout and in-competition according to a prescribed dietary protocol. For multiple-stage sports like triathlon which involves swimming, cycling, and running, multiple environments will be involved. Each environment consists of several and different resources. Obviously, resources will change from weight plate and barbell in a training session to micro- and macro nutrients in a dietary consumption and to force plate, and 3D motion capture system during a biomechanics analysis.

To fully model the TDC-cycle upper ontology, the definition of bridging axioms becomes crucial, to avoid the usage of relations outside their intended meaning. In doing so, relations are defined that hold between classes and between individuals (i.e., class- and instance-level relations), while specifying the kind of entities between which they are asserted, according to the previous domains of nutrition, training, biomechanics and stakeholder. Unambiguous relation for each meaning are defined using axioms. It clearly describes all possible ways in which a given relation is satisfiable or unsatisfiable. For instance, although *Exercise*, *Analysis*, and *DietaryProtocol* are aligned to *Process* in the upper ontology, which is performed in an environment, the defined *contains* diamond relation between *Process* and *Environment* concepts must clearly discriminate and validate which resources as well as the kind of environment are allowed. Putting it simply, while a gym is a possible instance of an environment for regular weightlifting training, it is usually not a lab for biomechanics or nutrition analyzes. It is mainly because both depends on quite different required resources and settings. Furthermore, the relation *actsOn* between *Process* and *Actor* are clearly discriminated. For example, only an athlete performs a snatch exercise, while only a nutritionist can prescribe a dietary protocol, and a coach and a biomechanist can realize a training session and analysis, respectively. In a similar way, axioms are defined among *Process* and *Stage*, alongside *Stage* and *Output*. The only relation that is universal is the one between *Plan* and *Process*.

With the TDC-cycle upper ontology on place, the domain ontologies from different information dimensions are integrated by alignment to it.

6.2 The Refactored Third-Iterated Training Ontology

By aligning terms of the sport information space, divided into its multiple dimensions of training, nutrition, biomechanics, and stakeholder, with a minimalist set of foundational classes modeled in the TDC-cycle upper ontology, each domain ontology is modeled as a low-level ontology which describes the details of those foundational concepts and their related properties for a particular information dimension (see Figure 6.2). Therefore, *Exercise*, the central concept of the previous second-iterated training ontology, is refactored as a subclass of *Process* class in the TDC-cycle upper ontology through *Snatch*, *Clean&Jerk*, and *Supplements* classes, while a gymnasium is a subclass of *Environment* class. Similarly, the TDC-cycle upper ontology concept of *Resource* is re-used to specify *Barbell* and *WeightPlate* as its subclasses, while barbell and body movements are refactored as two subclasses of *Output* class. Obviously, Bulgarian and Russian models are both refactored as *Plan* subclasses, while first pull, transition, second pull, turnover, catch, and recovery phases are refactored as subclasses of the class *Stage* of the TDC-cycle upper ontology. After refactoring the previous second-iterated training ontology around the TDC-cycle upper ontology concepts, the new ontology is complemented with new concepts (e.g., the three subclasses of *Supplement* class represented by *Good_Morning*, *Power_Snatch*, and *Front&BackSquat*) as well as data properties and relations (e.g., imported from the previous second-iterated training ontology) which are specific to the training domain. Finally and optionally, new axioms are added to the training ontology using relations offered by the TDC-cycle upper ontology, according to the previously mentioned bridging axioms.

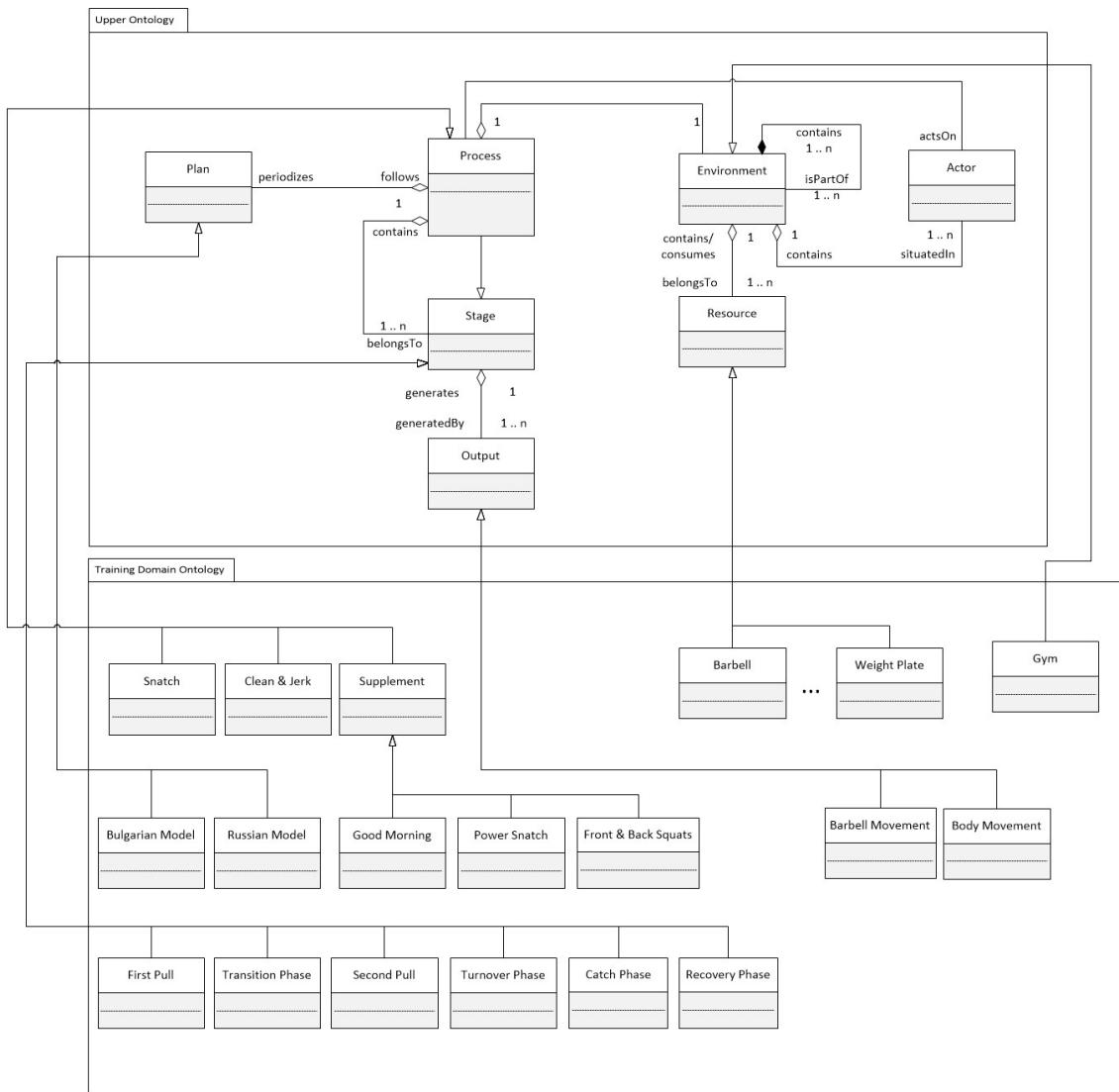


Figure 6.2. Third-iterated training domain ontology refactored around the TDC-cycle upper ontology.

6.3 The Refactored Third-Iterated Nutrition Ontology

Following a similar refactoring approach as above, the nutrition domain is modeled as a low-level ontology describing in details those foundational concepts of TDC-Cycle upper ontology and their related properties for nutritional information dimension. The central concept, *DietaryProtocol*, of the previous second-iterated training ontology is refactored as a subclass of *Process* class in the TDC-cycle upper ontology (see Figure 6.3), while the *HumanBody* concept is a subclass of *Environment* class. An athlete's body was envisioned as a receptacle of macro- and micro-nutrients, and so, it is defined as the main environment for the nutrition analysis. However, the nutrition environment can be envisioned as a composite of environments incorporating also the physical environment under which the energy expenditure measurement is realized, according to the used anthropometric and metabolic measurement devices (e.g., electromyography-, heart rate-, calorimetric-, mass spectrometric-, or stadiometric-based devices).

In doing so, it became obvious that data properties and axioms need to be introduced to clearly discriminate the meaning and usage of nutrition resources in consumables (i.e., macro- and micro-nutrients) and measurement devices (e.g., heart rate and spectrometric devices). However, we decided to model all kind of measurement and related physical environment as part of the biomechanics laboratory, and so simplifying the modeling of the central concept of nutrition ontology only around the dietary protocol (i.e., targeting only qualitative measurement). Therefore, the modeling of nutrition quantitative analysis techniques is differed and then modeled into the biomechanics domains. The *EnergyExpenditure* concept is refactored as a subclass of *Output* class. *Pre-Workout*, *In-Workout*, *Post-Workout*, and *In-Competition* are refactored as subclasses of the class *Stage* of the TDC-cycle upper ontology, while for each stage a given schedule is provided as subclasses of the class *Plan*. Therefore, the refactored nutrition ontology is then complemented with new concepts such as *Vitamin*, *Mineral*, *Fat*, *Protein*, *Carbohydrate*, *Drink*, *NaturalFood*, and *DietarySupplement*, which are specific to the nutrition domain. It also models the last three concepts as being composed by macro- and micro-nutrients.

From Figure 6.3, both *Analysis* and *DietaryProtocol* classes are subclasses of the class *Process*. For consistency purpose, bridging axioms are provided to discriminate between stages and compose each of them.

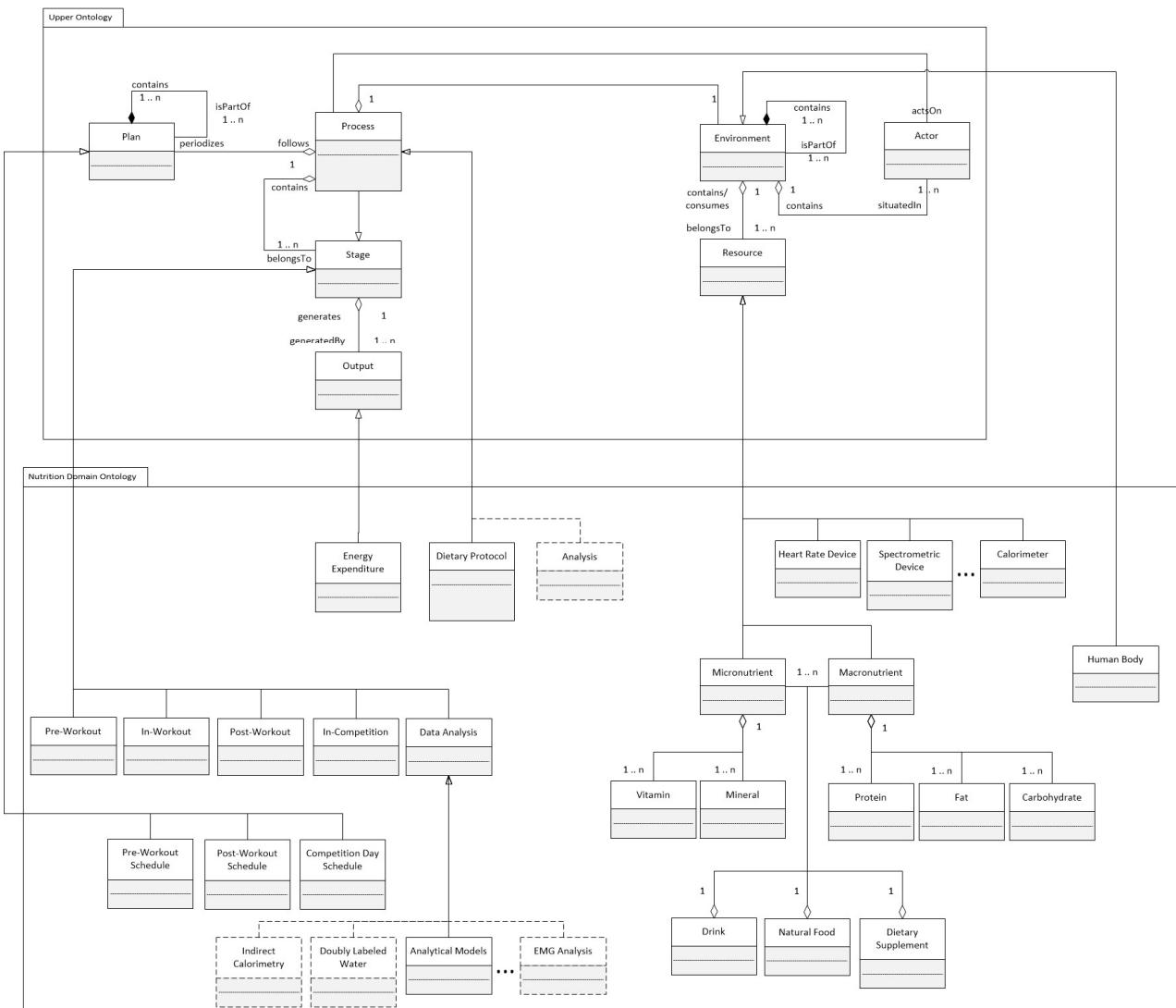


Figure 6.3. Third-iterated nutrition domain ontology refactored around the TDC-cycle upper ontology.

6.4 The Refactored Third-Iterated Biomechanics Ontology

The biomechanics domain is also modeled as a low-level ontology aligned to the TDC-Cycle upper ontology concepts and complemented with detailed biomechanics information already established in the second-iterated biomechanics ontology (see Figure 6.4). As the central concept of the biomechanics ontology, *Analysis* is refactored as a subclass of *Process* class in the TDC-cycle upper ontology. The environment for the biomechanics analysis is usually represented by the concept *Lab*, a subclass of *Environment*, which is equipped with several kind of resources/devices ranging from force to kinetics/kinematics for data capture (e.g., force plates, dynamometers, and 3D motion capture systems). Several kinds of output (e.g., body and barbell kinematics, power output and muscles' activities) can be reported during a biomechanical analysis and they are all refactored as subclasses of *Output* class. A biomechanical analysis is performed through several stages such data acquisition, data analysis and resources' calibration, whose classes are subclasses of the *Stage* class of the TDC-cycle upper ontology. Each individual scheduled time is refactored as a subclass of *Plan* class of the TDC-cycle upper ontology. Finally, the so far refactored biomechanics ontology is complemented with specific classes of this information dimension, such as analyzes' techniques (e.g., *MechanicalPowerAnalysis*, *VideoAnalysis*, *EMGAnalysis* and *IndirectCalorimetry*). Additionally, muscles' activities are measured on different muscles' regions/groups and therefore, the *MuscleActivity* concept is defined as a composite of *VastusLateralis*, *BicepsFemoris*, *PectineusGracilis* and so on. According to the decision made while modeling the nutrition domain toward only qualitative analysis, devices (e.g., electromyography-, heart rate-, calorimetric-, mass spectrometric-, or stadiometric-based devices) and quantitative measurement techniques (e.g., *IndirectCalorimetry* and *DoublyLabeled Water*) related to nutrition field are here modeled as part of the biomechanics ontology.

To conclude the declarative modeling of the weightlifting TDC-cycle ontology, the stakeholder domain starts by defining athletes, coaches, biomechanists, or nutritionists as subclasses of *Actor* class of the TDC-cycle upper ontology. Furthermore and similarly to the above refactored ontologies, the stakeholder ontology is complemented with specific imported concepts, data properties, and relations from the previous second-iterated ontologies.

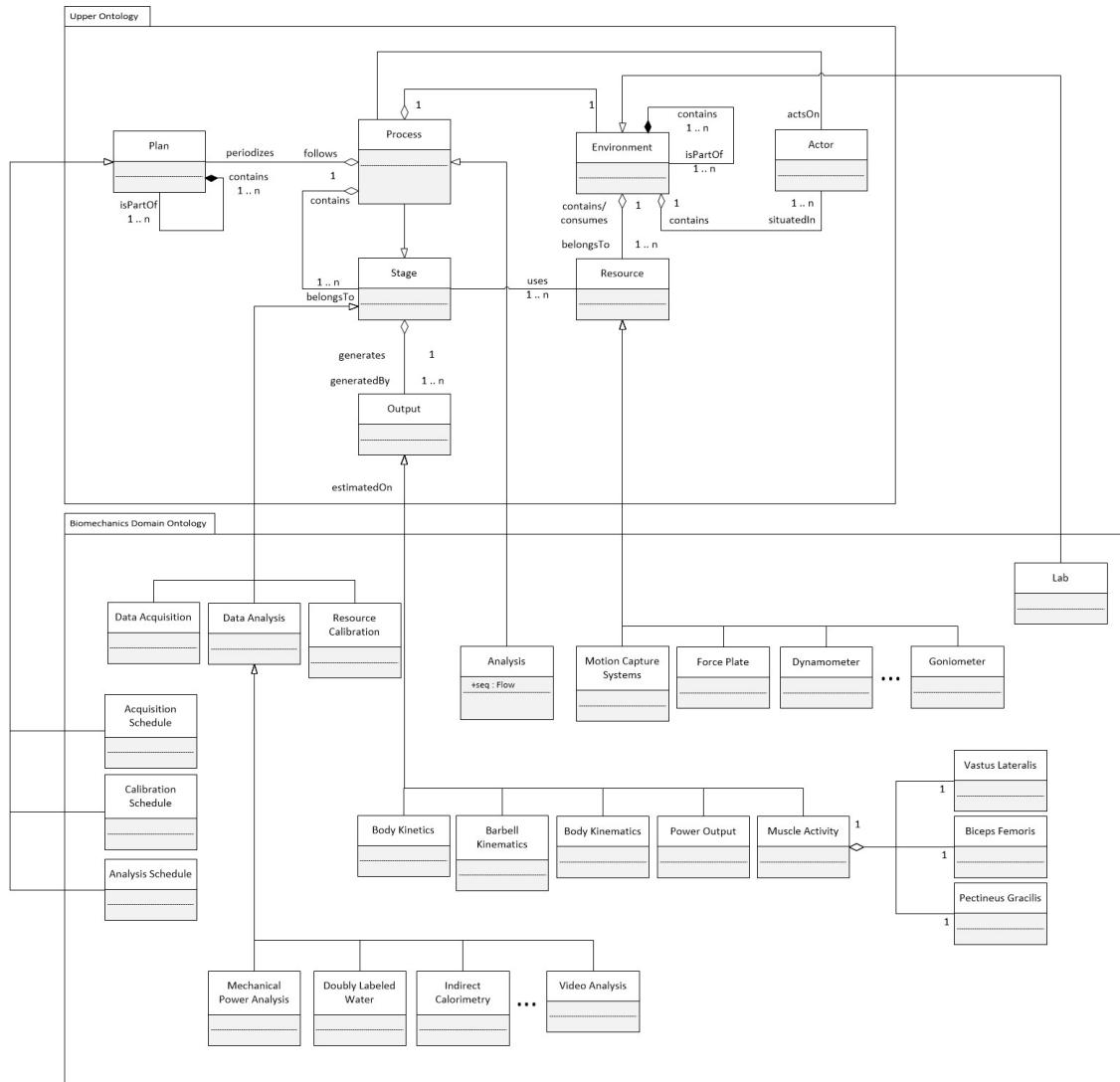


Figure 6.4. Third-iterated biomechanics domain ontology refactored around the TDC-cycle upper ontology.

6.5 Conclusions

The third-iterated domain ontologies were refactored by assigning super-classes and generic relations from a minimal TDC-cycle upper-level ontology as a foundation for their classes and relations, while ontologically modeling classes and relations in sport TDC-cycle ontology. The proposed upper ontology mainly offers a generic characterization for each individual sport domain ontology, according to the meaning of their central concepts, supported by relations at class- and instance-levels which are restricted through some bridging axioms for consistency purpose. This minimalist upper ontology was drafted as an integrated fragment of the task ontology (Peeters et al., 2014) and environment ontology (Ermolayev et al., 2008), to easily enable future compatibility with sport domain ontologies developed using any upper-level ontology.

Although still under development and following a whole refactoring process quite similar to the previously done for the second-iterated weightlifting TDC-cycle ontology, several works are recommended, such as:

- (i) Implementing a tool to help populating the FB with all individuals required to exercises the prescribed rules, and so, minimizing the needed total effort spent on such activity.
- (ii) Furthermore, it is need a way for tuning the prescribed rules in order to be easily applied to any work on the literature, while avoiding possible false positives.
- (iii) Devising, for example, artificial neural networks, where rhythmic execution is analyzed based on the reference athlete profile, alongside all other parameters, such as kinetics, kinematics, and applied forces, barbell velocities, and trajectories.
- (iv) Completing the moving to fourth generation of ontology building methodologies by later integrating existing ontologies, for instance, Basic Formal Ontology (BFO) (Arp et al., 2015), Foundational Model of Anatomy (FMA) (Rosse & Mejino, 2003) and so on. In so doing, we first recommended a study of the compatibility between the TDC-cycle upper ontology with different upper-level ontologies used by those existing ontologies.
- (v) Asserting data properties of the TDC-cycle task domain ontology with processed values outputted from artificial neural networks or dedicated regression equations.

CHAPTER 7

General Discussion and Conclusion

This final chapter reflects on the contribution of this thesis to the scientific domain of sport weightlifting, as well as on some lessons-learned used as advices for future work.

Summary

This PhD summarizes the initial work of a proposed larger research project to solve the existing contentious issue around the contemporary weightlifting training practices and analysis. Existing limitations and inconsistencies in the literature of weightlifting sport were deeply discussed in two paragraphs of Chapter 1, more precisely, the *Introduction* and *State of Art*. The specific aims of this PhD were, firstly, driven by an exploratory stage to better understand the contemporary weightlifting training and dietary practices during the TDC-cycle, and secondly, to leverage a knowledge framework to support individualized and holistic approach to snatch analysis, while obviating the identified limitations and inconsistencies. The aims of the PhD have been achieved through the modeling, designing and implementation of a rule- and ontology-based systems that progressed from its declarative to procedural knowledges, mainly trying to semantically model the whole weightlifting TDC-cycle, while iteratively tuning the semantic lifting rhythm rules toward the identification of corner cases.

The inherent complexity of weightlifting analysis comes from heterogeneous information dimensions related to biomechanics, dietary, and training domains and their related methodologies, which is more and more forced to adopt an integrated and collaborative analysis approach in order to achieve better reasoning and on-time decision making during the TDC-cycle. Therefore, we hypothesized that contemporary weightlifting analysis should target, as a whole, both dietary and mechanical specificities, with the latter addressed from both qualitative (i.e., training) and quantitative (i.e., biomechanics) perspectives. This summary paragraph of the concluding Chapter 7, also shortly described in separated paragraphs, the work done in each previous chapters, starting from Chapter 2, before presenting the main findings and answers, as well as future recommendations:

To better grasp the biomechanics perspective of the weightlifting analysis, experiments were conducted to investigate and define the biomechanical profile of weightlifter, using “Power output” as an indicator to assess performance changes. An integrated PCA and HCA approach was followed to find and/or understand possible similarities and hidden patterns of power output during snatch lifting among young weightlifters with different skills. These experiments concluded that for more conclusive answers, more robust classification method (e.g., artificial neural networks) should be applied, as tried by the existing weightlifting literature, but unfortunately also with inconclusive results.

The nutritional status of Thai weightlifters was identified through the use of dietary record and questionnaires. This exploratory study reported that a high proportion of Thai national team weightlifters were not in energy balance and so, failed to meet carbohydrate, protein, and micronutrient recommendations. The primary reason for such inadequate diets may come from the fact that some athletes lack of nutrition knowledge and express some nutritional misconceptions, so they are unable to make appropriate food choices. To close such knowledge gap, an ontology-based personalized dietary recommendation for weightlifting was modeled, designed and implemented to calculate the athlete's calories and nutrients need, based on the individual profile and recommend specific menus according to the training phase and weight goal. Populating the fact base of such ontology-based system was a labored task due to the huge dimension of *Food* concept, and so, requiring a lot of effort and time to insert individuals' data items in order to cover all available menus items.

For the design of the first-iterated TDC-cycle ontology, firstly, a methodology for building of ontologies was selected by clearly establishing steps, key modeling knowledges and design artefacts. Secondly, the weightlifting problem scenario was defined alongside the problem solving for improving weightlifting ability, by explicitly identifying the major non-logical axioms. Thirdly, an architecture for the *TDC Competency Questions Engine Architecture* was proposed with its main building blocks and stakeholders interplays. Finally, a minimalist weightlifting domain and task domain ontologies for a whole weightlifting TDC-cycle OWL- and Rule- Knowledge-based System was modeled, designed and implemented to seize, through testing and validation, some more insight about weightlifting TDC cycle and secondly, to speed up the reasoner performance.

The first-iterated weightlifting TDC-cycle ontology was refactored toward a much more flexible, modular and scalable features, through much more elaborated and extended ontologies, at each of the above identified domain levels of nutrition, training and biomechanics. For this second-iterated weightlifting TDC-cycle, four individual and self-contained ontologies were modeled, designed and implemented, including an explicit new stakeholder domain. The refactored fact base was quite fully populated to exercise the new refactored SWRL rules according to the new refactored ontologies.

The third-iterated weightlifting TDC-cycle ontology is a refactored version of the second-iterated one, toward a more generic-purpose task ontology as well as more

generic TDC-cycle problem-solving structure, supported by an abstract or generic upper ontology. Such generic-purpose task ontology serves as a foundation of the individual domain ontologies which are all integrated by alignment to it. It was modeled and designed around main abstract concepts of *Actor*, *Environment* and *Process* to easily model any other sport domain, while leveraging ease integration of existing similar upper ontologies.

7.1 Conclusions

The work reported in this thesis has the potential to advance the state-of-the-art in contemporary weightlifting TDC-cycle analysis, mainly due to the following reported findings while trying to answer the three research questions presented in *Research Questions of Chapter 1*:

- (i) *Finding 1: “The heterogeneity of information and involved stakeholders, demand for a collaborative analysis of the weightlifting TDC-cycle which is very complex and hard to be analytically- or statistically-only solved”.*

Finding 2: “Several approaches for the analysis of rhythmic execution have been described, but all of them fall short because they were performed in a very specific and constrained training context”. For instance, most of them address only specific and isolate weightlifting training specificity of body/barbell trajectory patterns, applied force on the barbell or velocity of movement, excluding completely athlete anthropometric features or comparison with top reference athlete data. Furthermore, most of them were biomechanical in nature.

We started by partially addressing both of the above findings by holistically and simultaneously integrating several knowledge domains, including task domain to an integrated and collaborative weightlifting analysis approach, assisted by several stakeholders, such as coaches, biomechanics, athletes and nutritionists.

- (ii) *Finding 3: “Semantics technology can promote external interoperability among researchers from different projects as well a kind of standardization which easily allows comparison and exportation of data and results from different experiments”.*

Finding 4: Additionally, semantics technology can reduce and even avoid home brew of a new solution, while being attractive to applied researchers with limited computational and statistical background.

Our proposal for both findings went toward the leveraging of weightlifting ontology-assisted analysis through logical reasoning. Ontology was also chosen as the modeling paradigm due to its expressivity and reasoning abilities to ensure understanding and semantic interoperability between involved interactors in a collaborative weightlifting TDC-cycle analysis.

- (iii) *Finding 5: “Existing weightlifting analysis cannot leverage real-time decision making to improve the lifting as well as promote lifting training personalization for each specific athlete”.*

Our proposal promotes the combination of the semantic analysis with analytical/statistical analysis, with the latter through numerical reasoning. Such combination also completes the answer to the first two findings by easily integrating qualitative with quantitative evaluations. Although not yet implemented, numerical reasoning can be directly integrated with logical reasoning through asserted data properties.

The proposed weightlifting TDC-cycle system as it is conceived, designed and implemented, can easily leverage the integration of qualitative and quantitative analysis through asserted data properties, for example, qualitatively by coaches or using analytical model of lifting rhythm. Notice that known ‘good’ rhythmic executions can have multiple small variations, that are not necessarily mistake, but probably leading to several false positives or negatives, when only numerical or semantic reasoning are used. Such cases can happen from quantitative perspective, for instance, due to inefficient data cleaning to remove outlier and noisy as well as recognizes missing values in the collected training data. To discover and study any kind of mismatched lifting rhythm, one can create different individuals through coach’ observation and biomechanics measurement and later comparing them by executing implemented SWRL rules.

7.2 Limitations

As any research work, the implemented solution for the weightlifting TDC-cycle has limitations, but the main one is due to the weakness of the collected practical problem-solving experiences, mainly regarding to the rhythmic execution evaluation. Several artificial data were used to assert data properties of created individuals stored in the fact base. Although, some data properties were asserted after manually calculating their values, using the numerical model applied in the existing works, the following reasons can be pointed to the weakness of the collected practical problem-solving experiences:

- (i) Most of the described experiments are performed in a specific training context, with different loads and repetitions;
- (ii) Most of the described experiments are only biomechanical-assisted, missing values from other involved domains of the weightlifting TDC-cycle;
- (iii) Most of the described experiments address only some lifting stages or phases and not all of them were applied to snatch lifting;
- (iv) Combining data from different experiments is not possible as they are collected under different training contexts and they also addressed different and specific goals as pointed by the three above points;
- (v) It is required years of dedicated training for an athlete to reach full potential with heavier athletes taking longer than lighter athletes;
- (vi) Access to top performance athlete's rhythmic execution data and their anthropometric features are quite impossible both in Portugal and Thailand. The same also applies for training and competitions data of regular athletes.

Another drawback can be pointed to the drafting and creation of one specific rule for each interpretation of conclusion and discussion paragraphs of each existing work in the literature, leading to a heavy task due to the diversity and amount of existing works. To solve this weakness is recommended the creation of generic SWRL rules with weighted atoms, later tuned for any given referenced work. However, this approach is not appealing to applied researchers with limited computational and statistical background.

7.3 Future Work

Drawing on the conclusion paragraph of Chapter 6, future work will encompass a logical progression of the proposed larger research project, starting with the full implementation of the third-iterated weightlifting TDC-cycle ontology. Therefore, the following main refinements of the current design are recommended:

- (i) Extending the TDC-cycle individual domains with physiotherapy and psychologic domains and related actors (e.g., physiotherapist and psychologist) to better approach recovering from injury as well as better management of lifting during competition (e.g., due to the chocking under pressure' phenomenon);
- (ii) Modeling other sport domains such as cycling, swimming, hurdling, long jump, triple jump or pole vault by aligning their ontologies to the TDC-cycle upper ontology;
- (iii) Devising, for example, artificial neural networks (i.e., for numerical reasoning), were rhythmic execution is analyzed based on the reference athlete profile, alongside all other parameters such as kinetics, kinematics (not appealing to applied researchers with limited computational and statistical background);
- (iv) Completing the moving to fourth generation ontology building methodologies by integrating existing upper ontologies;
- (v) Embedding complex mathematical expression for numerical reasoning in SWRL rules, as proposed by Alfonso Sánchez-Macián et al. (2007). Mathematical and problem semantics are separated to create rules that include complex mathematical equations and formulas requiring unsupported mathematical operators (i.e., not built-in to SWRL). OpenMath (Buswell et al., 2004) was used to represent the formula that is passed to a mathematical software tool.
- (vi) Furthermore, it is necessary a way for tuning the prescribed rules in order to easily apply them to any work on the literature, while avoiding possible false negatives and positives. To deal with such uncertainty of qualitative analysis techniques, Fudholi et al (2009) suggested the use of SWRL to build fuzzy ontology classes and properties mapping, and also calculations, while Bach et al. (2010) suggested the use of *Probabilistic Soft Logic* to weight rules and entities to reflect the level of confidence on them.

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Last but not least important, our credits go toward other researchers that we would like to acknowledge their ideas and hard-working experiments.

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APPENDIX

Appendix A: Ethical Approval



Ethics Committee

ETHICS OPINION

Process **CEFADE 05.2014**

The Ethics Committee of the Faculty of Sport from the University of Porto analyzed the project entitled "ONTOLOGY-BASED PERSONALIZED PERFORMANCE EVALUATION AND DIETARY RECOMMENDATION FOR WEIGHTLIFTING" presented by MSc. Piayorn Tumnark. Considering the project's characteristics, as well as the competence of the research team, the Ethics Committee addresses a positive opinion, because the ethical principles that govern this type of scientific work are respected.

Porto and Faculty of Sport, 15 of June from 2014

The chairman of the Ethics Committee,

A handwritten signature in blue ink, appearing to read 'M. P. Tumnark'.

Appendix B: Written Consent form



ใบยินยอมเข้าร่วมการวิจัย (Consent Form)

โครงการวิจัยเรื่อง: การศึกษาเกี่ยวกับรูปแบบการใช้พละกำลังของนักกีฬายกน้ำหนักระดับเยาวชนในขณะยกน้ำหนักในท่าสแนทซ์

วันที่ให้คำยินยอม วันที่.....เดือน..... พ.ศ.....

- ก่อนที่จะลงนามในใบยินยอมให้ทำการวิจัยนี้ ข้าพเจ้าได้รับการอธิบายจากผู้วิจัยถึงวัตถุประสงค์ของการวิจัย วิธีการวิจัย และมีความเข้าใจดีแล้ว
- ผู้วิจัยรับรองว่าจะตอบคำถามต่าง ๆ ที่ข้าพเจ้าสงสัยด้วยความเต็มใจ ไม่ปิดบังซ่อนเร้นจนข้าพเจ้าพอใจ
- ข้าพเจ้าเข้าร่วมโครงการวิจัยนี้โดยสมัครใจและมีสิทธิ์ที่จะบอกเลิกการเข้าร่วมโครงการวิจัยนี้เมื่อใดก็ได้
- ผู้วิจัยรับรองว่าจะเก็บข้อมูลเฉพาะเกี่ยวกับตัวข้าพเจ้าเป็นความลับ จะเปิดเผยได้เฉพาะในรูปที่เป็นสรุปผลการวิจัย การเปิดเผยข้อมูลของตัวข้าพเจ้าต่อหน่วยงานต่าง ๆ ที่เกี่ยวข้องต้องได้รับอนุญาตจากข้าพเจ้าแล้วจะกระทำได้เฉพาะกรณีจำเป็นด้วยเหตุผลทางวิชาการเท่านั้น
- ข้าพเจ้าได้อ่านข้อความข้างต้นแล้ว และมีความเข้าใจทุกประการ และได้ลงนามในใบยินยอมนี้ด้วยความเต็มใจ

ลงนาม.....ผู้ยินยอม
(.....)
ลงนาม.....พยาน
(.....)
ลงนาม.....ผู้ทำวิจัย
(.....)

Appendix C: Nutrition Status of Thai National Team Weightlifters



Nutrition Status of Thai National Team Weightlifters

Tumnark, P.^{1,2}, Phuchaiwattananon, O.³, Kerdchantuk, S.³, Conceição, F¹, Vilas Boas, J.P.¹

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INTRODUCTION

Weightlifting is one of the most powerful athletic activities in the world of sport. In Thailand, weightlifting is the most successful Olympic sport along with boxing. It is one of the only two sports in which Thailand has won gold, with three weightlifting gold medals won in the last three Olympic Games. Weightlifting demands extreme strength and power to lift very heavy weights in a controlled manner. The aim of these athletes is to build muscle bulk and target the main muscles that are used for the bar movement. A high level of muscularity is therefore required by both male and female competitors. Maintaining low body fat is also a physical requirement often demanded to optimize the power to weight ratio of lifters, helping to achieve best performance (1). Besides providing the energy for training and for its recovery, nutrition also promotes training adaptations, including skeletal muscle hypertrophy(2). The aim of this study was to diagnose the nutritional status of Thai Weightlifters.

Table1. Characteristics of the subjects presented as mean±SD

Groups	Age (yrs)	Weight (kg)	Height (cm)	BMI (kg/m ²)	% Body fat (%)
Male (n=18)	17.9 ± 2.8	71.7 ± 12.3	166.3 ± 5.9	25.7 ± 2.8	11.6 ± 3.4
Female (n=19)	18.7 ± 2.6	64.0 ± 20.9	156.0 ± 7.8	25.8 ± 5.6	20.6 ± 6.0

METHODS

The sample was composed of 37 weightlifters, aged 15-24 yr. They completed anthropometric assessment, 3-day food record analyzed for macro- and micronutrient intake. In order to report the result as accurately as possible, the researchers took a photo of all the food that subjects had been eaten and weight the items using a weighing scale. Energy expenditure was estimated using predictive equations (factorial method).

Figure1. Example of photos that was taken during 3-day food record collecting data



RESULTS

Mean energy intake was 2,655±270.6 and 2,150±282.8 kcal/day, estimated energy expenditure was 2,953.7±318.0 and 2,459.7±350.3 kcal/day for male and female, respectively. Of the athletes, 22.2% of males and 31.5% females consumed <4 g/kg carbohydrate, 66.6% of males and 63.1% of females consumed <1.6 g/kg protein, 11.1% of males and 31.5% of females consumed >35% of energy intake from fat. A large population of athletes did not meet Thai Recommended Daily Intakes: Thai RDI for vitamin B, vitamin C, Calcium, Phosphorus, Iron, Potassium, Sodium, Zinc, Copper, and Magnesium.

DISCUSSION AND CONCLUSION

A high proportion of weightlifters were not in energy balance, and so, failed to meet carbohydrate, protein and micronutrient recommendations. Suboptimal nutrition status may affect weightlifting performance and physiological development. More research is needed to understand the unique nutrition needs of this kind of athletes and inform sport nutrition practice and research.

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Figure2. Comparative individual results between estimated energy and energy obtained from food in male and female weightlifters

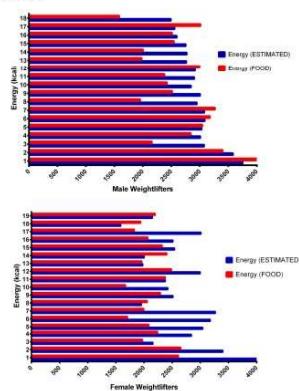


Figure3. Individual characteristics of macronutrient intake (carbohydrate, protein, fat) in male and female weightlifters

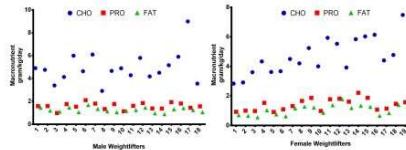
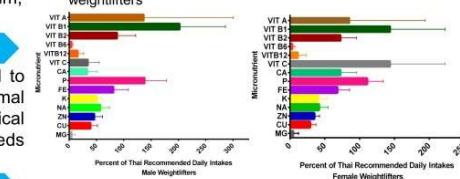


Figure4. Individual characteristics of micronutrient intake, in percent, compare with Thai RDI in male and female weightlifters



Appendix D: Thai-based Sport Knowledge Questionnaire

Below is the questionnaire template used to collect knowledge regarding sport nutrition of Thai weightlifters. The main objective is to determine sport nutrition knowledge of athletes and coaches. The questionnaire was adapted from Zinn et al. (2005) and modified to fit the Thai context. Most of questions were identical to the original sport knowledge questionnaire, excepted for some food items such as creamed rice, cheese, margarine, marmite, marshmallow, Chelsea bun, and some brand name sport/energy drinks (i.e., Mizone, Replace, Restore, V). These kind of food items are not familiar to Thai people as they do not consume it regularly. Therefore, these items were replaced to some other food items which are more practical and familiar to Thai people. However, before consider using this questionnaire, the contrast validity, internal consistency reliability, and test-retest reliability need to be performed.

This questionnaire consists of five main knowledge sub-categories (62 questions) as following: (i) General nutrition concept (21 questions) regarding macronutrients and micronutrients, (ii) Fluid (5 questions), (iii) Recovery (11questions), (iv) Weight control (14 questions), (v) Supplements (11 questions).

แบบสอบถามทางด้านโภชนาการ

คำชี้แจง แบบสอบถามนี้ประกอบไปด้วยคำถามทั้งหมด 62 ข้อ ในหลากหลายหัวข้อที่เกี่ยวข้องกับโภชนาการการกีฬา โปรดทำเครื่องหมาย ✓ ลงในช่องที่ตรงกับความคิดเห็นของท่านมากที่สุด (โปรดทำเครื่องหมาย ✓ ลงในช่อง เพียง 1 ช่องต่ออาหาร 1 ชนิด)

ทดสอบความรู้เรื่องสารอาหารที่จำเป็นต่อร่างกาย (21 ข้อ)

คุณคิดว่าอาหารดังกล่าวต่อไปนี้ เป็นแหล่งอาหารที่ให้สารอาหารประเภทใด

	คาร์บอไฮเดรต	โปรตีน	ไขมัน
1) เนื้อไก่	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2) ถั่วต่างๆ	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
3) ขนมปังขาว	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
4) เนย	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
5) อาหารเช้าซีเรียล	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
6) ข้าวสวย	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
7) ผลไม้	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
8) น้ำมันพืช	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
9) เนยถั่วลิสง	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
10) อะโวคาโด	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
11) เส้นกวายเตี้ย	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
12) น้ำผึ้ง	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
13) น้ำมันมะพร้าว	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

คุณเห็นด้วยกับข้อความต่อไปนี้หรือไม่

	เห็นด้วย	ไม่เห็นด้วย	ไม่แน่ใจ
14) อาหารที่มีคาร์บอไฮเดรตสูงจะช่วยลดการสลายของโปรตีนในร่างกาย	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
15) สารแทนนินในชาช่วยในการการดูดซึมธาตุเหล็ก	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
16) ผักใบเขียวเข้มถือเป็นแหล่งของธาตุเหล็กชนิดหนึ่งในอาหาร	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
17) วิตามินซีจะช่วยเพิ่มการดูดซึมธาตุเหล็ก	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
18) เมื่อดื่มน้ำไว้漫น้ำเพื่อส่วนเราจะได้รับโปรตีนในปริมาณที่มากกว่าการดื่มน้ำด้วยน้ำ	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
19) เมื่อดื่มน้ำไว้漫น้ำเพื่อส่วนเราจะได้รับแคลเซียมในปริมาณที่มากกว่าการดื่มน้ำด้วยน้ำ	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
20) วิธีง่ายๆ ที่จะได้รับแคลเซียมคือการรับประทานผักใบเขียว	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
21) เมื่อเราดื่มผลิตภัณฑ์นมที่ได้รับจากอาหาร ในกรณีที่ชอบกินนมฟรังทองกรอบ เรายังเลือกินนมผั่งทodorob	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

รายการเลือกกินนมผั่งทodorob ทดสอบครอบแผ่นหนามากกว่าแผ่นบาง

ทดสอบความรู้เรื่องการดื่มน้ำ/เครื่องดื่มเกลือแร่สำหรับนักกีฬา (5 ข้อ)

22. ในการฝึกซ้อมที่มีระยะเวลา 2 ชั่วโมง เรายังดื่มน้ำเพื่อชดเชยการสูญเสียเหงื่อของร่างกายในปริมาณเท่าใดจึงจะเหมาะสมที่สุด

- น้ำเปล่าขนาด 750 มิลลิลิตร 1 ขวด น้ำเปล่าขนาด 750 มิลลิลิตร 2 ขวด
 น้ำเปล่าขนาด 750 มิลลิลิตร 3 ขวด น้ำเปล่าขนาด 750 มิลลิลิตร 4 ขวด ไม่แน่ใจ

23. เครื่องดื่มชนิดใดต่อไปนี้ใช่เครื่องดื่มเกลือแร่สำหรับนักกีฬา

- สปอนเซอร์ ก๊อกเตอร์ กระทิงแดง เอ็มสปอร์ต ไม่แน่ใจ

24. เครื่องดื่มเกลือแร่สำหรับนักกีฬา ควรมีคาร์บอไฮเดรตเป็นส่วนประกอบในปริมาณเท่าใด

- 4-8 % 8-10 % 10-15 % 20-25 % ไม่แน่ใจ

25. เครื่องดื่มชนิดใดเหมาะสมที่สุด ที่จะดื่มก่อนการฝึกซ้อมที่มีระยะเวลา 2 ชั่วโมง

- น้ำผึ้ง ก๊อกเตอร์ โค้ก กระทิงแดง ไม่แน่ใจ

26. เครื่องดื่มน้ำใดเหมาะสมที่สุด ที่จะดื่มหลังการฝึกซ้อมที่มีระยะเวลา 2 ชั่วโมง

น้ำผลไม้

เกเตอเรต

โคลก

กระเทียมแดง

ไม่แนะนำ

ทดสอบความรู้เรื่องการพื้นทัวหลังฝึกซ้อม (11 ข้อ)

27. สารอาหารชนิดใดมีส่วนสำคัญช่วยให้ร่างกายพื้นทัวหลังการวิ่งเป็นเวลา 1 ชั่วโมง

คาร์บอไฮเดรต

โปรตีน

ไขมัน

วิตามินและเกลือแร่

ไม่แนะนำ

ข้อ 28-31 จงเลือกอาหารว่างชนิดใดชนิดหนึ่งระหว่าง 2 ชนิดที่ท่านคิดว่าเหมาะสมที่สุดเพื่อให้นักกีฬากินหลังฝึกซ้อม

28) ขนมปังขาว 4 แผ่นทาช็อกโกแลตยีห้อนเทลล่า 2 ช้อนโต๊ะ มันฝรั่งทอดกรอบ 1 ห่อ ไม่แนะนำ

29) ขนมปังถุงเกด 2 ชิ้น

ขนมปังไส้กรอก 2 ชิ้น

ไม่แนะนำ

30) ถุงมันเหลว 100 กรัม

แซนวิช 2 ถุง

ไม่แนะนำ

31) พายไก่ 2 ชิ้น

ชาลาเปาไส้หมูสับ 2 ชิ้น

ไม่แนะนำ

ข้อ 32-35 จงเลือกอาหารว่างชนิดใดชนิดหนึ่งระหว่าง 2 ชนิดที่ให้สารอาหารประเภทโปรไบเดรตในปริมาณที่มากกว่า

32) ขนมขี้น 100 กรัม ลูกอมเคลือบช็อกโกแลต อีม แอนด์ อีม 100 กรัม ไม่แนะนำ

33) ลูกกวาดอบแห้ง ½ ถ้วยตวง

พายไก่ 1 ชิ้น

ไม่แนะนำ

34) อกไก่ไม่ตัดหนัง 180 กรัม

ขนมปังขาว 2 แผ่น ทาเย็นส้ม 2 ช้อนโต๊ะ

ไม่แนะนำ

35) โคลก 1 กระป๋อง (330 มล.)

สลัดผัก 1 จาน

ไม่แนะนำ

36. เวลาที่เหมาะสมที่นักกีฬาควรจะได้กินอาหารหลังการฝึกซ้อม คือ

ภายใน 30 นาทีหลังการฝึกซ้อม

ภายใน 45 นาทีหลังการฝึกซ้อม

ภายใน 1 ชั่วโมงหลังการฝึกซ้อม

ระหว่าง 2-3 ชั่วโมงหลังการฝึกซ้อม

ไม่แนะนำ

37. ข้อใดต่อไปนี้อธิบายความหมายของ “ค่าดัชนีน้ำตาล (Glycemic index)” ได้ดีที่สุด

ปริมาณคาร์โบไฮเดรตในอาหารแต่ละชนิด

ค่าที่ทำให้เราทราบว่าอาหารที่ประกอบไปด้วยคาร์บอไฮเดรตสามารถเพิ่มระดับน้ำตาลในเลือดได้มากน้อยต่างกันแค่ไหน

ค่าที่ทำให้เราทราบว่าอาหารที่ประกอบไปด้วยโปรตีนสามารถเพิ่มระดับน้ำตาลในเลือดได้มากน้อยต่างกันแค่ไหน

ค่าที่ทำให้เราทราบว่าอาหารที่ประกอบไปด้วยคาร์บอไฮเดรตสามารถเพิ่มระดับความตันโลหิตได้มากน้อยต่างกันแค่ไหน

ไม่แนะนำ

ทดสอบความรู้เรื่องการเพิ่มน้ำหนักตัว (4 ข้อ)

คุณเห็นด้วยหรือไม่กับข้อความดังกล่าวต่อไปนี้

	เห็นด้วย	ไม่เห็นด้วย	ไม่แน่ใจ
38) โปรตีนถือเป็นสารอาหารที่สำคัญที่สุดที่นักกีฬาต้องได้รับมากที่สุดในมื้ออาหาร ถ้าต้องการเพิ่มมวลกล้ามเนื้อ	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
39) โปรตีนเองถือเป็นอาหารเสริมที่มีความจำเป็นอย่างมากในการเพิ่มมวลกล้ามเนื้อของนักกีฬา	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
40) นักกีฬาที่ต้องการเพิ่มน้ำหนักตัว (ในกรณีที่โปรแกรมการฝึกซ้อมเหมือนเดิม) สามารถทำได้โดย เพิ่มการดื่มน้ำผลไม้ 6 แก้วจากการกินอาหารในมื้อปกติ	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

41. นักกีฬาคนหนึ่งกินอาหารรือเป็นตามรายการอาหารต่อไปนี้: ข้าวสวย 3 ทัพพี อกไก่ไม่ตัดหนัง 150 กรัม และผักต่างๆ (บีฟโคลี แครอท กระหล่ำปลี) 2 ถ้วย ถ้าหากนักกีฬาคนนี้ต้องการเพิ่มมวลกล้ามเนื้อ เค้าควรต้องปรับเปลี่ยนรายการอาหารมื้อเย็นอย่างไรจึงเหมาะสม (โดยไม่ปรับเปลี่ยนรายการอาหารในมื้อเช้าน)

เพิ่มอกไก่เป็น 200 กรัม เพิ่มข้าวเป็น 6 ทัพพี และเพิ่มอกไก่ไม่ตัดหนังเป็น 180 กรัม กินอกไก่โดยไม่ต้องเอาหนังออก

เพิ่มผักเป็น 4 ถ้วย กินอาหารในปริมาณเท่าเดิม แต่ซ้อมให้หนักขึ้น ไม่แนะนำ

ทดสอบความรู้เรื่องการลดน้ำหนัก (10 ข้อ) และการใช้อาหารเสริม 11 ข้อ)

- ข้อ a-d หากนักกีฬาอยู่ในช่วงลดน้ำหนักและจำเป็นต้องเลือกินอาหารว่างในตอนเช้า อาหารว่างชนิดใดที่เขากล่าวเลือกิน
- | | | |
|---|---|--------------------------------|
| 42) <input type="radio"/> ไส้กรอกอีสาน 4 ไม้ | <input type="radio"/> แอลฟ์ลี 1 ผล | <input type="radio"/> ไม่แน่ใจ |
| 43) <input type="radio"/> มันฝรั่งทอดกรอบ 2 ถุง | <input type="radio"/> ชีเรียบาร์ 1 แท่ง | <input type="radio"/> ไม่แน่ใจ |
| 44) <input type="radio"/> ชาลาเป่า 1 ถูกเล็ก | <input type="radio"/> ช็อกโกแลตบาร์ 1 แท่ง | <input type="radio"/> ไม่แน่ใจ |
| 45) <input type="radio"/> ถั่วลิสงอบแห้ง 100 กรัม | <input type="radio"/> นมอัลมอนด์ 1 กล่อง | <input type="radio"/> ไม่แน่ใจ |
| 46) <input type="radio"/> โยเกิร์ต 1 ถ้วย | <input type="radio"/> กาแฟเย็นกับคุ๊กคี้ 2 ชิ้น | <input type="radio"/> ไม่แน่ใจ |
| 47) <input type="radio"/> เอเคคลร์ 2 ถูก | <input type="radio"/> ขนมจีบ 2 ถูก | <input type="radio"/> ไม่แน่ใจ |

คุณเห็นด้วย หรือ ไม่เห็นด้วย กับข้อความดังกล่าวต่อไปนี้

	เห็นด้วย	ไม่เห็นด้วย	ไม่แน่ใจ
หากนักกีฬาต้องการจะลดน้ำหนัก เขาควร...			
48) กินไส้กรอกอีสานให้น้อยลง และเพิ่มการกินอกไก่ไม่ติดมัน	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
49) ไม่กินข้าวหรืออาหารประเภทเส้นๆ หลัง 4 โมงเย็น	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
50) เลือกินนมขาดมันเนยแทนนมเบร์ยิว	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
51) เปเลี่ยนจากการกินโยเกิร์ต ผลไม้อบแห้งและของว่างต่างๆ มาเป็นโปรตีนเชค (Protein shakes)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
52) ครีอทีนเป็นอาหารเสริมที่เหมาะสมสำหรับนักกีฬาที่ต้องการเพิ่มแรงระเบิดหรือพลังกล้ามเนื้อ (power)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
53) เนื้อปริมาณครีอทีนที่ร่างกายสร้างขึ้นเองโดยธรรมชาติสะสมอยู่ในปริมาณที่ต่ำ การ	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
54) กินครีอทีนเป็นอาหารเสริมช่วยเพิ่มประสิทธิผลของครีอทีนให้มากยิ่งขึ้น	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
55) ครีอทีนเป็นอาหารเสริมที่ช่วยเพิ่มสมรรถภาพของนักกีฬา โดยมันจะไปช่วยเพิ่มกระบวนการเมtababolism ของไขมัน	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
56) ครีอทีนเป็นอาหารเสริมที่เหมาะสมสำหรับนักกีฬาที่ต้องการเพิ่มสมรรถภาพทางด้านความทนทาน (endurance)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
57) นักกีฬาควรได้รับวิตามินรวม	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
58) นักกีฬาควรได้รับธาตุเหล็กเสริมเมื่อรูสีกหนึ่งอย่างมากและมีอาการซีด	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
59) นักกีฬาควรได้รับวิตามินซีเสริมเป็นประจำ	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
60) นักกีฬาควรได้รับวิตามินบีเสริมเมื่อรูสีกไม่ค่อยมีแรง	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
61) อาหารเสริม hydroxyl-methyl butyrate (HMB) ช่วยเพิ่มสมรรถภาพให้นักกีฬา โดยมันจะไปช่วยให้มันในร่างกายแตกตัว	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
62) นักกีฬาควรได้รับเกลือเม็ดเมื่อมีอาการตะคริวระหว่างการฝึกซ้อม	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Appendix E: Used tools for Modeling the Ontologies

1. Semantic Web Technology

A) The Needs of Semantic Web Technology

Initially, computer was used for numerical computing but currently their predominant usages are for information processing, database application, text processing, and games. Therefore, the direction towards the view of computers has changed from entry points to the information superhighway (the capable of transferring all types of digital information at the high speed). This can be found presently in the web content which is generated automatically from databases. Apart from the existence of links that establish connections between documents, the main valuable tools are search engines (e.g., Yahoo, and Google). Although the search engines are the key success of the using today's web, some problems were associated with the usage of legacy or old search engines, such as: (i) *High recall, low precision*: there are many relevant and irrelevant pages retrieved together, (ii) *Low or no recall*: users do not get any answer for their request or the relevant pages are not retrieved, (iii) *Results are highly sensitive to vocabulary*, and (iv) *Results are single pages*: user is the one to initiate several queries to collect the relevant document.

The main obstacle to improve in older search engine technology was that the meaning of web content was not machine-accessible. Moreover, most information is available in weakly structure form (e.g., text, audio, and video). From the knowledge management perspective, older search engine technology suffered from limitation of the following areas: (i) only keyword based searching is permitted, (ii) extract information consumes more time and effort, (iii) removing outdated information is inconsistency and failure, (iv) new knowledge is still difficult for distributed and collection of documents are weakly structured, and (v) views and hiding information from the database are hard to realize.

Therefore, the Semantic Web was created to allow much more advantaged knowledge management systems:

- (i) It organizes knowledge in conceptual spaces according to its meaning;
- (ii) It supports maintenance by checking for inconsistencies and extracting new knowledge;

- (iii) It replaces keyword-based search by query answering. Requested knowledge will be retrieved, extracted, and presented in a human friendly way;
- (iv) It supports query answering over several documents;
- (v) It is possible to define who may view certain parts of information.

B) The Evolution of Web

The following table presents the various developed technologies that made the concept of the Semantic web possible.

Table1 The evolution of Web (Antoniou & vanHarmelen, 2004).

	Static	Dynamic	Syntax	Semantic
Encoding Creation	HTML Manually	+RDBMS Generated by server-side applications	+XML Generated by server-side applications based on schema	+RDF/OWL Generated by server-side applications based on schema
Users	Humans	Humans	Humans and applications	Humans and applications
Paradigm	Browse	Create/Query/Update	Integrate	Interoperate
Application	Browsers	Browsers	Process Integration, EAI, BPMS, Workflows	Intelligent, agents, Semantic engines



1995 2000 2005

The original Web was a vast set of static Web pages linked together. Many organizations still use static HTML files to deliver their information on the Web. However, dynamic publishing methods which offer great advantages are replacing the ones constructed from static HTML pages. The objective is to answer the inherent dynamic nature of businesses. That is, the information on the Web can be used by computers not only for display purposes, but also for interoperability and integration between system and applications. By enabling machine-to-machine exchange and automate processing, it will provide the information in such a way the computers can understand it. This becomes the objective of the Semantic Web which is “*to make possible the processing of Web information by computers*”. According to this definition, Semantic Web is an extension of current web in which information is well-defined meaning given, enabling better computers and people to work in cooperation”

(Berners-Lee et al., 2001). Currently, the evolution of web is undergoing. Different approaches are being sought for solution to combine Semantics to Web resources.

As illustrated in the Figure 1 (from the left to the right side of figure), new standard and languages are being investigated and developed to give meaning to resources and links of Syntactic Web.

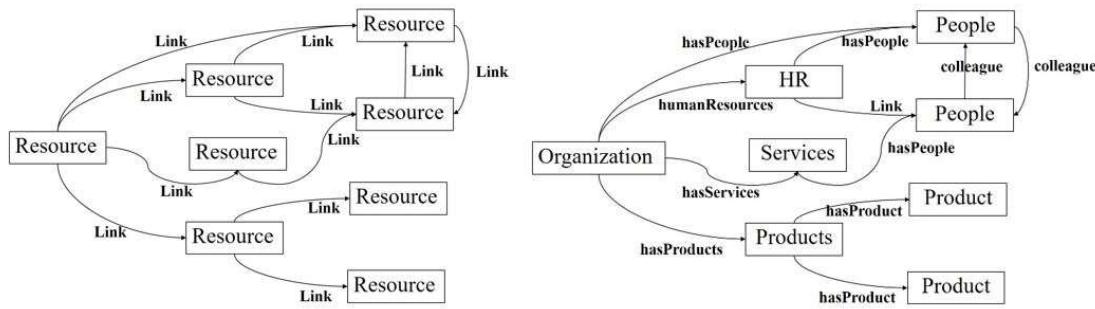


Figure 1 The evolution of the web (Antoniou & vanHarmelen, 2004).

C) Levels of Semantics

Semantics is defined as the study of meaning, in language or programming languages. It concerned with the relationship between signifiers such as words, phases, signs, and terms. It depends on the approaches, models or methods used to add semantics to terms. There are four different degree levels of semantics (see Figure 2) as follows:

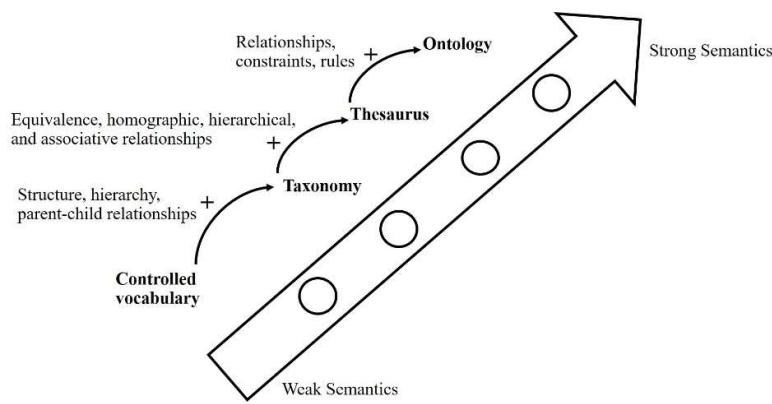


Figure 2 Levels of semantics (Antoniou & vanHarmelen, 2004).

- (i) **Controlled vocabulary:** A controlled vocabulary is a list of terms. It can be words, phased or notations that have been enumerated explicit. All term in a controlled of vocabulary should have an unambiguous, non-redundant definition. Table 2

is an example of controlled vocabulary that was used by Amazon.com for customer to search their products.

(ii) *Taxonomy*: It is a subject-based classification that arranges the terms in a controlled vocabulary into a hierarchy. Figure 3 is an example of the taxonomy arrangement in a home.

(iii) *Thesaurus*: Thesaurus is a networked collection of controlled vocabulary terms with conceptual relationships between terms. A thesaurus is an extension of taxonomy which allows terms to be arranged in a hierarchy and also allows other statements and relationships to be made about the terms. Table 3 shows the semantic relationships of a thesaurus suitable example.

(iv) *Ontology* can be defined as a vocabulary of concepts and relations which is rich enough to enable user to express knowledge and intention without semantic ambiguity. It describes domain knowledge and provides an agreed-upon understanding of a domain. Ontologies are collections of statements written in a language such as RDF and OWL that define the relations between concepts and specify logical rules for reasoning about them. Computers will understand the meaning of semantic data on a web page by following links to specified ontologies. Ontologies establish a joint terminology between members of a community of interest. These members can be human or automated agents. The basis of ontology is conceptualization and consists of the identified concepts (e.g., objects, events, beliefs) (Gilles et al., 2011). Figure 4 presents an example of ontology.

Books	Electronics	Travel
Popular Music	Camera & Photo	Cell phone & Services
Music Downloads	Software	Outlet
Classical Music	Tools & Hardware	Auctions
DVD	Office Products	zShops
VHS	Magazines	Everything Else
Apparel	Sports & Outdoors	Scientific Supplies
Yellow page	Outdoors Living	Medical Supplies
Restaurants	Kitchen	Indust Supplies
Movie Showtimes	Jewelry & Watches	Automotive
Toys	Beauty	Home Furnishings
Baby	Gourmet Food Beta	Lifestyle
Computers	Musical Instrument	Pet Toys
Video Games	Health/Personal Care	Art & Hobbies

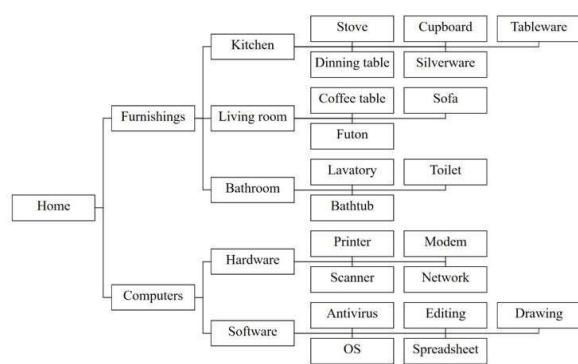


Table 2 Controlled vocabulary used by Amazon.com.

Figure 3 Example of a taxonomy (Reprinted from Antoniou & vanHarmelen, 2004).

Table 3 The semantic relationships of a Thesaurus (Antoniou & vanHarmelen, 2004).

Semantic Relation	Definition	Example
Synonym Similar to Equivalent Used for	A term X has the same meaning as a term Y.	“Report” is a synonym for “document”.
Homonym Spelled the same Homographic	A term X is spelled the same way as a term Y, which has a different meaning.	The “tank” is a military vehicle, is a homonym for the “tank” which is a receptacle for holding liquids.
Broader Than (Hierarchic: parent of)	A term X is broader in meaning than a term Y.	“Organization” has a broader meaning than “financial institution”.
Narrower Than (Hierarchic: child of)	A term X is narrower in meaning than a term Y.	“Financial institution” has a narrower meaning than “organization”.
Associated Associative Related	A term X is associated with a term Y, i.e., there is some unspecified relationship between the two.	A “nail” is associated with a “hammer”.

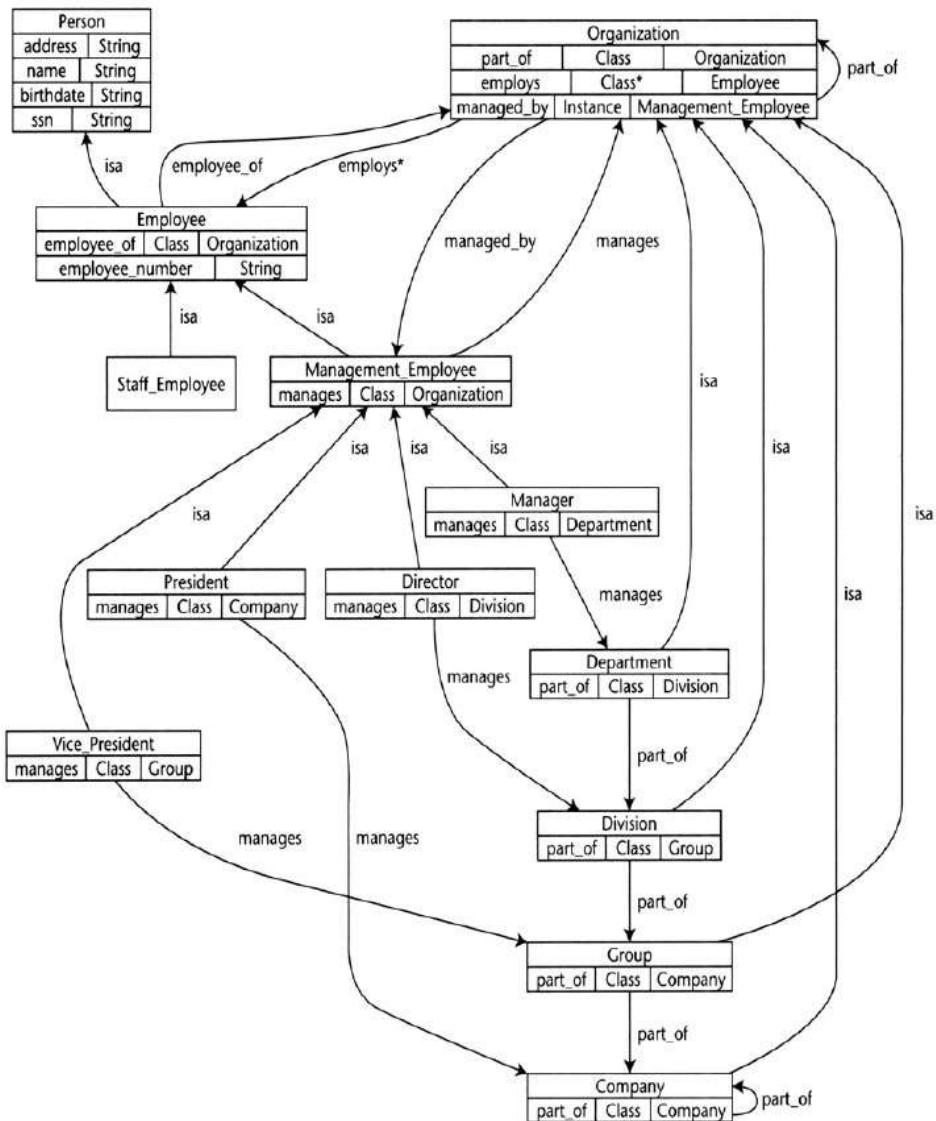


Figure 4 An example of ontology (Antoniou & vanHarmelen, 2004).

D) Layered Architecture of Semantic Web

Semantic Web is the new generation Web that aimed to present information in a machine-manageable way, not only for display purposes, but also for automation, integration, and reuse across applications (Berners-Lee et al., 2001). Moreover, semantic Web can be used for explicitly declaring the knowledge embedded in many Web based applications, integrating information in an intelligent way, providing semantic based access to the Internet, and extracting information from texts. Generally, HTML is the standard structured document published on the Internet. It promotes the growth of the Web due to its simplicity. However, it seriously obstructs advanced applications such as processing, understanding, and semantic interoperability of information contained in several documents. Semantic Web as the new generation Web is able to express information in precise and machine-interpretable form. Moreover, intelligent services such as information brokers, search agents, and information filters are enabled with greater functionality and interoperability. Semantic Web promotes Web based application with both semantic and syntactic interoperability. The explicit representation of meta-information, which accompanied by domain theories (i.e., ontologies) will enable a Web to provide a qualitatively new level of service. Extremely knowledgeable systems with various specialized reasoning services may ultimately be created through this process.

The architecture of semantic web is illustrated in Figure 5. It consists of six layers as follows:

- (i) *Uniform Resource Identifiers (URI)* is a fundamental component of the current web. It provides a unique identification of resources and the relationship between these resources. A uniform resource locator (URL) refers to the subset of URI that identifies resources via a representation of their primary access mechanism. For example:

The URL <http://dme.uma.pt/jcardoso/index.htm> identifies the location from where a Web page can be retrieved.

- (ii) *Unicode* provides a unique number for every character independently of the underlying platform, program, or language. Previously before the Unicode was created, various different encoding systems have been used. It made the manipulation of data complex due to the diverse encoding. There was always

the risk of encoding conflict because two encodings could use the same number for two different characters, or use different numbers for the same character. Examples of well-known encoding systems include ASCII and EBCDIC.

- (iii) *Extensible Markup Language (XML)* layer with XML namespace and XML schema definitions assure that there is a common syntax used in the semantic Web. XML namespaces allow specifying different markup vocabularies in one XML document. XML schema serves for expressing schema definition of a particular XML document.
- (iv) *Resource Description Framework (RDF)* stay on top of XML for representing information about resources in a graph form. RDF is based on triples O-A-V, which form a graph data with a relation among an object (a resource), an attribute (a property), and a value (a resource). RDF Schema (RDFS) defines the vocabulary of RDF model. It provides a mechanism to describe domain-specific properties and classes of resources to which those properties can be applied, using a set of basic modeling primitives (e.g., class, subclass-of, property, sub property-of, domain, range, and type). However, RDFS is rather simple and it still does not provide exact semantics of a domain.
- (v) *Ontology* comprises of a set of knowledge terms (e.g., the vocabulary, the semantic interconnections, simple rules of inference, and logic for some particular topic). Ontologies applied to the Web in order to create the Semantic Web. Ontologies offer a number of advantages, including facilitating knowledge sharing, providing reusable Web contents, Web services, and applications. Few of the ontology languages are DAML (DARPA Agent Markup Language), OIL (Ontology Interference Layer), and OWL (Web Ontology Language). The development of OWL is starting from description logic and DAML+OIL. OWL is a set of XML elements and attributes, with well-defined meaning, that are used to define terms and their relationships. There are three types of OWL: (i) *OWL-Lite* for taxonomies and simple constraints, (ii) *OWL-DL* for full description logic support, and (iii) *OWL-Full* for maximum expressiveness and syntactic freedom of RDF. For ontology representation, it is widely used OWL-DL. In practice, ontologies are often developed using integrated, graphical, ontology authoring tools, e.g., Protégé, OilED, OntoEdit, Vitro, WebODE, and ontoRAMA.

(vi) *Logic, Proof, Trust, and Digital Signature* The logic layer is used to enhance the ontology language further and it allows the writing of application-specific declarative knowledge. The proof layer involves in the actual deductive process, the representation of proofs in Web languages, and proof validation. Finally, the trust layer will emerge through the use of digital signatures and other kinds of knowledge.

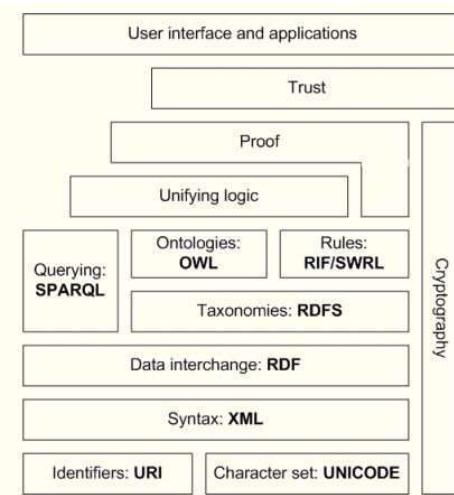


Figure 5 Semantic Web (Berners-Lee et al., 2001).

2. Ontology Development Tool

There are many tools available for ontology editing as shown in the Figure 6. The comparison of ontology editing tools have been described and compared in different articles with different criteria (Alatrish, 2013; Buraga et al., 2006; Dhingra & Bhatia, 2015; Funk et al., 2007; Kapoor & Sharma, 2010; Norta et al., 2010). In our study, Protégé tool, developed by Stanford University, was used for ontology development.

A) *The Protégé Ontology Editor*

Protégé is a free, open-source Java-based platform, which provides ontology developers a suite of tools to develop knowledge-based ontologies. It is available to download at <http://protégé.stanford.edu>. Protégé implements a rich set of knowledge-modeling structures and actions. It supports the creation, visualization, and manipulation of ontologies in various representation formats. It can be customized to provide domain-friendly support for creating knowledge models and entering data.

Furthermore, it can also be extended by a plugin architecture. Protégé allows the definition of classes, class hierarchy's variables, variable-value restrictions, and the relationships between classes and the properties of these relationships. There are two main ways of developing ontologies. The first one is the *Protégé-Frames editor* which enables users to build and populate ontologies that are frame-based, in accordance with the Open Knowledge Base Connectivity protocol (OKBC). The second one is the *Protégé-OWL editor* which enables users to build ontologies for the Semantic Web, in particular OWL; Web Ontology Language. As part of its update, Protégé now includes an interface for SWRL (Semantic Web Rule Language). It sits on top of OWL to do math, temporal reasoning, and adds Prolog-type reasoning rules (Emhimed, 2012; Saripalle et al., 2013). The significant advantage of Protégé over the other exist tools is that it supports tool builders, knowledge engineers, and domain specialists simultaneously, while the others are typically targeted at the knowledge engineer and lack flexibility for meta-modeling (Kapoor & Sharma, 2010). The most popular type of plug-ins are tab plugins which provide advanced capabilities such as visualization, ontology merging, version management, and inference.

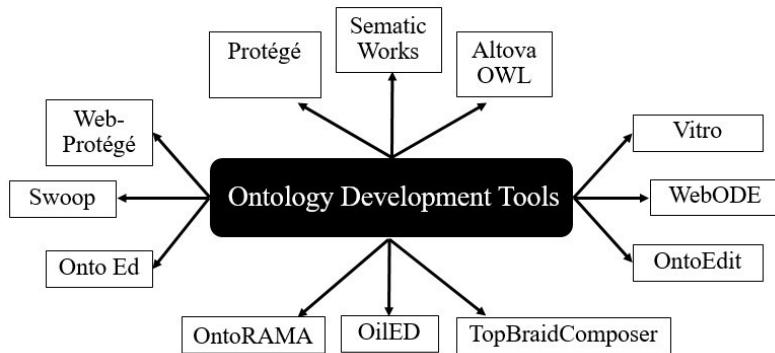


Figure 6 Different Ontology Development Tools (Adapted from Dhingra & Bhatia, 2015).

B) SWRL (Semantic Web Rule Language)

The cores of Semantic Web languages are OWL and SWRL. OWL was developed to construct ontologies. These ontologies are created by building hierarchies of classes describing concepts in a domain and relating the classes to each other using properties. The important characteristic of OWL-DL is that it provides strong *decidability* guarantees. The consistency checking and inference processes are guaranteed to terminate with definite conclusions no matter how complex the underlying ontologies. However, its limitations are poor support for reasoning with data

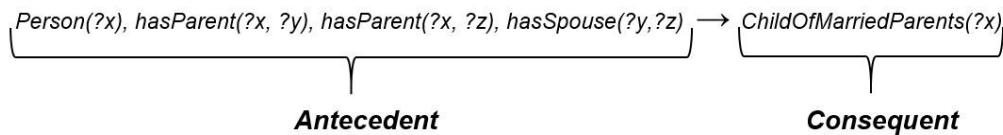
values and poor or no representation for certain types of interrelationships between multiple entities in an ontology.

The Semantic Web Rule Language (SWRL) (Horrocks et al., 2004) was proposed to expand OWL-DL expressiveness by adding rules to OWL. SWRL allows users to write rules that can be expressed in terms of OWL concepts and that can reason about OWL individuals. Semantically, SWRL is built on the same description logic foundation as OWL. Also, strong formal guarantees are provided when performing inference. It is considerably more expressive power than OWL alone, particularly when dealing with complex interrelationships between OWL individuals, or when reasoning with data values. With these advantages, SWRL rapidly became the OWL's rule language.

SWRL rules are divided in two parts (i) **the antecedent**; also called body and (ii) **the consequent** or head. It has the form of:

[antecedent] → [consequent]

Following is an example of adding SWRL rule described in Protégé saying that an individual X from the *Person* class, which has parent Y and Z (Y has spouse Z) belongs to a new class *ChildofMarriedParents*:



From this rule, if Ivan has Lenka and Martin as Parents. Lenka has Martin as a Spouse. Then, Ivan belong to the class *ChildOfMarriedParents*

C) SQWRL (Semantic Query-Enhanced Web Rule Language)

A query language called SQWRL has developed to support the knowledge extraction. It is an extension of SWRL rule language to support querying of OWL ontologies. SQWRL is implemented as a built-in library using the standard SWRL built-in mechanism. A pattern specification for a query is taken from rules' antecedent while a retrieval specification is taken from rules' consequent. Any valid SWRL antecedent is a valid SQWRL pattern specification. SWRL's built-in libraries are used as an extension point (O'Connor & Das, 2009). An example of the core operator in SQWRL is *aqwrl:select*. The select operator takes one or more arguments, which are variables

in the pattern specification of the query, and builds a table using the arguments as the columns of the table.

Following is an example of query retrieves all persons in an ontology with a known age that is less than 9, together with their ages:

Person (?p) ^ hasAge (?p,?a) ^ swrlb:lessThan (?q,9) → sqwrl:select (?p?a)

This query will return pairs of individuals and ages with one row for each pair. By using the *orderBy* and *orderByDecesending* built-ins, the results can be ordered.

Following example is a query to return a list of persons ordered by age:

Person (?p) ^ hasAge (?p,?a) → sqwrl:select (?p?a) ^ sqwrl:orderBy (?a)

The left side of a SQWRL query operates like a standard SWRL rule antecedent with its associated semantics. The atom *Person (?p)* will match not only all OWL individual that are directly of class *Person*, but will also match individuals that are entailed by the ontology to be individuals of that class. Therefore, all variables that would be bound in a SWRL rules antecedent will also be bound in a SQWRL pattern specification. SQWRL does not support subqueries, but it is achieved by using the intermediate inferences made by SWRL rules. This mechanism is used to decompose the complex queries.

D) Ontology Based Reasoning: Pellet

Pellet is an open source OWL-DL reasoning engine developed in Java (Sirin et al., 2007). It is a complete and capable OWL-DL reasoner with a number of unique features. Pellet reasoner is used for checking:

- (i) *Consistency*: to ensure that an ontology does not contain any contradictory facts;
- (ii) *Concept satisfiability*: to checks if it is *possible* for a class to have any instances. If class is unsatisfiable, then defining an instance of the class will cause the whole ontology to be inconsistent;
- (iii) *Classification*: to ensure that the complete class hierarchy is created. It computes the subclass relations between every named classes;
- (iv) *Realization*: to find the most specific classes that an individual belongs to. If there is any exist inconsistency, reclassification will be necessary.