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Indoor and outdoor localisation for sports practice using IMU from smart vests

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Resumo

Atualmente, a Educação Física (EF) carece de métricas objetivas e quantificáveis para avaliar a atividade física e saúde dos alunos. Para suprimir essa lacuna, o consórcio TexP@CT está a desenvolver um colete inteligente para Educação Física (SV4PE), que inclui uma Unidade de Medição Inercial (IMU) posicionada na vértebra T8 da coluna e sensores de eletrocardiograma (ECG). O SV4PE registra e analisa dados durante as aulas de EF, fornecendo feedback em tempo real e pós-sessão ao professor. A capacidade de analisar os movimentos dos alunos durante as aulas de Educação Física é de especial importância, fornecendo informações sobre distâncias e níveis de atividade. Com esse desafio em mente, esta tese focou-se no desenvolvimento de um sistema de localização em ambientes interiores e exteriores para calcular a trajetória de crianças e desenvolver um conjunto de métricas quantitativas para esta disciplina.

Foi realizada uma revisão sistemática para avaliar os métodos de localização baseados em IMU existentes e identificar lacunas na investigação, especialmente no que diz respeito a sistemas com um único sensor. Os resultados fundamentaram a escolha dos métodos para a solução implementada, que inclui as seguintes etapas: detecção de passos, estimativa do comprimento da passada, correção da orientação e estimativa da trajetória. Duas pipelines distintas foram executadas, uma para métricas em tempo real e outra para análise posterior. Para a primeira, a detecção de passos foi realizada com base na magnitude dos dados de aceleração, e o comprimento da passada foi estimado com base na altura e no gênero do sujeito. Esses valores foram utilizados para definir uma estimativa de velocidade para feedback em tempo real.

A pipeline de pós-sessão aplicou a Transformada Wavelet Contínua (CWT) para detecção de passos e o algoritmo de Weinberg para estimativa do comprimento do passo. Os filtros de Mahony e Madgwick foram escolhidos para a etapa de correção de orientação. A estimativa da trajetória serviu de base para o cálculo das métricas offline, nomeadamente: distância total percorrida, distância por esforço e tempo despendido em ataque e defesa.

A pipeline implementada foi avaliada em dois conjuntos de dados, alcançando estimativas de trajetória precisas, considerando as limitações do uso de uma única IMU em processos de localização. Foi calculado um erro de distância total de 1,10 m (4,25%), fornecendo uma boa base inicial para melhorias futuras. A pipeline desenvolvida foi testada com dados provenientes do protótipo do SV4PE, alcançando resultados promissores para a solução proposta.

Trabalhos futuros irão focar-se no desenvolvimento de algoritmos adaptativos para a estimativa do comprimento da passada e no desenho e teste de métodos aprimorados de correção de orientação. A exploração do efeito dos dados de magnetômetro nos filtros de Mahony e Madgwick, assim como testes adicionais com o protótipo do SV4PE, são outras melhorias previstas.

Em última análise, este trabalho demonstra a viabilidade de sistemas de localização baseados apenas numa IMU montada nas costas, particularmente em contextos como a educação física, onde não é necessário alcançar precisão submétrica. As métricas desenvolvidas visam auxiliar e complementar os professores, melhorando a objetividade e a qualidade da EF.

Abstract

Currently, Physical Education (PE) lacks objective, quantifiable metrics to evaluate students' activity and health. To address this gap, the TexP@CT consortium is developing a Smart Vest for Physical Education (SV4PE), which includes an Inertial Measurement Unit (IMU) placed at the T8 spinal position, and electrocardiogram (EEG) sensors. The SV4PE records and analyses data during PE classes and provides live and post-hoc feedback to the teacher. Of special importance is the ability to track the movements of the students during the PE classes, retaining information on distances and activity levels. With this challenge in mind, this thesis focuses on developing an indoor and outdoor localisation system to calculate the trajectory of children and develop a set of quantitative metrics.

A systematic review was conducted to assess existing IMU-based localisation methods and identify research gaps, particularly concerning single-sensor systems. The results were a basis for the choice of methods for the implemented pipeline, which contained the following stages: step detection, step length estimation, heading correction, and trajectory estimation. Two different pipelines were executed, for live and offline metrics. For the first, step detection was calculated using the magnitude of the acceleration data, and step length depended on the subject's height and gender. The values were used to define a velocity estimation for live feedback.

The post-session pipeline applied Continuous Wavelet Transform (CWT) for step detection, and Weinberg's algorithm for step length estimation. Mahony and Madgwick's filters were chosen for the heading correction stage. The trajectory estimation served as the basis for calculating offline metrics, namely, total distance covered, distance per effort, and time spent on attack and defence.

The implemented pipeline was evaluated on two datasets, achieving accurate trajectory estimations, considering the limitations of single-IMU sensor usage for localisation processes. A total distance error of 1.10m (4.25%) was calculated, providing a good first basis for further improvements. The developed pipeline was tested with values from a prototype of the SV4PE, achieving promising results for the solution.

Future work will focus on the development of adaptive algorithms for step length estimation and the design and testing of improved heading correction methods. Exploring the effect of magnetometer data in Mahony and Madgwick's filters, as well as further testing with the SV4PE prototype, are some other improvements.

Ultimately, this work shows the feasibility of back-mounted IMU-only localisation systems, particularly in contexts such as sports education, where sub-meter precision is not required. The metrics developed seek to assist and complement teachers, improving the objectivity and quality of PE.

UN Sustainable Development Goals

The United Nations Sustainable Development Goals (SDGs) provide a global framework to achieve a better and more sustainable future for all. It includes 17 goals to address the world's most pressing challenges, including poverty, inequality, climate change, environmental degradation, peace, and justice.

The specific Sustainable Development Goals mentioned have the following names:

SDG 3 Ensure healthy lives and promote well-being for all at all ages

SDG 4 Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all

SDG	Target	Contribution	Performance Indicators and Metrics
3	3.8	Increasing activity engagement during Physical Education classes, improving general health and encouraging the practice of sports	Feedback of activity in live and offline metrics
4	4.5	Reducing subjectivity in Physical Education evaluation by providing clear data of students' effort in the classes	Quantitative metrics of activity

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Simão Francisco

“The real way to gain happiness is to give it to others”

Robert Baden-Powell

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List of Acronyms

AHRS	Attitude and Heading Reference Systems
ANN	Artificial Neural Network
APs	Access Points
AoA	Angle of Arrival
CFR	Channel Frequency Response
CIR	Channel Impulse Response
CoM	Centre of Mass
CoP	Centre of Pressure
CPN	Collaborative Pedestrian Navigation
CSI	Channel State Information
CV	Coefficient of Variation
CWT	Continuous Wavelet Transform
DR	Dead Reckoning
DoA	Direction of Arrival
ECG	Electrocardiography
EKF	Extended Kalman Filter
GONASS	GLObalnaya NAVigatsionnaya Sputnikovaya Sistema
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning System
HDR	Heuristic Drift Reduction
IC	Initial Contact
ILCKF	Improved Loosely Coupled Kalman Filter
IMU	Inertial Measurement Unit
IR	Infrared
KF	Kalman Filter
LED	Light Emitting Diode
LGW	Level Ground Walking
LiDAR	Light Detection and Ranging
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MEMS	Micro-Electro-Mechanical Systems
MLP	Multi-Layer Perceptron
MM	Map Matching
mmWave	millimetre-Wave
MSCE	Mean Step Count Error
MSLE	Mean Step Length Error
MTE	Mean Trajectory Error
MTPE	Mean Trajectory Percentage Error

NLOS	Non-Line-Of-Sight
PDR	Pedestrian Dead Reckoning
PE	Physical Education
PIR	Passive Infrared
PoA	Phase of Arrival
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
RFID	Radio Frequency Identification Device
RMSE	Root Mean Square Error
RS	Runs
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RTof	Return Time of Flight
RWF	Restrained Weighted Fusion
SLAM	Simultaneous Localisation and Mapping
SPE	Step Position Error
SS	Signal Strength
STD	Standard Deviation
SV4PE	Smart Vest for Physical Education
SVR	Support Vector Regression
SVM	Support Vector Machine
TDE	Total Distance Error
TE	Trajectory Error
TDoA	Time Difference of Arrival
ToA	Time of Arrival
ToF	Time of Flight
TO	Toe-Off
UWB	Ultra-wide band
VLC	Visible Light Communication
WiFi	Wireless Fidelity
WLANs	Wireless Local Area Networks
WP	Work Package
WPANs	Wireless Personal Area Networks
WSN	Wireless Sensor Network
WT	Wavelet Transform
ZARU	Zero Angular Rate Update
ZUPT	Zero Velocity Potential Update

Chapter 1

Introduction

1.1 Context and Motivation

The integration of wearable technology into sports and education in recent years has opened new opportunities for monitoring movement and performance, encouraging healthy lifestyles. For Physical Education (PE) classes, wearable sensors can provide new ways to improve engagement and progress assessment. Traditionally, PE assessment relies on teachers' observation and feedback, which is limited in terms of objectivity and scalability.

To address these challenges, research is being conducted on new smart textiles and wearable sensors capable of collecting data in a sports' context. Sensors like Inertial Measurement Units (IMUs) can provide insights into movement patterns and, in conjunction with electrocardiography (ECG) sensors, evaluate the intensity levels of training. These sensors have been embedded in textiles, providing innovative solutions without the need for external infrastructure.

Localisation in PE classes can provide several insights to the educators, namely, total distance covered by the students, or characteristic patterns of movement. However, implementing localisation systems with minimal sensors, particularly based solely on IMU data, is a technical challenge. Most state-of-the-art solutions include a multitude of sensors placed across different body segments, and some may require external sensor systems to correct for sensor drift. These approaches present implications in system costs, setup complexity, and user comfort.

With that in mind, developing an infrastructure-independent localisation system using a single IMU becomes an appealing objective. If achieved, this system could present accurate tracking of students during PE classes without requiring additional equipment or compromising mobility. The developed thesis explores this possibility while also understanding the present limitations and studying their effects on the localisation task for both real-time and offline applications.

1.2 TexP@CT - WP5 PP#17

This thesis was developed within the scope of the TexP@CT initiative [1], a Portuguese innovation consortium that aims to promote the research and development of smart textiles and digital trans-

formation in the national textile and clothing industry. This work falls under the Work Package 5 (WP5): Smart and Functional Textiles for Health and Sports, which focuses on developing wearable systems for monitoring biomechanical and physiological data in real-world environments. The PP#17 - Smart Suit for Sport Training conceived a Smart Vest for Physical Education, which, in this document, shall be labelled as SV4PE for easier referencing, to support the evaluation and monitoring of training and PE classes.

The vest incorporates two key technologies:

- A single IMU, with accelerometer and gyroscope, placed at the eight thoracic vertebra, T8, spinal position, representing the centre of mass;
- Textile ECG electrodes that retrieve cardiac data during movement.

This solution aims to provide real-time and post-session analysis of user activity to aid educators in monitoring and evaluating the students in PE.

1.3 Problem Statement

The SV4PE integrates a single IMU at the T8 position to minimize discomfort and maximize wearability. However, this minimalistic setup presents some technical limitations:

- The T8 placement does not provide foot-ground interaction, needed for correction techniques;
- The absence of a magnetometer hinders a potentially valuable heading compensation mechanism;
- No reliance on external infrastructures is desired, but limits heading correction capabilities.

Rather than aiming for sub-meter precision, the challenge in this thesis is to develop and evaluate a localisation pipeline that fits PE applications. Small localisation errors are critical in industrial or clinical contexts, but can still provide valuable insights in PE. A localisation system that can replicate the movement patterns and general position of an athlete, even with a few meters of error, could significantly enrich PE feedback and facilitate group monitoring.

This thesis addresses two questions:

1. **Can meaningful localisation be achieved using a single, back-mounted IMU without magnetometer or external infrastructure?**
2. **What information can be gathered from a minimalistic localisation system, when applied in sports?**

This project thus aims to contribute not only to the development of localisation systems, using different methods and technologies, but also to understand the acceptable trade-offs of these systems in the context of PE.

1.4 Objectives

This thesis aims to develop a system to be applied in the SV4PE solution and achieve a set of online and offline metrics, aiming to support activity monitoring in PE and sports training settings.

To support this goal, this thesis defines the following objectives:

1. Develop a complete localisation pipeline based on a single back-mounted IMU, including:
 - Step detection and step length estimation;
 - Heading estimation using orientation filters (e.g., Mahony, Madgwick);
 - Trajectory reconstruction in indoor and outdoor conditions.
2. Evaluate the role of the magnetometer in heading estimation:
 - Compare orientation filters with and without magnetometer input;
 - Assess whether satisfactory localisation accuracy can be achieved without magnetic data.
3. Investigate drift compensation strategies for heading estimation:
 - Explore the impact of segmentation, initial heading correction, and dataset-specific tuning;
 - Identify methods suitable for use without external reference points.
4. Design and implement real-time and offline metrics, including:
 - Real-time velocity estimation;
 - Distance travelled, time spent in predefined zones, attacking motion definition and intensity estimation.
5. Assess the overall accuracy and usefulness of the proposed system in a sports context:
 - Determine whether the achieved accuracy is acceptable for PE class applications;
 - Highlight the trade-offs between simplicity and precision in real-world use cases.

1.5 Dissertation Structure

The thesis starts with an introduction in Chapter 1, which contextualizes the motivation of the project, and the TexP@CT consortium. The introduction presents the problem and objectives, as well as the structure of the document. A background on localisation is introduced in Chapter 2, providing the definition and context of localisation solutions for indoor and outdoor environments. It introduces common techniques and technologies used in localisation systems. The chapter concludes with an overview of the key challenges faced when developing these systems.

Chapter 3 presents a systematic review of recent literature focused on localisation methods using IMUs. It explores which algorithms and methods to apply and what hybrid localisation systems can be combined using IMUs. This chapter highlights the research gaps regarding single IMU strategies for localisation, while also indicating what strategies have already been applied in similar contexts to the SV4PE.

Next, Chapter 4 shows the materials and methods used in this work. This includes a description of the used datasets and the proposed pipeline and its methods. Additionally, this chapter outlines the desired metrics for both real-time and offline analysis.

Chapter 5 presents the results obtained with the proposed methods. It starts with an example of the live acquisition metrics, followed by the first evaluation of step detection and step length estimation. Next, a comparison of the several pipelines developed is done, including a data analysis of the results obtained. It ends with an example of possible outcomes of offline metrics.

Chapter 6 has the discussion of the results and a summary of the findings. It presents the different challenges faced, and the usefulness of the developed methods in different contexts, and their educational value. A comparison with other works from the systematic review is conducted, and the limitations of the current system are presented.

Finally, the document ends with the overall conclusions and future work in chapter 7.

Chapter 2

Background on Localisation

2.1 Introduction on Localisation

Localisation or positioning is a process used to track objects in relation to multiple reference points within a predetermined area. It is an attempt to find the position of devices, mobile or fixed (like smartphones, drones, beacons, and vehicles), using certain fixed nodes and mobile computing devices [2]. This information can be used across many fields, including industrial manufacturing, healthcare, agriculture, autonomous vehicles, mobile robots and human motion tracking [3].

Localisation systems can be distinguished based on their application environments. The primary distinction is made between outdoor and indoor localisation, since these must be managed differently, having different characteristics and requirements for determining position [3].

Outdoor localisation typically relies on large-scale systems, specifically Global Navigation Systems (GNSS) such as Global Positioning System (GPS), GLObalnaya NAVigatsionnaya Sputnikovaya Sistema (GLONASS), Galileo, and Beidou [4]. These systems receive synchronized radio signals from satellites, ideally along a clear line-of-sight.

In indoor environments, due to the presence of various obstacles like walls, roofs, and other structures, GNSS signals are not suitable for localisation. The obstacles cause signal attenuation, blockage and heavy signal multipath [5]. Consequently, dedicated solutions are required for indoor localisation. These include the use of other types of signals, like Wireless Fidelity (WiFi), Ultra-wide band (UWB), and Bluetooth, and sensors, like inertial sensors [2]. Most of the techniques used in indoor environments depend on infrastructure (like beacons or tags) or leverage existing infrastructure (like WiFi access points) [6].

In order to understand the requirements and challenges of both indoor and outdoor localisation, this chapter will go through the most common approaches and briefly explain the different techniques and technologies used. Section 2.2 presents some methodologies used for localisation, based on the techniques used, like signal strength and angles of received signals. Section 2.3 explores the different types of sensors and technologies used to apply the mentioned techniques. The challenges of both indoor and outdoor localisations are presented in section 2.4. The conclusions are presented in section 2.5.

2.2 Typical Localisation Methods

Localisation methodologies represent the core techniques, principles, and algorithms used to process data and determine an subject's position. These are used with different types of sensors and technologies [2, 7], which will be reviewed in this section.

2.2.1 Received Signal Strength Indicator (RSSI)

Received Signal Strength (RSS), or RSSI, is a metric that quantifies the power of a radio signal received by a device [8]. RSS is the signal power, typically measured in decibel-milliwatts (dBm) or milliwatts (mW), while RSSI is a relative measurement, having arbitrary units. The principle exploited by RSSI-based localisation is that radio signal power attenuates with the increasing distance from the transmitter. The ratio RSS/RSSI indicates the distance between the transmitter (Tx) and receiver (RNx), being a higher ratio correspondent to a lower distance. RSSI measurements are particularly used in wireless technologies, like WiFi, Bluetooth and UWB beacons. A simple path-loss propagation model [9] in combination with RSSI can help determine a distance, d , between Tx and RNx, using equation 2.1:

$$RSSI = -10n \times \log_{10}(d) + A, \quad (2.1)$$

where n is the path loss exponent and A is the RSSI value at a reference distance from the receiver.

RSS based localisation requires trilateration or N-lateration, for accurate estimation of position. With at least three reference points, RSS can give the distance between each and the device, then basic geometry is applied to retrieve the device's position, as shown in figure 2.1. A common limitation of this technique, albeit being simple and cost efficient, is the poor localisation accuracy due to signal interferences stemming from attenuation.

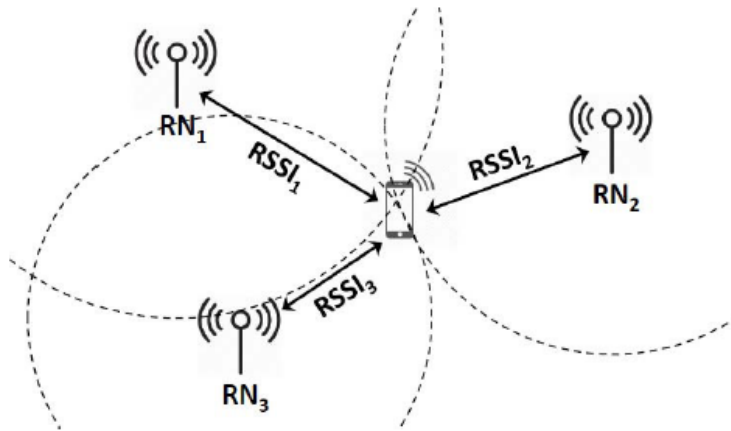


Figure 2.1: RSSI-based localisation [7]

2.2.2 Channel State Information (CSI)

Channel Impulse Response (CIR), or its Fourier pair Channel Frequency Response (CFR), works similarly to the RSS, having higher granularity and capturing both the amplitude and phase responses of the channel at different frequencies. The CSI is a complex quantity written in a polar form as

$$H(f) = |H(f)|e^{j\angle H(f)} \quad (2.2)$$

where, $|H(f)|$ is the amplitude response and $\angle |H(f_i)|$ the phase response of the frequency f_i of the channel [8]. This channel information can be used in localisation systems to infer the position of a device based on the spatial variations in amplitude and phase across multiple sub-carriers.

2.2.3 Fingerprinting and Scene Analysis

Scene analysis based localisation techniques rely on environmental surveys to obtain fingerprints or features of the environment where the localisation system is to be used [10]. Beforehand, different RSSI or CSI measurements are collected in an offline phase. These are compared with online measurements once the system is deployed to estimate the subject location. The matching between online and offline measurements can be done via several methods, namely:

1. **Probabilistic methods** - measure the likelihood of the subject being in the position 'x' when the RSSI values obtained in online phase are 'y' [11].
2. **Artificial Neural Networks (ANN)** - the NN is trained with RSSI values and the corresponding coordinates in the offline phase, providing the estimated position when receiving RSSI values in the online phase. The Multi-Layer Perceptron (MLP) network is an example of a commonly used ANN for localisation [11].
3. **k-Nearest Neighbour (kNN)** - kNN algorithms uses online RSSI values to obtain the k-nearest matches of the known locations using root mean square error (RMSE) [11]. The final estimate corresponds to an average or weighted average of the nearest matches.
4. **Support Vector Machine (SVM)** - SVM is a supervised learning model that can be trained to classify location regions or regress position estimates based on features such as RSSI, as suggested in Liu et al. [11].

2.2.4 Angle of Arrival (AoA)

Angle of Arrival is described as the angle at which a transmitted signal arrives at a receiver. Using antenna arrays at the receiver, the position is determined by exploiting the time difference of arrival or phase shift of the signal across the array elements [12]. A key advantage of the AoA when compared with other methods is that it can estimate position with fewer reference points (two for 2D and three for 3D). However, it requires more complex hardware and careful calibration than RSS methods. Figure 2.2 shows how AoA can be used to determine the subject location.

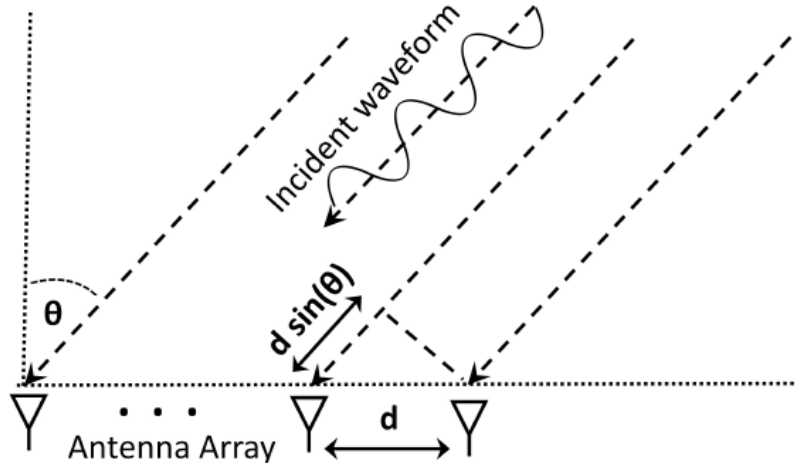


Figure 2.2: AoA-based localisation [7]

2.2.5 Time of Flight (ToF) / Time of Arrival (ToA)

Time of Flight or Time of Arrival is a technique that determines position by measuring the signal propagation time between a transmitter T_x and a receiver R_x . The distance is calculated by multiplying the velocity of light $c = 3 \times 10^8 \text{ m/sec}$. As it can be seen in figure 2.3, using three different reference nodes, basic geometry can be applied to determine the device's position [12].

When using ToF, it is crucial to have a strict synchronization between the transmitters and the receivers. For that reason, timestamps are usually transmitted with the signals. ToF's accuracies are dependant on the signal bandwidth and the sampling rate. Low sampling rates can reduce the ToF resolution, since the signal can arrive between sampled intervals. Line of sight is a common error inducer, due to the presence of obstacles that deflect the emitted signals.

2.2.6 Return Time of Flight (RToF)

RToF represents the round-trip (from transmitter to receiver and back) signal propagation time. The mechanism is similar to the ToF. The benefit of using RToF relies on the more moderate synchronization between transmitter and receiver. However, RToF's accuracy is affected by the same factors of sampling rate and bandwidth, but more severely since the signal is transmitted and received twice. The distance between a transmitter i and a receiver j can be calculated by the equation 2.3 [12]:

$$D_{ij} = \frac{(t_4 - t_1) - (t_3 - t_2)}{2} * c \quad (2.3)$$

where c is the speed of light, t_1 and t_2 are the times of transmission and reception of the first signal, and t_3 and t_4 for the second signal.

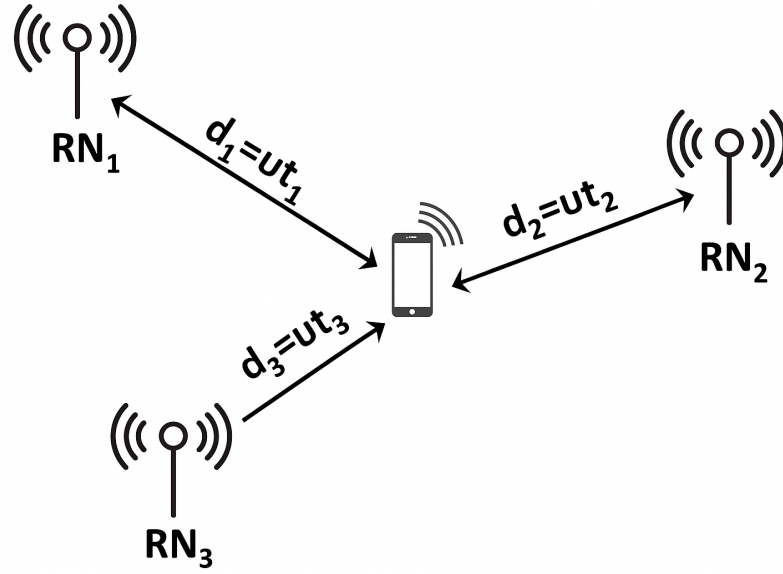


Figure 2.3: ToF-based localisation, adapted from [7]

2.2.7 Time Difference of Arrival (TDoA)

Time of Difference of Arrival differs from the ToF technique, because it uses the difference in signals propagation times from different transmitters, instead of the absolute signal propagation. The TDoA measurements are then converted into physical distance values by multiplying with the speed of light (c) [12]. The receiver location is now in the hyperboloid given by the equation 2.4 [12] :

$$L_{D(i,j)} = \sqrt{(X_i - x)^2 + (Y_i - y)^2 + Z_i - z)^2} - \sqrt{(X_j - x)^2 + (Y_j - y)^2 + Z_j - z)^2} \quad (2.4)$$

where (X_i, Y_i, Z_i) are the coordinates of the transmitter i and (x, y, z) are the coordinates of the receiver/user. This technique also requires at least three transmitters, as can be seen in figure 2.4, and its accuracy depends on the signal bandwidth, sampling rate and direct line of sight. The synchronization between the transmitters is required, but not with the receiver.

2.2.8 Phase of Arrival (PoA)

PoA based approaches estimate the distance between transmitter and receiver by measuring the phase or phase difference of signals. As seen in figure 2.5, the phase difference at different antenna in the antenna array can be measured and used to obtain the subject's location. The common assumption is that the signals transmitted are pure sinusoidal, with the same frequency and zero phase offset [13]. For higher accuracy, clear line of sight is required.

2.2.9 Dead Reckoning

The Dead Reckoning (DR) technique consists of the estimation of the present location of the device using a previously calculated location and the inertial sensor data. Pedestrian Dead Reckoning

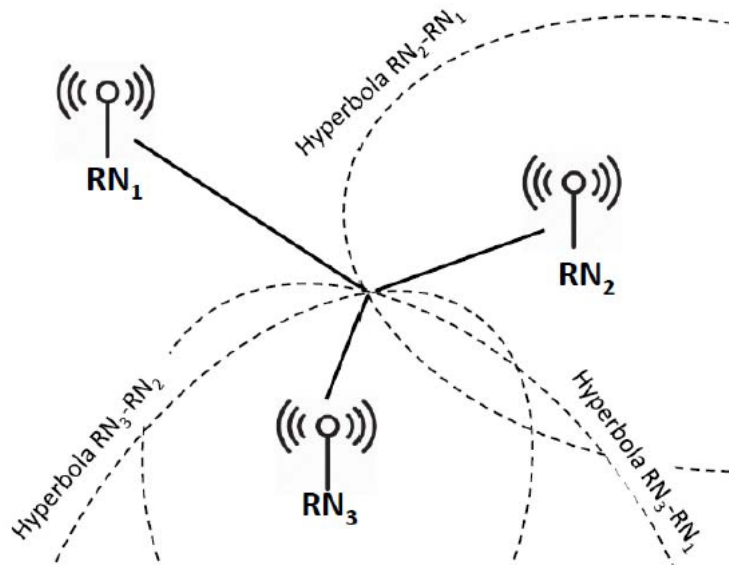


Figure 2.4: TDoA-based localisation [7]

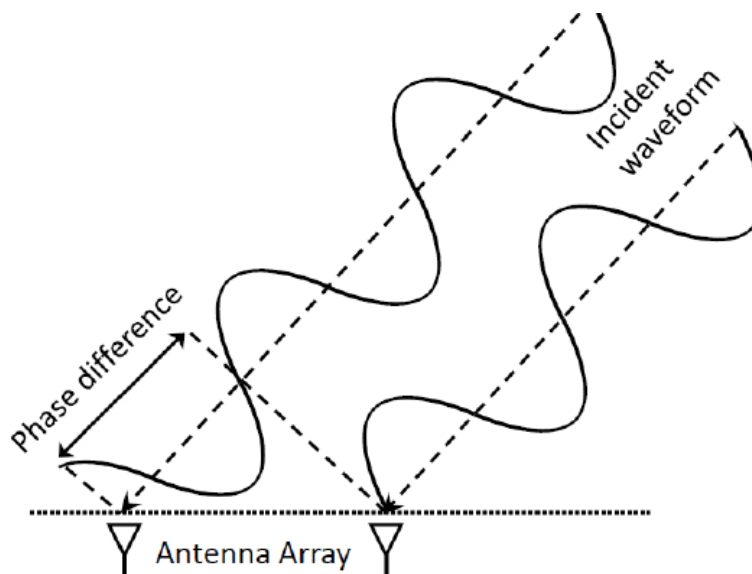


Figure 2.5: PoA-based localisation [7]

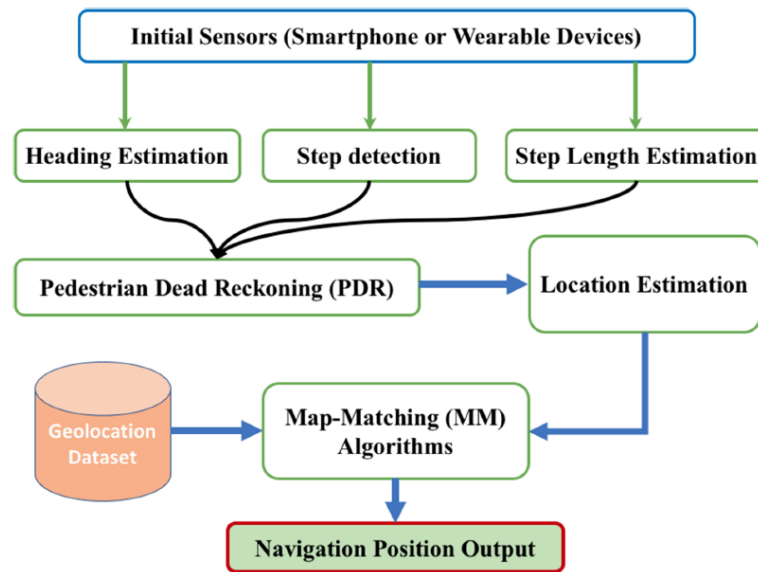


Figure 2.6: Combination of the PDR and MM techniques [2]

(PDR) has three main steps: heading estimation, step detection and step length estimation [14].

The required elements for DR are presented in figure 2.6. The heading estimation process consists of using gyroscope and sometimes magnetometer data to determine the direction in which the subject is moving.

Step detection can be achieved by several methods using the accelerometer data, usually the vertical axis, since it gives information regarding the contact of the foot with the ground. The step length estimation uses the accelerometer data to determine the acceleration in the direction of the step, and determine the exact distance covered in each step.

PDR is a low-cost solution with relative ease of implementation, being used in several solutions. However, PDR faces challenges regarding the accumulation of errors from sensor noise and drift. For that reason, PDR is frequently used in combination with other solutions to overcome these challenges [15].

2.2.10 Map-Based Localisation

Map-based localisation techniques rely on maps, i.e., pre-existing representations of the environment, to estimate the position of the device relative to that map. These approaches anchor the position estimate to fixed environmental features within the map, reducing cumulative errors of techniques like DR [16].

2.2.10.1 Map Matching

Map matching (MM) is a technique that aligns a currently estimated position with the geographical information present in a digital map. This process can employ machine learning algorithms,

including pattern recognition and matching [17]. Figure 2.6 shows how DR can be combined with MM.

2.2.10.2 Simultaneous Localisation and Mapping (SLAM)

SLAM aims to predict a subject's position and simultaneously create a map of the unknown environment using data from different sensors. The map is incrementally constructed, as the subject explores unknown areas, or updated upon revisiting known locations [18]. Although, SLAM faces challenges in dynamic scenes, where moving elements or reconfigurations of the scenery may occur.

2.2.11 Hybrid Techniques

Many combinations of the above-mentioned techniques have been applied, since each has unique challenges, which can be compensated with the other different sensors and methods. Some examples are the combination of AoA and RSSI [19], PDR and RSSI-fingerprinting [20], etc.

Each combination aims to create more reliable and accurate systems, while avoiding the disadvantages of hybrid systems, namely:

- Higher-cost infrastructure
- Higher time and memory complexity
- Higher power consumption
- Error accumulation

2.3 Employed Localisation Technologies

The above mentioned techniques use a variety of sensors and equipments to achieve localisation, from radio communication technologies to light and acoustic based technologies. In this section, the associated sensors and technologies used in localisation are now presented.

2.3.1 WiFi

IEEE 802.11 standard, commonly known as WiFi, is a widely adopted technology used for creating Wireless Local Area Networks (WLANs) and providing access to internet in different environments. Initially, WiFi had a range of about 100 meters [21], which is now increased to about 1 kilometer [22]. WiFi is a highly prevalent technology for localisation due to its widespread availability and its signal propagation capabilities.

WiFi is present in most of the current devices and is one of the most widely studied localisation technologies [7], using different localisation techniques like RSSI, ToF and TDoA. The large presence of WiFi in devices implies that existing WiFi access points can be used as reference

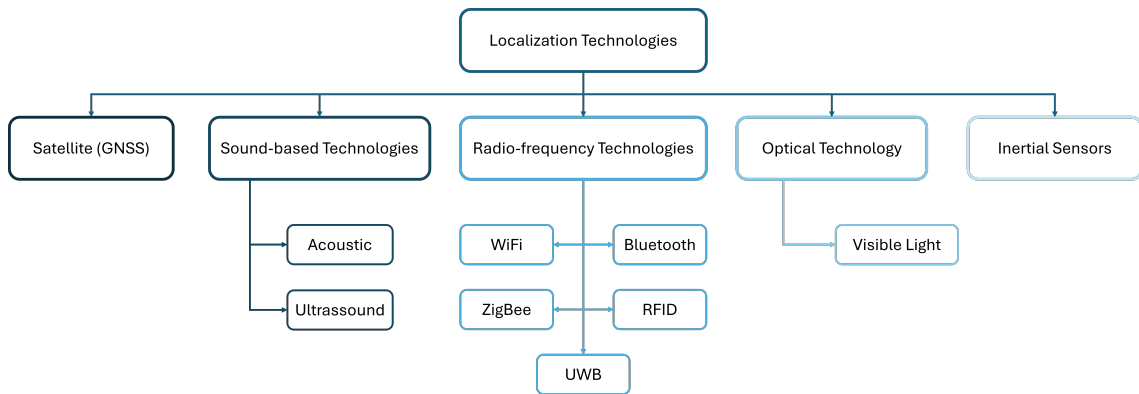


Figure 2.7: Localisation technologies

points for signal collection [23], creating basic localisation systems without the need for additional infrastructure [24].

WiFi is subject to multipath effects, interference and noise from obstacles and other devices. These phenomena lead to signal attenuation and unpredictable fluctuations on the signals. Current research aims to mitigate these challenges and improve overall accuracy.

2.3.2 Bluetooth

Bluetooth (or IEEE 802.15.1) is an electromagnetic signal technology designed for creating Wireless Personal Area Networks (WPANs) to connect devices over short ranges, within a certain personal space. Similar to WiFi, Bluetooth is present in most of the modern mobile devices, making localisation techniques less infrastructure dependant [25]. Techniques like RSSI, AoA, ToF and fingerprinting are used with Bluetooth devices [7]. Like other radio frequency technologies, Bluetooth signals are susceptible to multipath effects, signal attenuation, and fluctuations, lowering its accuracy [26].

2.3.3 ZigBee

ZigBee is also a wireless communication technology, based on the IEEE 802.15.4 [27], primarily created for Wireless Sensor Networks (WSN). ZigBee's design protocol prioritizes low cost, low data rate, and high energy efficiency. While favourable for the localisation of sensors within a WSN environment, ZigBee is not readily available on the majority of user devices, making it less common for localisation techniques. This technology uses RSSI measurements to estimate the position of the devices in a specific area [28].

2.3.4 Radio Frequency Identification Device (RFID)

RFID is a wireless technology that uses radio signals to identify and track subjects equipped with electronic tags, enabling real-time monitoring without physical contact or line-of-sight [29]. An RFID system consists of a reader that communicates with different tags. The RFID tags emit data

that the RFID reader can read using a predefined RF and protocol. The systems can be active or passive, depending on the presence of a battery and the range of the signal transmission.

RFID uses RSSI with unique tag (IDs) and applies phase-based localisation techniques, achieving higher accuracy than RSSI-based methods [3].

2.3.5 Ultra-Wideband

UWB is characterized by transmitting ultra-short pulses, typically less than 1 nanosecond in duration, over a very large bandwidth, usually greater than 500 MHz [30]. UWB uses a very low duty cycle, resulting in reduced power consumption. The technology has been primarily used for short-range communication systems.

UWB is particularly interesting for indoor localisation, since it is immune to interference from other signals, due to its drastically different signal type and radio spectrum, and can penetrate a variety of materials and obstacles. This technology has been researched and new hybrid techniques have emerged, like Vandermeeren and Steendam [31] with a PDR/UWB positioning system.

2.3.6 Optical Technology

Optical technologies use light signals in the visible and infrared (IR) spectrum and are commonly employed in localisation systems and motion tracking. Unlike radio frequency signals, optical signals cannot penetrate walls or obstacles, which limits their applicability in complex environments. However, these systems are often characterized by relatively low costs, straightforward installation, and short operational ranges, making them suitable for controlled indoor settings.

Visible Light Communication (VLC) uses visible light, typically emitted by Light Emitting Diodes (LEDs), and received by photodiodes or digital cameras. Techniques like fingerprinting, RSSI, and angulation can be used with this technology. The technology can cover wide ranges, but requires line of sight for accurate localisation [32].

Optical motion capture systems are part of the gold standard for position and biomechanical studies. Marker-based systems use multiple cameras to track reflective markers placed on the body, offering high accuracy and temporal resolution. Markerless systems, in contrast, use computer vision to estimate body pose without physical markers, enabling more natural movement capture. While generally less precise, marker-less systems are gaining popularity due to their convenience and recent improvements in algorithmic accuracy [33].

2.3.7 Sound-based sensors

Sound-based localisation systems estimate position using sound wave propagation, typically through either acoustic or ultrasound signals. Both approaches rely on time-based measurements like ToF or phase shift but differ in frequency range, accuracy, and environmental suitability.

2.3.7.1 Acoustic signals

Acoustic signal based localisation uses microphone sensors to detect acoustic signals emitted by sound sources and estimates the subject location in respect to the reference nodes. These systems use ToF and phase shift to estimate the relative position and velocity [34].

Acoustic-based systems can achieve high localisation accuracy, but typically only when operating within the audible frequency range (below 20 kHz). This limitation often requires additional infrastructure and may introduce sound pollution, making such systems less suitable for certain environments.

2.3.7.2 Ultrasound

Ultrasound based localisation uses ToF measurements of ultrasound signals ($>20\text{kHz}$) and the sound velocity to calculate the distance between transmitter and receiver nodes. This technology can provide centimetre level accuracy [35] and track multiple nodes at the same time, while being energy efficient.

An RF pulse usually assists in the synchronization of the ultrasound signal. A challenge of this technology is the sound velocity, which changes when humidity and temperature changes.

2.3.8 GNSS

GNSS is a satellite navigation system that has worldwide coverage. Systems like GPS, GLONASS, BeiDou, and Galileo are examples of GNSSs that have been implemented. Since GNSS chipsets are a usual component of smartphones, they have high availability.

GNSS uses triangulation to identify the device's position, by receiving signals from several satellites. GNSS is the most used technology in regards to outdoor localisation, but presents many challenges for indoor positioning, like high multipath signals and deteriorated geometry.

To overcome the challenges, GNSS systems are often combined with other technologies, like inertial sensors [36].

2.3.9 Inertial Measurement Unit

IMUs play a significant role in localisation, providing information about the target's motion and orientation. Micro-Electro-Mechanical Systems (MEMS), including accelerometers, gyroscopes, pressure and magnetometer sensors are among the used sensors in IMUs. Usually, IMUs are composed of a three-axis accelerometer and a three-axis gyroscope. Other sensors can be added to complement the IMU.

Accelerometers provide acceleration along an axis, which can be used to detect and estimate subject's movement. They are stable in stationary conditions, but the gravitational acceleration affects the acceleration in dynamic conditions, creating the need for gravity compensation [37]. Gyroscopes measure angular velocity, which can be used for heading estimation. However, motion artifacts, such as noise and cumulative drift errors, make the outputs of these sensors unreliable in

long recordings. Many solutions have been described to fuse the high-frequency information of the gyroscope with the low-frequency information of the accelerometer, or even adding data from other sensors like the magnetometer [37]. Magnetometers provide readings of the geomagnetic field, functioning as a compass to provide orientation relative to the global-frame. This can be used to compensate the gyroscope drift and heading estimation. Magnetic field is influenced by the presence of materials, systems, or objects with magnetic or magnetizing properties, which makes these sensors unreliable in environments with various devices with said materials.

Due to their low-cost and widespread availability in many devices, IMU sensors provide an easy location estimate which can be compensated or used to compensate other technologies. IMU are then widely used in hybrid-techniques [38].

2.4 Research Challenges

Localisation systems face several challenges, regarding both the techniques and technologies used. Firstly, signal propagation has inherent limitations, especially in indoor environments. Phenomena such as multipath effects and Non-Line-Of-Sight (NLOS) propagation distort the signal characteristics, which leads to inaccurate distance or angle measurements. Additionally, diffraction, reflection, scattering, and external interference from other devices can all affect the signals and reduce localisation accuracy. For time-based methods, like ToF and TDoA, precise synchronization is critical, which is sometimes difficult to maintain. These signal-related issues can significantly impact the accuracy and reliability of localisation systems, lowering performance in complex environments.

Other challenge arises from sensor and device heterogeneity. Using different sensors with varying hardware components and software attributes causes received signal characteristics and sensor measurements to vary significantly from device to device. This decreases localisation performance and limits the applicability of developed systems to be used across different hardware.

The handling of large amounts of data, specifically in systems using fingerprinting or machine learning, poses a new challenge for localisation systems. This, coupled with energy efficiency problems and infrastructure cost, creates a need for the development of new, lightweight and inexpensive solutions, that can still achieve the high accuracies desired and store the sheer volume of data generated.

Machine learning approaches create also the need for vast datasets to train the developed models. Acquiring this data is a time-consuming task that can limit the deployment of these solutions. Augmentation strategies can be applied to create synthetic data that mimics real-world observations.

Ultimately, researchers of localisation systems face the challenge of developing systems that can effectively balance multiple, often competing, performance metrics like accuracy, cost, computational complexity, power consumption, and real-time operation.

2.5 Summary of Localisation

Localisation is a complex process in constant development, that uses a variety of techniques and technologies, both in indoor and outdoor environments. Several methodologies were explained, such as RSSI, AoA, ToF, and Dead Reckoning. These offer different approaches to extract the position of a subject based on signal characteristics or sensor data. Map-based methods introduce anchoring to refine the position estimates. Hybrid approaches are being applied in the literature, complementing each methods' benefits and challenges. Each technique has its own challenges like accuracy, cost, and complexity.

A wide range of technologies support these localisation techniques. Wireless communication standards such as WiFi, Bluetooth, ZigBee, UWB and RFID are widely used, since they are present in most of current devices and their signal properties are well adapted for localisation processes. Optical, acoustic, and ultrasound systems are alternative approaches that require specific infrastructure. GNSS is the dominant solution for outdoor positioning. IMU sensors offer valuable motion data and allow their integration with other sensors in hybrid localisation systems. The choice of technology is based on the specific application, environment, and system constraints.

The development of accurate and reliable localisation systems has several challenges. Signal-related phenomena such as multipath effects, NLOS conditions, and environmental variability are constant factors of signal degradation and lower performance. Device and sensor heterogeneity coupled with synchronization requirements and data processing demands lead to complex infrastructure and system design. Data-driven approaches require extensive datasets and computational resources. Achieving scalable, cost-effective, and high-accuracy localisation is the main objective and remains a challenging in localisation research.

IMU-based Dead Reckoning stands out as a technique that can be used with relative low cost and high adaptability for hybrid solutions. However, DR methods suffer from accumulated errors over time, leading to drift and inaccurate position. Combining IMU with other technologies might be a good solution to mitigate this drift and enhance overall localisation performance.

Building upon the different localisation techniques and technologies, and the different challenges that localisation systems face, the subsequent chapter will introduce a systematic review on the current solutions for indoor and outdoor localisation, focusing on IMU-based solutions.

Chapter 3

Systematic Review

3.1 Introduction of IMU-based Localisation Systems

Physical Education is a school subject that promotes physical activity, motor skill development, and healthy lifestyles among students [39]. However, physical activity performance and engagement evaluation remain subjective tasks, with high dependency according to the person assessing the exercise. Typically, evaluation depends on visual observation and verbal feedback from the teachers. The current methods present challenges such as high degrees of subjectivity and difficulty in application to a whole class simultaneously.

The SV4PE is a wearable smart vest incorporating an IMU and embedded ECG electrodes to meet the presented challenges. Designed by the *TexP@CT Consortium*, this smart vest will implement several analytical algorithms for physical exercise metrics' extraction, enhancing objectivity and scalability in PE assessment.

One of the desired metrics is the localisation and tracking of students during classes. Since a single IMU positioned in the middle back (level of spinal vertebrae T8) was chosen for the solution, it is fundamental to identify which algorithms can be integrated into SV4PE. The designed solution is intended for this specific application scenario, but isn't without its shortcomings, as it needs to sacrifice accuracy to maintain complexity, costs, and applicability in check.

This systematic review aims to analyse and retrieve existing methodologies used in recently developed localisation systems with IMU sensors. We aim to apply them and use them as a basis for our developed solution.

Regarding the organisation of the chapter, the first section (3.2) presents the research methodology applied. Sections 3.2.1 and 3.2.2 include the research questions and the inclusion and exclusion criteria used in this review, respectively. The selection process is fully explained in Section 3.2.3, and the data gathered from the articles is presented in Section 3.3. Section 3.4 presents an overview of the methods found in the set of records, whose findings are then described and summarised in section 3.5.

The term IMU is used across this review to refer to any inertial sensors used in the presented articles, containing at least one accelerometer and/or gyroscope.

3.2 Research Methodology

This chapter presents a systematic review about the application of inertial sensors for localisation challenges, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) methodology ([40]). It can be summarised in the following steps:

1. A set of research questions is defined to determine the scope of the review;
2. Inclusion and exclusion criteria are identified to characterise further and bound the research questions;
3. A search query is defined and executed across relevant digital libraries - IEEE Xplore, PubMed, Scopus and Web of Science - to identify studies of interest for the topic;
4. The search results are merged, and the duplicates are removed;
5. The filtered results are then screened using the predefined inclusion and exclusion criteria to obtain a set of relevant articles;
6. These articles are classified according to the number and type of sensors and the localisation processes, and their features are extracted, mapped and analysed.

3.2.1 Research Questions

This systematic review aims to assess and present an overview of the current methods of localisation performed using IMUs. Thus, the following set of research questions was formulated:

RQ1: What technologies can be combined with IMU sensors to determine the localisation of a person?

RQ2: What combinations of IMU sensors are currently used for indoor and/or outdoor localisation?

RQ3: How can we correctly determine the localisation using a single IMU sensor, without other infrastructures and ideally without a magnetometer?

RQ1 represents the general goal of the review. The equipment, for which this research is being conducted, has a single IMU in the mid/upper back (spinal level T8), close to the centre-of-mass (CoM) of the user. Thus, the primary goal is to find localisation solutions that encompass the limitations of the used device. The objective of RQ2 is to retrieve the different state-of-the-art infrastructures used in combination with the IMU sensor for localisation and the various placements of the IMU sensors in the body. Finally, RQ3 aims explicitly to gain insights into using the different methodologies to achieve localisation with IMU sensors.

3.2.2 Inclusion and Exclusion Criteria

The articles in this review were assessed based on the following inclusion and exclusion criteria.

3.2.2.1 Inclusion Criteria

IC1: Any research, presenting novel solutions and/or methodologies, written in English, which is openly available.

IC2: Any articles that explicitly include the use of inertial sensors/IMUs for localisation of humans.

3.2.2.2 Exclusion Criteria

EC1: Articles that are not original research (e.g., reviews, surveys)

EC2: Articles that do not use inertial sensors/IMUs directly to determine the user's localisation.

EC3: Articles that, whilst using IMU sensors, do not provide the localisation and/or mapping of the user's movements.

EC4: Any work not applied to human studies (e.g., animals, robots).

3.2.3 Study Selection Process

To identify relevant articles, a search query had to be developed. The first step was to define the topics for the query, followed by selecting appropriate keywords for each topic. Table 3.1 displays the five topics containing their respective keywords used in the search query. The keywords in each topic (e.g. IMU, Position, ...) are combined by the "OR" query operator, while different topics are connected with a logic "AND" query operator.

Table 3.1: Keywords and topics chosen for PRISMA search query

IMU	Position	Wearable	Environment	Sports
Inertial Measurement Unit OR IMU OR Inertial Sensor OR Accelerometer OR Gyroscope	Position OR Location OR Localisation OR Localization OR Tracking OR PDR	Wearable OR Body-Worn Sensors	Indoor OR Outdoor	Physical Education OR PE Class OR Sports Tracking OR Sport OR Movement in Children

Four separate searches were conducted using the following databases: *IEEE Xplore*, *PubMed*, *Scopus*, and *Web of Science*. Those were either **full, including all five topics**, or **narrow, excluding "Sports"**, and for an extension of 5 or 10 years. Table 3.2 contains the number of results for each search.

Having previously determined the inclusion and exclusion criteria, the screening process was carried out with the records from the narrow search over the last 5 years. The results of this process are schematically depicted using the PRISMA flow diagram in Figure 3.1. The final set of eligible studies had 53 articles included in this review for further analysis.

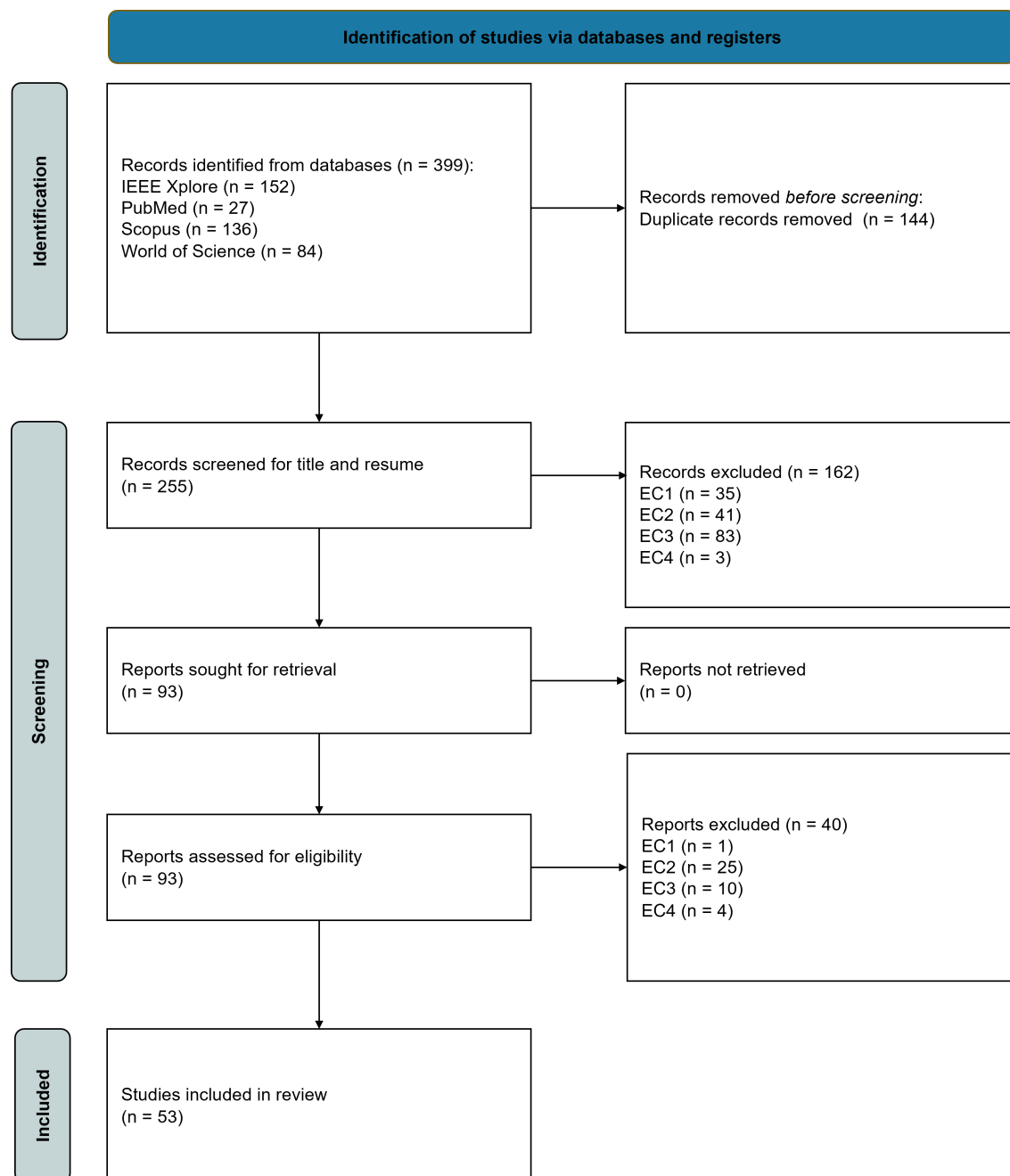


Figure 3.1: PRISMA flow diagram

Table 3.2: Number of records obtained per search query. N5: Narrow search (last 5 years), F10: Full search (last 10 years)

Search	N5	F5	N10	F10
IEEE Xplore	152	2	272	3
PubMed	27	5	38	8
Scopus	136	11	223	23
WOS	84	5	152	11
Total	399	23	685	45

3.3 Data Analysis

This review assesses the current developments and methods used for subject localisation, using IMU sensors. However, since a wide range of solutions are presented in the records, the first step was to organise and evaluate the different methodologies before moving to their characterisation. This section will analyse the differences in the set of articles.

3.3.1 Localisation Type

Localisation techniques vary significantly when performed indoors and/or outdoors. The presence of obstacles and infrastructure in indoor environments leads to difficulty using some sensors, like GPS and GNSS. In the case of outdoor environments, the lack of infrastructure and potential noise sources impact the application of technologies like ultra-wideband sensors UWB.

Figure 3.2 indicates the percentage of articles corresponding to indoor and/or outdoor localisation techniques. A total of 34 articles (64%) provide a solution solely for indoor localisation, and 4 articles (8%) for outdoor, only 15 out of the 53 articles (28%) create a localisation for both environments. As physical education (PE) classes are performed indoors and outdoors, a method that can be applied to both scenarios is preferred.

3.3.2 Inertial sensors' body placement and number

Inertial sensors provide information about the acceleration and angular velocity of the body they are attached to. The amount and type of information that can be gathered from these sensors are affected by the number and placement of the sensors in the human body.

Equipment costs, sensor synchronisation and combination are factors that decide the number of sensors in a localisation system. As shown in Figure 3.3, a single inertial sensor was used in 38 of the 53 selected articles (73%). However, as discussed in the following subsection, single IMU configurations are more often used than configurations that employ systems with multiple interconnected IMUs.

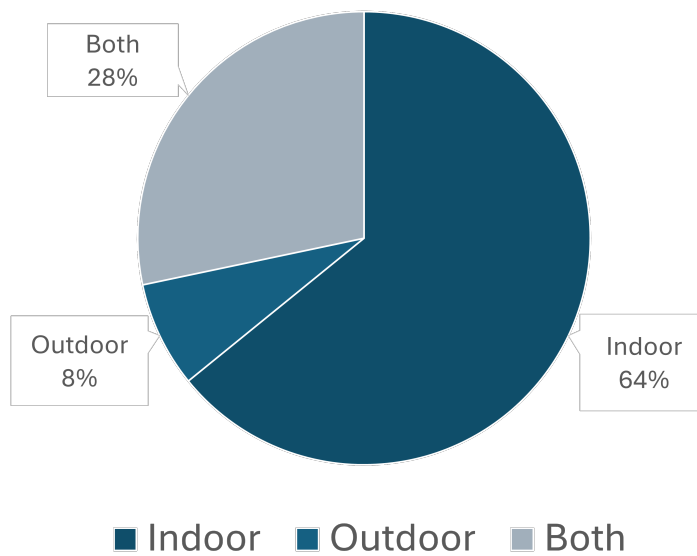


Figure 3.2: Distribution of articles' localisation techniques in indoor and outdoor settings

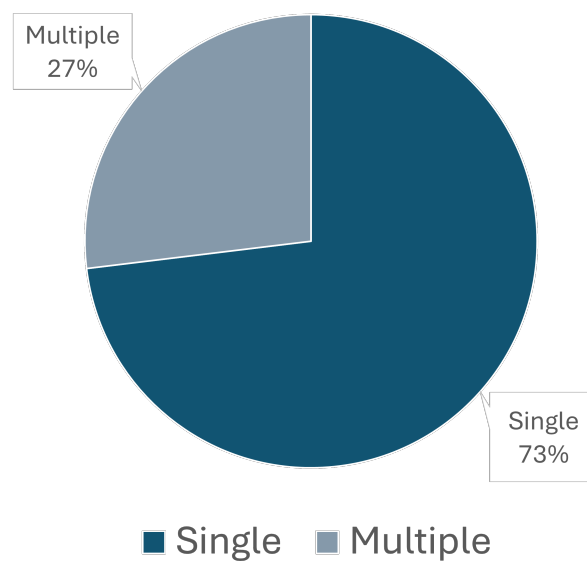


Figure 3.3: Distribution of articles' choice between single or multiple inertial sensors

Regarding IMU placement, figure 3.4 contains the placements reported in the articles chosen for this review. Table 3.3 presents the number of articles with single and multiple sensors in each placement. The most common placement was on the foot, which was used in 13 articles with a single IMU and 1 method with multiple IMUs, followed by the waist, hand, and chest. The systematic review found no article that employs a single IMU system with a T8 placement on the body, which our solution intends to perform.

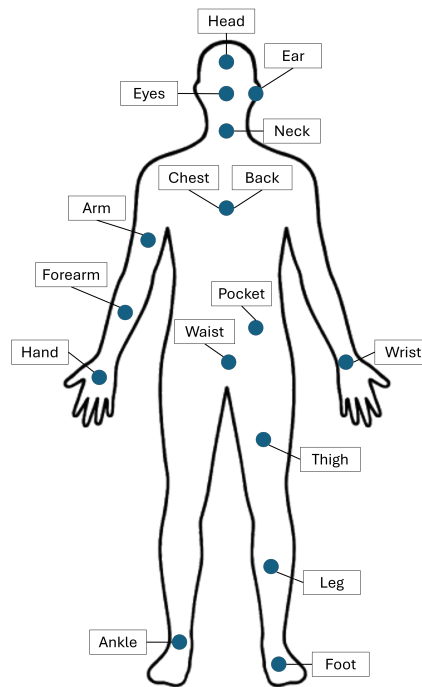


Figure 3.4: Placements of IMU sensors in this review

Table 3.3: Number of records for each sensor placement

Single sensors		Multiple sensors	
ankle	1	back	1
chest	3	chest and foot	1
foot	13	chest, camera and LiDAR	1
glasses	1	ear and pocket	1
hand	4	head, hand and thigh	1
head	2	lower body	3
neck	1	phone and ear	1
phone	3	shanks	1
pocket	2	waist	2
thigh	1	watch and waist	1
upper body	1	wearable	1
waist	5	whole body	1
wearable	1		
Total	38	Total	15

3.3.3 Role of the IMU sensor in localisation

Every article selected used inertial sensors for localisation. However, the methodologies range from using just a single IMU sensor to using multiple sensors, including ones other than IMUs. Thus, figure 3.5 summarises the number of records regarding the usage of IMU sensors.

As we can see, from the 53 articles, 19 use only IMU sensors, but the most common approach is to combine IMUs with other types of sensors. The limited information that can be extracted from IMU sensors incites using other sensors to create more accurate localisation methods. UWB sensors were the most common among different types and were primarily used in indoor environments.

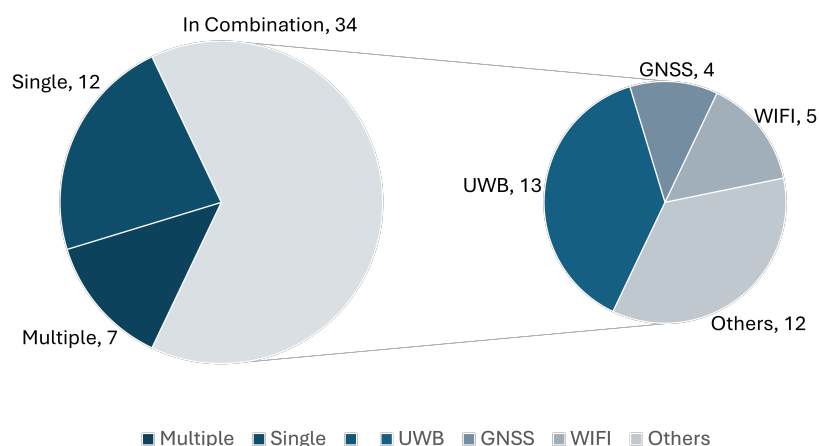


Figure 3.5: Number of records according to the usage of IMU: single, multiple or in combination with other sensors, like Ultrawide Band Sensors, Global Navigation Satellite Systems, and WiFi

3.4 Methodologies found

This section discusses the significant findings from the articles, following an order of importance and similarity to our solution. For that reason, we decided to subdivide the section regarding the usage of IMU. Firstly, we present the methods that use other types of sensors besides inertial, like UWB, GNSS, WiFi and others; next, the projects which use multiple inertial sensors; finally, the articles with single IMUs, from farthest to closest to the CoM.

3.4.1 IMU and other sensors

Inertial sensors give information about movement, including acceleration, angular velocity and orientation. Although IMUs are not explicitly designed to provide accurate localisation, this technology can be adapted to provide relevant estimates, especially when combined with external sensors.

Sensor systems, such as UWB for indoor and GNSS for outdoor localisation, were the most common solutions present in the set of records for this review. In this section, we primarily explore UWB, GNSS and WiFi sensors, since they were present in at least 4 records each, and then a small overview of the other methods used.

3.4.1.1 UWB

UWB is a short-range, high-bandwidth communication technology that uses very low energy pulses [41]. This technology allows for high data transference and reduced multipath interference, being effective in indoor positioning [42]. Algorithms such as TOA, direction of arrival (DOA), and signal strength (SS) [43] are used to describe UWB. Hybrid systems, like TOA/SS, combine techniques to improve location estimation accuracy [43]. UWB enables accurate location estimates without the need for complex estimation algorithms [43].

Over the years, UWB solutions have increased due to their high resolution in the time domain, which is helpful in indoor environments [42]. It has been used in diverse medical monitoring, security, and asset tracking applications. Factors that enhance the positioning performance of UWB include environmental knowledge and node cooperation [42].

From the set of records, 13 sources present systems where UWB aids IMU-based localisation systems, correcting for IMU drift and improving overall accuracy. While all approaches suggest the strengths of both UWB and IMU, their specific techniques and applications differ. The sources show several methods to combine UWB and IMU for enhanced localisation:

IMU-aided UWB Correction: Some articles focus on using IMU data to correct errors inherent in UWB measurements. For example, Qin et al. [44] and Karuparthi and Padir [45] use IMUs to detect and compensate for NLOS errors that affect UWB signal accuracy.

UWB-aided IMU Correction: On the contrary, other studies prioritise IMU-based localisation and use UWB as an aid to mitigate the drift that naturally occurs in the primary sensors. Zhang et al. [46] and Holzke et al. [47] describe systems where UWB provides absolute position updates, correcting the cumulative errors of the IMU. Holzke, Golatowski, and Timmermann [48] also uses UWB to calibrate PDR systems, using the trend of the position measurements to derive absolute orientations of strides, to correct the IMU orientation.

Data Fusion for Enhanced Accuracy: Many sources describe fusing UWB and IMU data using algorithms such as Kalman filters (KF). Zhang et al. [46], Holzke et al. [47], and Pascucci et al. [49] describe methods that use sensor fusion with KF for iterative compensation to achieve better accuracy. To address the challenges of NLOS propagation, Jiang et al. [50] proposes the fusion of range measurements and inertial measurements. For the same challenge, Wang et al. [51] makes use of machine learning, proposing a neural network-aided factor graph optimisation (NN-FGO) method, which integrates IMU and UWB sensor data for collaborative pedestrian navigation (CPN). Santoro et al. [52] uses ultra-wideband localisation and IMU data fusion to retrieve athletes' positions. S. M. Sharifuzzaman Sagar et al. [53] propose UWB-IMU fusion-based relative-position systems. Naheem and Kim [54] fuses the UWB position observation with the zero velocity potential update (ZUPT) algorithm, described in further detail in section 3.4.3, using an improved loosely coupled Kalman filter (ILCKF). Belli, Davoli, and Ferrari [55] presents a cloud-oriented IoT architecture for indoor-outdoor localisation, integrating UWB with other sensors besides IMU that can detect events of interest. The work of Mahmoud et al. [56] presents a multi-sensor indoor pedestrian tracking system composed of off-the-shelf, low-cost commer-

cial sensors and connected embedded platforms, backed up by a high-end time-synchronised 3D ground-truth system.

3.4.1.2 GNSS

GNSS uses satellites to provide worldwide coverage and information about a particular object's localisation. Several types of GNSS exist, like GPS, GLONASS, Galileo, and Beidou. GNSS is commonly applied in outdoor navigation, since it relies on signals from different satellites to determine the positions through triangulation [57]. It is sometimes combined with other sensors, like IMUs, to improve the localisation accuracy.

In the set of records, 5 articles used GNSS, primarily to provide outdoor localisation. In [58], an inertial navigation system is described, using ZUPT when a stance is detected. The raw estimate is then corrected by GNSS position and velocity. Similarly, Rabb and Steckenrider [59] estimates the trajectory using multi-sensor fusion and a probabilistic step model, with ZUPT. Combining IMU data with GPS provided a maximum a posteriori (MAP)-type technique for non-Gaussian estimation.

Another way of data fusion was implemented in [60]: it uses an Extended Kalman Filter (EKF) to integrate a CNN velocity estimation model and GNSS data to improve PDR, correcting the IMU drift. Belli, Davoli, and Ferrari [55] uses GNSS separately from the IMU sensor, being the first used for outdoor positioning and the last for indoor.

Even though it is not common, Li, Zhu, and Renaudin [61] uses GNSS carrier phase signals in indoor environments, using light to help correct PDR. The LIGHT algorithm (Light Indoor GNSS MacHine-learning-based Time Difference Carrier Phase) uses ML to select the usable GNSS carrier phases and is fused with PDR to perform a more robust indoor/outdoor localisation. Thus, it proposes a new approach for a seamless transition between different environments.

3.4.1.3 WiFi

WiFi systems rely on access points (APs) to transmit and receive signals, which can then be used to connect a device to a network. For indoor positioning, WiFi is used as a reference value for the target location. A signal strength map is created by measuring the characteristics of WiFi signals like RSSI, which can be used to estimate a device's location based on the observed signal. Thus, WiFi fingerprinting and triangulation can replace GPS in indoor positioning.

This technique, however, has some limitations related to the susceptibility of signals to refraction, reflection, diffusion, and dispersion, which can affect localisation accuracy. Combining IMU sensors may improve accuracy and robustness in those cases, as in some retrieved articles.

Simoes et al. [62] separated the localisation between macro and micro-locations. The first uses WiFi and calculates RSSI, but the inertial sensors and cameras determine a more precise position. Similarly, Niu et al. [63] uses WiFi fingerprinting to classify movements detected by the IMU and records their WiFi readings. By detecting these typical behaviours and assigning them to an RSSI

value in the radio map, the AtLAS algorithm [63] can then give a position based on the activity and WiFi signal.

KAILOS [64] is a hybrid positioning system that combines WiFi fingerprinting, Bluetooth and PDR positioning techniques to estimate location. It aims to be a straightforward mapping method, making it possible to use without Bluetooth or an IMU sensor. The opposite occurs in [65], where a map is used as an input and the user's location is determined using WiFi fingerprinting and PDR. The system uses landmarks with known positions, such as doors, turning and altitude landmarks, to assist in localisation.

An EKF is used in [66] for multimodal sensor fusion, combining augmented WiFi and IMU data. This article uses 2 different networks: CDAELoc to estimate global coordinates and DbDIO to estimate relative motion paths, which are then fused using an EKF.

3.4.1.4 Other sensors

Besides the already presented primary solutions, alternative sensor types were described in combination with IMUs to achieve more accurate localisation methods. These are subsequently presented and grouped by their characteristics, such as visual, active signal, or passive data collection sensors:

- **Optic sensors**

Sensors that primarily rely on capturing light or reflections to build a spatial understanding:

Visual capture systems contain devices that provide relevant visual information of motion and the environment in which the user is located. Based on the literature reviewed, studies that use cameras in combination with IMU often develop methods that employ visual odometry and SLAM algorithms [56, 62, 67]. One article describes a method that computes the motion of users, achieving collaborative localisation and mapping of multiple subjects to generate floor plans [67]. Mahmoud et al. [56] uses stereo vision to extract features that allow the camera's motion estimation. Stereo vision is also used in [62] to implement an obstacle detection algorithm and help provide a micro-location in the developed system. Similarly, Ogata, Tanaka, and Kourogi [68] uses cameras to identify visual markers combined with PDR to estimate a subject's walking trajectory.

Alternatively, Light Detection and Ranging (LiDAR) sensors [69] use laser light to create a 3D representation of a surveyed environment, which can be used in indoor localisation [70]. The distance between the sensor and an object is measured by the time it takes for a light pulse to travel towards an object and return. LiDAR sensors can be used in different dimensions, ranging from 1 [71] to 3 dimensions [56, 72], and also in combination with other methods like SLAM [56]. A 1D LiDAR is proposed to promote step size calibration in [71]. Mahmoud et al. [56] uses a 3D LiDAR in combination with the SLAM method. Wang et al. [72] fuses a 3D LiDAR with inertial sensor data to measure the 3D distance between the shank and the ground. Even though the added 3D representation can be helpful, its complexity is inadequate for the solution we want to create.

- **Active signal sensors**

Sensors that emit signals and measure their reflections or responses:

A millimetre-Wave (mmWave) radar is a sensor that emits frequency-modulated continuous wave chirps and measures the time-of-flight of the reflected signals. Dai et al. [73] uses the radar measurements and converts these into point clouds, representing the 3D space. The space is then saved in panoramic images, which are later processed to extract motion information and fuse with IMU data for localisation.

Likewise, ultrasound sensors use time-of-flight with high-frequency sound waves. In [74], a map point calculation algorithm combines the ultrasound data with trajectory information to construct the map model. PDR-SLAM is then used to integrate the walking trajectories and reconstructed maps seamlessly.

A radio map can be constructed using ZigBee sensors in indoor localisation. Al Mamun, Anaya, and Yuce [75] describes a localisation method in which ZigBee modules are used as APs with known locations, and the RSSI is analysed to create the radio map. The IMU provides heading information used to correct the RSSI values and improve the accuracy of the localisation estimates.

Yang et al. [76] uses auditory cues to correct the innate IMU drift. An estimated gazing drift can be calculated by providing binaural sounds from the location of an annotated object and measuring the user's gaze. This drift is then interpreted as the IMU drift in the heading during the recalibration phase of the method.

- **Passive data collection sensors**

Sensors that rely on environmental data, without emitting signals:

Different sensors can measure pressure and provide information about the user's heading and/or actual position. In [77], high-resolution plantar pressure insoles were used to recognise the walking mode, based on the different pressure points. After the recognition, a compensation value is applied to correct the real-time position provided by the IMU. In [78], the pressure is measured using a load-sensing floor, giving information about the centre of pressure (CoP) of the subject's foot. This information is fused with the CoP calculated using the Inverted Pendulum model with the IMU data.

Passive Infrared (PIR) sensors detect infrared radiation emitted by objects that generate heat. Pham, Yang, and Sheng [79] deployed 8 PIR sensors on the ceiling to cover the area of the experiment and retrieved a rough location estimate. IMU data is then fused with the PIR data using a particle filter, estimating a more accurate indoor position.

Lastly, a solar cell sensor that measures lighting conditions can close the loop when returning to a known location, allowing for IMU drift correction [80].

In summary, complementing IMUs with other sensors' data can be helpful to overcome challenges like sensor drift or lack of data. However, most sensors presented imply added costs and

sometimes specific infrastructure, which are not widely available. Therefore, the benefit of adding new sensors should be thoroughly assessed, considering factors like cost, added accuracy, precision and robustness.

3.4.2 Multiple IMUs

Multiple IMU systems have been developed and implemented in biomechanical studies to address the limitations of single IMU systems, improving accuracy and deepening the possible studies, like to infer subject kinematics. These range widely in number and sensor placement of the IMUs.

Since localisation is mainly connected with gait when using inertial sensors, lower limb sensor placements are often used to understand the gait mechanisms. Li, Zhou, and Li [81] presents a real-time human motion tracking approach that uses lower limbs' kinematics to improve tracking accuracy. If a foot is in contact with the ground, a zero-velocity state can be used as an estimation point for gait calculations. When no foot is in contact, the model uses acceleration integration on the pelvis to estimate the displacement. Also using lower limb kinematics and limb segment measurements, Tjhai and O'Keefe [82] developed a method that segments the gait stances and uses forward kinematics for step length estimation. Based on the pelvis-mounted IMU and Kalman filtering, heading orientation is then used to estimate position via PDR. Finally, Li et al. [83] proposed a 7-sensor configuration in the lower limbs for real-time motion capture. It uses a ZUPT-aided Extended Kalman Filter (EKF) data fusion method to fuse the 9-axis sensor data and a Heuristic Drift Reduction (HDR) method to calibrate the accumulated error of the heading angle.

Some approaches try using sensors positioned in different body segments. Song et al. [84] used deep learning and sensor fusion to improve pedestrian tracking accuracy. With 3 inertial sensors, located on the head, hand and thigh, a feature extraction process was carried out, using 2 different encoders. These features were then used in data fusion techniques: concatenation, primal weighted fusion and restrained weighted fusion (RWF). RWF was chosen, as it allows for dynamic assessment and adjustment of sensor relevance and reduces the absolute trajectory error. The framework DeepIT [85] aims to overcome motion noise by fusing data from a smartphone and smart earbuds. It uses Long Short-Term Memory (LSTM) models to estimate translations and angle increments on both the pocket and ear, applying angle drift compensation and reconstructing the complete trajectory.

Other inertial sensor placement options try to replicate the user's CoM to get more accurate representations of the whole body movement. Kawecki, Oleksy, and Januszkiewicz [86] used two IMU sensors located on an insole and in the chest area, each with a different impact on the localisation algorithm. The first measures the acceleration from the foot and classifies the step length based on that acceleration. The second is used to obtain the orientation using the magnetometer. The data is then used to get a hybrid localisation method, reducing the maximum error of total displacement by 60%. Using waist-mounted gyroscopes, Nasr and Nadeem [87] proposed a system that detects opposite-direction hip rotations during stance and swing phases of walking, avoiding the requirements of a fixed magnitude threshold for mid-swing points. The inverted pendulum model was combined with Weinberg's method for step length calibration.

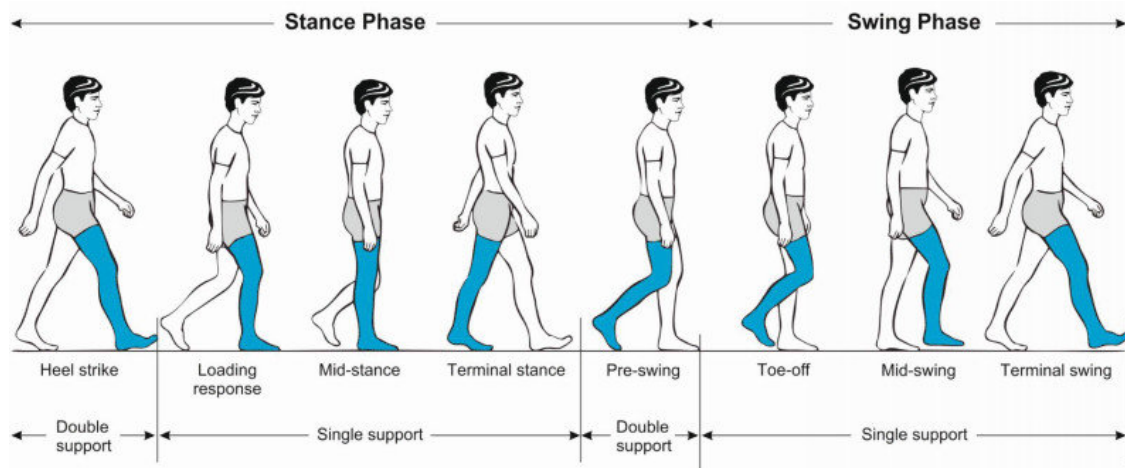


Figure 3.6: Representation of the gait cycle [91]

3.4.3 Single IMUs

Localisation using a single IMU is a current research topic that has benefits and challenges. Since there is only one sensor, the costs are reduced and the implementation is more straightforward. However, the accumulated drift and difficulty in representing the whole body make it a challenging application. Recently, several methods have been developed and are presented in this section regarding the position of the sensor on the human body.

Foot: Positioning the IMU sensor on the foot allows the use of the ZUPT, which states that, during the stance phase, the velocity is approximately zero when the foot is in complete contact with the floor. Figure 3.6 represents the different segments of the gait cycle, including the swing and stance phase, and the initial contact (or heel strike) and toe-off moments. The ZUPT method is used in recent systems [88–90], since it can be used as a corrector for the drift. Similarly, the Zero Angular Rate Update (ZARU) is used during the stance phase, in which the angular rate is approximately zero [88].

Kalman Filter is an algorithm developed for optimal state estimation, which can be used for error correction and sensor fusion. It can be of different types, but it is primarily used for the correction of drift errors [88, 90, 92] and map-matching [89].

Other methods like trapezoidal integration [93], map building [92] and "multiple hypothesis testing" [89] help correct the drift of the sensor and improve the pedestrian navigation system.

Ankle: Zhao et al. [94] uses an adaptive stride length model and a multiplicative EKF to estimate the step length and heading angle, respectively. It also encompasses a Complementary Filtering and Target Error Compensation for vertical height estimation, which assists PDR in the user's positioning.

Head: Hou and Bergmann [95] uses a head-mounted IMU sensor to improve accuracy during tracking times. It combines PDR with SLAM to estimate heading direction and step length, while simultaneously generating a map. Repeated trajectories allow recalibration and update the probabilistic map.

Handheld: Handheld devices can be troublesome to get an accurate user localisation, but are similar to a real-world scenario. Fu et al. [96] analyses different AI algorithms in pedestrian navigation: SELDA (Pedestrian Stride-Length Estimation Based on LSTM and Denoising Autoencoders), for step length estimation and RoNIN (Robust Neural Inertial Navigation) for positioning. When compared with non-AI algorithms, they performed better in various environments.

Pocket: Being a daily position of common devices like smartphones, Fu et al. [97] studied the effect of outfit differences on localisation accuracy. Thus, a PDR framework with Support Vector Regression (SVR) was used as the localisation method, showing that tight outfits led to more accurate and consistent results, while loose outfits introduced variability. Good performance was achieved for similar outfit types (RMSE 3–7 m).

Waist: Waist-mounted IMU sensors can propose an interesting approach to single IMU localisation since they provide better data from the user's CoM.

Several studies use the waist as a position for single IMU [98–100]. KF is shared in the 3 articles, complementing it with other methods on their systems. Xiong et al. [98] used Reference Azimuth Angle to estimate and correct the heading gyro bias. Hajati and Rezaeizadeh [99] and Do et al. [100] have an extra classification algorithm, a random forest for user identification and a median filter for motion mode detection, respectively.

3.5 Summary of the Systematic Review

This systematic review aimed to understand the methods currently used for localisation with IMUs and other complementary sensors. A total of 53 articles compose the set of records, describing systems that use single or multiple IMUs to determine location, often in combination with other sensors such as UWB, GNSS, and WiFi. This set generally shows what is currently being implemented in localisation solutions, but some gaps exist in the articles presented.

According to the set of records, only one implemented solution uses a single IMU at the chest and none at the back of the user. However, we know that it is inaccurate since several articles use this IMU positioning on the body. This can be due to either the search query or the exclusion criteria. Regarding the search query, the keywords "outdoor" and "indoor" were used to narrow the number of articles from 3849 to the final 399. We noticed that these keywords focused the query on articles that specified these types of localisation and avoided using the word "localisation" in the position of sensors. This led to the articles presented being more accurately related to the topic. Still, it could have discarded potentially relevant articles for this review, namely those with a single IMU sensor near the CoM. Despite the lack of articles with a closer setup to our solution, the results are still valuable in understanding the benefits and disadvantages of using single IMUs for localisation.

In the results section, we divided the articles into three different types, according to the use of the IMU sensors. In table 3.7, we briefly summarise all the articles included in this review and their sensor types. The type given to each article was "Other" if the IMU is used in combination with other types of sensors, "Multiple" if there was more than one IMU sensor, or "Single" if a

single IMU is used in the proposed solution. Regarding the results, different studies are measuring accuracy in various ways, which complicates the analysis of different methods. In fact, localisation is generally measured with errors of distance, especially total distance, but the values are presented in different scales and rarely in percentages. Additionally, errors of the position during the movement are rarely present, making it difficult to infer about the similarity of the trajectory achieved.

The combination of IMUs with other types of sensors aimed to bypass the natural drift of inertial sensors. UWB was the most common sensor in indoor settings, and GNSS outdoors, being both generally available and reliable. As shown in Table 3.4, using other sensors to complement the IMUs can reduce estimation errors in total distance and provide other information. However, compared with table 3.6, we can see that the improvements in the errors are not enough to justify the use of other sensors in our project.

Table 3.4: Best performing fusion systems

Study #	Best Result	Distance	Method Highlights
[78]	5 cm RMSE	10–30 m	Smart floor + smartwatch IMU
[54]	0.24 m RMSE	10–73 m	UWB+IMU foot fusion
[50]	30 cm RMSE	50–130 m	Robust ranging-IMU SLAM (asymmetric noise modelling)
[65]	0.94 m mean error	190 m	RSSI + IMU fusion with KD-tree

Since our solution's objective is to retrieve students' localisation during classes, the total distance can amount to thousands of meters at the end of a class period. With that in mind, even some meters of error will not be significant, so using other sensors introduces synchronisation issues, higher costs and harder to manage connections. Hence, these are not optimal for our solution.

The articles that describe multiple inertial sensors were analysed, achieving good results in accuracy. Sensor fusion techniques were commonly applied, such as KF and lower-limb movement tracking. Table 3.5 shows the best results using multiple IMU sensors, which performed even better than some systems that used other types of sensors. This proves that IMU sensors are sufficient to achieve good results in localisation.

Table 3.5: Best Multiple IMU systems

Study #	Best Result	Distance	Method Highlights
[72]	Step length RMSE ~ 2.25 cm	5–220 m	Shank-mounted LiDAR-IMU gait analysis
[77]	0.05 mm std deviation	13.6 m	Pressure insoles + IMU

Finally, while cost-effective and easier to implement, single IMU sensor methods had more challenges in overcoming innate drift, leading to a diversity of methods applied. The most common placements of the single inertial sensors were the foot, which used ZUPT to reduce drift, and the waist, which was closer to the CoM. Table 3.6 presents the best results using only a single IMU sensor. It is worth mentioning that the distance measured in these methods is largely greater than

in previous systems, with a similar error. This proves that achieving localisation using a single IMU during an extended period is possible.

Table 3.6: Best single IMU systems

Study #	Best Result	Distance	Method Highlights
[98]	0.39% distance error (after 1.3 km)	~1270 m per trial	Online gyro bias calibration
[99]	0.45–0.96% distance error	190–4700 m	Waist-worn PDR + Random Forest gait recognition
[94]	1–2% horizontal error + 1.5 cm height	40–90 m	Ankle IMU with 3D stride model
[95]	0.34 m RMSE	~10 min paths	HeadSLAM using only head-mounted IMU

In summary, no article described a similar sensor approach to our solution: a single IMU sensor close to the centre of mass (CoM) (T8), which may be due to the research query and/or the exclusion criteria. Despite that, the set of records presents several approaches which can be helpful in our solution. The multiple and single IMU approaches sustain the fact that acquiring accurate positioning without external sensors is possible. Approaches like KF and Particle Filtering are methods worth considering.

Our solution presents an intriguing approach for localisation, due to the novelty of sensor positioning, single IMU usage and localisation methods.

Table 3.7: Summary of Indoor Localisation Studies

Article	Main Method	Accuracy Measure	Value	Distance	Notes	Sensors Type
[84]	Multi-node fusion IMU	ATE	~1.28 m	326 m	Multi-sensor LSTM fusion	Multiple
[81]	Multi-model human motion tracking	Positional errors	<5%	Room-scale	Multiple IMUs on body parts	Multiple
[87]	Waist-mounted gyroscopes	Stride length error	~3%	7 m per trial	Two gyroscopes, simple setup	Multiple
[86]	T-shirt + shoe sensors	Max error	2.0 m	19-20 m	Adaptive step length + direction	Multiple
[82]	Lower-limb kinematics	relative error	0.74%	36 m	Step-based INS-like modeling	Multiple
[83]	Real-time IMU motion capture	Mean error	<15 cm	15-30 m loops	ZUPT-aided EKF	Multiple
[85]	DeepIT fusion (earbud + phone IMUs)	MTE	15.8 m	18,000 m ² areas	Robust to motion noise	Multiple
[76]	Ear-AR spatial audio + IMU	Drift	~5 m	Up to 180 m	Object identification + AR	Other
[67]	Collaborative visual-inertial + floorplan	Sub-meter accuracy	-	15-30 m loops	Visual loop closures	Other
[68]	THINKLET marker + IMU	Accurate trajectory matching	-	22 x 8 m room	Marker-PDR fusion	Other
[61]	LIGHT-PDR GNSS fusion	Error	7.43 / 33.64 m	419 / 1545 m	Machine learning-aided GNSS fusion	Other
[58]	Foot-mounted GNSS-INS	Horizontal error	1-10 cm	~50 m	GNSS cycle slip filtering	Other
[60]	CNN speed + GNSS fusion	RMSE	~13.5 m	100-200 m	EKF fusion improves drift	Other
[59]	MFF mode-finding filter	RMSE	0.776 m	3.75-4 km	Simulation-based only	Other
[71]	Interactive helmet-based IMU+LiDAR	Error	~1-1.5 m	20-30 m	First responders, AR	Other
[72]	Shank-mounted LiDAR-IMU	Step length RMSE	~2.25 cm	5-220 m	3D gait and trajectory	Other
[73]	mmWave radar + IMU fusion	Visual drift	~<1 m	20-30 m	First responder use	Other
[79]	PIR + IMU sensor fusion	Mean Error	0.125-0.137 m	35-45 m	Home privacy-preserving tracking	Other
[77]	Pressure insoles + IMU	STD Dev	0.05 mm	13.6 m	Step segmentation improvement	Other
[78]	Floor tile + smartwatch + IMU	RMSE	5 cm	10-30 m	Multi-user tracking enabled	Other
[80]	SolarSLAM light-based loop closure	RMSE	1.24; 1.86 m	250;380 m	Battery-free solar sensor fusion	Other

Table 3.7: Summary of Indoor Localisation Studies (continued)

Article	Main Method	Accuracy Measure	Value	Distance	Notes	Sensor Type
[74]	PDR-SLAM (UWB + IMU)	Error visually	$\sim < 1$ m	10 m	Firefighter navigation	Other
[55]	UWB + RTK GNSS cloud IoT	Error	10 cm - 2 m	20-minute walk	Worker monitoring	Other
[54]	Foot-mounted UWB+IMU fusion	RMSE	0.24-0.27 m	10-73 m	ILCKF NLOS rejection	Other
[44]	IMU-aided UWB NLOS compensation	RMSE	5-11 cm	10-20 m	Robust to occlusions	Other
[46]	Low-cost UWB-IMU fusion	Dynamic error	5-7 cm	25 m	Gait tracking possible	Other
[47]	UWB + PDR industrial tracking	Error	0.08-0.26 m	~ 10 m per path	EKF fusion tested	Other
[49]	Adaptive human tracking (warehouse)	Mean error	0.22-0.49 m	50-100 m	Step length calibration included	Other
[56]	Multi-sensor wearable fusion	RMSE	0.82 m	> 200 m	UWB + IMU + Stereo vision	Other
[51]	Collaborative FGO pedestrian SLAM	Error improvement	37-65%	150 x 75 m garage	Activity-aided constraints	Other
[53]	Relative UWB-IMU positioning	Mean error	31 cm	~ 10 m	Loosely-coupled wearable positioning	Other
[50]	D-iSAM2 UWB-IMU robust SLAM	Average error	30 cm	50-130 m	1Hz UWB tolerance	Other
[52]	Team sport UWB-IMU D-TDoA	Static/Dynamic Error	20-55 cm	8 m loops	Athlete wearable system	Other
[48]	UWB step-based stride calibration	Bias	2.5 cm	8 x 22 m	Per-stride calibration	Other
[45]	Quadrant-based IMU-UWB	Quadrant Accuracy	100%	500-700 m total	Emergency responder use	Other
[62]	LWPL + i-PDR + Wi-Fi	Average error	~ 0.4 m	10-50 m	Hybrid learning and PDR	Other
[64]	IoT-based KAIST Wi-Fi	Average error	2.4 m	50-100 m	Platform independent	Other
[63]	Activity-based indoor localisation	Median user error	0.57 m	Full apartments	Object labeling 93%	Other
[66]	WIO-EKF Wi-Fi + IMU fusion	APE	2.53 m	25-50 m	EKF + deep learning	Other
[65]	Map-aided PDR + RSSI	Mean error	0.94 m	190 m	KD-tree matching	Other
[75]	FaStER radio map creation	Best in category	-	40 m	Body effect compensation	Other
[98]	Online heading gyro calibration	Distance error	0.39%	~ 1270 m per trial	Pure IMU	Single
[88]	Hybrid ZUPT + AFM navigation	TTDE	$< 1.3\%$	13 km total	Indoor and outdoor	Single

Table 3.7: Summary of Indoor Localisation Studies (continued)

Article	Main Method	Accuracy Measure	Value	Distance	Notes	Sensor Type
[99]	Waist PDR + gait ID	Error	0.45-0.96%	190/4700 m	Random forest stride personalization	Single
[94]	Single ankle sensor 3D tracking	Horizontal error	1-2%	40-90 m	Vertical error ~ 1.5 cm	Single
[96]	AI-PDR gait vs. sampling	SELDA RMSE	~ 8 m	2.17 km	AI vs. classical comparison	Single
[100]	Waist IMU wireless displacement	Long path error	1.43%	14-114 m	Step resets + lift riding	Single
[93]	Foot IMU event-based correction	Qualitative gait match	-	~ 900 -1500 m	Continuous outdoor walking	Single
[92]	Heading correction + map matching	Final error	< 1 m	65.8 m	Building constraint map	Single
[95]	Head-mounted IMU SLAM	RMSE	0.34 m	~ 10 min paths	SLAM-based loop closures	Single
[97]	Outfit impact PDR AI (tight vs loose)	RMSE tight/loose	3-7 m	200-400 m	Clothing strongly affects results	Single
[89]	MHT map-matched INS	Error	< 1 m	500 m	No external infrastructure	Single
[90]	3D PDR/INS + barometer fusion	3D error	~ 1.2 -1.3 m	59 m	Stairs and 3D updates	Single

Chapter 4

Materials and methods

This chapter provides insight into the project’s workflow, including several algorithms and datasets used. Firstly, the datasets are described, explaining the reason for each of them why each was selected. Figure 4.3 represents the general system, starting with the acquisition of data and then developing the solutions for both online and offline metrics. Finally, it delineates the different evaluation metrics.

4.1 Datasets

Two datasets were used in the development of this thesis. The first one, NONAN GaitPrint [101], was used to evaluate the step detection and step length algorithms, since it provides a ground truth on the steps. The second, Brantley [102], was used for the trajectory estimation, due to the presence of magnetometer and raw gyroscope data. In both, the data from the T8 IMU sensor was used.

4.1.1 NONAN GaitPrint

The NONAN GaitPrint dataset consists of a set of inertial data, focusing on gait patterns, across an indoor looping track. It provides whole-body kinematics from the Noraxon Ultium Motion [103], including spatio-temporal foot placement variables. The data was collected from 35 healthy individuals (ages 19-35) across two separate sessions.

The trials were conducted on a 200-meter indoor looping track at a self-selected pace, as show in figure 4.1. Each participant performed 18 four-minute trials. The dataset includes acceleration, angular velocity, position, and orientation for each sensor, sampled at 200 Hz, and exported from the Noraxon MyoResearch 3.18.126 software [104]. It also contains a ground truth of the gait patterns, including the different classifications of step length, swing and stance phases, and times of steps.

Having been exported from this software, the presented data had already undergone some pre-processing on the signal. Since the raw accelerometer was provided, the algorithms for step detection and step length could be applied with no constraints. However, the gyroscope data provided



Figure 4.1: NONAN dataset course: Photography (a) and Diagram (b) [101]

had been previously filtered by the software. This filtering process, embedded in the program and unavailable to us, could not be reversed, making the data not suited for the desired heading estimation algorithms. With that in mind, the dataset was used to validate the step detection and step length algorithms, using the ground truth of the steps. To explore the heading estimation algorithms, a new dataset with raw data of the accelerometer and gyroscope was procured.

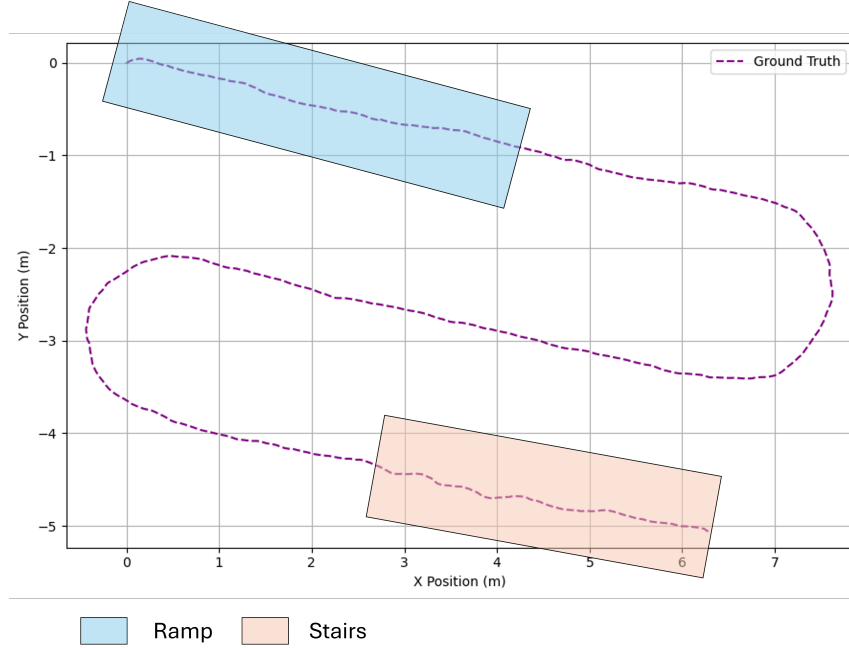
4.1.2 Brantley

This dataset consists of multimodal recordings of full-body human locomotion across different walking modalities. It includes electroencephalography (EEG), electromyography (EMG), and IMUs data. For our purposes, we only used the inertial data.

The trial course consisted of a ramp, level ground walking, and stairs, like we can see in figure 4.2. The participant starts on top of the ramp, descends it, makes a 180° turn, walks across a level ground linear path, does another turn and climbs the stairs. Each recording contains two trials ran sequentially. A trial is composed of 2 runs, starting one from the ramp and the next from the stairs.



(a) Photography of the course



(b) Diagram of the course

Figure 4.2: Brantley dataset course: Photography (a) and Diagram (b) [102]

4.1.2.1 Dataset segmentation

In the unprocessed data, there is no event marker to distinguish between the four runs that compose the trial, so the first step was to segment the data.

Every recording begins from a resting position at the start of the course. The first step was to analyse each recording and remove the initial samples from the motionless stage before segmentation. To segment the data, the *raw_orientation_y* was used, since its value will approximate zero when a full 180° turn occurs.

Two different segmentations were done: runs (RS) and level ground walking (LGW). The first corresponds to the samples between every three turns; the second, to the samples between the first and second turns of each run. From the LGW sections, a safety buffer of 100 samples from the start and end was removed to eliminate potential remaining segments from the turn phases. The results of the segmentation can be seen in section 5.3.

After segmentation, the raw accelerometer, gyroscope and magnetometer data were used to test heading correction and trajectory estimation algorithms, using the previously developed step detection and step length algorithms.

4.1.3 Technical specifications

The datasets varied in the number of sensors and resolution between them and when comparing with the SV4PE solution. Tables ??, ??, and ?? include the sensor specifications of NONAN GaitPrint dataset, Brantley’s dataset and SV4PE, respectively.

Specification	IMU (ACC)	IMU (GYR)
Number of channels	3	3
Resolution	16 bit	16 bit
Input full-scale	± 200 G	± 7000 dps
Sample rate	200 Hz	200 Hz

Table 4.1: NONAN dataset’s sensor specification for accelerometer and gyroscope

Sensor	EEG	EMG	IMU (ACC)	IMU (GYR)	IMU (MAG)
Number of sensors/channels	60 EEG + 4 EOG	12 channels (6 per leg)	3 channels	3 channels	3 channels
Resolution	16 bit	16 bit	16 bit	16 bit	16 bit
Input full-scale	$\pm 1000 \mu V$	± 1.5 mV	± 16 G	± 2000 dps	$\pm 800 \mu T$
Sample rate	1000 Hz	1000 Hz	30 or 60 Hz	30 or 60 Hz	30 or 60 Hz

Table 4.2: Brantley dataset’s sensor specification for EEG, EMG, accelerometer, gyroscope, and magnetometer

Sensor	ECG	ACC	GYR
Number of channels	1	3	3
Resolution	16 bit	16 bit	16 bit
Input full-scale	± 2.5 mV	± 8 G	± 500 dps
Sample rate	1000 Hz	1000 Hz	1000 Hz

Table 4.3: SV4PE sensor specification for ECG, accelerometer, and gyroscope

4.2 Developed metrics

One of the objectives of the SV4PE solution is to provide metrics related to the movement and position of the students, both in online and offline phases. Figure 4.3 represents the different methods used for these metrics, which will be later discussed. Due to the unavailability of a ready prototype, the different methods were tested using the previously presented datasets, and only a final proof of concept test on data acquired on the vest was done.

4.2.1 Live metrics

The project aims to have a real-time analysis and display of data during PE classes, namely velocity of movement and intensity of effort. With this information, the educator can understand in real-time how the students are performing, and make suggestions to the training. In this work, we focused on extracting a velocity estimate to be presented in real-time.

The SV4PE acquires inertial data from an IMU with accelerometer and gyroscope, and ECG data, which are concatenated in packets of data. The data is received at set intervals of two seconds, and our algorithm calculates the steps and estimates the velocity.

The raw acceleration is received and a low-pass filter of 10 Hz cut-off frequency is applied to the samples. The algorithm proceeds to apply a gravity removal function and moves on to the step detection function, analysing the gait cycle.

The gait cycle, as shown in figure 3.6, is the sequence of motions between two consecutive initial contacts (ICs) of the same foot, having a stance and swing phase. In the stance phase, the foot remains in contact with the ground, and during the swing phase, the foot moves forward in preparation for the next step. Step detection aims to detect the IC, when the heel strikes on the ground, and sometimes the toe-off (TO), when the swing phase starts. This detection is made mostly using the vertical acceleration, since it is the most impacted axis at the IC.

Step detection is the first step of PDR and can be done using many methods, like peak detection on the magnitude of the acceleration, application of a wavelet transform (WT), or even machine learning approaches. While algorithms using machine learning or WT could potentially give more information on the gait cycle, the chosen method for the step detection was a peak detection using the magnitude of the accelerometer data, since the objective is to apply it in real-time.

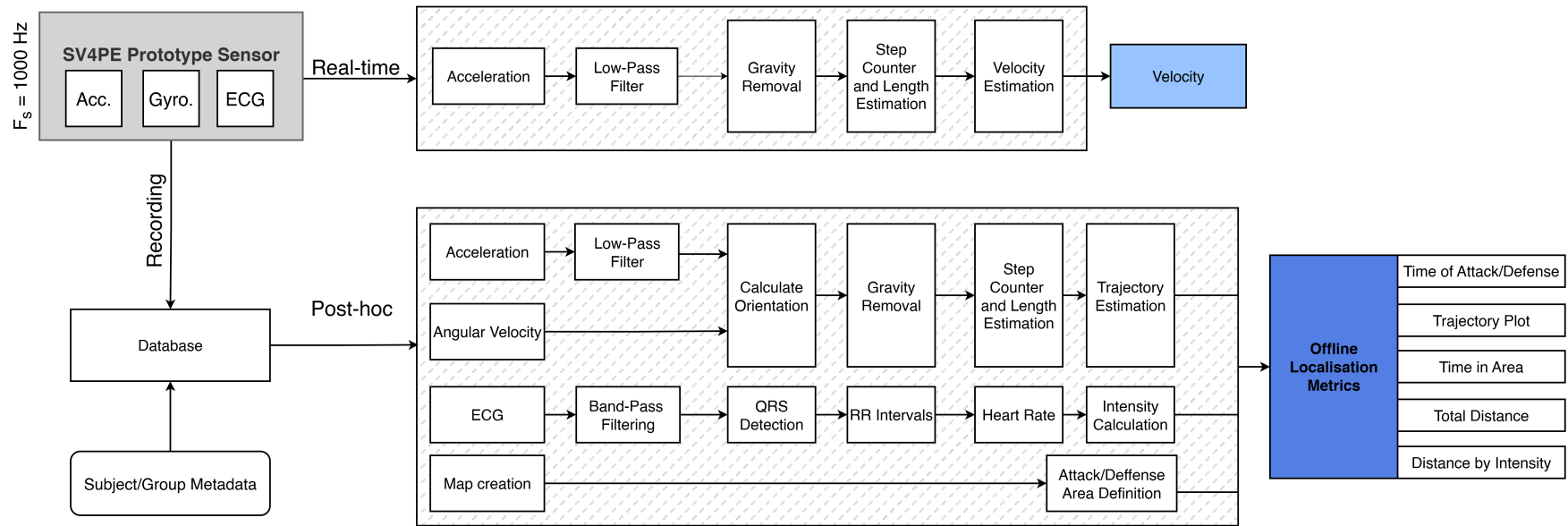


Figure 4.3: Fluxogram of the developed methods

Table 4.4: Cadence correspondence according to the calculated velocity

Velocity (m/s)	Cadence
0	"Stopped"
< 0.8	"Low"
0.8 ≤ v < 2	"Average"
≥ 2	"High"

Magnitude of acceleration data is a scalar value that represents the overall acceleration vector, calculated by the equation:

$$a_{mag} = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (4.1)$$

By detecting the peaks in the magnitude of acceleration, we can determine the IC moments, as seen in figure 3.6. The detected times correspond to the beginning of the step, and the next peak the end of the step. The step detection was applied at 250 sample windows, using a threshold of 80% of the maximum value of magnitude in the package. This threshold was defined iteratively, considering the accelerometers' noise and evaluated in training sessions with the SV4PE.

Next, the step length was calculated. Normally, the step length algorithm aims to be adaptive to the gait pattern or the characteristics of the person. In this case, we used a step length calculation based on the sex and height of the person, based on the equation 4.2:

$$step_length = \frac{0.41 * height}{100}(male); \quad step_length = \frac{0.415 * height}{100}(female) \quad (4.2)$$

Having both the number of steps and step length, a rough velocity is calculated using the equation 4.3:

$$velocity = \frac{(Total_steps * step_length)}{Total_duration} \quad (4.3)$$

A cadence value was then assigned to the package, depending on the velocity calculated. Table 4.4 contains the different values assigned for the cadence. The values were chosen using approximations of the normal speed of walking, jogging, and running speeds for an adult.

The values of cadence were then used to calculate the effort level in combination with the ECG data.

4.2.2 Offline metrics

After the PE classes, the data is stored in a database and used for calculating offline metrics. By calculating the trajectory of the student during the class, several metrics can be calculated, like distance travelled or attack and defence strategies. Similarly to the live metrics, the accelerometer and gyroscope data were used to produce a PDR trajectory estimation.

The accelerometer data is first filtered to remove noise, using a Low-Pass Butterworth filter of 4th order with cut-off frequency of 5 Hz, similar to ones found in the literature [105]. This data was used in combination with the angular velocity from the gyroscope to estimate the heading, using both Mahony [106] and Madgwick's filters [107].

Attitude and Heading Reference Systems (AHRS) are systems that provide 3D orientation of an object, specifically the attitude (Roll and Pitch) and the heading (Yaw). The AHRS toolbox [108] is an open source Python toolbox that contains several algorithms, including Mahony and Madgwick's, and so was used in this work.

Mahony filter is an AHRS algorithm that uses data from IMU sensors (accelerometer, gyroscope and magnetometer) to estimate the orientation of an object. It works by using the accelerometer and magnetometer data as references for heading correction (gravity and magnetic north, respectively). It is a computationally lightweight solution that can be applied in real-time orientation estimation.

Madgwick filter is a sensor fusion algorithm used in AHRS to combine data from the IMU sensors. It uses a gradient descent algorithm to minimize the error from the estimate to the sensor measurements. The gyroscope provides the angular rate information, which is corrected using the references of the accelerometer and magnetometer. This algorithm is more accurate than Mahony in many scenarios and is robust to noisy sensor data.

To estimate the orientation, both the Mahony and Madgwick filters were used, and later compared to understand which presented better results in this scenario. Having the heading estimate, the gravity was removed from the accelerometer data before the PDR algorithms.

Step detection was performed using a Continuous Wavelet Transform (CWT). A CWT is a signal processing technique that breaks a signal into wavelets that preserve the time and frequency of the original signal. A CWT coefficient is calculated at each time and scale, revealing how well the signal matches the wavelet at the specific point.

As shown in figure 4.4, when applied to the vertical acceleration, the CWT can help determine the moments of IC of gait cycles. If the CWT is applied to the first output signal, the resulting peaks represent the TO of the gait. This was applied in a lower-back IMU in [109], serving as a reference for the developed method.

Previous work was developed by the research group, to determine the best order, type of wavelet and scales to be applied. The chosen values for this work were a 10th order CWT with *gaus1* wavelet shape. The dynamic threshold was set to 0.55 of the signals' amplitude, for the peak detection. This value was decided empirically, based on previous work and testing configurations.

Step Length estimation was performed using Weinberg's equation [110]. It linearizes the relationship between acceleration amplitude and step length, by the following equation:

$$L = k * \sqrt[4]{A_{peak} - A_{min}} \quad (4.4)$$

where L is the estimated step length, k is an empirical scaling factor, and A_{peak} and A_{min} represent, respectively, the minimum and maximum values of acceleration during a step. The

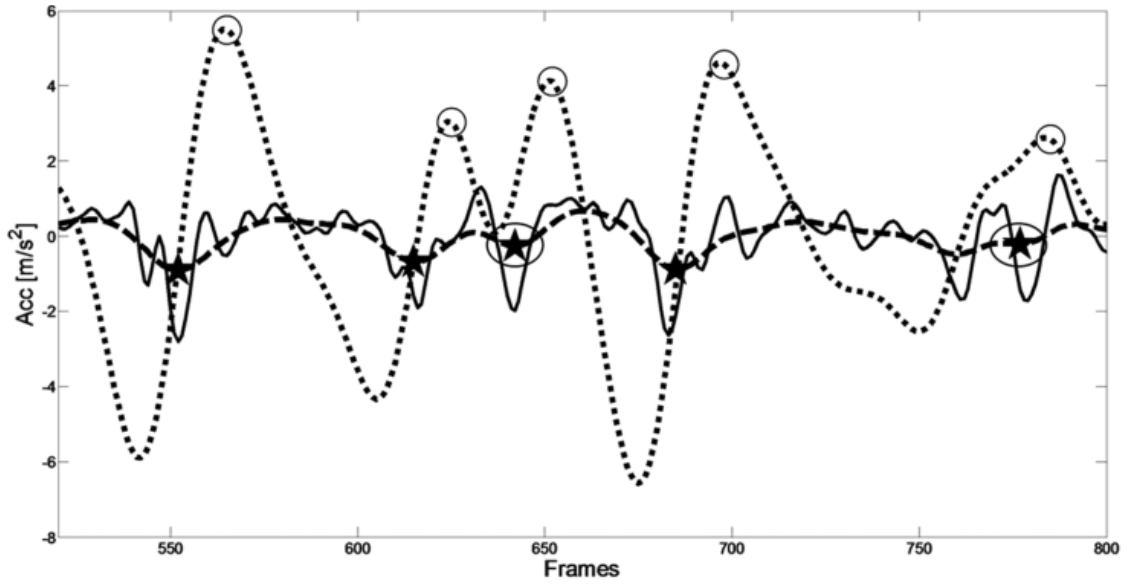


Figure 4.4: CWT applied to the vertical acceleration, showing IC and TO [109]

value k is a user-specific constant that depends on individual gait characteristics, such as leg length, walking speed, footwear and walking surface. This value can be calibrated using the following equation:

$$k = \frac{L_{\text{true}}}{\sqrt{a_{\text{max}} - a_{\text{min}}}} \quad (4.5)$$

Finally, the trajectory is estimated using the previously calculated steps and heading.

Intensity values were previously computed from ECG recordings, via calculated heart rates and a ratio dependent on the subject's age. The map creation uses the input of the type of sport (i.e. football, running) and the field dimensions. This map defines the areas of game, in order to be used in the definition of attack or defence action.

Attack was defined as the movement towards the adversary area, with a buffer of x degrees on the heading estimate. Using football as an example, if a player from the left side field would have a heading of -45° to 45° , considering a buffer of 45° , that step would be considered an attack action. On the contrary, a heading of 135° to 205° would be considered a defence action. These angle values were arbitrarily chosen to consider various values of heading as possibilities for each action.

Having the trajectory, intensity, field and actions calculated, the desired metrics can be calculated.

4.2.2.1 Desired metrics

- **Total Distance**

Using the points of the trajectory, the total distance can be defined as the sum of the displacement at each point, as shown in equation 4.6. This provides a general knowledge of

the student's movement across the entire class period.

$$TotalDistance = \sum_{i=1}^{N-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \quad (4.6)$$

- **Distance by intensity**

Similarly, the distance is calculated at each step and the sum of the distances in each intensity category is given. This allows to understand how intense was the training of the student during the class.

- **Trajectory Plot**

The trajectory plot allows the teacher to see the field and play areas, as well as the movement of the student across the field. It can also have the information of the attack and defence actions plotted with a different colour.

- **Time in Area**

By combining step timestamps with location data, it is possible to determine how much time a student spends in each specific area. This metric can help reveal whether a player adopted a more offensive or defensive role during the class or game.

- **Time of Action**

Similarly to the previous metric, we can calculate the time that each student spent defending and attacking, based on the heading of the student at a given moment.

4.3 Evaluation metrics

Several evaluation metrics were used, as it can be shown next:

- **Accuracy:**

Evaluates the performance of classification models, by measuring the proportion of correct predictions out of all predictions, as shown in equation:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (4.7)$$

- **Mean Absolute Error (MAE):**

Measures the average absolute difference between predicted and actual values, using the equation:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4.8)$$

where y_i is the true value, $\hat{y}_i$ is the predicted value, and n is the number of observations.

During the rest of this thesis, several errors will be calculated using the MAE, having different names to ease the comprehension

- **Standard Deviation (STD)** Measures the amount of variation or dispersion, using the formula:

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (4.9)$$

where s is the sample standard deviation, x_i represents each data point, $\bar{x}$ is the sample mean, and n is the number of data points.

- **Coefficient of Variation (CV):**

Measures relative variability by expressing the standard deviation as a proportion of the mean. It is defined as:

$$CV = \frac{\sigma}{\mu} \quad (4.10)$$

and often presented as a percentage:

$$CV(\%) = \left(\frac{\sigma}{\mu} \right) \times 100 \quad (4.11)$$

where σ is the standard deviation and μ is the mean.

Chapter 5

Results

This section contains the results obtained during the development of this work. Firstly, section 5.2 focuses on the development of step detection and step length estimation algorithms, and their validation. Section 5.3 outlines the progressive steps taken to improve the localisation methods, and section 5.4 presents the numerical data from these methods. Finally, section 5.6 demonstrates possible outputs of the desired offline metrics.

5.1 Live metrics

As explained in section 4.2.1, the project aims to deploy live metrics during PE classes, which are currently in testing.

The step detection and step length estimation were done by detecting peaks in the magnitude of the acceleration and by applying equations 4.2, respectively. The velocity is then calculated using equation 4.3 and the values are displayed in a monitor, as can be seen in figure 5.1.

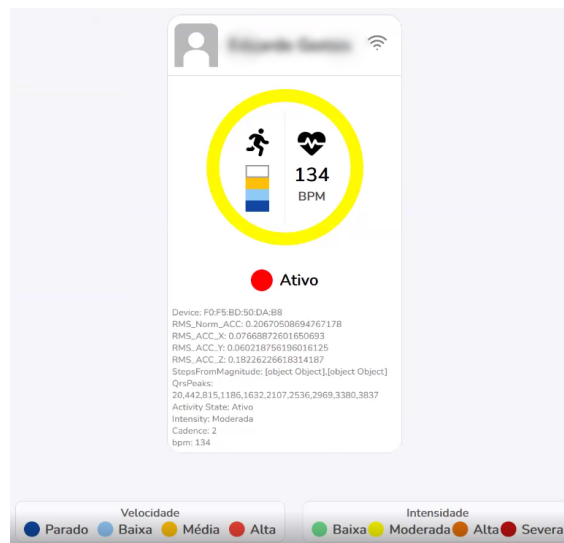


Figure 5.1: Live metrics of the student, including velocity, intensity of effort, and heart rate

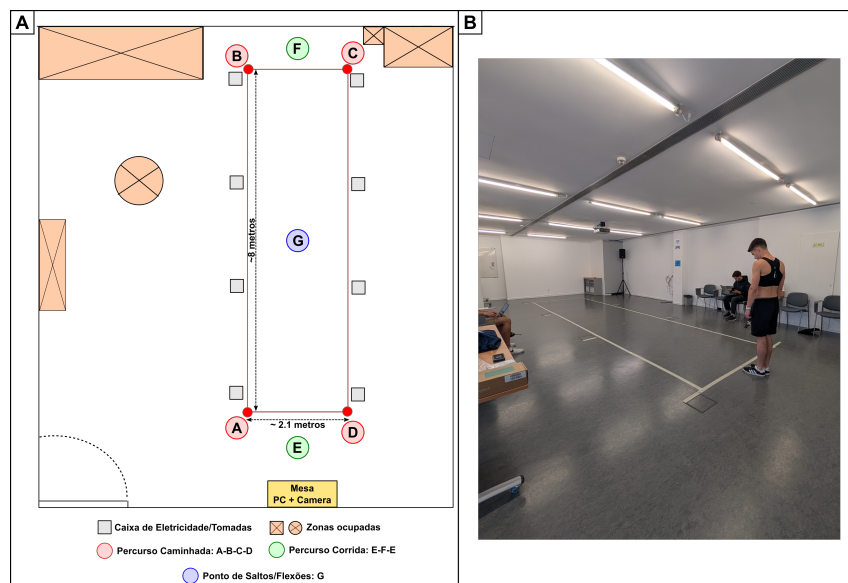


Figure 5.2: SV4PE prototype test recording course: diagram (A) and photography (B)

Currently, pilot tests are being developed to evaluate the accuracy of live metrics. One of the test recordings is shown in figure 5.2, with a schematic representation of the ground truth trajectory. Three different velocities were tested in the rectangular path: walking clockwise (Cx), jogging (Jx), and walking anti-clockwise (CIx). Each velocity was tested three times.

As an example, the velocities of the recording C1 were calculated post-session, and the results are presented in table 5.1. The mean velocity was 0.42 m/s, representing a low velocity in the four possible estimates.

5.2 NONAN Gait

The NONAN Gait dataset provides a ground truth on steps' characteristics. Since the major challenge resides in the heading estimation, this dataset was used to create reliable step detection and step length estimation, diminishing the possible future errors in localisation.

Table 5.1: Cadence outputs of the live metrics algorithm, when applied to recording 'C1'

Cadence	Occurences
"Stopped"	2
"Low"	21
"Average"	0
"High"	0

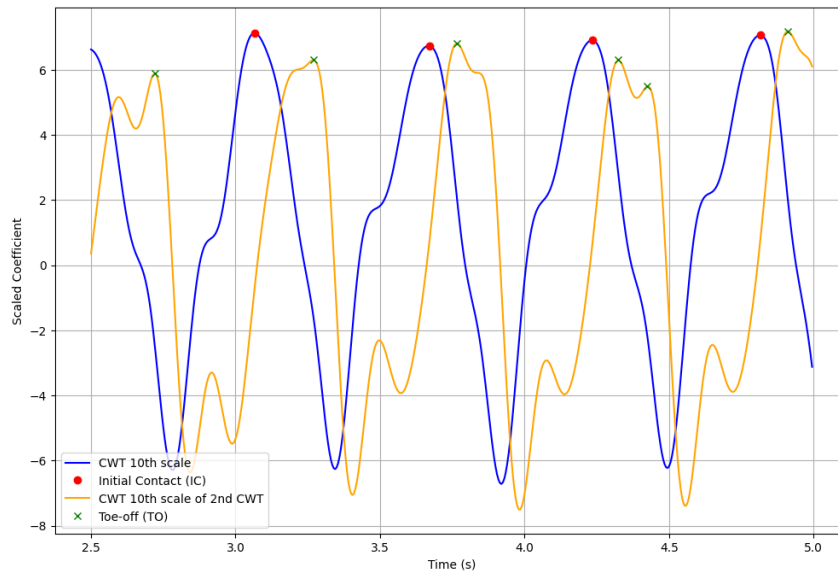


Figure 5.3: Step detection using CWT

5.2.1 Step Detection

The three separate algorithms, based on peak detection of vertical acceleration, magnitude and CWT, produced the following results. CWT, as explained in chapter 4, is used to detect initial contact and toe-off moments, providing information on key gait events such as heel-strike and toe-off. These events mark the beginning and end of the stance phase, with a subsequent heel-strike indicating the completion of one step and the start of a new gait cycle.

Table 5.2: Mean Step Count Error (MSCE) for the three step detection algorithms

Method	MSCE (m)	MSCE (%)
Vertical acceleration	3.50	0.83
Magnitude	3.89	0.92
CWT	4.50	1.07

All three methods were tested on the dataset, with the results presented in Table 5.2. The recordings consist of data from a small circuit (approximately 185 meters), with a reduced number of steps, all yielding similar results, of approximately 1% of error in the detection of steps, when compared with the ground truth. The chosen method was the CWT, since it accounts for less controlled settings and different environments, and, most importantly, gives more valuable information on gait events. Figure 5.3 represents the detection made by the CWT.

Step length estimation was performed using Weinberg's algorithm, and the results were compared with the ground truth of the dataset. The factor k was adapted arbitrarily for this dataset, having a value of 0.5. Table 5.3 contains the errors of the step length across the different algorithms. The error in step length had mean values of around 2 centimetres, and the total distance of

walking estimated had errors similar to the literature [94].

Table 5.3: Mean Step Length Error (MSLE) and Total Distance Error (TDE) for each step detection algorithm

Method	MSLE (m)	TDE (m)	TDE (%)
Vertical acceleration	0.020	8.35	3.02
Magnitude	0.020	7.85	3.17
CWT	0.020	8.16	2.44

5.3 Trajectory Estimation

Brantley dataset provides the raw acceleration and gyroscope data, as well as magnetometer data, and a ground truth for position, retrieved from the XSens MVN motion capture system [111]. Firstly, the data was used to estimate a heading for each recording, which, combined with the step detection and step length algorithms previously developed, was used to estimate the trajectory. A total of twenty recordings were used, from four different participants.

The Mahony and Madgwick’s methods were applied with the raw accelerometer and gyroscope data, using the following parameters:

- Mahony: $K_p = 0.5; K_i = 0.0$
- Madgwick: $\beta = 0.1$

After applying both heading estimation algorithms in conjugation with the previous step detection and step length estimation algorithms, an estimate of the trajectory was performed, which can be seen in Figure 5.4. In both cases, since several runs were done in succession, the accumulated drift of the gyroscope data made the localisation inaccurate over the whole recording. A segmentation process was then applied to attempt the localisation on fewer samples.

The segmentation process was performed in three consecutive steps, as shown in Figure 5.5. Firstly, using the pitch provided by the Xsens MVN [111], the full 180° turns were detected 5.5a. Then the four different runs were segmented, removing the initial samples and detecting the change of run every third turn 5.5b. Finally, the straight segments were detected between the first and second turns of each run 5.5c.

Having finished the segmentation stage, the pipeline was applied on the different runs and LGW, and trajectories were plotted (figure 5.6). Although the shape of the trajectory and total distance were similar to the ground truth, the initial heading still contained an initial drift not compensated by the heading estimation filters. Since the dataset did not have a segmentation prior, the initial heading was found iteratively, and the heading was corrected, as shown in Figure 5.7.

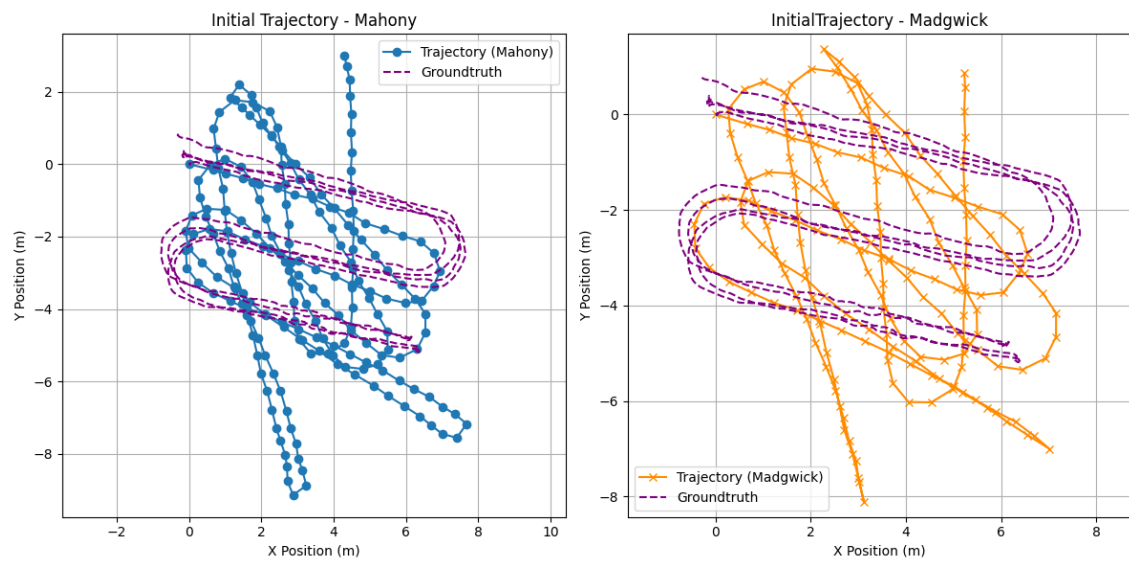


Figure 5.4: First attempt at localisation using Mahony and Madgwick's heading estimation algorithms

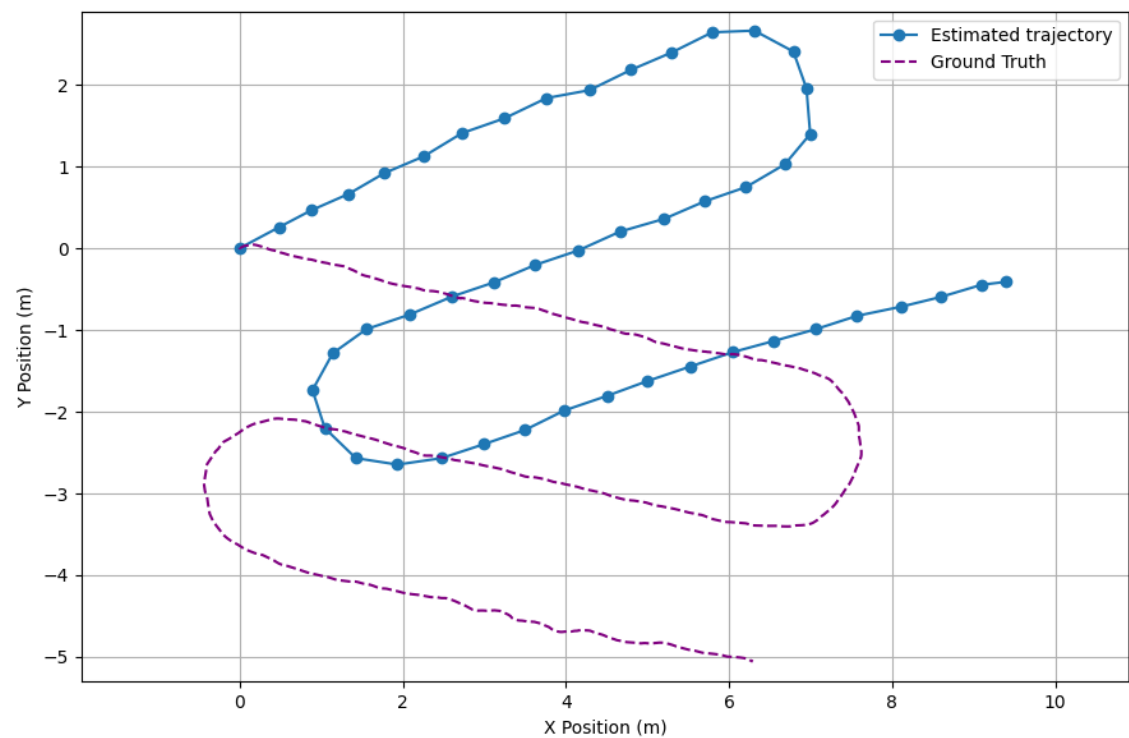
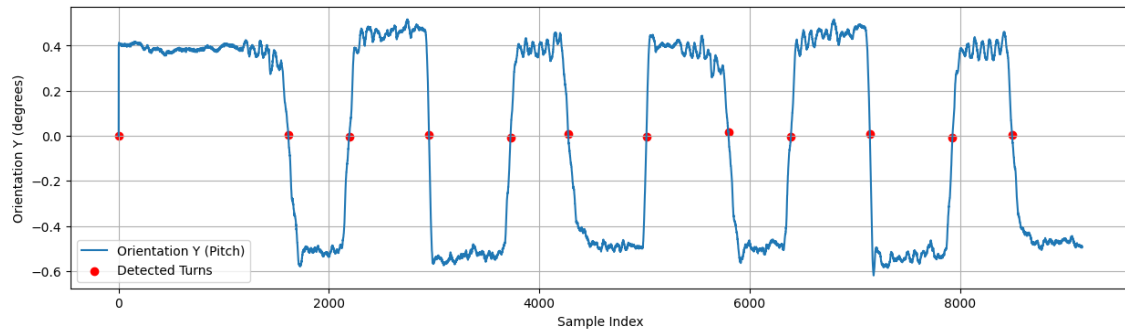
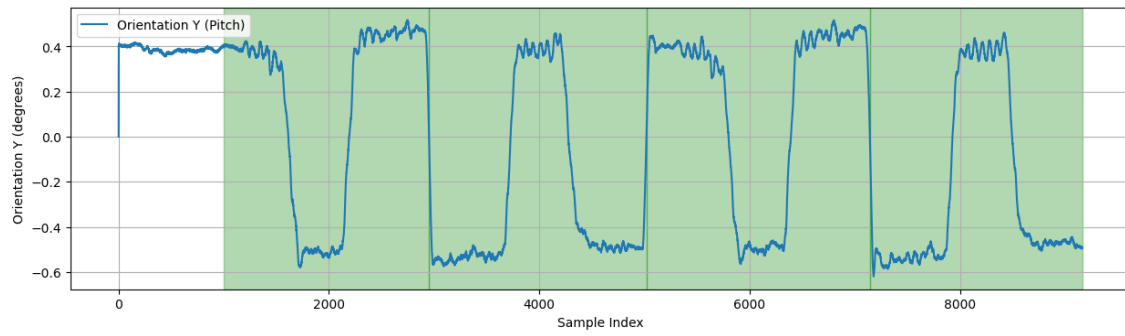


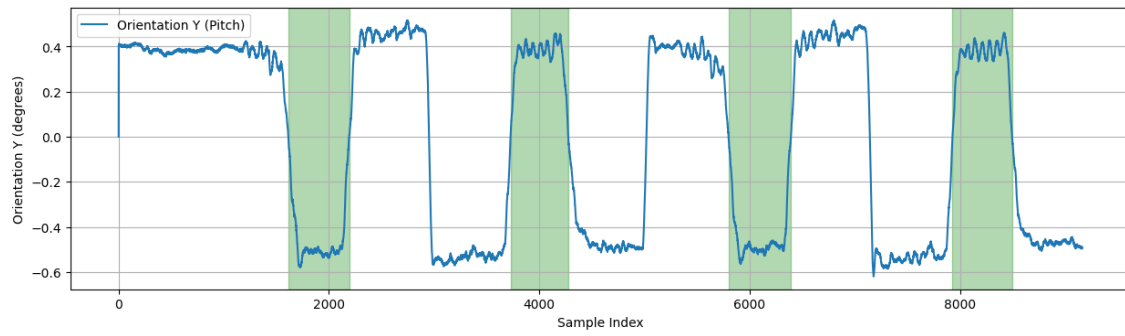
Figure 5.6: Initial plot of the estimated trajectory after segmentation



(a) Full turn detection



(b) Run detection



(c) LGW detection

Figure 5.5: Dataset segmentation across different detection stages: (a) 180° turn detection, (b) Run detection, and (c) LGW detection.

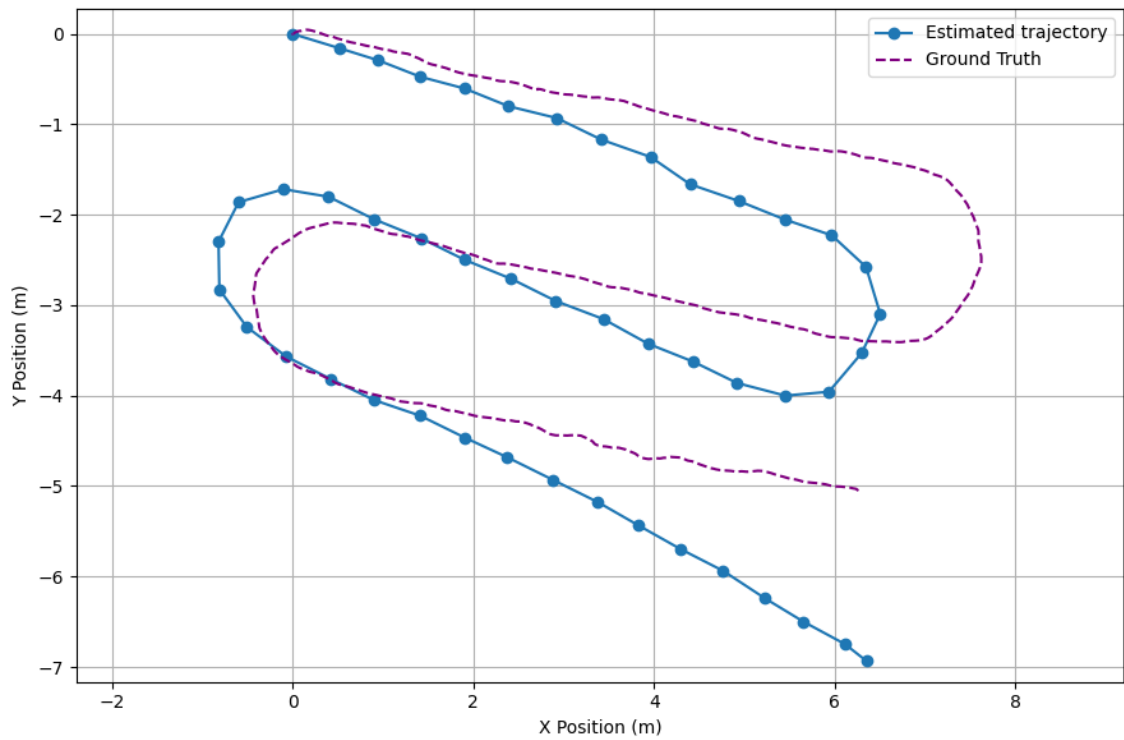


Figure 5.7: Plot of the estimated trajectory after initial heading correction

The obtained trajectory better represented the actual movement of the participant; however, this could still be improved. Since both the Madgwick and Mahony filters can use magnetometer data to compensate for the gyroscope drift, we tried using the magnetometer data provided in the dataset, expecting it to improve the accuracy of the trajectory estimation.

Figure 5.8 provides an example of the different heading estimations, which consisted in using Mahony or Madgwick filter, and using or not the magnetometer data. In both algorithms across the different recordings, the usage without the magnetometer (5.8a and 5.8c) was more similar to the real trajectory than when the magnetometer was present (5.8b and 5.8d). This might be due to the provided magnetometer data having already been subjected to filtering and compensation. Without knowing the specific pre-processing steps, the data could not be used directly in the Mahony and Madgwick algorithms, but used instead as means of comparison. In 5.8e, we can see a representation of the developed step detection and step length estimation algorithms being applied with the corrected orientation given by the XSens software, which presented an accurate estimation of the trajectory.

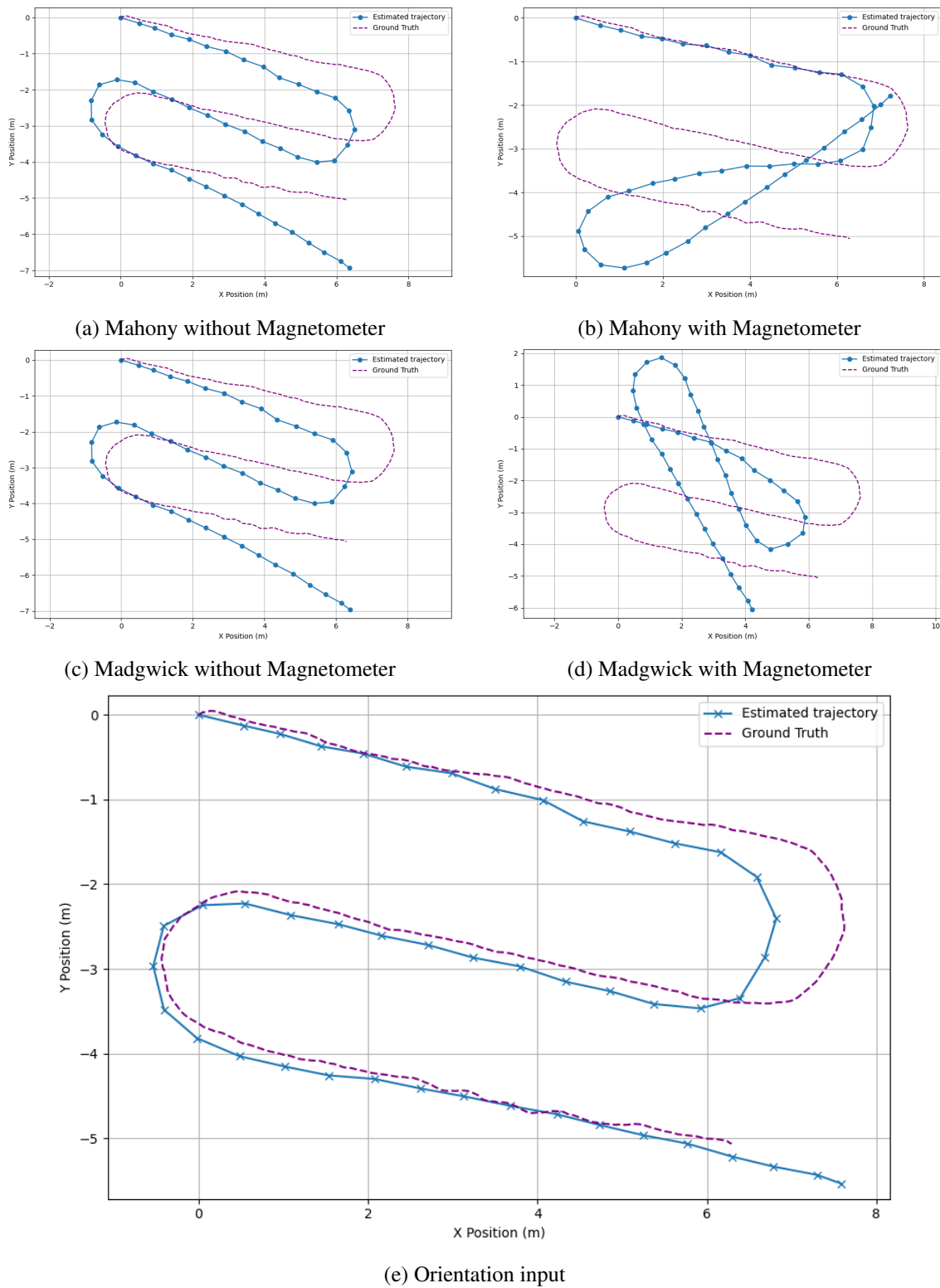


Figure 5.8: Calculated trajectories with different orientation filters compared to ground truth.

Regarding the CWT step detection, an adaptive threshold of 0.60 times the maximum value was used for peak detection. For step length estimation, the value k was set to 0.415 for the

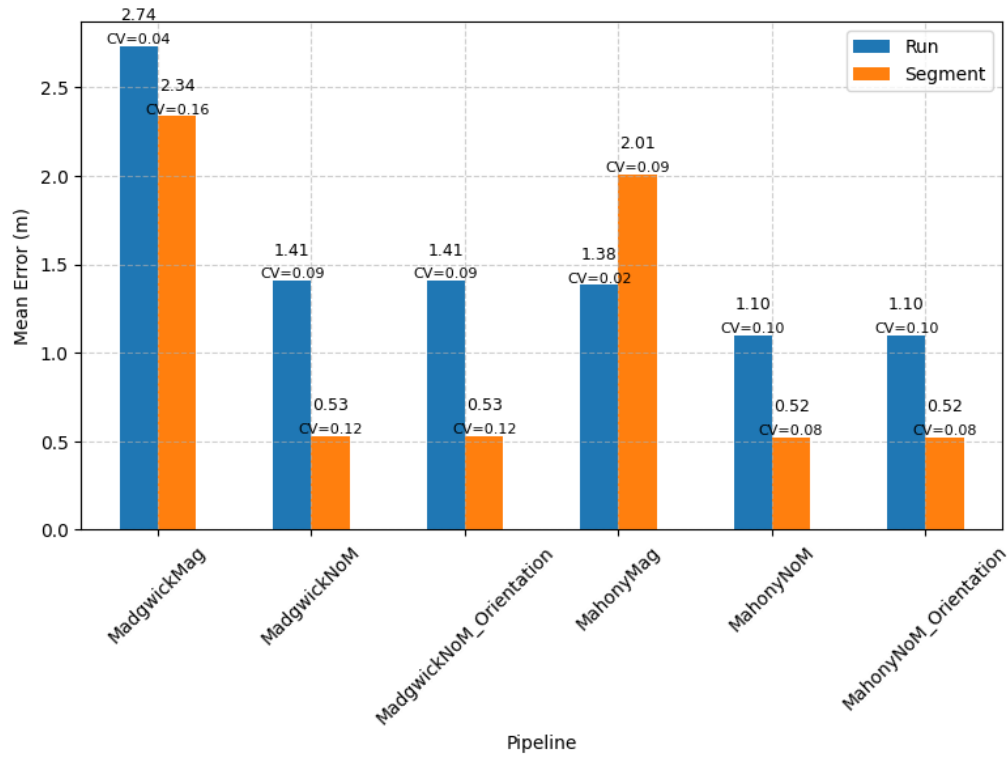


Figure 5.9: Mean TE for each of the pipelines, across the different RS and SS

Runs and 0.7 for Straight Segments. The following section provides numerical data regarding the different methods and estimated trajectories.

5.4 Data analysis

The localisation was evaluated by two major metrics: Trajectory Error (TE) and Step Position Error (SPE). The TE gives information regarding the step detection and step length algorithms, evaluating the total distance travelled by the participant. The SPE makes a comparison between the estimated position at each step with the ground truth, representing an overall similarity between the shape of the estimated and true trajectories. These metrics were applied for both runs and segments, for the twenty recordings used.

Figure 5.9 represents the mean TE for the different RS and LGW, with the STD and CV values. Since this metric depends only on step detection and step length estimation, the values for the pipelines that use the Xsens orientation are the same as the ones without a magnetometer. Generally, the errors are inferior in the pipelines that do not use magnetometer data and smaller in LGW compared with RS. It is also noticeable that the values are smaller using Mahony when compared with Madgwick pipelines. However, in Figure 5.10, which shows the mean TE in percentage, we can see that the errors in the LGW are higher than the ones on RS.

Figure 5.11 shows the mean SPE for the different RS and SS, also with STD and CV values. The usage of magnetometer resulted in higher SPE, probably due to the available data having

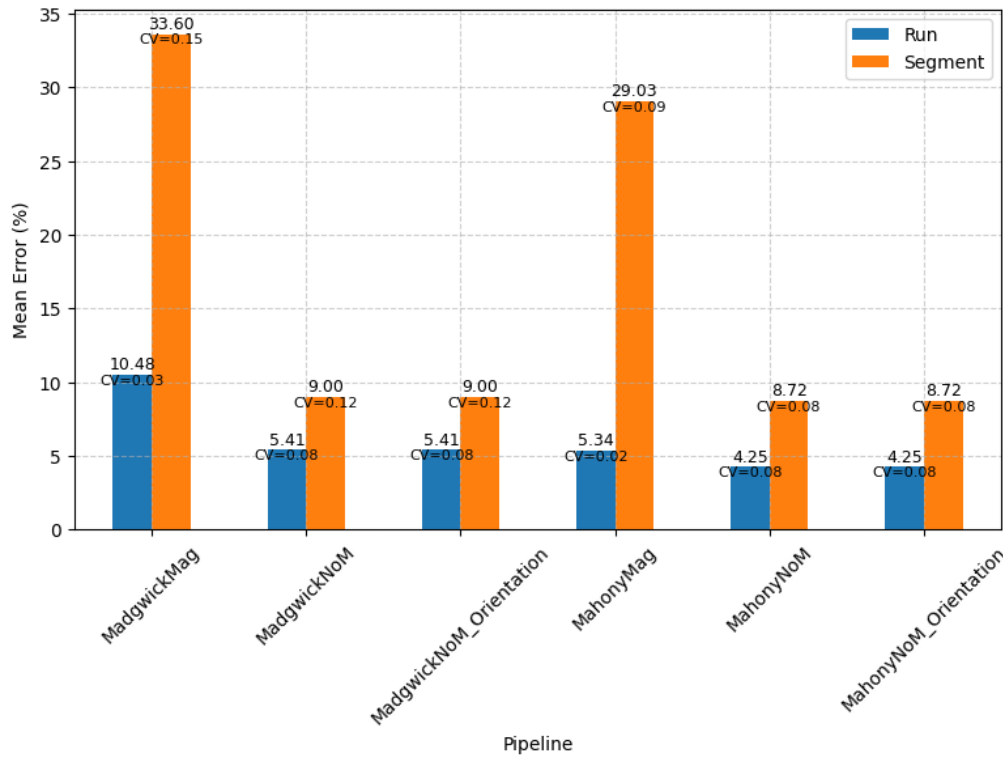


Figure 5.10: Mean TE for each of the pipelines, across different RS and SS, in percentage

already been pre-processed in the XSens software. When comparing the pipelines without magnetometer data with the pipeline that uses the heading provided by the XSens, it is noticeable that they produce similar errors. Considering that the heading in the later pipeline is the same as the ground truth, we can infer that both headings are similar, and that the error is mainly due to the step detection and step length estimation algorithms.

Another analysis was made for the different types of RS and SS, with the mean TE and SPE. Since the trajectory is different between odd and even runs (starting with the ramp and stairs, respectively), and since the heading drift will grow during the recording, studying the effect of the number of the run and the metrics obtained might be valuable. Tables 5.4 and 5.5 contain the mean TE and SPE for each of the runs and straight segments. In figure 5.12, it can be seen that the SPE is higher in the second and fourth runs, which may be due to the start of the run on the stairs, accumulating more errors in step detection and step length.

Table 5.4: Mean Trajectory Error and Step Position Error for each run

Run	MTE (m)	SPE (m)
1	1.257	1.606
2	1.542	2.574
3	1.689	1.868
4	1.597	2.869

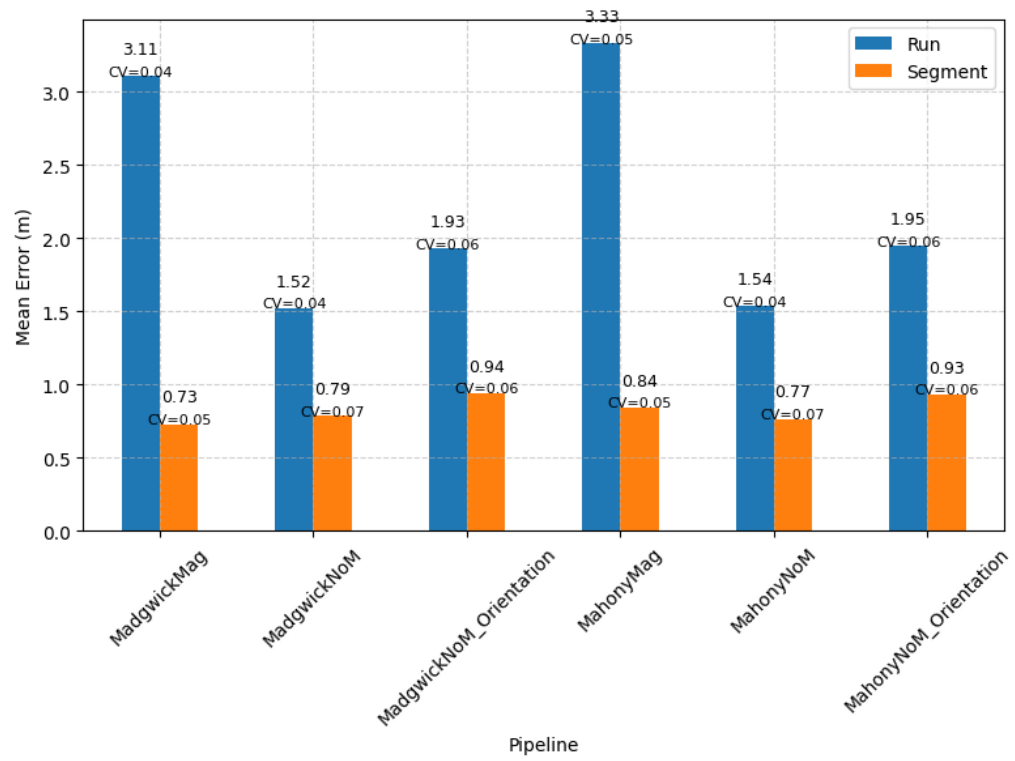


Figure 5.11: Mean SPE for each of the pipelines, across different RS and SS

Table 5.5: Mean Trajectory Error and Step Position Error for each straight segment

Segment	MTE (m)	SPE (m)
1	1.107	0.853
2	1.033	0.790
3	1.249	0.899
4	1.111	0.780

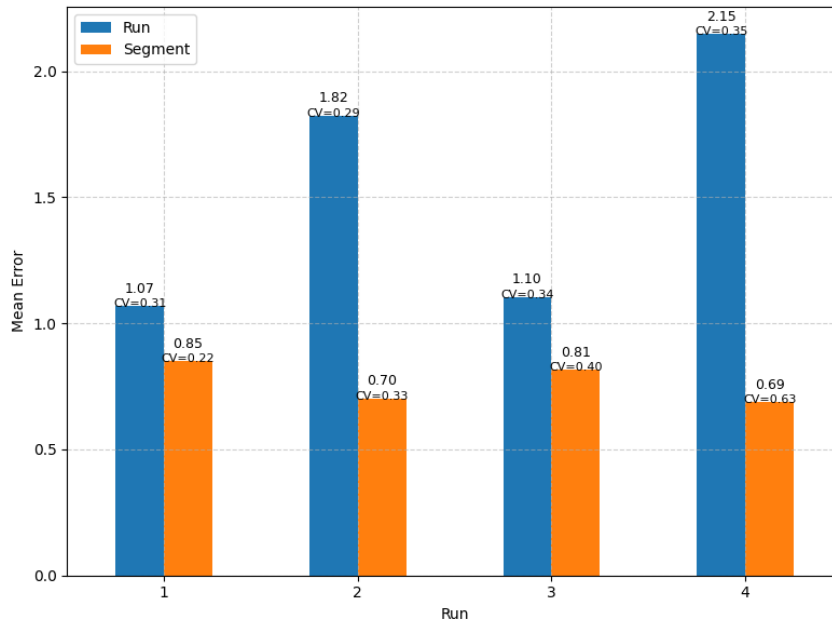


Figure 5.12: Mean Trajectory Error for different runs and segments

Besides the mean values of TE and SPE, the maximum and minimum of these errors were also evaluated. Tables 5.6 and 5.7 provide information about the maximum and minimum TE across different runs and segments, while tables 5.8 and 5.9 do it for SPE.

Table 5.6: Minimum and Maximum Trajectory Errors for each run

	Run	Participant	Segment	TE (m)	Orientation Filter
Minimum	1	7	8	0.051	Madgwick
	2	8	7	0.012	Madgwick
	3	9	9	0.082	Mahony
	4	9	2	0.020	Mahony
Maximum	1	10	3	5.862	Madgwick
	2	10	4	7.043	Madgwick
	3	10	3	20.326	Madgwick
	4	10	2	17.401	Madgwick

5.5 SV4PE Trajectory Test

The developed algorithms were then applied to the recordings made using the prototype of SV4PE explained in section 5.1. A total of 10 recordings were tested, being the C3 and CI2 recordings discarded due to signal loss and failed protocol, respectively.

Figure 5.13 shows one of the estimated trajectories of the trials with SV4PE. Although the drift is noticeable, turns can be detected and the overall rectangle shape of the trajectory can be seen. Further segmentation and heading compensation could lead to better results.

Table 5.7: Minimum and Maximum Trajectory Errors for each straight segment

	Run	Participant	Segment	TE (m)	Orientation Filter
Minimum	1	9	10	0.024	Mahony
	2	9	9	0.004	Madgwick
	3	10	4	0.018	Mahony
	4	9	10	0.025	Mahony
Maximum	1	10	3	4.114	Madgwick
	2	10	3	3.532	Madgwick
	3	10	9	4.232	Madgwick
	4	10	2	3.366	Madgwick

Table 5.8: Minimum and Maximum Step Position Errors for each run

	Run	Participant	Segment	SPE (m)	Orientation Filter
Minimum	1	9	9	0.652	MadgwickNoM
	2	10	3	0.974	MahonyNoM
	3	10	3	0.508	MadgwickMag
	4	10	2	1.128	MahonyNoM
Maximum	1	8	4	4.812	MahonyMag
	2	9	4	6.822	MahonyMag
	3	8	9	5.586	MadgwickMag
	4	9	10	9.476	MadgwickMag

Table 5.9: Minimum and Maximum Step Position Errors for each straight segment

	Run	Participant	Segment	SPE (m)	Orientation Filter
Minimum	1	9	3	0.256	MahonyMag
	2	7	8	0.375	MadgwickMag
	3	9	3	0.129	MahonyMag
	4	9	3	0.307	MadgwickMag
Maximum	1	8	7	1.653	MahonyNoM_Orientation
	2	8	7	1.957	MahonyNoM_Orientation
	3	8	7	2.631	MahonyNoM_Orientation
	4	8	7	2.568	MadgwickNoM_Orientation

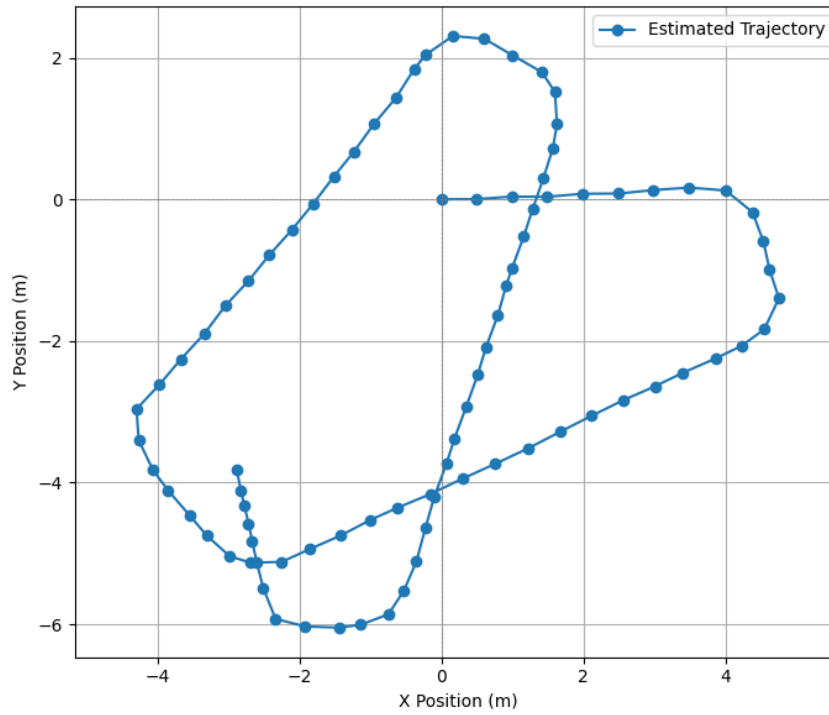


Figure 5.13: Estimated trajectory of trial 'C1', using the developed algorithms

The following tables present the values obtained for the errors of the total distance moved, each representing one of the different values of k , Weinberg's method factor. Figure 5.10 shows the best results on the group of trials, achieving an error of 18.04 %. Though a significant error, its value is higher due to the combination of walking and jogging modes. Table 5.11 presents the best results for jogging, achieving an error of 3.87 meters, and table 5.12 shows the best results for walking, with errors of 3.38 meters. This shows the necessity for adaptive factor k compensation in order to produce better results, specifically in situations with constant change of gait patterns.

Furthermore, the incorporation of further pre-processing, segmentation, and heading correction could all present significant improvements to these preliminary results.

Table 5.10: Mean Trajectory Error and Mean Trajectory Percentage Error (MTPE) across trials with SV4PE prototype ($k=0.600$)

Trials	MTE (m)	MTPE (%)
All	7.290	18.04
Walking	4.220	10.44
Jogging	12.410	30.72
Inverse Walking	3.000	7.42

Table 5.11: Mean Trajectory Error and Mean Trajectory Percentage Error across trials with SV4PE prototype (k=0.415)

Trials	MTE (m)	MTPE (%)
All	10.260	25.39
Walking	14.090	34.87
Jogging	3.870	9.59
Inverse Walking	12.380	30.65

5.6 Offline metrics

Having the estimated trajectory, different offline methods were created and applied to the trajectory data from the NONAN dataset. Firstly, a function is used to define the field, depending on the sport and dimensions. This can then be plotted, as shown in Figure 5.14. This function also defines field zones, which will be used for determining activity modes.

The trajectory can then be plotted in the desired field, as shown in Figure 5.15.

By defining the area in which the player is defending and having information about the intensity of the workout, the desired metrics were calculated. Table 5.13 shows the developed metrics and the inputs required to achieve them. Figure 5.16 shows an example of the plotting of a football recording, using the NONAN dataset, with the definitions of attack and defence according to the heading.

Table 5.12: Mean Trajectory Error and Mean Trajectory Percentage Error across trials with SV4PE prototype(k=0.650)

Trials	MTE (m)	MTPE (%)
All	8.420	20.83
Walking	3.380	8.37
Jogging	16.810	41.61
Inverse Walking	3.510	8.69

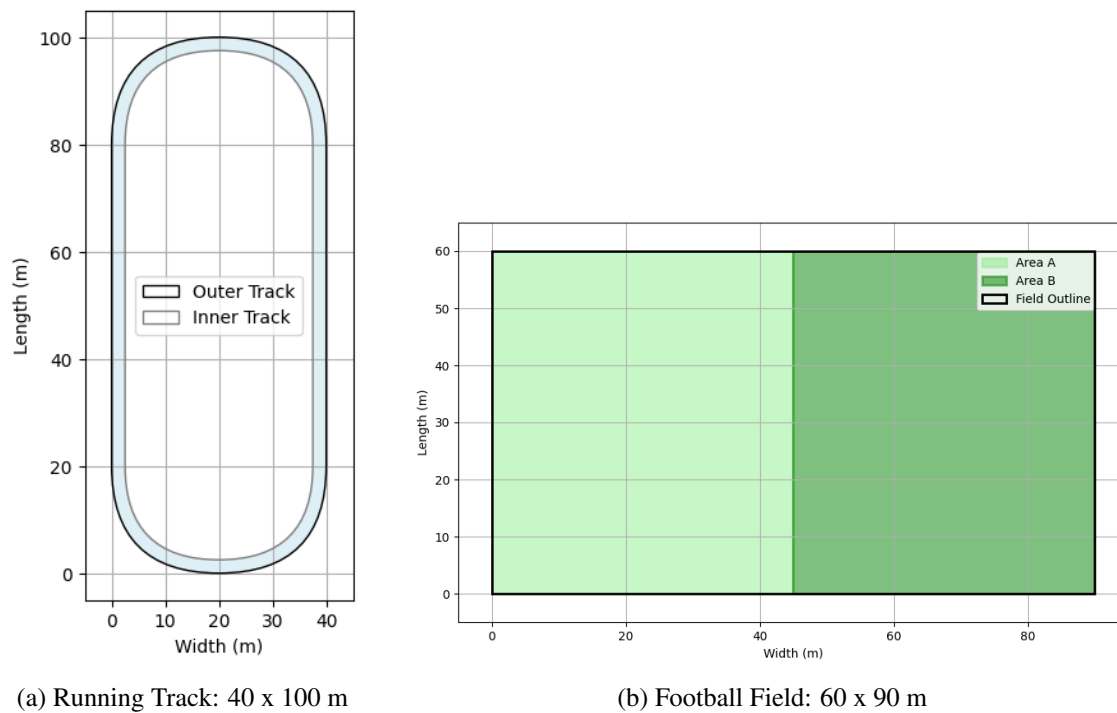


Figure 5.14: Illustrations of sports areas: (a) running track and (b) field with zones.

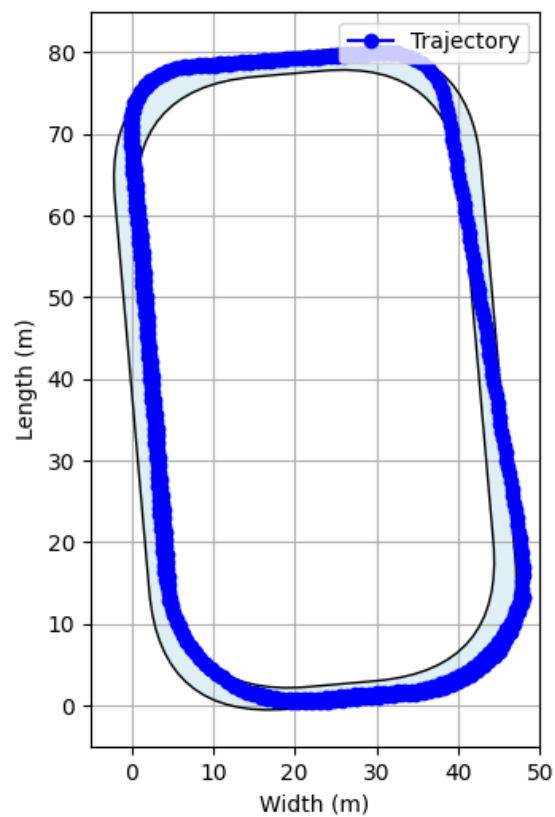


Figure 5.15: Running track with plotted trajectory

Table 5.13: Inputs required for each of the developed metrics

Metric	Inputs
Time in Area	Area; Trajectory
Total Distance	Trajectory
Distance by Intensity	Intensity; Trajectory
Time of Attack/Defence	Area; Heading
Trajectory Plot	Field; Trajectory

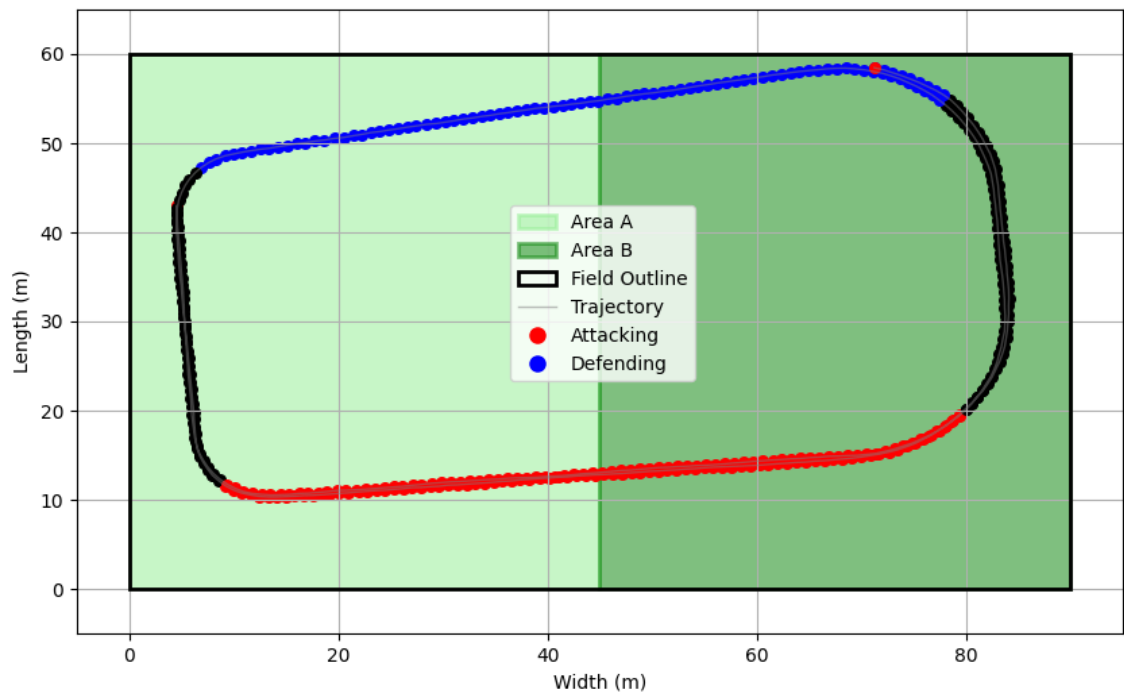


Figure 5.16: Trajectory plot in field, with attack and defence actions' identification

Chapter 6

Discussion

6.1 Summary of Main Findings

This work aimed to develop and validate a localisation system using a single IMU sensor placed at the T8 position, to be used in both real-time and post-session analysis of PE classes. Two datasets were used to evaluate different components of the localisation pipeline: the NONAN GaitPrint [101] dataset for step detection and step length estimation, and the Brantley dataset [102] for trajectory estimation and heading corrections.

Prior to the algorithm development, a systematic review was conducted to better understand the challenges and methods used when developing localisation systems with IMU sensors. A total of 53 articles were selected and divided based on the implementation of IMUs. Although the best results were obtained in systems that fused information from other types of sensors, single and multiple IMU approaches still achieved positive results, serving as the basis of our analytical solution. Table 3.7 contains a summary of the methods and results of the set of articles, which was used to retrieve the several methods applied in this work.

Regarding step detection, several methods were tested, like vertical acceleration peak detection, magnitude-based detection, and CWT. All methods had a similar values of step detection error, so CWT was selected for use in offline analysis, due to its robustness across less controlled environments. Additionally, application of CWT allowed for a better teasing of gait events, as IC and TO. This proves to be an advantage when compared with other methods, as most of them can only detect an IC, lacking an understanding of the gait cycle and the difference between the stance and swing phases. For live metrics, a magnitude-based step detection was applied, since it was computationally lighter and easier to implement, due to the temporal requirements of the real-time solution.

Step length estimation diverges in approaches for live and post-session metrics. Step length estimation, based on the gender and height of participants, was applied for real-time velocity calculations, and Weinberg's algorithm was applied in offline metrics. A total distance error of 2.44% was achieved in controlled conditions for the offline metrics, similar to other single IMU localisation methods reviewed. In table 3.7 from the conducted systematic review, we can see

examples of current localisation systems and their measures. As can be seen, Zhao et al. [94] presents a similar error to the TDE of our solution (table 5.3), making these algorithms suitable for further application.

For trajectory estimation, Mahony and Madgwick filters were applied to estimate heading using accelerometer and gyroscope data. When considering the full recordings of Brantley’s dataset [102], the integration of gyroscope data over long periods is noticeably affected by drift. To accommodate for this drift, a segmentation strategy was applied to isolate distinguishable segments of the run. Further improvement was achieved by fine-tuning the initial heading estimate. The usage of the datasets’ pre-processed magnetometer data was not beneficial for the results, probably due to prior undisclosed filtering steps.

Quantitative analysis across twenty recordings showed that Mahony’s filter yielded slightly lower trajectory errors when compared to Madgwick’s. The SPE and TE metrics varied across runs and straight segments, but prove the feasibility of using a low-complexity pipeline for accurate localisation.

Finally, a set of offline metrics was implemented, including total distance travelled, time in field zones, and classification of actions based on heading and localisation. These metrics demonstrated the system’s capacity to generate insights for educators and sports professionals in a post-activity setting.

6.2 Interpretation and Implications

The results of this work highlight the viability of using a single IMU sensor to develop indoor and outdoor localisation systems, specifically in sports settings. The proposed pipeline (step detection, step length estimation, heading correction, and trajectory reconstruction) was designed with simplicity and adaptability, aiming to be useful in both real-time and post-session analysis.

6.2.1 Step Detection and Step Length Estimation

The use of the CWT for step detection was successful in capturing both the initial contact and toe-off events of gait cycles. This method provides more adaptability over simpler approaches when facing environmental noise and varied gait patterns, such as climbing and descending stairs. The algorithm’s robustness is confirmed by the close match with the ground truth (MSCE of 1.07%, table 5.2).

Weinberg’s equation for step length estimation provided a reliable approximation, achieving an error of 2.44% over the total distance walked (table 5.3). However, the need for parameter optimization is a challenge when facing the variety of gait patterns of PE classes. When changing datasets, and velocities in live metrics, the outcome varied significantly when changing Weinberg’s factor k . More careful testing with different gait patterns should be performed to verify the algorithm’s adaptability to different situations. An adaptive inference of the value of k could present a good solution for this challenge.

These findings suggest that CWT-based step detection and rule-based step length estimation (Weinberg's equation and equation 4.2) can be viable in real-life applications, especially when high accuracy is not necessary.

6.2.2 Trajectory Estimation and Orientation Filtering

Trajectory estimation relies heavily on accurate heading calculations. Filters like Mahony and Madgwick are capable of estimating orientation, but cannot provide an accurate heading over long periods. Normally, these are accompanied by segmentation, initial heading correction, and calibrations during the runs. As shown in the results of the review (table 3.4), the best results, like [54] and [65], were achieved using calibration via external sensors, specifically UWB and RSSI techniques. With that in mind, creating calibration methods that could be implemented during PE classes, like passing through a specific point or doing a set of exercises while facing one calibration target, could further improve the developed methods and achieve greater localisation accuracy.

Furthermore, the lack of a magnetometer for compensation of heading, alongside difficulty in procuring public datasets with magnetometer raw data, made the comparison of methods even more challenging.

The segmentation of recordings into individual runs and straight segments significantly improved localisation accuracy by reducing drift accumulation, as it can be seen in figure 5.4. Additionally, the iterative correction of the initial heading estimate further enhanced the accuracy of the estimated trajectory. These are nonetheless specific measures for this dataset, and there is a need to find better ways to either segment a recording or introduce ways to calibrate the heading automatically.

The Mahony filter consistently produced lower trajectory and step position errors. This might be due to a lack of parameter optimization in Madgwick's algorithm. However, both could create relatively accurate localisation estimates. As previously mentioned, the magnetometer data available was not in its raw form, which explains the increase in error when this data is included in both filters. When comparing the trajectory output of the filters without magnetometer and the trajectory using the corrected heading from XSens, the errors values are similar, due to the inherited error of the step detection and step length estimation processes. This similarity suggests a good approximation between the heading estimated from the filters and the ground truth.

Another comparison was made regarding different runs and the effects of challenging environments in the accuracy of the localisation. As previously shown, the second and fourth runs in each recording had mean step position error of nearly twice as the other runs. This lead to the conclusion that starting with the stairs, a more challenging environment for localisation, lead to accumulation of drift earlier in the run and overall, worst results. Even though this scenario will not be common, further studies should be conducted during PE classes, including different speeds, jumps and more complex circuits, in order to evaluate the accuracy of the system in different movement modalities.

The findings demonstrate that, with basic correction, accurate trajectories can be derived without relying on external infrastructure or complex sensor fusion. Further improvements like correction points across recordings and adaptive filter variables' estimation could produce better trajectory estimations, with sub-metre accuracies.

6.2.2.1 Comparison between datasets

To compare the datasets and prototype used in this study, we computed the mean absolute error (MAE) over known distances for the NONGAIT, Brantley, and Prototype datasets. This comparison allows for an objective assessment of performance across conditions and subjects. Table ?? shows the results obtained in this work. When comparing with the results from the systematic review in table 3.7, we can infer that the preliminary results of this thesis are relatively similar to those found in the literature. This is promising since future improvements like adaptive step length or calibration processes could improve the results obtained. While environmental conditions, sensor placement consistency, and subject variability introduce natural variation, the results demonstrate that the proposed pipeline performs consistently well across datasets, with average errors remaining within an acceptable range for physical education applications.

Table 6.1: Comparison of mean absolute trajectory error across datasets (level-ground walking)

Dataset	Distance (m)	Mean Absolute Error (m)	Relative Error (%)
NONGAIT	330	8.16	2.44%
Brantley	25	1.10	4.25%
Prototype	20	7.29	18.04%

6.2.3 Offline Metrics and Educational Value

The development of offline metrics adds a practical value to the system beyond trajectory reconstruction. For instance, understanding the total distance covered by a student can help in the assessment of standardized exercises, like the "mile run" or "shuttle run". Other examples are the distance covered within a certain intensity level, or the time of attack and defence, which can help distinguish between the effort of students in the same class/team.

These metrics are relevant in the context of PE classes, providing educators with information regarding student movement quality and participation. Additionally, the identification of patterns and sports, can help in further sports' research.

Overall, the simple nature of the developed pipeline makes it suitable for educational applications, where ease of use, robustness, and informative feedback are prioritized.

6.3 Comparison with Previous Work

The results of this work prove that accurate pedestrian localisation can be achieved using a single inertial sensor positioned at the T8 vertebra, albeit being a less common sensor placement. As highlighted in the systematic review, most studies in the field favour IMU placements on the foot, ankle, or waist, which are positions that facilitate drift correction techniques like ZUPT. The T8 placement provides an accurate representation of the CoM of the user, but limits the applicability of compensation mechanisms, making both step detection and step length estimation more challenging.

Additionally, in contrast to most studies that use single IMU sensors, the system developed avoids the use of magnetometers, relying only on accelerometer and gyroscope data. This decision is based on the requirements for TexP@CT, validating its ability to provide an accurate localisation. The results show that heading estimation using Mahony and Madgwick filters, combined with segmentation and heading correction, can produce positioning estimates with similar errors to the literature [94].

Across both datasets, localisation performance remained within acceptable bounds. In the NONAN dataset, a total distance error of 2.44% was achieved over a 185-meter course. In the Brantley dataset, trajectory estimation had a minimum TE of 0.012 meters over a 25-meter segment. Mean TE values ranged between approximately 1.0 and 1.7 meters, depending on the segment and filtering method, with Mahony generally outperforming Madgwick.

This preliminary solution also proves to be effective in a real-life application. In a first attempt to apply the algorithms to data acquired from the prototype of SV4PE, the trajectory identified the different turns and kept the total distance errors to a few meters. Furthermore, a simple change of k values produced errors of less than 8% and was able to adapt to the different walking speeds and trajectories. This first test, allied to the previous results and the live and offline metrics proposed, creates a solution that, with some refinements, can be of great aid in the problem of PE classes' monitoring and evaluation.

While these results may not match the sub-meter precision of systems using multiple IMUs and/or external infrastructure, they demonstrate that meaningful localisation can still be achieved with a single, back-mounted sensor.

6.4 Limitations

6.4.1 Sensor Placement and Absence of ZUPT

Although the T8 placement was chosen to balance comfort and practicality in sports and education settings, it limits PDR techniques, such as ZUPT, which are commonly applied in foot-mounted systems to correct the drift. As a result, compensating for the cumulative integration errors becomes more complex and possibly reliant on other sensors/infrastructures.

With that in mind, methods like SLAM and Particle Filter are currently being developed, aiming to correct the heading drift in alternative ways. Furthermore, heading correction moments, as

exercise protocols including defined times for re-calibration, are being designed to create automatic heading corrections in longer recordings.

6.4.2 Lack of Magnetometer

Magnetometer data in public datasets for Localisation is scarce, and when present, it has prior filtering and processing applied. This is challenging, since algorithms like the Mahony and Madgwick filters work best when having magnetometer data.

New datasets are being searched to have an accurate comparison when using Mahony and Madgwick filters. Additionally, a current objective is to create a public dataset using SV4PE to mitigate the problem of a lack of datasets.

6.4.3 Dataset Constraints

The validation relied on two public datasets, neither of which was collected with the T8 placement of SV4PE in mind. Moreover, the datasets differ in quality and preprocessing, making the analysis and application of the data a difficult task. Also, the lack of running data or complex sports environments makes it hard to evaluate the reliability of the proposed pipeline in these settings.

With the continuation of the tests, we aim to produce a more accurate evaluation of our solution, adapting the different variables and pre-processing steps to the SV4PE.

6.4.4 Segmented Evaluation

Trajectory estimation was evaluated by segmenting the recordings into shorter runs. While this improves accuracy, it does not reflect the performance over continuous, unsegmented recordings. In real-life applications like PE classes, segmentation can be unavailable, creating the need for whole dataset evaluation.

We are currently trying to find other ways to avoid segmentation, like creating heading correction points or creating automatic segmentations.

6.4.5 Prototype Integration and Real-World Testing

Real-time validation with the TEXP@CT smart vest will face other challenges, like multiple vests synchronization, server communications and data transmission, indoor and outdoor environments transitions, and differences between subjects and sport modalities.

A series of prototype tests is being conducted regarding communications and multiple device synchronization, with other tests being designed.

Chapter 7

Conclusions

This thesis explored the development and evaluation of a minimalistic localisation framework using a single IMU positioned at the T8 vertebra, to be applied in sports environments for real-time and offline analysis. The goal was to achieve localisation with a low-cost setup while maintaining acceptable levels of accuracy and robustness across various sports modalities. The developed framework consisted of step detection, step length estimation, heading correction, and trajectory reconstruction, using different methods for live and offline processing. The work was carried out in the context of WP5-PP#17 of the TexP@CT consortium, to be used in the SV4PE solution.

A systematic literature review contextualized this work, showing that while multiple-IMU and infrastructure systems dominate the field, few studies explore single-IMU systems for localisation placed near the CoM, particularly without magnetometer input. The work in this thesis addresses this gap, with an emphasis on simplicity and wearability. Unlike commercial solutions such as CATAPULT [112], which relies on GPS and is not suitable for indoor PE settings, this framework was developed for magnetometer-free operation and minimal hardware, providing a novel contribution to real-world localisation under constrained conditions.

For online metrics, a peak detection algorithm was applied to the acceleration magnitude, with a low computational cost, making it suitable for real-time applications. Step length, estimated using the gender and height of the participants, was combined with the step detection to produce a dynamic velocity calculation. Although simpler than the applied offline methods, this approach provided reliable outputs, supporting immediate student feedback to the PE teacher.

For offline analysis, a more robust pipeline was implemented. Step detection was performed using CWT, combined with Weinberg's formula for step length estimation. Mahony and Madgwick filters were tested for heading estimation using only accelerometer and gyroscope data, following the SV4PE configuration. Initial heading correction and trajectory segmentation helped mitigate drift, with the Mahony filter slightly outperforming in most trials. Trajectory estimation performed better without magnetometer input, likely due to pre-processed magnetometer data. The best pipeline achieved a total distance error of 1.10 meters (4.25%), with TE as low as 0.012m over 25m segments, and average TE ranging from 1.0m to 1.7m across trials, demonstrating the feasibility of single-sensor, infrastructure-free localisation. This confirms the innovation of this

approach: by operating without magnetometer data, it paves the way for low-complexity, embedded implementations without compromising core performance.

While quantitative metrics varied slightly across trials, the average absolute position error remained within an acceptable range, particularly given the minimal sensor setup. The results demonstrate that accurate localisation can be achieved with a single, strategically placed IMU, provided that proper signal processing and adaptive algorithms are applied.

7.1 Recommendations and Future Work

While this work introduced important perspectives on how localisation can be implemented with minimal sensors, some improvements can be made.

- **Real-World Testing with Smart Vest Integration**

Integrating the proposed pipeline into the TEXP@CT smart vest and validating its performance in live scenarios is necessary to prove the usability of the developed methods. By experiencing in real conditions, feedback can be taken into account and improvements made on the pipeline.

- **Continuous Tracking with Drift Compensation**

While segmentation was useful in this specific dataset scenario, introducing more extensive recordings and drift mitigation strategies, such as correction based on field constraints or landmarks, or learning-based heading estimation, can significantly improve the proposed pipeline. Compensation via RSSI is also a technique worth considering.

- **Adaptive Step Length Estimation**

The Weinberg-based step length method used is static once calibrated. Future iterations could integrate adaptive step length models based on real-time gait variability, using techniques like machine learning approaches.

- **Magnetometer Studies**

Since the validation with the use of pre-processed magnetometer data was not able to give information about the added benefits of using magnetometer data in both heading estimation filters, further studies with magnetometer data should be done.

- **Dataset Development and Children Testing**

In the WP5-PP#17 of TexP@CT, one of the objectives is to introduce this solution to different schools. With that in mind, designing recordings and collecting data from children in the context of PE can help improve the accuracy of the developed algorithms. Furthermore, this dataset could be made public in order to improve research in sports with children further.

- **Broaden applications of the developed method**

Besides the sports context of this project, the results of this thesis could be applied to other

applications, especially in environments where external infrastructure is unavailable. Examples of possible applications are patient tracking in hospitals and elderly care centres, or the development of tele-rehabilitation products.

7.2 Final Remarks

Usually, due to drift accumulation and lack of heading compensation, IMU sensors are coupled with other sensors and techniques or avoided as a stand-alone technology. In this thesis, it is shown that thoughtful algorithm design can improve the outcome of trajectory estimation and that accurate positioning can be achieved with fewer sensors. This is promising for applications where external infrastructure is not available. For instance, the developed framework can be used in other applications, like patient tracking in hospitals and elderly care facilities, or the development of tele-rehabilitation products. Specifically in sports, where the introduction of sensors must not affect the performance of athletes, the current framework could provide information without requiring added sensors, improving the feedback given by teachers and coaches.

Future work should focus on prototype integration and real-world testing, as well as improving heading compensation without relying on segmentation. Exploring adaptive step length models, calibration techniques, or even calibration-free heading estimation techniques could further enhance the system's robustness.

To sum up, PE students' monitoring and objective evaluation are the current biggest challenges in sports education, due to the multiple tasks of gathering data whilst also coordinating the classes for teachers. This project aims to solve these challenges by providing accurate positioning of students during PE classes, as well as other calculated metrics, for live and posterior analysis. These metrics aim to represent the overall performance of the students during the classes, and by that means, complement the teachers in their evaluation, making it more objective.

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