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Underwater Acoustic Positioning and Control for Autonomous Docking of Autonomous Underwater Vehicles

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Resumo

O processo de realizar acoplamento de veículos subaquáticos autônomos (VSAs) continua a ser um problema complexo de resolver de forma eficiente, uma vez que o VSA tem de ser capaz de navegar desde a sua posição atual até à posição da estação de acoplamento. Isto inclui a necessidade de obter informações de posicionamento precisas, bem como um método para gerar uma trajetória que conduza o submarino de forma segura até ao seu objetivo, e ainda um esquema de controlo capaz de manter o veículo nessa trajetória planeada ao longo de todo o processo.

Este trabalho endereça o desenvolvimento de uma solução de controlo e navegação para um VSA partir de uma posição inicial tendo em vista atingir uma estação de acoplamento. No que refere à navegação, foi desenvolvida uma abordagem baseada num sistema de posicionamento USBL. Os dados fornecidos por este sistema são fundidos com informações de outros sensores através de um filtro de Kalman estendido. Para gerar a trajetória desde a posição do VSA, no momento em que a sequência de acoplamento é iniciada, até à localização da estação de acoplamento, foi implementada uma função de navegação K-R, que retorna uma trajetória que evita todos os obstáculos no caminho. Para garantir que essa trajetória é seguida, um controlador PID é utilizado. Por fim, é ainda implementado outro controlador para posicionar e manter o VSA à mesma profundidade da estação de acoplamento.

A solução de acoplamento desenvolvida é posteriormente testada em vários ambientes simulados distintos, de forma a avaliar o seu desempenho neste conjunto diverso de situações de acoplamento.

Os resultados das simulações demonstram que a solução de acoplamento proposta conseguiu guiar com sucesso o VSA até à estação de acoplamento e evitar todos os obstáculos nos vários ambientes testados.

Palavras chave: acoplamento, navegação, posicionamento

Abstract

The docking process of autonomous underwater vehicles (AUVs) remains a complex problem to solve in an efficient manner, as the AUV must be capable of navigating from its current position to that of the docking station. This includes the need to obtain accurate positioning information, as well as a way to generate a trajectory that safely leads the submarine to its goal, and a control scheme that is capable of maintaining the vehicle in this planned trajectory throughout the whole process.

This work addresses the development of a control and navigation solution for an AUV to start from an initial position with the objective of reaching a docking station. With regard to navigation, an approach based on a USBL positioning system was developed. This positioning data is combined with information from other sensors with an extended Kalman filter. In order to generate a trajectory from the AUV's position at the time the docking sequence is initiated to the location of the docking station, a K-R navigation function is implemented, returning a trajectory that avoids every obstacle in the way. To ensure said trajectory is followed, a PID controller is also used. Lastly, another controller is implemented to position and hold the AUV at the depth of the docking station.

The developed docking solution is then tested in various different simulated environments, in order to assess its performance in this diverse set of docking situations.

The simulation results demonstrate that the proposed docking solution successfully guides the AUV to the DS and avoids all obstacles across the various environments tested.

Keywords: docking, navigation, positioning

United Nations Sustainable Development Goals

The Sustainable Development Goals (SDGs) of the United Nations provide a global framework to promote innovation, sustainable development, and the protection of our planet. The work developed in this project, focused on a solution for AUV docking operations, directly and indirectly contributes to these SDGs, particularly through technological advancements in underwater robotics, improved operational efficiency, and the reduction of the environmental impact of underwater missions. Table 1 summarizes the alignment of this project with the relevant SDGs, highlighting the associated targets, contributions, and performance indicators.

Table 1: Alignment of the project with Sustainable Development Goals (SDGs)

SDG	Target	Contribution	Performance Indicators and Metrics
13	13.3	Facilitates climate-related monitoring and data collection in remote underwater environments by providing reliable docking for long-term operations.	Number of autonomous missions performed; volume of collected environmental data; operational time increase due to automated underwater recharging.
14	14.1	Enables sustainable and efficient monitoring of marine environments by supporting autonomous AUV operations with minimal human intervention.	Reduction of manual inspection missions; improved mission endurance via autonomous docking; energy consumption metrics.

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Abbreviations and Symbols

List of Abbreviations

AUV	Autonomous Underwater Vehicle
DRL	Deep Reinforcement Learning
DS	Docking Station
DVL	Doppler Velocity Log
EKF	Extended Kalman Filter
GPS	Global Positioning System
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
KF	Kalman Filter
KR	Koditschek and Rimon
LBL	Long Baseline
MPC	Model-predictive Control
PI	Proportional-integral
PID	Proportional-derivative-integral
SBL	Short Baseline
USBL	Ultra-Short Baseline
ZEM	Zero Effort Miss

List of Symbols

General Symbols

h	Sampling time
ε	Measurement noise
ϕ	Roll angle
θ	Pitch angle
ψ	Yaw angle
$p_n = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$	Position vector
$\Theta = \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix}$	Orientation vector
$v_l = \begin{bmatrix} u \\ v \\ w \end{bmatrix}$	Linear velocity vector in the body-fixed frame
$\omega = \begin{bmatrix} p \\ q \\ r \end{bmatrix}$	Angular velocity vector in the body-fixed frame
$\eta = \begin{bmatrix} p \\ \Theta \end{bmatrix}$	Generalized position vector
$v = \begin{bmatrix} v_l \\ \omega \end{bmatrix}$	Generalized velocity vector in the body-fixed frame
τ_{act}	Control Forces vector

Environment

$v_c = \begin{bmatrix} V_{cx} \\ V_{cy} \\ V_{cz} \end{bmatrix}$	Ocean current velocity
--	------------------------

Sets

$\mathcal{C}$	Configuration space
$\mathcal{O}$	Obstacle region
$\mathcal{F}$	Free space

Kalman filtering

H	Measurement matrix
R_{ekf}	Measurement noise covariance matrix
Q_{ekf}	Process noise covariance matrix

KR Navigation Function

k	Navigation function gain
L	Distance scale of the operational space
β_i	Squared distance between the AUV and i_{th} obstacle
η_s	Path speed scaling factor
$\nabla N = \begin{bmatrix} N'_x \\ N'_y \end{bmatrix}$	Gradient of the KR navigation function

Controllers

δ_r	Rudder angle
δ_s	Stern angle
K_p	Proportional gain
K_d	Derivative gain
K_i	Integral gain

Chapter 1

Introduction

1.1 Motivation

Autonomous underwater vehicles (AUVs) are presently used in a wide array of different underwater missions, including mapping and exploration of the sea floor, as well as geological surveys. Their use is also not limited to scientific purposes, with AUVs being employed in commercial settings such as the offshore oil and gas industry sectors, as well as in military and security-related operations.

Recent innovations in the design of underwater docking stations make it possible for AUVs to recharge, upload data, and even receive new tasks by docking to these stations, which can be deployed far from surface vessels, allowing AUVs to remain underwater for weeks or even months without the need to resurface.

However, developing a solution that performs the entire docking process efficiently remains a difficult problem to solve.

As such, the motivation for this work stems from the need to develop an efficient docking maneuver that guides the AUVs to the docking station, following an optimal trajectory that avoids all present obstacles and no-fly zones.

1.2 Description of the problem

The problem at hand is a situation that occurs every time an AUV has to recharge or transfer data during its mission. So, when the need for docking is identified, the AUV must be able to navigate from its current location to the docking station. To successfully complete this task, several challenges must be addressed, namely: the vehicle must be able to accurately estimate its own position in this underwater environment throughout the whole maneuver; it must generate a feasible trajectory to the docking station that takes into account the AUV's movement constraints

and avoids all collisions with any possible obstacles in the way; and it must be able to reliably follow this trajectory.

1.3 Approach

This approach entailed the development of an architecture whose modules are illustrated in Figure 5.1 and are briefly described below, following the order in which they were implemented. The entire solution was developed and tested using Matlab and a REMUS 100 AUV model developed by Thor I. Fossen [1]. To this end, we started by working with this model, with the aim of understanding how initial conditions affect the AUV's movement, what inputs should be given to the model to have the AUV move in a desired way, and analysing the way ocean currents influence the submarine's trajectory.

Then, the focus shifted towards the positioning aspect of our problem where, in order to find a solution to the insufficiently accurate IMU measurements and the need to combine them with the more accurate acoustic measurements provided by the USBL system, the Kalman filter and the Extended Kalman filter were studied, with the latter being implemented due to its ability to linearize the nonlinear dynamics of the AUV around the current estimate.

Then, to generate the reference that guides the AUV to the DS, the Koditschek and Rimon navigation function described in [2] was implemented. This approach proposes the use of a potential function that assigns lower values (attractive potentials) to areas closer to the DS position, which is defined as the global minimum of this function, and higher values (repulsive potentials) to areas far from this goal or near obstacles. Then, the gradient of the function is calculated in order to determine the direction of the steepest descent, which will be used as the heading reference for the AUV, guiding it from its initial position toward the DS.

To solve the control problem, two controllers were implemented, one for yaw control and another for pitch control, to ensure that the vehicle follows the yaw reference provided by the KR navigation function and maintains the desired depth.

Finally, the solution was tested with simulations of many different docking situations.

1.4 Structure of the Dissertation

In addition to the introduction, this dissertation contains 6 more chapters. In Chapter 2, an explanation of the background is provided. In Chapter 3, the state of the art is described, and related works are presented. Chapter 4 provides a contextualization and description of the problem addressed in this work. In Chapter 5 an explanation of the approach followed to solve the problem is provided and Chapter 6 shows the results of the simulations and tests. Lastly, in Chapter 7, we conclude by discussing the final results, lessons learned, and future work to be done on the topic.

Chapter 2

Background

2.1 Ultra-Short Baseline Acoustic Positioning System

Ultra-Short Baseline (USBL) is an acoustic positioning system utilized to determine the location of underwater objects.

The system has a transceiver mounted on a vessel that transmits an acoustic pulse that is received by a transponder. The transponder will then reply with its own acoustic pulse. When the transceiver detects this response, it measures the time between the transmission of the initial signal and the reception of the reply from the transponder and uses this information to calculate the distance between the equipment [3].

This system also includes an array of closely placed transducers, which form the ultra-short baseline that the system is named after. These transducers allow for the calculation of the angle between the transceiver and the transponder by applying the phase-difference method [3].

Ultra-short baseline is only one of three main classes of underwater acoustic positioning systems, with the other two being known as short baseline (SBL) and long baseline (LBL) systems [4].

As described in [4], SBL systems have some similarities with USBL systems since both do not need seafloor-mounted transponders making them suitable options to track underwater vehicles from moving or anchored vessels; The SBL's accuracy improves with transducer spacing, which means that this system is better applied in cases where they are operated from larger vessels. In such cases, the results provided by SBL are similar to those of seafloor-mounted LBL systems, making them a good option for high-accuracy applications.

The third class of underwater acoustic positioning systems, LBL, comprises an array of baseline transponders mounted on the seafloor, which serve as reference points that will be used to pinpoint target positions; Other transponders mounted on the positioning targets send acoustic interrogation signals to the baseline transponders that reply with their own acoustic pulses. This

makes it possible for the target to calculate its position by measuring the gap between its current location and each of the baseline transponders [5].

It is important to note that these underwater acoustic positioning systems rely on acoustic waves and their speed underwater. In the marine environment, the speed of an acoustic wave is approximately 1500 m/s [6]. However, this value is not constant and depends on the density of the water, which in turn varies with temperature, salinity, and pressure (which is higher at higher depths). As such, the finite velocity of the acoustic signals means that these systems will have propagation delays that are proportional with distance. So, for a distance of 1500 m, there will be a one-second delay, and for shorter distances this delay will be shorter and less noticeable.

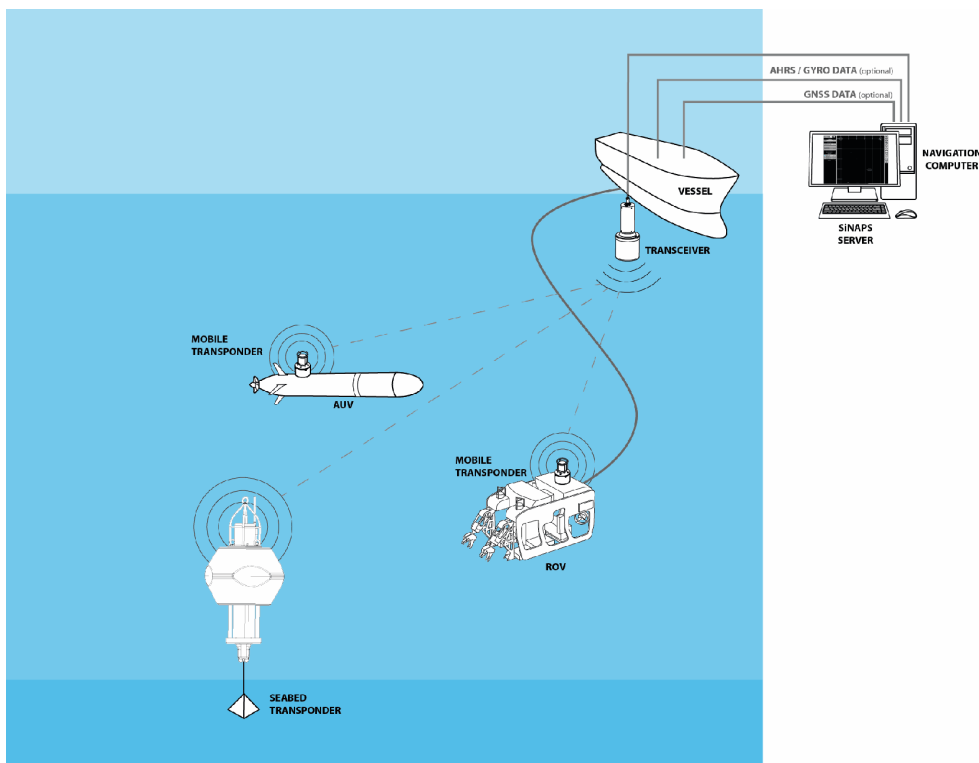


Figure 2.1: USBL schematic from Evologics[3].

2.2 Kalman Filter

In this section, the concept of Kalman filtering will be presented, closely following the definitions provided in [7] and [8].

The Kalman Filter is an algorithm used in order to obtain minimum-variance estimations of the state of dynamic systems in noisy or uncertain environments by combining measurements with the dynamic model that describes the system.

The algorithm implemented by the filter is a recursive one that runs iteratively. Whenever new measurements are obtained, the state estimate is updated and, assuming all noises are Gaussian, the output of the algorithm minimizes the mean square error of the estimation.

In short, the objective of the filter is to estimate x given observations y and our system is described by the following set of equations [8]:

$$x_{n+1} = A_n x_n + B_n u_n + w_n \quad (2.1)$$

$$y_n = H_n x_n + v_n, \quad (2.2)$$

where x_n is the state vector at time step n , A_n is the state matrix, B_n is the input effect matrix, u_n is the control input vector, and w_n is the process noise, which is, as mentioned above, assumed to be Gaussian, that is $w_n \sim \mathcal{N}(0, \mathbf{Q}_n)$; the vector y_n is the output (measurement) vector, H_n is the measurement (or observation) matrix, and v_n is the measurement noise, also assumed to be Gaussian - $v_n \sim \mathcal{N}(0, \mathbf{R}_n)$. It should also be noted that the process and measurement noises, w_n and v_n , respectively, are uncorrelated.

From here we can estimate the mean and covariance of x_n , expressed as $\hat{x}_n$ and P_n , respectively, by following the algorithm below [7][8]:

Algorithm 1 Kalman Filter

```

1: Initialization:
2:   Set initial state estimate  $\hat{x}_0$  and covariance  $P_0$ .
3: for  $n = 1, 2, \dots$ , do
4:   Predict:
5:      $\hat{x}_{n+1}^- = A_n \hat{x}_n + B_n u_n$ 
6:      $P_{n+1}^- = A_n P_n A_n^T + Q_n$ 
7:   Update:
8:      $e_{n+1} = y_{n+1} - H_{n+1} \hat{x}_{n+1}^-$ 
9:      $S_{n+1} = H_{n+1} P_{n+1}^- H_{n+1}^T + R_{n+1}$ 
10:     $K_{n+1} = P_{n+1}^- H_{n+1}^T S_{n+1}^{-1}$ 
11:     $\hat{x}_{n+1} = \hat{x}_{n+1}^- + K_{n+1} e_{n+1}$ 
12:     $P_{n+1} = P_{n+1}^- - K_{n+1} S_{n+1} K_{n+1}^T$ 
13: end for

```

Here, e_{n+1} represents the innovation, K_{n+1} the Kalman Gain, and S_{n+1} the predicted measurement covariance.

2.3 Extended Kalman Filter

The extended Kalman Filter is a variation of the Kalman Filter which expands the standard KF in order to handle nonlinear systems. This is achieved by linearizing the aforementioned systems

using first-order approximations based on the Jacobian matrix. In this more general approach, the system is described with these equations [7]:

$$x_{n+1} = f_n(x_n) + w_n \quad (2.3)$$

$$y_n = H(x_n) + v_n . \quad (2.4)$$

In equation 2.3, f_n represents the nonlinear functions that will be linearized as follows [7]:

$$F_n = \left. \frac{\partial f_n(\mathbf{x}_n)}{\partial \mathbf{x}_n} \right|_{\mathbf{x}_n = \hat{\mathbf{x}}_{n-1|n-1}} . \quad (2.5)$$

While in equation 2.4, H denotes the measurement matrix.

2.4 Path and Trajectory

Although often treated as equivalent and used interchangeably, the concepts of path and trajectory have different meanings.

A path is simply a term that refers to the sequence of points that define the route that a certain object takes from one place to another, without any notion of time.

However, a trajectory specifically defines a sequence of points indexed by time. In short, a trajectory is the path followed by an object over time.

Chapter 3

State of the Art

Positioning and control of multiple AUVs for the successful docking of these vessels is one of the main challenges in achieving optimal performance and efficiency in marine missions.

As such, many different approaches have been developed to try to solve these problems, in order to execute the most efficient docking maneuvers.

3.1 Approach

In this section, a description of how this state-of-the-art review was organized is presented.

The main criteria considered to choose the most relevant sources were if the study is widely cited, how relevant it is to our specific situation, and also how recent it is, in order to ensure that the newer techniques and methods are being analysed and considered as well.

For example, the books cited in [9] and [10] are widely used as references by multiple other studies in this area of marine engineering. In addition, the concepts presented in [7] and [4] are also extensively referenced by other publications in their fields.

Further, recent studies with other solutions to the AUV docking problem were also reviewed. Some notable examples of this are presented in the studies in [11] and [12].

Lastly, the studies in [13],[14] and [15] are widely acknowledged and referenced publications in the field of AUV docking and modelling.

3.2 Positioning and Navigation

As explained in [10], due to their ability to propagate across long distances, acoustic signals are widely used in subaquatic applications and, more relevant to our case, in docking maneuvers.

Many solutions combine Ultra-Short Baseline, a type of acoustic positioning, with other localization methods to solve the positioning requirement and provide an accurate localization of the AUVs.

In [16], the docking station uses several estimates, USBL being one of them, to estimate the position of the AUV, namely: telemetry messages sent from the AUV, visual markers and the planned course, speed and orientation of the AUV. This data is subsequently fused using an unscented Kalman Filter. The main limitations of this approach are the considerable latency introduced by the acoustic channel used by the USBL system and the telemetry messages, the fact that the visual markers only work at very short distances and, lastly, the planned course, speed and orientation reliability depends on how well the AUV can actually follow these references.

In [12] extra-USBL methods include visual feature measurements for close ranges and the use of Inertial Measurement Unit (IMU), Doppler Velocity Log (DVL), forces and torques generated by actuators and pressure sensor data, as well as Apriltag markers utilized to further increase the docking procedure's robustness. The resulting data serves as the input for an Unscented Kalman Filter which provides the estimations for the Inertial Navigation System. This positioning method was shown to be more accurate than the other similar approaches tested that did not include the USBL system, the approach that includes the USBL system being the one that results in the smallest positioning error. Even in conditions of reduced visibility, where the use of Apriltag markers is not possible, the method demonstrated high reliability.

In [14], while the AUV is still a considerable distance from the docking station (out of range of the USBL system), the submarine approaches the dock using a number of different systems, including the global positioning system (GPS), the inertial navigation system (INS) and DVL. Closer to the docking station, USBL is combined with a vision guidance method, with the former being used to home the AUV to the DS in relatively longer ranges (starting from 100m of the docking station position) and the latter being responsible for terminal guidance (last 25m meters). During the USBL-based navigation part of the docking procedure, an EKF based integrated navigation algorithm is used. The use of both the USBL system and the vision guidance method results in a solution that overcomes the shortcomings of each of the systems alone.

The navigation problem is solved in [13] with a DVL-assisted dead reckoning system integrated with periodic GPS measurements. This approach has the downside of needing the AUV to surface to obtain the GPS updates used before the homing phase.

In [11] the vehicle incorporates an IMU, a DVL, and a pressure sensor to estimate linear and angular velocities, orientation, and depth. An EKF is also used to combine unprocessed noisy measurements with filtered ones, both resulting from the aforementioned components. The use of the EKF resulted in an improvement in the performance of the tested Deep Reinforcement Learning (DRL) algorithms, although it also increased the time they took to learn the task. In this work, these DRL algorithms are used in combination with a reward function to improve the performance of the docking maneuver over time.

The approach presented in [17] assumes the existence of a forward facing camera in the AUV that allows the implementation of a simple light tracking algorithm for terminal homing. As such, the performance of the method can be impacted in conditions of reduced visibility.

3.3 Trajectory planning

Another important aspect of the docking sequence is the planning of the trajectory from the AUV to the DS. This is handled in [16] by having the DS collect all the existing restrictions on the trajectory and subsequently defining the free space for it. After this, an iterative search algorithm attempts to identify a straight line that satisfies the minimum length necessary for the execution of the docking procedure. If such a line cannot be found, layers of large circles are stacked on top of each other to fulfill the required length.

Another approach applied in [12] begins by aligning its orientation and then its depth and horizontal position with a docking cone. After completing this process, the vessel moves forward towards the cone, starting the docking process as soon as the vehicle is inside the defined docking cone.

In [14] the information provided by the navigation methods is used to define a fixed approaching path to be followed by the AUV. [13], takes a similar approach with its docking procedure, also following a fixed approach path.

A different approach is taken in [11], testing different Deep Reinforcement Learning (DRL) algorithms for the trajectory planning task, as well as for the control of the AUV.

In [17] the trajectory is generated using a Dubins set producing a smooth trajectory between the target waypoints. This approach proved to be very reliable, due to the fact that even in case of an unsuccessful docking attempt, the method has the capacity to retry the maneuver achieving a success chance of 99% by the fourth attempt.

Notably, in most of these approaches, a method for obstacle avoidance is not mentioned.

3.3.1 Navigation Functions

One approach to solving the trajectory planning problem is navigation functions, which can be separated into two main types: those based on artificial potential functions and those that use control barrier functions.

The work in [18] introduces the navigation function, a special artificial potential function, which guarantees collision-free motion of the robot and assures convergence to the target from virtually any initial position.

The approach presented in [2] applies the navigation function introduced in [18] to a specific docking situation involving a moving submarine with a cage acting as a DS and the intention is to dock the AUV to it, while avoiding the no-fly zones defined around this vessel and any other obstacles. This approach proved to be reliable in a wide variety of initial starting positions; however a careful tuning of the function parameters is necessary to result in feasible trajectories.

In [19], a more conventional artificial potential method is also used, where the available region is divided into a high-resolution grid that will be explored to find a free path to the goal. In this implementation, each grid cell has its own potential, with the target and its surrounding elements

being attributed with attractive potentials, while obstacles get repulsive potentials. This guarantees that the resulting path will lead the AUV to the goal while avoiding obstacles in the way.

3.4 Control

Similarly to the previous section, the different publications analyzed design the AUV control in a distinct way. The solution presented in [16], uses three different control laws that can be parameterized according to user preference - Zero effort miss (ZEM) is applied for distant targets and Proportional-integral-derivative control (PID) and Model-predictive control (MPC) are used for proximate targets. This method resulted in reliable docking maneuvers, with a 72% success rate and docking errors of less than 5 cm. The tests also showed that the performance of this method was particularly reactive to the parameters of the PID controller.

The approach implemented in [12] employs a point-to-point line-of-sight guiding system, which provides the controller with the necessary position and orientation references. This controller comprises of a Proportional-integral-derivative with feedback linearization. The approach developed in this work proved to be highly robust with success rates above 96%, with most failed cases being a result of other system errors unrelated to the docking algorithm.

The method presented in [14] utilizes pure pursuit guidance to drive the AUV to the DS.

The control in [13] is performed by outer and inner PID loops for heading and depth. During the homing phase of the maneuver, pure pursuit guidance is used. For the final approach, closer to the DS, a cross-track controller is used instead.

A study carried out in [20] of how different control methods perform in the docking of AUVs in the presence of ocean currents found that among the controllers tested, a touchdown controller was the best option when we have the precise location of the DS as well as the vector of ocean current velocity and the AUV moves at 1 m/s, while in a more realistic scenario where the location of the DS is estimated using USBL and the ocean current velocity vector with DVL, then a cross-track proved to be the optimal choice. Finally in the third testing scenario, where the only difference from the previous one is the speed of the AUV - which is in this case 0,3 m/s - the sliding path controller exhibited the best performance.

The control problem is solved in [21] with a nonlinear backstepping adaptive controller that keeps position and velocity errors asymptotically stable using feedback control and adaptive control techniques to ensure that the effect of estimation errors is removed. This method models the uncertainty in the dynamics of the AUV, improving the accuracy of the maneuver and avoiding unwanted impacts with the DS.

In [17], approach navigation is performed using an implemented integral line-of-sight controller. In the terminal homing phase, a nested pitch-depth PID controller is employed. Analogously, the yaw angle is also controlled by a PID that tries to keep the vehicle aligned with a beacon.

3.4.1 Aborting the Docking Maneuver

When a problem occurs during the docking maneuver and the procedure fails or has to be canceled, the design developed by [16], has the capacity to communicate this occurrence to the surface vessel and wait for incoming commands from a remote operator or autonomously restart the maneuver, as well as offering the possibility to implement other ways to handle these setbacks. To detect if all docking conditions are met, [12] uses a score-based system, in which, when a certain condition is met, a score value is attributed to it. If these values fall below a defined limit, the procedure is aborted, and the operation, which is designed using a state-machine approach, enters a docking error state.

3.5 Docking Stations

Regarding the mounting setup of the docking station, two main possibilities are presented in the examined publications - it is either fixed on the seafloor or mobile but connected physically to a surface vessel. Some exceptions to these options were also encountered.

The DS presented in [16] is a different AUV that functions as a DS, so it is mobile and has high maneuverability, but is tethered to a surface vessel.

To test and evaluate the performance of their work [12], utilized a DS mounted on a test basin.

The simulations executed in [20] the DS is mounted on the bottom of the virtual ocean.

In [14], the DS utilized can be cabled to a seafloor observatory node.

The DS presented in [13] is connected to the power and communication infrastructure of a seafloor observatory.

In [11], the docking procedure is designed for a DS with fixed position.

The tests in [17] were performed initially with the docking station mounted on the side of a pool and then on a moving small vessel. Open water tests were also performed, in which the DS was mounted on a surface vessel.

3.6 Terminal Speed, Latching and Data and Energy Exchanges

The terminal speed varied between the different studies, with velocities ranging from 0,3 to 1 m/s.

With respect to data and energy exchanges, the docking station setups studied provide both once the docking procedure is complete.

3.7 Discussion

The reviewed studies revealed considerable diversity in the solutions proposed for each aspect of the AUV positioning and docking procedure. From navigation to path planning and control,

each paper suggests a different methodology which is often implemented to suit the specific environment conditions, docking setup, and performance requirements for which the solution was developed. This suggests that there is a wide range of possible solutions to our problem and that there is not yet a single optimal solution.

This diversity in approaches makes it challenging to compare the results in different papers, as each method leads to differing performance results that depend on the specific conditions and objectives in each of the reviewed studies.

Chapter 4

Formulation

4.1 Context

An AUV is a type of robotic submarine that does not require a human supervisor and controller in order to function and operates without the need for a physical connection or tether to a separate vessel on the surface.

This autonomy, combined with their relatively small size, low energy consumption, and wide area working range, makes them ideal for deep-sea missions in treacherous conditions, as these submersibles are both a cheaper and more efficient option than manned missions.

Furthermore, the fact that multiple AUVs can be deployed and work in parallel establishes these vessels as one of the best options for scientific research and extensive data collection, such as seafloor exploration and mapping, climate monitoring studies, and many other marine biology and environmental applications. Moreover, as mentioned in [10], in recent times AUVs are also used in commercial and military applications.

However, the untethered design of these vessels means that they require recharging of the respective batteries and a way to upload all the data gathered throughout their uptime. So, in order to avoid having to resurface the submarines whenever they need to perform any of the operations above, something that is both costly and time consuming, it is much more effective to have an underwater docking station that allows for recharging of the marine robot as well as the aforementioned data transfers.

Thus, the problem of planning and performing the docking maneuver of an AUV stems from the need to maximize the efficiency of missions that use these underwater vehicles.

Therefore, to successfully execute this procedure, it is necessary to implement a docking procedure which must be able to plan and accurately follow the generated trajectory from the AUV's position at the time said procedure is initiated to the position of the docking station, while avoiding possible obstacles that may be in the way as well as any no-fly zones that may exist around the docking station.

4.2 Vehicle Model

The vehicle model employed in this work represents the state of the vehicle with twelve state variables.

Six of these represent velocity components defined in the body-fixed frame. Linear velocities denoted by u , v , and w corresponding to surge, sway, and heave, respectively, and the angular velocities p , q , and r , known as roll, pitch, and yaw rates. The remaining six variables describe the vehicle's position and orientation in the Earth-fixed frame [1].

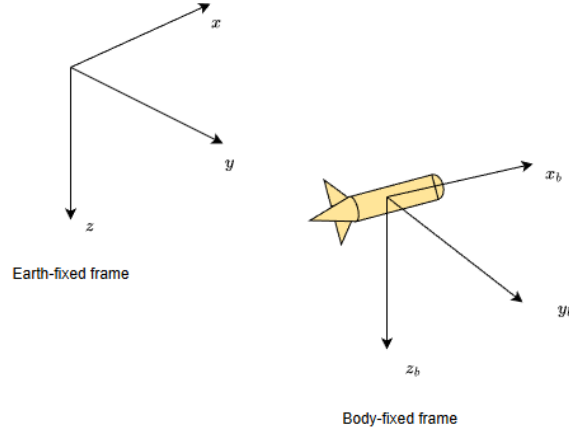


Figure 4.1: The Earth-fixed frame and the body-fixed frame.

The Earth-fixed frame is fixed to a point on the surface of the Earth in accordance with the North-East-Down system, with the x-axis pointing north, the y-axis pointing east and the z-axis pointing down towards Earth's center. It is important to note that for maritime applications, this frame is treated as an approximation of an inertial frame and is considered as such in this vehicle model [15].

The position is defined by the coordinates x , y , z and the orientation represented by the Euler angles roll (ϕ), pitch (θ), and yaw (ψ).

The following dynamic equations, as presented in [15], describe how these variables evolve over time and how the velocities in both frames relate to each other.

$$\dot{\eta} = J(\Theta)v, \quad (4.1)$$

with $\eta = [p_n^\top \Theta^\top]^\top$, where $p_n = [x \ y \ z]^\top$ represents the linear position of the AUV and $\Theta = [\phi \ \theta \ \psi]^\top$ represents the Euler angles, where both p_n and Θ are expressed in the Earth-fixed frame. The velocity vector is defined as $v = [v_l^\top \ \omega^\top]^\top$, with linear velocity $v_l = [u \ v \ w]^\top$ and angular velocity $\omega = [p \ q \ r]^\top$, with v_l and ω represented in the body-fixed frame, and $J(\cdot)$ is the transformation matrix as seen below [15]:

$$J(\Theta) = \begin{bmatrix} R_{zyx} & 0_{3 \times 3} \\ 0_{3 \times 3} & T_{zyx} \end{bmatrix}, \quad (4.2)$$

where R_{zyx} and T_{zyx} are the following matrices [15]:

$$R_{zyx} = \begin{bmatrix} \cos \psi \cos \theta & -\sin \psi \cos \phi + \cos \psi \sin \theta \sin \phi & \sin \psi \sin \phi + \cos \psi \cos \phi \sin \theta \\ \sin \psi \cos \theta & \cos \psi \cos \phi + \sin \phi \sin \theta \sin \psi & -\cos \psi \sin \phi + \sin \theta \sin \psi \cos \phi \\ -\sin \theta & \cos \theta \sin \psi & \cos \theta \cos \phi \end{bmatrix} \quad (4.3)$$

$$T_{zyx} = \left(\frac{1}{\cos \theta} \right) \begin{bmatrix} \cos \theta & \sin \phi \sin \theta & \cos \phi \sin \theta \\ 0 & \cos \phi \cos \theta & -\sin \phi \cos \theta \\ 0 & \sin \phi & \cos \phi \end{bmatrix}. \quad (4.4)$$

In order to include the effects of ocean currents in the vehicle's dynamics, equation 4.1 can be slightly adapted as shown in [15]:

$$\dot{\eta} = J(\Theta)v + v_c, \quad (4.5)$$

here, $v_c = [v_{cx} \ v_{cy} \ v_{cz} \ 0 \ 0 \ 0]$ denotes the current velocities in the Earth-fixed frame.

In addition to equation 4.1, in order to describe the dynamics of the AUV, the following equation must also be considered [15]:

$$M\dot{v} + C(v)v + D(v)v + g(\eta) = \tau_{act}, \quad (4.6)$$

where M , C and D are, respectively, the constant inertia and added mass matrix of the vehicle, the Coriolis and centripetal matrix, and the Damping matrix. The vector of restoring forces and moments is denoted as $g(\eta)$ and τ_{act} represents the vector of forces from the actuators in the body-fixed frame [15].

A more detailed explanation of this model can be found in [15].

As mentioned above, for the simulations performed in this work, a Matlab model of the REMUS 100 AUV developed by Thor I. Fossen [1] will be utilized.

Some of the parameters of this model are listed below in Table 4.1.

4.3 Measurement Model

The measurements used in our simulations are generated by adding Gaussian noise to the output of the model so that we have measurements with error resembling what we would get in a real-world scenario.

Table 4.1: REMUS 100 AUV parameters

Parameter	Symbol	Value
Mass	m_{AUV}	31.9 (kg)
AUV length	L_{AUV}	1.6 (m)
AUV diameter	D_{AUV}	0.19 (m)
Maximum speed	v_{max}	2.5 (m/s)
Maximum propeller speed	n_{max}	1525 (rpm)
Platform area	S	0.2128 (m^2)
Added moment of inertia in roll	r_{44}	0.3 (-)
Center of Gravity w.r.t. Center of Origin	r_g^b	$[0 \ 0 \ 0.02]^\top$ (m)
Center of Buoyancy w.r.t. Center of Origin	r_b^b	$[0 \ 0 \ 0]^\top$ (m)

Therefore, to simulate the positioning measurements obtained by a IMU, the following model was employed:

$$\begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix}, \quad (4.7)$$

where $\varepsilon_n \sim \mathcal{N}(0, \sigma_n^2)$.

For the acoustic measurements, the same strategy was implemented, but Gaussian noises with less variance were used to represent the more accurate data that this source provides us with:

$$\begin{bmatrix} \tilde{x}_a \\ \tilde{y}_a \\ \tilde{z}_a \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} \varepsilon_{a1} \\ \varepsilon_{a2} \\ \varepsilon_{a3} \end{bmatrix}. \quad (4.8)$$

As such, similar to the noises in equation 4.7, $\varepsilon_{an} \sim \mathcal{N}(0, \sigma_n^2)$, with $\varepsilon_{an} < \varepsilon_n$.

The same approach was followed to simulate real-world measurements for the remaining nine states of the vehicle (the three orientation variables and the six velocities), also obtained by the IMU, as shown in equations 4.9, 4.10, and 4.11:

$$\begin{bmatrix} \tilde{\phi} \\ \tilde{\theta} \\ \tilde{\psi} \end{bmatrix} = \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix} + \begin{bmatrix} \varepsilon_{o1} \\ \varepsilon_{o2} \\ \varepsilon_{o3} \end{bmatrix} \quad (4.9)$$

$$\begin{bmatrix} \tilde{u} \\ \tilde{v} \\ \tilde{w} \end{bmatrix} = \begin{bmatrix} u \\ v \\ w \end{bmatrix} + \begin{bmatrix} \varepsilon_{v1} \\ \varepsilon_{v2} \\ \varepsilon_{v3} \end{bmatrix} \quad (4.10)$$

$$\begin{bmatrix} \tilde{p} \\ \tilde{q} \\ \tilde{r} \end{bmatrix} = \begin{bmatrix} p \\ q \\ r \end{bmatrix} + \begin{bmatrix} \epsilon_{w1} \\ \epsilon_{w2} \\ \epsilon_{w3} \end{bmatrix}, \quad (4.11)$$

where $\epsilon_{on} \sim \mathcal{N}(0, \sigma_{on}^2)$, $\epsilon_{vn} \sim \mathcal{N}(0, \sigma_{vn}^2)$, and $\epsilon_{wn} \sim \mathcal{N}(0, \sigma_{wn}^2)$.

For all of these measurements, except for the acoustic ones, the defined update rate was 10 Hz.

4.4 Ultra-short Baseline

The acoustic measurements described in equation 4.8 model the measurements that would be provided by the USBL system mentioned in Section 2.1 in a real world scenario.

Assumption 0 - In close proximity to the DS the communications with the AUV are considered to be periodic. As such, a new acoustic measurement is considered available every ten seconds, providing a more accurate positioning measurement than the IMU measurements available at the previously mentioned 10 Hz rate.

In order to simplify the problem, a few assumptions were made in this part of the work. First, the variation of propagation delays with respect to distance was not considered (in a real-world scenario an acoustic signal that travels 1500 m takes one second to arrive, whereas if it travels just 150 m then it will only take 100 ms); Lastly, the exact simulation would introduce extra difficulties, because the time between consecutive pings is not constant and the speed of sound in water is approximately 1500 m/s. Hence, this simplification was made for the purpose of simulating docking for short distances.

4.5 Obstacles

Obstacles in this work can be any environmental boundaries such as the seabed as well as man-made structures scattered around the environment and are modelled mainly as circles; however, elliptical representations are also possible and may be used if this shape provides a more accurate approximation of the real obstacle.

Each obstacle $O_i, i \in \{1, \dots, n\}$ is a polygon, that is, a two-dimensional figure composed of a finite number of line segments connected to form a closed shape.

Assumption 1 - Each obstacle is over-approximated by the circle of minimum radius C_i containing the polygon that it represents. The set of all circles is C .

Assumption 2 - In this work, it is considered that the position of every obstacle in the environment is known a priori.

4.6 Problem Description

In this section, the problem and the challenges that will be addressed in this work are presented.

Consider the situation where an AUV needs to dock to the DS either for charging or data transfer. The goal of this project is to develop a method that generates a trajectory that guides the AUV from its current position to the DS, while safely avoiding all obstacles that may be found along the way.

In order to closely follow this trajectory, the submarine must also have its own controllers, which ensure that the AUV follows the references it receives as inputs.

To improve the AUV's positioning accuracy during this maneuver, the system includes periodic acoustic position updates provided by a USBL system, which must be fused with the measurements provided by the IMU sensor with the objective of obtaining the best possible estimates of the vehicle's position. The measurements of the orientations and linear and angular velocities are also provided by an IMU.

Now we present a formal description of the problem:

Given

- Docking station DS located at $X_0 = \{x_0, y_0, z_0\}$ with orientation $\Theta_0 = \{\phi_0, \theta_0, \psi_0\}$.
- AUV impacted by ocean currents and modelled by equations 4.1, 4.5, and 4.6 and departing from the starting position $X_s = \{x_s, y_s, z_s\}$.
- N obstacles represented by $C = \{C_1, \dots, C_N\}$.
- USBL is located at the docking station and has one modem mounted on the AUV.

Assumption 3 - There always exists an AUV feasible path connecting the initial position of the AUV and the docking station.

Assumption 4 - The AUV is equipped with a low-cost IMU that provides full-state measurements with Gaussian noise.

Problem

Derive an EKF to estimate the variables given by equations 4.7, 4.8, and 4.9 and a feedback control approach that ensures that the AUV reaches a ε neighbourhood of the docking station, while aligned with it, in bounded time T and avoiding all obstacles.

In figure 4.2, an example of the problem described is depicted. Here, the AUV needs to dock and must then be able to generate and follow a trajectory that safely guides it to the DS, avoiding all the obstacles that surround it.

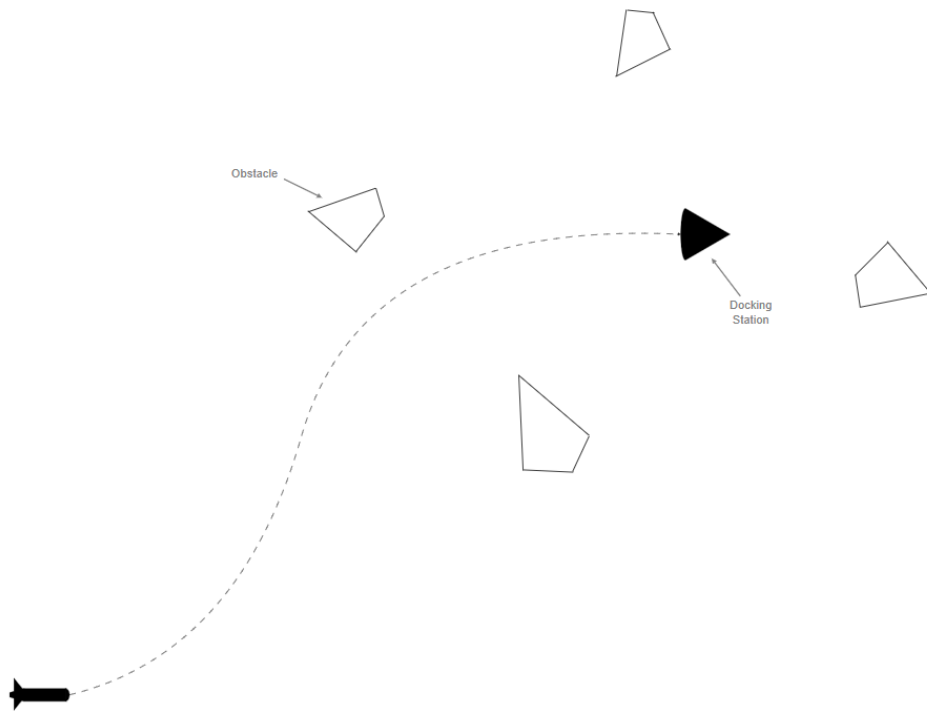


Figure 4.2: Example of a situation where a docking solution is required.

Chapter 5

Approach

5.1 Functional Blocks

In the figure below, a block diagram illustrating the complete architecture of the solution is shown:

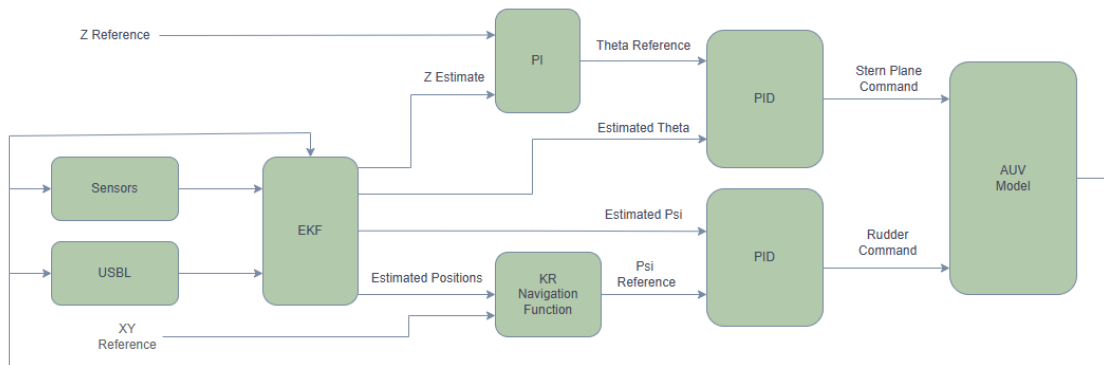


Figure 5.1: Block diagram of the developed solution.

In this chapter, each component of this architecture and its implementation will be explained.

5.2 Matlab Implementation

As previously mentioned, the implementation of this docking solution relied on a Matlab model of the REMUS 100 AUV originally created by Thor I. Fossen [1]. This model was used in both the formulation and development of this work, as well as for the simulations and tests conducted to validate it.

Thus, in order to understand how the model worked and how the vehicle behaved given different inputs and starting conditions, the first phase of this project focused on testing these different situations and cases.

More specifically, these simulations were conducted to observe the impact of different currents on the movement of the AUV and to understand how to make the AUV move in a desired way, first guiding the submarine along a circular path and then simulating a maneuver where it submerges and subsequently resurfaces.

In our Matlab model, the ocean currents are modeled as shown in equations 5.1, 5.2, and 5.3:

$$v_{cx} = v_{hc} \cdot \cos(\beta v_{hc}) \quad (5.1)$$

$$v_{cy} = v_{hc} \cdot \sin(\beta v_{hc}) \quad (5.2)$$

$$v_{cz} = w_{vc} , \quad (5.3)$$

where v_{hc} is the horizontal speed of the ocean current, β is the horizontal direction of the current, and w_{vc} denotes the vertical speed of the ocean current. Finally, v_{cx} is the ocean current velocity component in the x-direction, v_{cy} is the ocean current velocity component in the y-direction and v_{cz} is the ocean current velocity in the z-direction.

For these initial tests, the velocity of the AUV was 1 m/s. In the simulations in which the ocean currents were considered, the velocity of the ocean currents was 0,5 m/s. Lastly, no measurement errors were considered in this initial phase of the project, where the main focus was to better understand how the model works. Thus, true values of the state variables were used in these simulations.

In the figures below, the circular path simulations in both conditions can be seen.

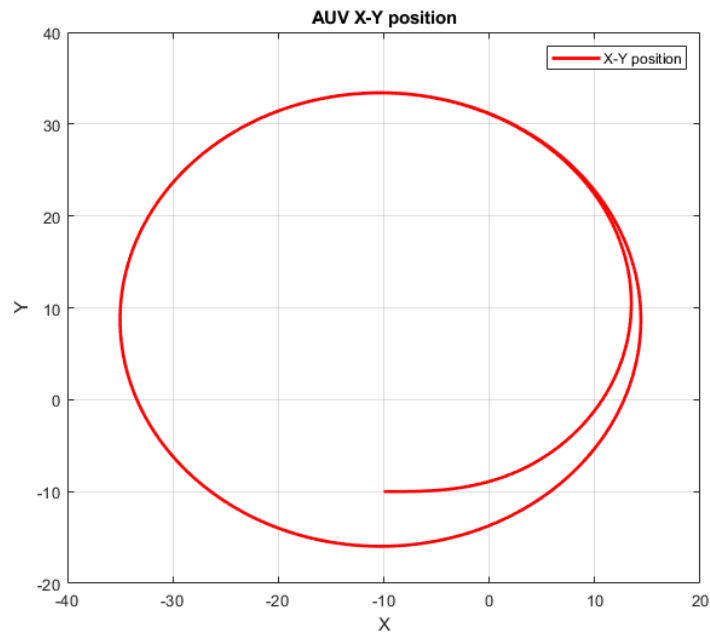


Figure 5.2: AUV Position in the XY plane.

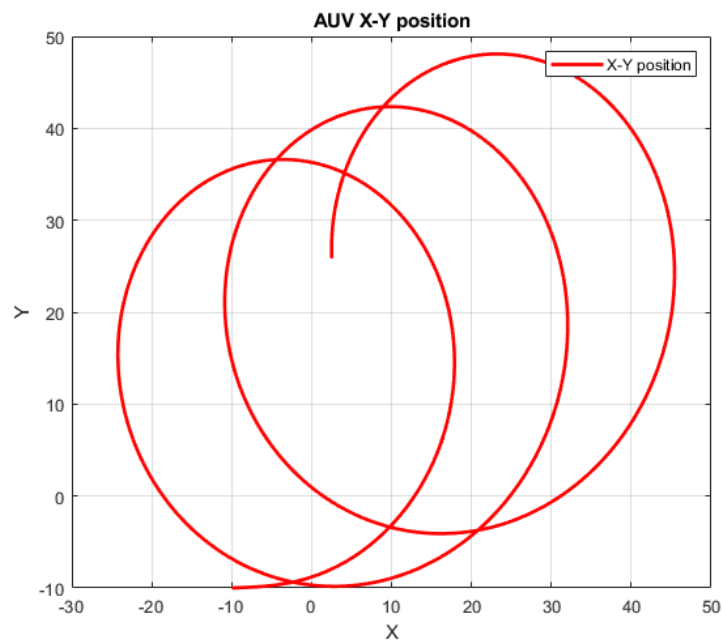


Figure 5.3: AUV Position in the XY plane in the presence of ocean currents.

As illustrated in 5.2, the AUV follows the intended circular motion in the absence of ocean currents. In contrast, when ocean currents are present, the AUV drifts in the current direction.

Then, work started on the development of the docking solution itself. First, by working on the EKF as described in Section 5.4, and then by implementing the navigation function and the controllers necessary to follow the trajectory it provided, as explained in Sections 5.5 and 5.6, respectively.

The final phase of the work involved performing the simulations to validate and assess the results of what was achieved.

5.3 World Model

The world model defined in this work, within which our AUV functions, can be described as a parallelepiped in 3D space with obstacles scattered in specific locations representing environmental boundaries or man-made structures. These obstacles are modelled as explained before, in Section 4.5.

This workspace can be abstractly represented with the configuration space $\mathcal{C}$, which includes all possible orientation and position configurations of the AUV and is defined as $\mathbb{R}^3 \times SO(3)$. In addition, $\mathcal{O}$ defines the subset of $\mathcal{C}$ that comprises all AUV configurations that would intersect with any of the obstacles in the environment, while $\mathcal{F}$ represents the free space, which consists of all the collision-free configurations the AUV can take.

Therefore, planning a docking trajectory can be described as finding a path in the free space $\mathcal{F}$ between the initial configuration of the AUV and the position of the DS while avoiding the obstacle space $\mathcal{O}$.

5.4 Filter

With the purpose of obtaining better estimates of the position variables of the AUV throughout the entire docking procedure by fusing the periodic acoustic position updates provided by the USBL system with other sensor data and also to provide better estimates of the AUV's orientations and handle the nonlinearities of the movement of the AUV, an EKF was implemented.

The EKF was chosen over the traditional Kalman filter because our system is a nonlinear system. As such, and considering the KF can only be used for linear cases, the EKF was implemented instead.

As stated in Section 4.4, the system was designed to receive these USBL updates every ten seconds, which means that the filter needed to be able to make estimates with the USBL measurements when they were available and without them when they were not. In the last case, IMU measurements would be the only input of the EKF for estimates of the position variables.

The state vector x_{n+1} , used in equation 2.3, is given by:

$$x_{n+1} = \begin{bmatrix} v_l^\top & \omega^\top & p_n^\top & \Theta^\top \end{bmatrix}^\top. \quad (5.4)$$

In the absence of acoustic measurements, the measurement vector y_n , previously mentioned in Equation 2.4, is given by:

$$y_n = \begin{bmatrix} \tilde{x} & \tilde{y} & \tilde{z} & \tilde{\phi} & \tilde{\theta} & \tilde{\psi} \end{bmatrix}^\top, \quad (5.5)$$

while in every iteration where an acoustic measurement is available, the measurement vector y_n is as follows:

$$y_n = \begin{bmatrix} \tilde{x} & \tilde{y} & \tilde{z} & \tilde{\phi} & \tilde{\theta} & \tilde{\psi} & \tilde{x}_{usbl} & \tilde{y}_{usbl} & \tilde{z}_{usbl} \end{bmatrix}^\top, \quad (5.6)$$

In addition, the process and measurement noises w_n and v_n , are zero mean Gaussian noises and the Jacobian matrix F_n is used to linearize the system around the current estimate, as described before in Section 2.2.

When no acoustic measurements are available, the measurement matrix is as follows:

$$H = \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 3} & H_{position} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & H_{orientation} \end{bmatrix}, \quad (5.7)$$

with

$$H_{orientation} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad H_{position} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \quad (5.8)$$

In the presence of a new acoustic measurement, the measurement matrix H is defined differently to fuse the measurements from both sources:

$$H = \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 3} & H_{position} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & H_{orientation} \\ 0_{3 \times 3} & 0_{3 \times 3} & H_{acoustic} & 0_{3 \times 3} \end{bmatrix}, \quad (5.9)$$

with

$$H_{acoustic} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \quad (5.10)$$

The main challenge of this part of the work was the filter tuning process, as it was necessary to adjust the measurement noise covariance matrix R_{ekf} and process noise covariance matrix Q_{ekf} . First, by defining the values of matrix R_{ekf} to match the noise of the modelled sensors and then manually adjusting the values of matrix Q_{ekf} , so as to improve the performance of the filter and its estimates.

In figures 5.4 and 5.5 it is possible to observe the EKF output for the position variable x , in red, and compare it to the noisy measurement of x , in black, and the true value of this state variable, in magenta. The results shown in these figures were obtained using the same simulation parameters as those used in the final simulations, which are detailed in Table 6.2, presented in the next chapter.

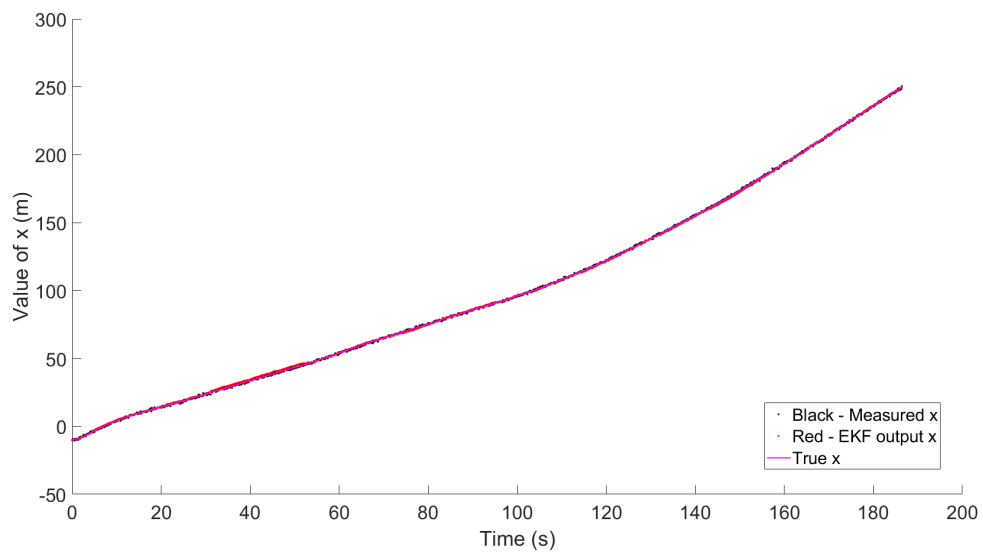


Figure 5.4: Output of the EKF for position variable x compared to true and noisy values.

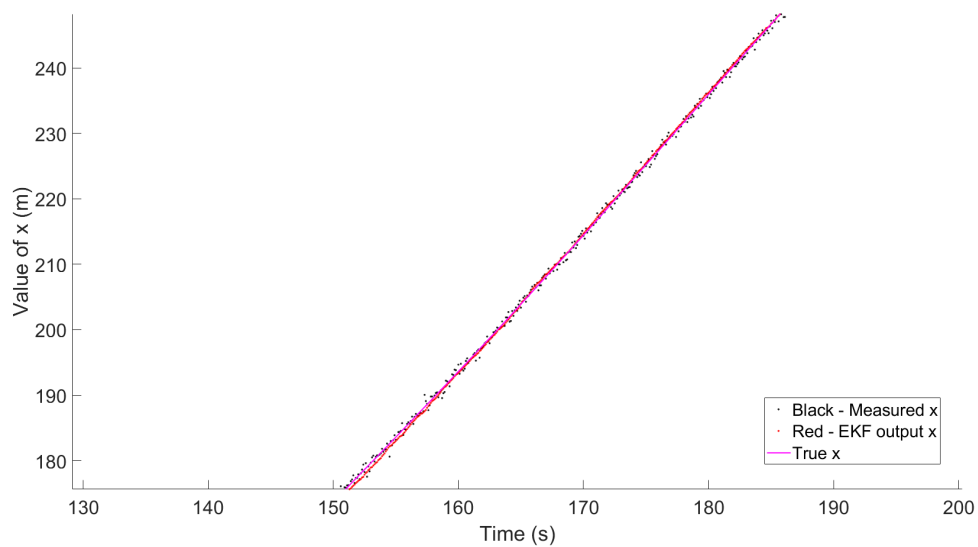


Figure 5.5: Zoomed in output of the EKF for position variable x compared to true and noisy values.

5.5 Navigation Function

To solve the requirement of creating a collision-free trajectory from the AUV position at the beginning of the docking maneuver to the position of the DS, the navigation function developed in [2] and previously mentioned in Section 3.3.1 was implemented.

The formula of this function is as follows [2]:

$$N(p(t)) = \frac{\|\tilde{p}_g(t)\|^2 / L}{\left[\left(\|\tilde{p}_g(t)\|^2 / L \right)^k + \prod_{i=0}^{M-1} \beta_i \right]^{1/k}}, \quad (5.11)$$

where $\tilde{p}_g(t) = p(t) - p_g(t)$ (here $p(t)$ and $p_g(t)$ represent the positions of the AUV and the goal, respectively, at time t); L denotes the distance scale of the space and serves as a normalization factor; $\beta_i = \tilde{p}_i^T(t) W \tilde{p}_i(t) - 1$ represents the square of the distance to the i^{th} obstacle's boundary, with $\tilde{p}_i(t) = p(t) - p_{oi}(t)$ (here $p_{oi}(t)$ is the position of the i^{th} obstacle) and $W = \text{diag}(\frac{1}{a_i^2}, \frac{1}{b_i^2})$ where a_i and b_i define the size of the model of the i^{th} obstacle; Lastly, k is a parameter that modifies the resulting potential field, with an increase in k resulting in a steeper transition between higher and lower values of N . The value of N is between 0 and 1, with 0 being the value of N at the position of the goal (the DS position) [2].

It is important to note that, to force the AUV to approach the dock in alignment with its axis, the y-axis component of $\tilde{p}_g(t)$ is calculated as shown below:

$$\tilde{p}_{gy}(t) = 2(p_y(t) - p_{gy}(t)). \quad (5.12)$$

From equation 5.11, the heading reference used to guide the AUV is obtained by determining the gradient of N and using the x and y components of this gradient to calculate ψ_{ref} as shown by equations 5.13, 5.14, and 5.15 [2]:

$$\dot{p}(t) = V_a \begin{bmatrix} \cos \psi \\ \sin \psi \end{bmatrix} - V_s \begin{bmatrix} 1 \\ 0 \end{bmatrix} = -\eta_s(t) \nabla N(p(t)) \quad (5.13)$$

$$V_a^2 = (\eta_s(t) N'_x + V_s)^2 + (\eta_s(t) N'_y)^2 \quad (5.14)$$

$$\psi_{ref}(t) = \tan^{-1}(\eta_s(t) N'_y, \eta_s(t) N'_x + V_s). \quad (5.15)$$

The terms of equation 5.13, where V_a and V_s denote the speeds of the AUV and the submarine (which has a DS mounted to it), can be rearranged to obtain equation 5.14, where N'_x and N'_y are the x and y components of the gradient of the navigation function. This equation allows us to calculate $\eta_s(t)$, a parameter that scales the speed, so as to keep the AUV's speed constant throughout the

maneuver. Lastly, using equation 5.15 we can calculate the heading reference, ψ_{ref} , the AUV must follow to reach the position of the DS [2].

In [2], as the equations suggest, the work was designed with a moving DS in mind; however, in our approach, the position of the DS is fixed. As such, in our simulations the value of V_s is 0.

A more detailed description of this method and its development can be found in [2].

The last step of this phase of the work was to define the values of the parameters k and L for each of the simulated environments. This was necessary because, while it was possible to find a single combination of values for k and L that resulted in the AUV navigating within less than two and a half meters of the goal (position of the DS) for every simulated environment tested, our objective was to consistently finish the docking procedure with the AUV as close as possible to the DS. As such, first a value for k was selected that allowed a path to be found in all the environments tested. The next step was to gradually decrease the threshold from two and a half meters to the lowest value that the AUV could successfully reach while finding a value for L that made this requirement possible. Finally, the threshold was defined at 0.5 m and a different value of L was found for each simulation, which allowed this threshold to be hit, increasing the precision of the docking maneuver.

In this phase of the work, it was also observed that by manually placing "artificial" obstacles near the goal (position of the DS), the AUV would reach the docking position without the need to find a very specific value for L , in other words, when this technique was used, the docking maneuver would be successful with many different values for the parameter L , while previously finding a value for L that made the AUV consistently navigate within 0,5 m of the DS could be time consuming, as for certain environments, only a reduced number of possibilities for the value of L would result in a successful docking maneuver. These obstacles are named "artificial" obstacles because they do not represent real obstacles and are not used to model them. Their only purpose is to improve the docking sequence.

5.6 Controller

In order to follow the trajectory generated by the KR navigation function and adjust and maintain the AUV at the desired depth, two different controllers were developed.

To control the yaw angle of the AUV a PID controller was designed and implemented. This controller adjusts the rudder angle δ_r to minimize the error between the current estimated heading angle $\hat{\psi}$ and the reference heading angle ψ_{ref} provided by the KR navigation function.

The PID control law used is as follows:

$$\delta_r = -Kp \cdot ssa(\hat{\psi} - \psi_{ref}) - Kd \cdot \dot{r} - Ki \cdot \psi_{int} , \quad (5.16)$$

with Kp , Kd , and Ki representing the proportional, derivative, and integral gains, respectively; Further, $ssa(\cdot)$ is a function that calculates the smallest signed angle between $\hat{\psi}$ and ψ_{ref} and r

denotes the yaw rate. Finally, ψ_{int} is the integral heading error, which is obtained using Euler's method as observed in equation 5.17:

$$\psi_{int} = \psi_{int} + h \cdot ssa(\hat{\psi} - \psi_{ref}) , \quad (5.17)$$

where h is the sampling time of the simulation.

The depth controller is implemented as described in [9], which is designed using successive loop closure where a depth autopilot sets the reference pitch angle θ_{ref} that is subsequently fed to the PID that adjusts the stern angle δ_s , as described by equations 5.18 and 5.19:

$$\theta_{ref} = Kp_z \cdot ((\hat{z} - z_{ref}) + (1/T_z) \cdot z_{int}) \quad (5.18)$$

$$\delta_s = -Kp_\theta \cdot ssa(\hat{\theta} - \theta_{ref}) - Kd_\theta \cdot q - Ki_\theta \cdot \theta_{int} . \quad (5.19)$$

In equation 5.18, θ_{ref} is the desired pitch angle to achieve the depth goal, Kp_z denotes the proportional gain of the depth control PI, $\hat{z}$ and z_{ref} represent the estimated depth and depth reference, respectively; Lastly, T_z is the time constant for the integral action and z_{int} is the integral depth error [9].

In equation 5.19, Kp_θ , Kd_θ , and Ki_θ represent the proportional, derivative, and integral gains, respectively; while $ssa(\cdot)$ calculates the smallest signed angle between the estimated pitch angle $\hat{\theta}$ and reference pitch angle θ_{ref} ; Finally, the pitch rate is denoted by q and θ_{int} is the integral depth error. [9].

Both z_{int} and θ_{int} are calculated using the same method as ψ_{int} :

$$z_{int} = z_{int} + h \cdot ssa(\hat{z} - z_{ref}) \quad (5.20)$$

$$\theta_{int} = \theta_{int} + h \cdot ssa(\hat{\theta} - \theta_{ref}) . \quad (5.21)$$

The last step in the development of our control system was the tuning of all the gains. In this process, there is a trade-off between having a faster response and avoiding oscillations and overshoot. As such, this tuning phase followed similar steps for the two PIDs and the PI. First, the proportional gain was adjusted until a fast but still stable response was obtained, and then, for the case of PIDs, the derivative gains were tuned followed by the integral gains; for the PI controller, which does not have a derivative term, the integral gain was tuned after the proportional one, by adjusting the value of T_z .

Finally, it is important to note that both controllers have an anti-windup mechanism. This is necessary as our AUV is limited by how much it can turn, limits defined as the maximum rudder and stern angles. This constraints lead the respective actuators to saturate and, in order

to prevent their integrators from accumulating errors and, as a result, cause overshoots the anti-windup algorithm stops this accumulation of errors.

5.7 Discussion

In this chapter, the approach and steps followed to develop the solution to the AUV positioning and docking problem were presented.

As described, work started with the study of the AUV model, which was essential to learn the AUV's dynamics and the simulated environment and allowing for an enhanced understanding of the key aspects that will influence the work using this model.

The first step in the development of the docking solution was the filter. In this stage, an EKF was implemented in order to handle the nonlinear nature of the AUV's motion as well as allow for the sensor fusion necessary to improve the positioning estimates of the AUV. The main challenge of this section of work was the tuning process, which required many adjustments until a reliable performance was obtained.

Next, the focus shifted towards the implementation of a KR navigation function that generated a collision-free trajectory for the AUV to follow, by providing at each step a heading reference for the AUV's controller to track.

Finally, the controllers were designed with the goal of following the heading reference mentioned above and the depth reference corresponding to the position of the DS. Once again, the main challenge of this part of the work was the tuning of the gains of each controller, in order to avoid saturation when possible and excessive actuation while still providing fast responses.

In the next chapter, the results of the simulations and experiments conducted to assess the work will be shown and discussed.

Chapter 6

Simulation Results

This chapter presents the results of the simulations conducted to evaluate the performance of the docking solution. These simulations were executed following a structured test plan designed to analyse the performance of the method in a wide variety of scenarios.

Throughout the development phase of this project, a series of simulations were performed to test, validate, and refine the various components of our solution: the EKF, the controllers, and the navigation function.

Once this phase was completed, the test plan was formulated and followed as described in the following section.

6.1 Test Plan

After completing the development of this docking method, its performance was evaluated in multiple different environments and conditions by assessing the proximity of the AUV to the DS in the XY-plane, using the error in this plane as a metric for determining the success of the docking sequence in each environment.

As such, this test plan will include simulations with different combinations of the following parameters: the distance between the AUV and the DS when the docking process begins; whether the "artificial" obstacles mentioned in the end of Section 5.5 were used; if there are obstacles in the way between the AUV and the DS, and finally, if ocean currents were present. In total, there are sixteen different combinations of these parameters, and, therefore, these sixteen different scenarios were designed and simulated, each scenario being simulated five times.

Table 6.1: Scenarios Tested

Scenario Number	Distance to Goal	Artificial Obstacles	Ocean Currents	Obstacles
9	Far	Yes	Yes	Yes
10	Far	Yes	Yes	No
11	Far	Yes	No	Yes
12	Far	Yes	No	No
3	Far	No	Yes	Yes
4	Far	No	Yes	No
2	Far	No	No	Yes
1	Far	No	No	No
13	Close	Yes	Yes	Yes
6	Close	Yes	Yes	No
14	Close	Yes	No	Yes
5	Close	Yes	No	No
15	Close	No	Yes	Yes
8	Close	No	Yes	No
16	Close	No	No	Yes
7	Close	No	No	No

The simulation parameters used are shown in Table 6.2:

Table 6.2: Simulation parameters

Quantity	Symbol	Value
Extended Kalman Filter		
USBL noise covariance matrix	R_{usbl}	$0.05I_3$ m
noise covariance matrix	R	$[0.25 \ 0.25 \ 0.025]$ m
noise covariance matrix	R	$0.035I_3$ rad
Process noise covariance matrix	Q_{ekf}	$[q_v \ q_w \ q_p \ q_o]$
Linear velocity noise covariance matrix	$[q_v]$	$[0.0024 \ 0.0024 \ 0.0024]$
Angular velocity noise covariance matrix	$[q_w]$	$[0.002 \ 0.002 \ 0.002]$
Position noise covariance matrix	$[q_p]$	$[0.003 \ 0.003 \ 0.003]$
Orientation noise covariance matrix	$[q_p]$	$[0.002 \ 0.002 \ 0.002]$
KR Navigation Function		
Navigation function gain	k	10
Distance scale of the space	L	-

In particular, the parameter L is assigned a different value in some of the simulations to result in more accurate docking maneuvers, as detailed in 5.5. In addition, the obstacles in every simulation examined in this chapter were modelled as circles with a 5 meter radius. Lastly, in the simulations where ocean currents were considered, they were defined with a horizontal velocity v_{hc} of 0.3 m/s and a horizontal direction β of 30 degrees.

6.2 Simulation results

This section presents a selection of the sixteen simulated scenarios, allowing for an assessment of how various parameter combinations effect the AUV's trajectory.

The following eight scenarios were chosen to demonstrate the impacts and differences caused by the different combinations of the four parameters on the resulting path and to show how the value of the parameter L had to be adapted to better suit each scenario.

Scenario 1 - This first simulation presents the case where the goal is far away (approximately 354 meters from the AUV's initial position), there are no artificial obstacles close to the goal, no obstacles in the way to that goal, and there are no ocean currents. The result of this simulation can be observed in figure 6.1, where the colour gradient represents the value of the Navigation Function at each point, with the function value approaching zero as the distance to the goal decreases.

Scenario 2 - In the second simulation, there are two obstacles, whose positions are represented by a black dot in their center, on the way between the AUV and the DS (Figure 6.2). The other three parameters remain the same as in the first simulation.

In both cases, the docking sequence was successful; however, it is clear that the trajectory followed in the first scenario is shorter and more direct, while in the second the AUV has to avoid the obstacles in its way, resulting in a longer route. As noted previously, in order to adapt to this different environment where obstacles are present and allow for the successful completion of the docking sequence in the second scenario, a different value for L was used (2000, as opposed to 1850 in scenario 1).

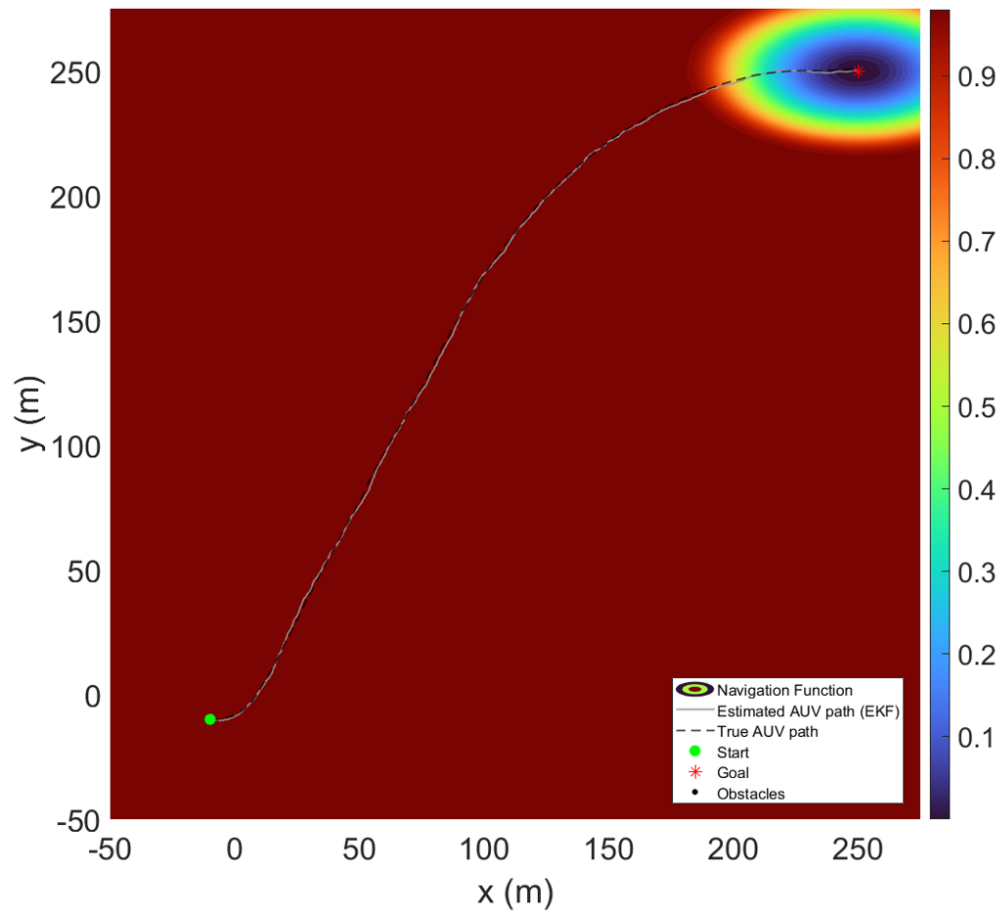
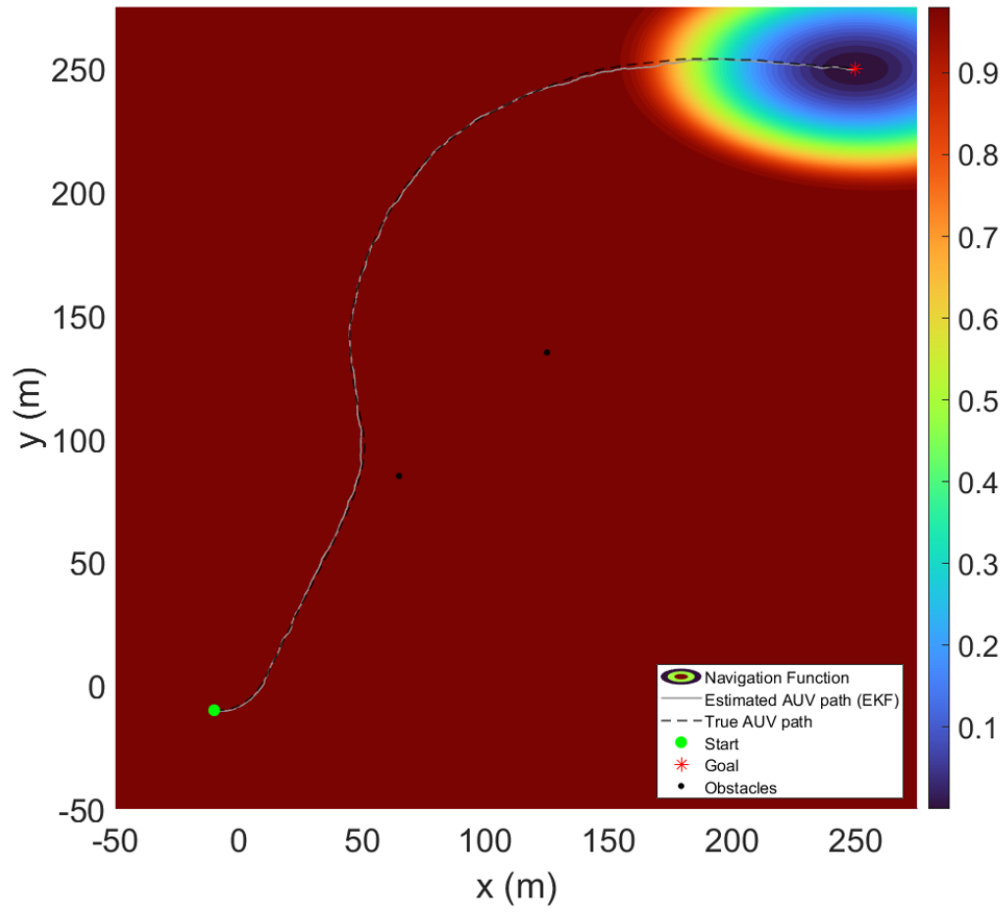


Figure 6.1: Scenario 1 - note that $L = 1850$.

Figure 6.2: Scenario 2 - note that $L = 2000$.

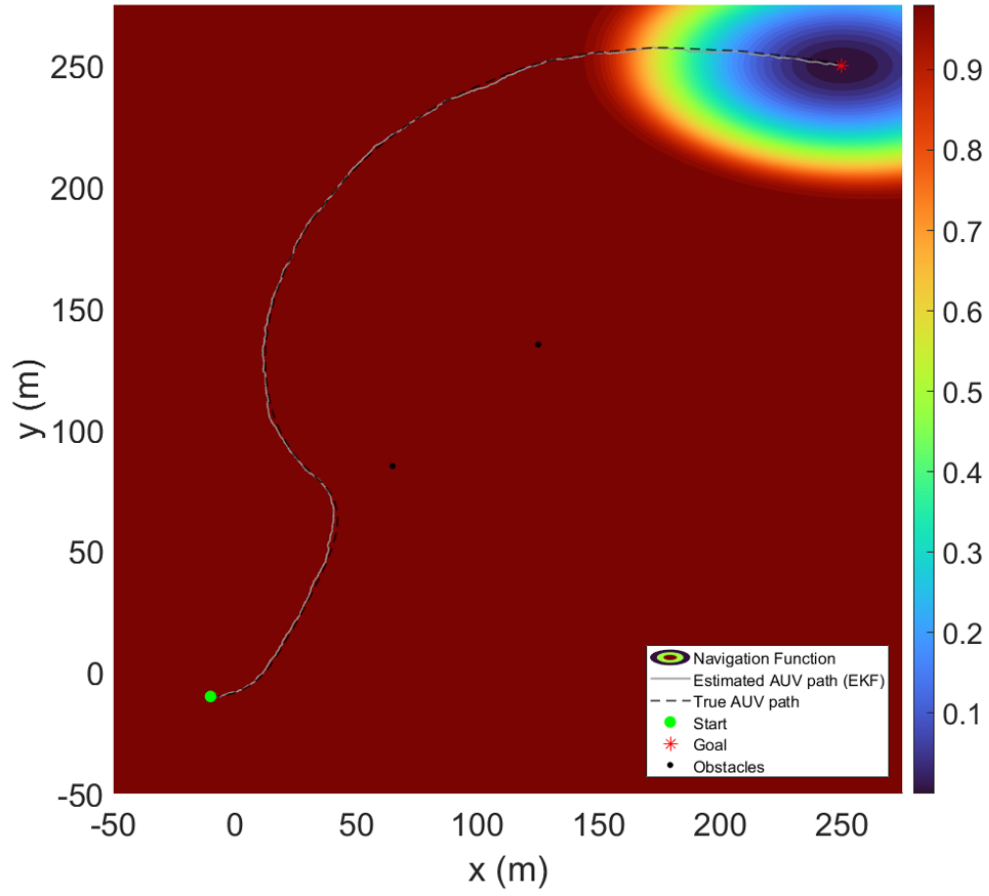


Figure 6.3: Scenario 3 - note that $L = 2500$.

Scenario 3 - The third simulation tests a situation similar to the second, the only difference being the presence of the ocean currents. In this case, the value of the navigation function parameter L was further increased, leading to another successful docking maneuver. However, once again, the resulting AUV trajectory is slightly longer than before (Figure 6.3).

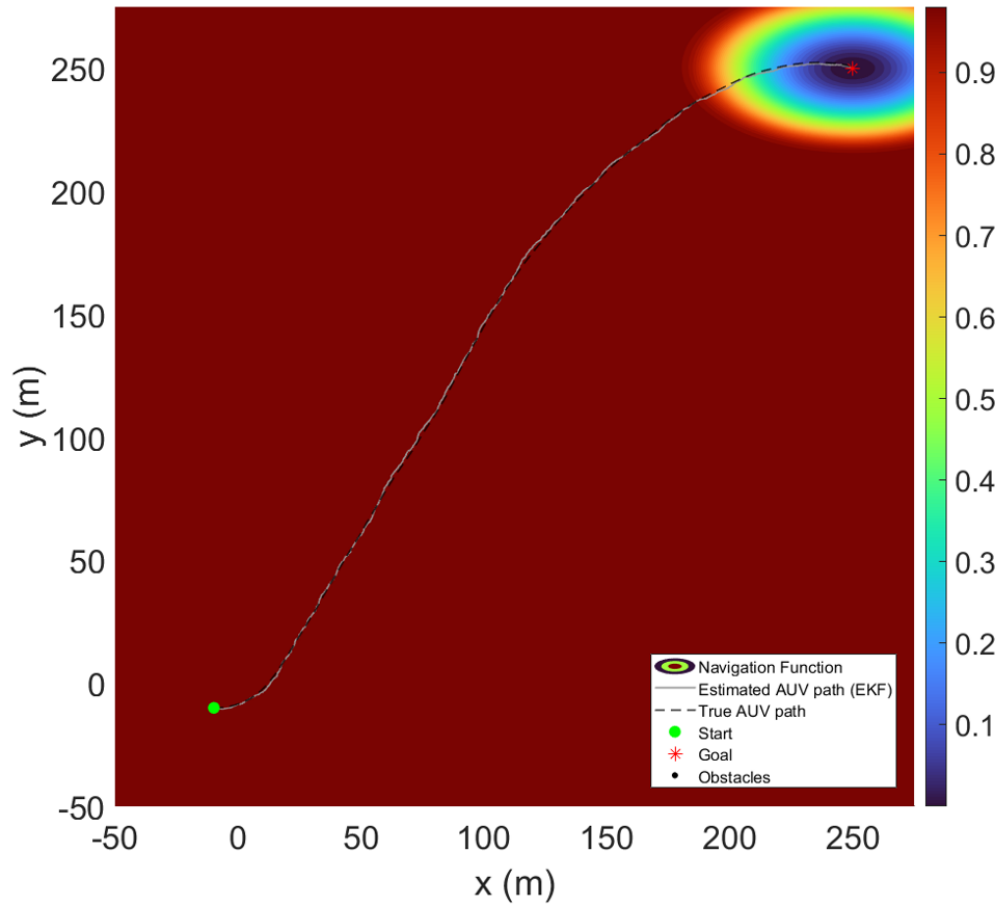


Figure 6.4: Scenario 4 - note that $L = 1900$.

Scenario 4 - In Figure 6.4, a scenario similar to the first is shown. The presence of ocean currents is the only parameter that changes between these two scenarios, as in the first there were no ocean currents but in scenario four they are considered. In this case, where the AUV does not need to avoid any obstacles on the way to the DS, the ocean currents do not influence the resulting trajectory as much, with a small increase of L from 1850 to 1900, relative to the value used in Scenario 1, enough to allow the docking sequence to take place.

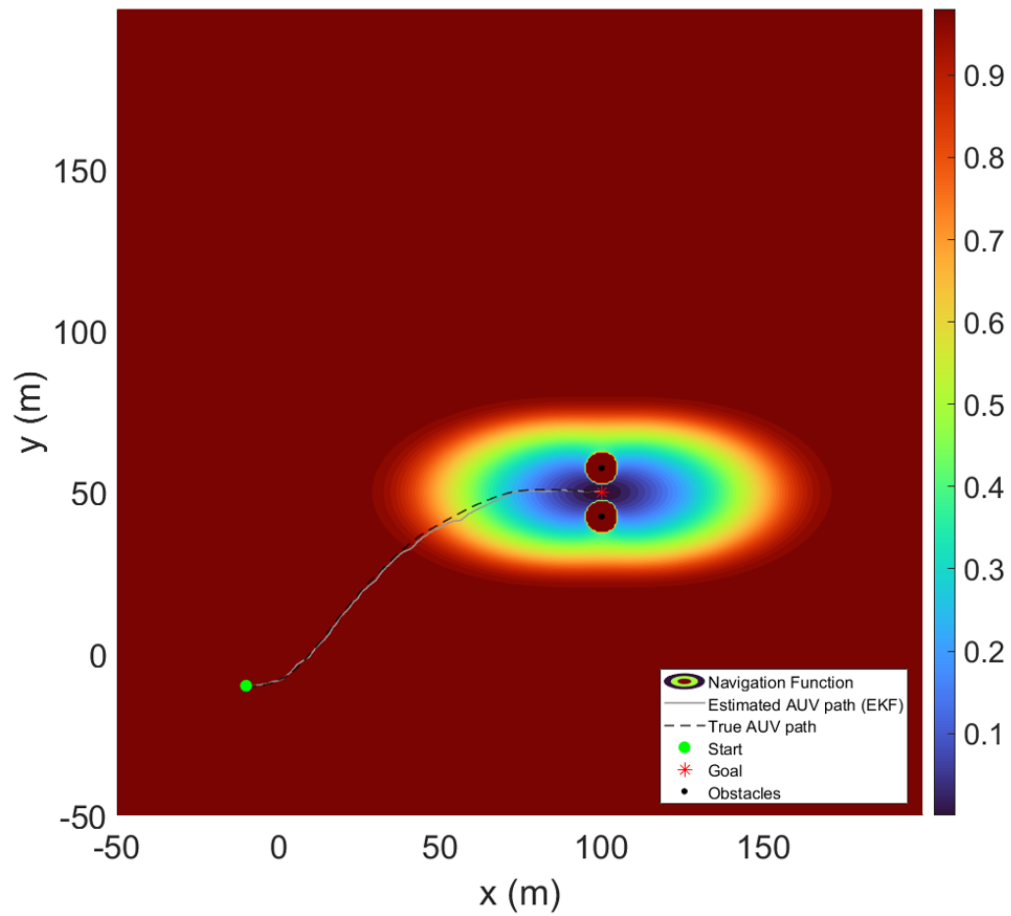


Figure 6.5: Scenario 5 - note that $L = 1500$.

Scenario 5 - Figure 6.5, presents a case where the DS is closer to the goal (approximately 112 meters from the AUV's initial position), there are no obstacles in the way between the AUV and the DS, ocean currents are not considered, and two "artificial" obstacles are placed above and below the DS in order to facilitate the tuning of the navigation function parameter L . With the introduction of the "artificial" obstacles, finding a value for L that results in a successful docking sequence becomes a significantly easier task, as the range of admissible values becomes considerably larger.

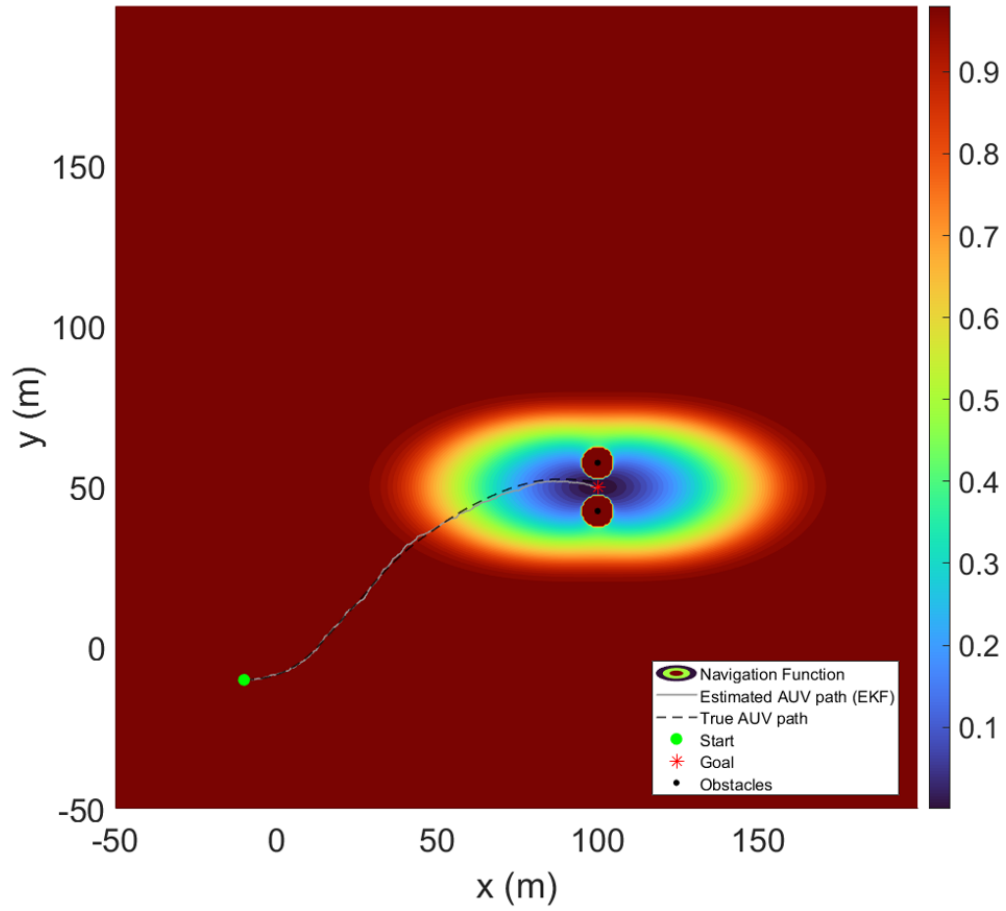


Figure 6.6: Scenario 6 - note that $L = 1500$.

Scenario 6 - Figure 6.6, presents a scenario comparable to scenario 5, with the only difference being that scenario 6 accounts for ocean currents. Notably, both simulations used the same value for L and the AUV navigated to the DS as intended, however it is possible to see the effect the currents had on the path, as the AUV follows a slightly longer path with less sharp turns.

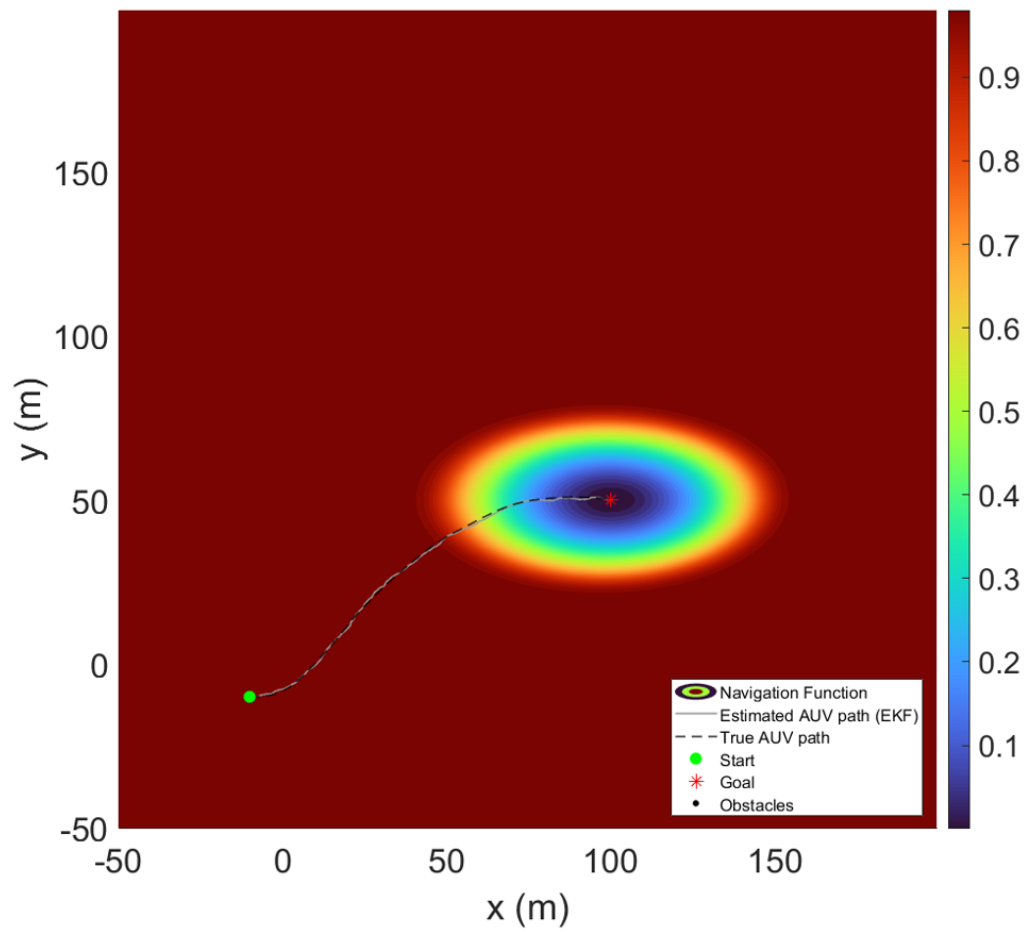


Figure 6.7: Scenario 7 - note that $L = 1500$.

Scenario 7 - Figure 6.7, demonstrates a similar scenario to scenario 5; however, in this case no "artificial" obstacles were placed close to the DS.

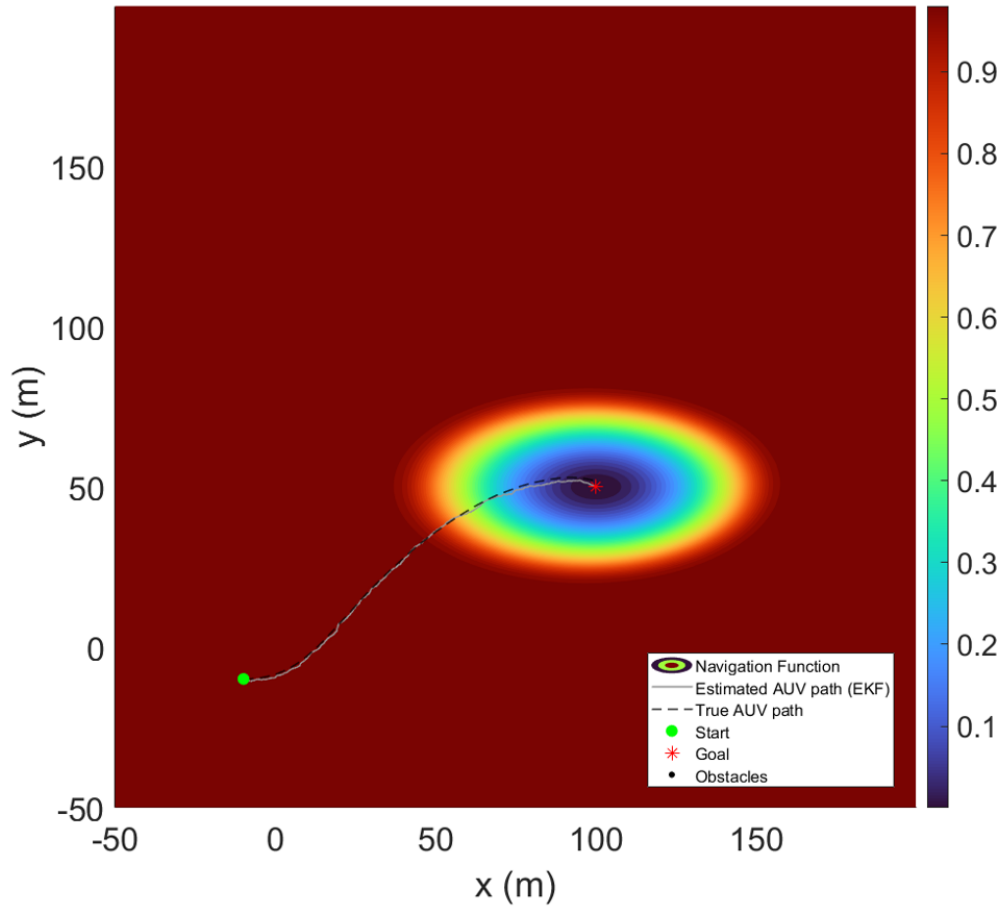


Figure 6.8: Scenario 8 - note that $L = 1690$.

Scenario 8 - Figure 6.8, builds on scenario 7 by considering the presence of ocean currents. Notably, the value of the navigation function parameter L had to be increased from 1500 to 1690 for the docking sequence to be successful.

These last four figures demonstrate the utility of the "artificial" obstacles in some cases. Due to the fact that using them meant that the docking sequence was successful in both scenarios 5 and 6, using the same value for the navigation function parameter L , which means that no adjustments were required for either simulation to work. In contrast, in Scenarios 7 and 8, the absence of the "artificial" obstacles required adjusting the value of L for each scenario.

6.3 Discussion of the Results

This chapter presented the results of the simulations conducted to assess the performance of this docking process in multiple different environments and scenarios.

As previously mentioned, in addition to the eight scenarios presented in Section 6.2, eight additional scenarios were simulated, resulting in a total of sixteen different combinations of the four parameters defined in Section 6.1. Each of the sixteen scenarios was simulated five times in order to obtain the docking errors and corresponding average error of each scenario, providing a more complete assessment of the docking solution's performance.

In table 6.3, the docking errors and respective averages, resulting from each of these simulated environments, are shown:

Table 6.3: Docking error for each scenario (in meters)

Distance to Goal	Artificial Obstacles	Ocean Currents	Obstacles	E_1	E_2	E_3	E_4	E_5	Avg.
F	Y	Y	Y	0.3420	0.4098	0.3643	0.3343	0.4569	0.3815
F	Y	Y	N	0.4203	0.4256	0.3835	0.3759	0.4426	0.4096
F	Y	N	Y	0.4414	0.3658	0.3483	0.4392	0.4654	0.4120
F	Y	N	N	0.3109	0.3941	0.4161	0.3567	0.4017	0.3759
F	N	Y	Y	0.4646	0.4087	0.4137	0.3541	0.4357	0.4154
F	N	Y	N	0.4283	0.3658	0.3629	0.4553	0.3656	0.3956
F	N	N	Y	0.2476	0.3156	0.4395	0.3648	0.3426	0.3420
F	N	N	N	0.4826	0.4123	0.3070	0.4917	0.4550	0.4297
C	Y	Y	Y	0.4924	0.4729	0.4150	0.4768	0.3930	0.4500
C	Y	Y	N	0.4494	0.2919	0.3582	0.2778	0.3934	0.3541
C	Y	N	Y	0.3238	0.4585	0.2937	0.2977	0.3308	0.3409
C	Y	N	N	0.3267	0.4627	0.3358	0.3820	0.3775	0.3769
C	N	Y	Y	0.4665	0.3384	0.4435	0.4504	0.4810	0.4360
C	N	Y	N	0.4090	0.4646	0.4164	0.3844	0.4046	0.4158
C	N	N	Y	0.3653	0.3729	0.3044	0.3373	0.4861	0.3732
C	N	N	N	0.3789	0.3701	0.2812	0.2108	0.2827	0.3047

In the first column of Table 6.3, "C" denotes a simulation where the distance to the goal (DS) was close (approximately 112 meters from the AUV's initial position) and "F" is used for simulations where the goal was further away (approximately 354 meters from the AUV's initial position). In columns 2,3 and 4, "N" is used when the parameter defined in that column's first row is not present in the simulation, and "Y" is used in case it is present.

Upon examination of Table 6.3, it can be concluded that in all simulations for every scenario tested, a docking distance of less than 0.5 meters was consistently achieved, thereby satisfying the docking threshold defined in Section 5.5 and confirming that the docking sequence was successful in all simulations conducted.

Chapter 7

Conclusions and Future Work

7.1 Conclusion

The work presented in this thesis focused on the development of a docking approach for AUVs that could successfully plan and follow a collision-free trajectory from the starting position of the AUVs to the position of the DS, while incorporating acoustic positioning measurements from an USBL system to improve the position estimates of the vehicle.

In order to achieve this goal, work started with the study of the Matlab AUV model, which would be used to develop the whole project and perform the simulations.

Subsequently, an EKF which allowed fusing of positioning data from a USBL acoustic positioning system with measurements from other onboard sensors was designed, in order to obtain better estimates of the position of the AUV throughout the whole docking sequence.

Then, a KR navigation function was implemented. This function generated collision-free trajectories from the vehicle's current position to the DS. In addition, it also accounted for environmental constraints, avoiding all obstacles between the AUV and the DS. The final step was the design of a set of controllers capable of tracking the planned trajectory and keeping the AUV at the same depth as the DS, ensuring that the AUV could follow the given trajectory and safely arrive at the DS.

The resulting solution was capable of successfully completing the docking process in all simulated environments and scenarios.

During the development of this project, several important lessons were learned.

First, and perhaps most importantly, I learned how crucial it is to structure and divide a large project like this into smaller tasks, focusing on one problem at a time.

In addition, another lesson learned was the process of controller tuning, specifically, how we should focus on the effect each of the gains has on the output of the controller one at a time, so that we can understand what happens when we change the value of each of these gains.

Another lesson learned was that correctly interpreting the results of the simulations and critically analysing their implications were essential to identifying and understanding the main problems that remained at each stage of the development phase of the project, which in turn accelerated the overall development process.

Lastly, I gained valuable knowledge of various concepts in underwater robotics, including the principles behind several control, positioning, navigation, and guidance methods commonly employed in marine robots.

7.2 Future Work

The docking solution developed in this work has shown satisfactory results. However, some aspects can be explored further to improve its performance.

Developing a method for obstacle detection is one of the avenues that should be investigated in future work, as for this project, it was assumed that the position of every obstacle was known a priori, something which is not always realistic.

In addition, in future work, the USBL model can be refined further to better represent the behavior of the real-world USBL positioning system.

Currently, the docking solution relies on manual tuning of its parameters k and L . Future work should explore ways to implement automatic tuning of these parameters to improve the quality of the docking maneuver.

Another potential future investigation should perform a detailed analysis of other trajectory planning options and compare their performance with that of the KR navigation function.

Future work should also include the design of a sequence to abort the docking process in the event that necessary conditions for successful docking are not verified, for example, when the docking maneuver starts too close to the DS and the AUV does not have time to align itself with the DS.

Lastly, the docking solution should be implemented and tested on a real AUV to truly assess how it performs in a real-world scenario.

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