Numerical Research of Obstacle Detection Using Forward Looking Sonar Model Based on a Beam of Rays

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KEYWORDS

Forward-Looking Sonar modelling; a beam of rays model; obstacle detection

ABSTRACT

More often, Autonomous Underwater Vehicles (AUVs) are used in underwater space to carry out different missions from both civilian and military domains. One of the sensors needed underwater for autonomous motion is the Forward Looking Sonar (FLS), which is used mainly for obstacle detection. The paper undertakes the problem of the FLS modelling for testing and verifying, e.g. different obstacle detection algorithms. The model based on a beam of rays has been implemented for the popular type of FLS and then verified in a simulational environment.

INTRODUCTION

Unmanned Underwater Vehicles (UUV) are increasingly used underwater robots in various types of underwater inspection and scientific research [1]. Underwater space is a very difficult environment for both the diver and the underwater vehicle to work [2]. Compared to the terrestrial or surface environment [3], the underwater environment is characterized by reduced visibility, increased motion resistance, and the impact of large disturbances, especially in the form of sea currents [4]. In addition, there may be both moving and stationary objects underwater that are obstacles to UUVs. Unmanned underwater vehicles can be remotely operated ROV (Remotely Operated Vehicle) or operate autonomously AUV (Autonomous Underwater Vehicle).

In the case of using AUVs in underwater inspection, there is a need to replace the operator's senses with underwater sensors [5]. The signals from the sensors should be efficiently processed for interpretation, and final decision-making of the autonomous system [6], [7]. One of the key areas necessary to obtain the autonomy of UUV operation is the detection of underwater obstacles, as well as often surface obstacles [8], particularly those submerged in water, and then avoiding obstacles to avoid collisions (Obstacle Detection (OD) processing and Obstacle Avoidance (OA) manoeuvres).

OD&OA problems can be classified by different criteria. The basic division concerns whether we deal with a global or local problem. In the case of a global approach, when we have information about various obstacles in the environment, OD&OA becomes a non-linear optimization problem. An example is the problem of rocket trajectory programming for the purpose of destroying a manoeuvring target while avoiding a static obstacle at a certain avoidance distance [9]. To solve this problem in the case of many mobile vehicles, where it is essential to avoid collisions not only with static but also dynamic obstacles (other robots), good results are obtained using the artificial potential field method [10]. In addition, obstacle avoidance trajectory control optimization problems can be solved using non-linear programming [11][12], heuristic algorithm [13], and graph search methods, including the A* algorithm [14] and the D* algorithm [15].

In the case of a local approach, i.e. the AUV operates in a locally known and globally unknown environment with different types of obstacles, non-linear methods are used for obstacle avoidance trajectory planning. The following examples of methods used to solve this problem can be found in the literature: Artificial Potential Field (APF) method [16], Evolutionary Algorithm (EA) [17] and Genetic Algorithm (GA) [18], the PSO (Particle Swarm Optimization) algorithm [19], or a combination of several artificial intelligence methods [20], [21]. Compared to the classical methods of optimization, the algorithms mentioned above usually lead to global or near-global solutions. At the same time, it should be emphasized that this type of algorithm has an iterative nature of finding a solution. During the iterative tuning process, they quite often arrive at local solutions. Getting stuck by these algorithms in such places of consideration space is an issue that must be faced when using them.

Regarding the FLS models or general sonar models, the most appropriate seems to be the approach based on a beam of rays, where each ray examines a different point in underwater space. One of the examples is included in [22]. Moreover, the work includes the proposition of data processing, including (1) filtering and segmentation, (2) feature extraction, (3) tracking

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and final (4) map building. In the next paper [23], similar sonar modelling is included together with the seabed modelling. To achieve the aim of the research, single beam sonars, horizontal FLSs and finally, side scan sonars are considered. Each model of the sonars was described by simulator pseudo code helping in own code preparation.

The paper undertakes problems of sonar modelling using a beam of rays representation. Such a model is very efficient for obstacle detection, but it can be quite computationally demanding depending on the sonar parameters. Presented in the paper, numerical research of the sonar model shows the processing time of the AUV motion for the sonar model with different parameters.

In the next section, the results of the analysis of the sonar operation are included, i.e. minor limitations of OD using sonar are described. In the following two sections, seabed and sonar models are presented using mainly visualisations of their working due to the limitation of the paper length. Then, the results of numerical research are inserted and discussed. At the end of the paper, the conclusions are presented.

SONAR OPERATION

After the literature analysis, as well as own experience from research in the field of underwater robotics, it should be stated that the following factors should be taken into account when researching the OD&OA system:

• FLS sonar operating parameters

The data recorded by the FLS during the measurement of the observation target is subject to Gaussian noise, refraction in the underwater environment, and interference with other signals. In addition, observing an unfamiliar environment with an FLS depends on the sonar viewing range, detection range, resolution, and operating frequency.

• Sonar operation close to the bottom or surface of the water

In the case of FLS operation close to the bottom and surface of the water, the obtained information on targets should be interpreted in conjunction with the data on the current position in the AUV space to eliminate falsely detected obstacles at the bottom or surface of the water. It should be borne in mind that the different types of bottom and the degree of waving of the water surface will affect the amount of reflected hydroacoustic wave.

• Types of obstacles

When an AUV is tasked with an unfamiliar underwater environment, it encounters various types of obstacles, such as simple convex obstacles, complex convex obstacles, and complex vortex obstacles. Therefore, it is very difficult to develop a single obstacle avoidance algorithm for different types of obstacles. In addition, obstacles can be stationary or dynamic and vertical or horizontal.

• Restriction of AUV movement

The manoeuvrability of the AUV will be affected by equipment such as rudders, including thrusters and propeller configuration. In an unknown underwater environment, the AUV will also be affected by unknown factors such as sea currents and, in the near-water layer, sea waves. Therefore, it is necessary to consider the influence of AUV motion constraints on trajectory planning and AUV control [24].

• Avoiding obstacles

AUVs can operate in an unfamiliar underwater environment, and it is inevitable to detect an obstacle in the AUV's planned trajectory. Therefore, the AUV is expected to be able to avoid obstacles in a timely manner to ensure safe and reliable manoeuvring during mission execution.

SEABED MODEL

The map generation algorithm is based on the following inputs:

• Resolution of the bottom map, i.e. the number defining the division of the distance of 1 meter into discretized sections res

• Bottom dimensions in meters in the x and y axis $dimX$ and $dimY$

• Number of obstacles nO

• Depth of the modeled water reservoir $depth$

• Bottom corrugation height $height$

The resulting bottom map is stored in two two-dimensional matrices:

1. Matrix of bottom depth and/or heights associated with the bottom of obstacles at a given point $Map1$
2. The reflection coefficient matrix of a given bottom point and/or obstacle $Map2$

Figure 1 illustrates the first of the above-mentioned matrices for the following values of input parameters: $res = 1$, $dimY = 100$, $dimX = 100$, $nO = 20$, $depth = -10$, $height = 0.5$.

The seabottom map generation algorithm first generates the bottom ripple using sine and cosine harmonic functions with an amplitude equal to the height parameter at the given depth. Then, at randomly selected points, it generates rectangular or hemispherical obstacles. Obstacle dimensions have random values in a given range of values.

Reflectance values are also randomized from a specified range of values. The final selection of reflection coefficients is planned based on experimental research using selected sonar for various types of bottoms, e.g. sandy, grassy, etc., and selected types of obstacles, e.g. vertical wall, a spherical object with seabottom, etc.

The model of the bottom and the obstacles associated with it presented above seems to be the least computationally complicated model, which will be important in the case of optimizing various methods of avoiding obstacles to be implemented in the next task. The Project envisages using AUVs to identify UXOs, i.e. moving mainly near the bottom. For the purpose of testing the detection and avoidance of obstacles located near the water surface, it is expected to generate similar matrices containing information about the undulation of the water surface and obstacles floating close to the surface, e.g. other vessels.

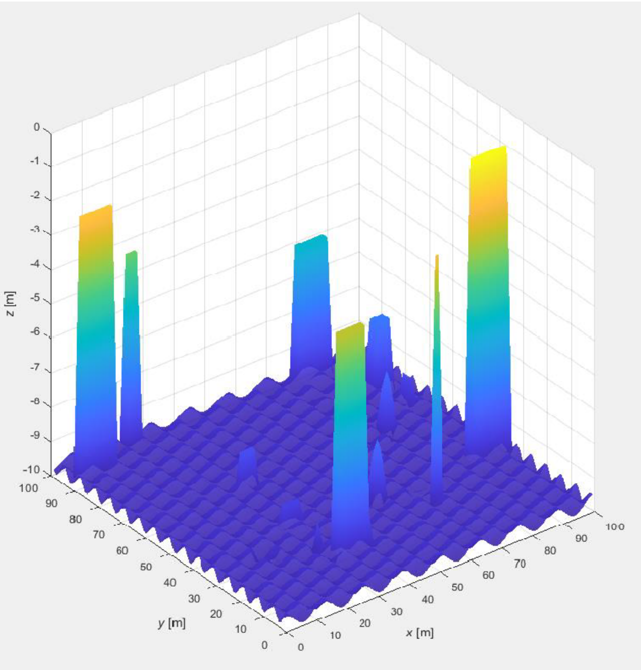

Fig. 1. Visualization of the depth of the bottom and the heights associated with the bottom of obstacles for a resolution of 1 and a bottom size of 100x100m

SONAR MODEL

The algorithm of sonar operation requires the following inputs:

- Coordinates of the localization of the sonar in relation to the AUV centre of gravity $coorSon$
- AUV orientation angles $orien$
- Angle range, resolution and viewing distance $sector$
- Sonar beam angle $width$
- The minimum and maximum range of sonar vision $rmin$ and $rmax$
- Maps and their parameters as listed in the previous section

The sonar obstacle detection algorithm works in two 'for' loops. In the outer loop, the angle of the beam generation system ang is increased from the minimum value $angmin$ to the maximum value $angmax$ with a step determined by the mechanical resolution of the sonar $angres$. The inner loop, on the other hand, increases the sonar viewing distance $dist$ from the minimum value to the maximum value in steps determined by the map resolution. In the inner 'for' loop, the ranges of the beam area in space in azimuth $azimmax$ and elevation $elewmax$ are calculated for given latitude and $dist$ parameters. The coordinates of the beam fill rays are then generated so that all points in the environment at the end of the sonar beam can be tested for bottom or obstacles (Fig. 2 and 3).

Increasing the line-of-sight in this loop ensures that obstacles closest to the sonar can be detected. After detecting an obstacle, information about it in the form of the bearing angle, the distance of the position relative to the sonar and the strength of the reflected signal is saved in the matrix $target$. The signal power is calculated as the average of the obstacle powers obtained

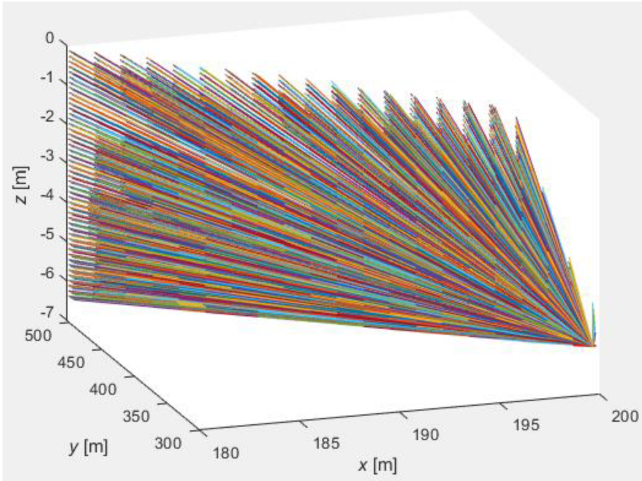

Fig. 2. Visualization of single beam rays for 50m viewing distance

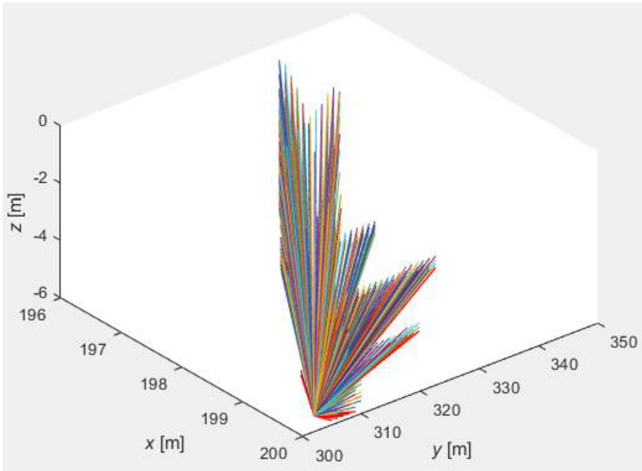

Fig. 3. Visualization of single beam rays for 10m viewing distance

at the ends of the rays forming the beam. In addition, the algorithm checks each time whether the possible radius does not go beyond the range of the environment, i.e. beyond the values of $dimX$ and $dimY$ variables. It should be noted that the computational complexity of the obstacle detection algorithm performance increases with beam size (beam spread angle and maximum sonar view range) but also with environment resolution (bottom and obstacle map resolution).

RESULTS OF NUMERICAL RESEARCH

Numerical research of the sonar model implemented in Matlab using a beam of rays was carried out in the following stages:

1. Checking the generation of rays for various sonar parameters
2. Verification of object detection at different AUV positions in an environment with obstacles
3. Verification of bottom detection with different AUV orientations
4. Comparison of processing times for different sonar parameters

The first three tests were carried out on the CPU i7/Windows 10 platform, while the fourth test, due to the high calculation time, was on the 6xGPU/Windows 10 platform.

As part of the first test, the correctness, including, above all, the completeness of generating beam rays for various sonar and beam settings, was checked. This allowed us to eliminate several programming errors. Fig. 4 visualizes the sonar beam rays in an obstacle environment generated for the following parameters: angle ±45° and line-of-sight 50m for xyz position coordinates equal to (40m, 50m, -8.5m) and orientation angles $orien = (0°, 0°, 90°)$. Based on the visualization, it can be seen that the beam space is evenly covered by the generated rays.

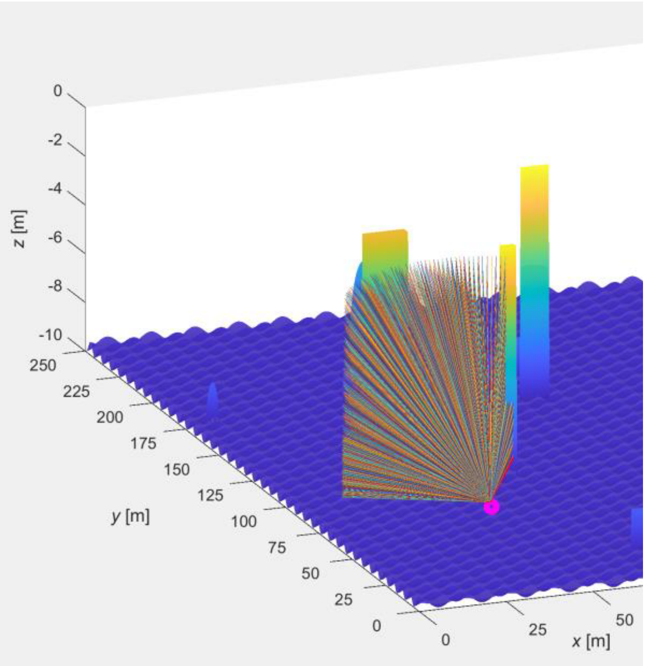

Fig. 4. Visualization of ±45° sonar beam rays at 50m line-of-sight for AUV at xyz position (40m, 50m, -8.5m) and Euler angles $orien = (0°, 0°, 90°)$

As part of the next test, various objects were detected in a simulation environment at different positions and an AUV course. In all these tests, the heel and trim angles of the submersible vehicle were kept at zero. One example is shown in Fig. 5.

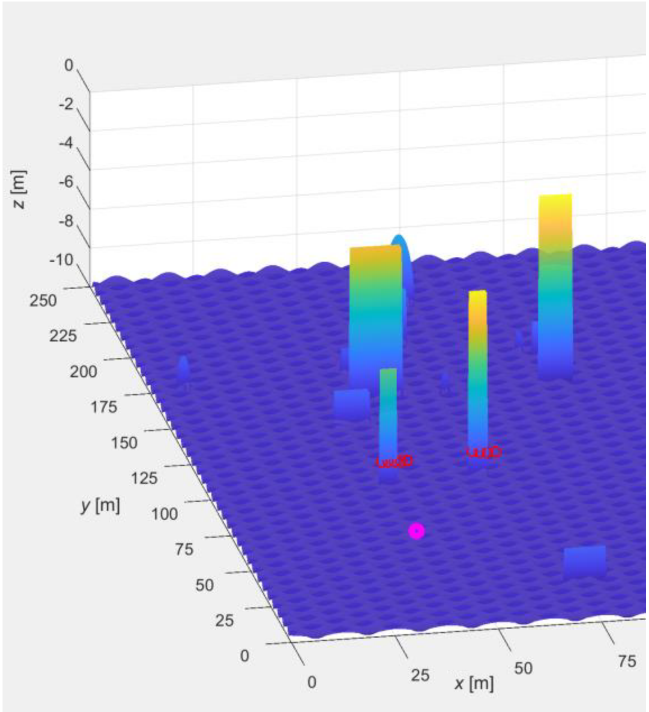

Fig. 5. Visualization of AUV (pink dot) and detected obstacles (red dots) for sonar at ±45° angle and 50m line-of-sight and AUV at xyz position (40m, 50m, -8.5m) and orientation angles $orien = (0°, 0°, 90°)$

Fig. 5 visualizes the AUV (pink circle) and detected obstacles (red circles) for the ±45° sonar angle at 50m line of sight and the AUV at the xyz position (40m, 50m, -8.5m), with orientation angles $orien = (0°, 0°, 90°)$. You can see that obstacles have been detected correctly. In addition, lower target power was obtained for the lower obstacle, which is planned to be used in mapping and, eventually, collision avoidance systems. Sometimes the obstacles detected went beyond the obstacles in the environment. This is due to the width of the beam. For some bearings, the beam "hooks" on the obstacle only to a small extent.

In subsequent tests, sea bottom detection was tested for AUVs with a specific trim angle (Fig. 6) and/or heel angle.In both cases, the specific arrangement of the points illustrating the bottom detected by a given beam allows us to state that the developed algorithm correctly detects obstacles. During the development of the mapping system, it is planned to analyze the orientation of the AUV, which will allow the classification of such objects as the sea bottom. This method of analysis during movement close to the water surface should also apply to detect an obstacle due to the reflection of the beam from the wavy surface of the water.

In the last stage of the research, the developed algorithm for detecting obstacles using sonar was tested for different variants of sonar settings (Table I) and the same AUV trajectory (Fig. 7) in terms of calculation time.

The results of the conducted tests are illustrated in Fig. 8.

According to the data in Table 1. from variant no. 1 to 6, we have an increase in the angle of view of the sonar beam from ±10° to ±60°, and from variant no. 7 to 12, an increase in the viewing distance of the sonar beam from 20m to 70m. While variants 13 to 18 examined the impact of mechanical sonar resolution on processing time.

CONCLUSIONS

In the paper, numerical research on a beam of rays model of sonar mounted on board AUV has been examined together with modelled obstacle installed on the sea bottom.

Evidently, an increase in the viewing distance of the sonar model results in a non-linear increase in computational time. This is due to the increasing number

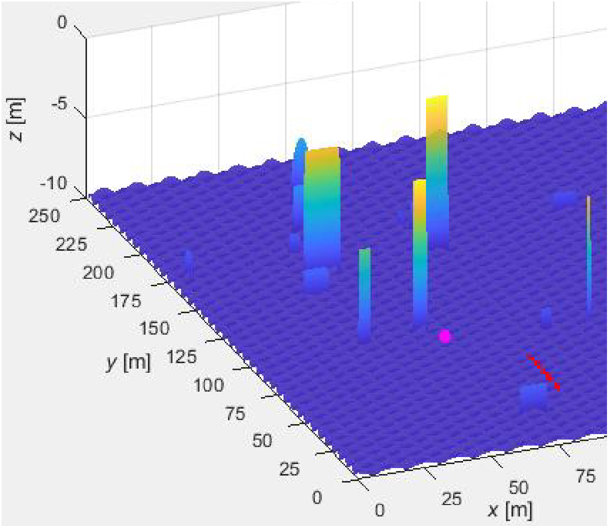

Fig. 6. Obstacles detected (red dots) for ±30° sonar and 40m line of sight, mounted on AUV (pink dot) at xyz position (55m,55m,-6.5m) and angles $orien = (0°, 5°, 0°)$

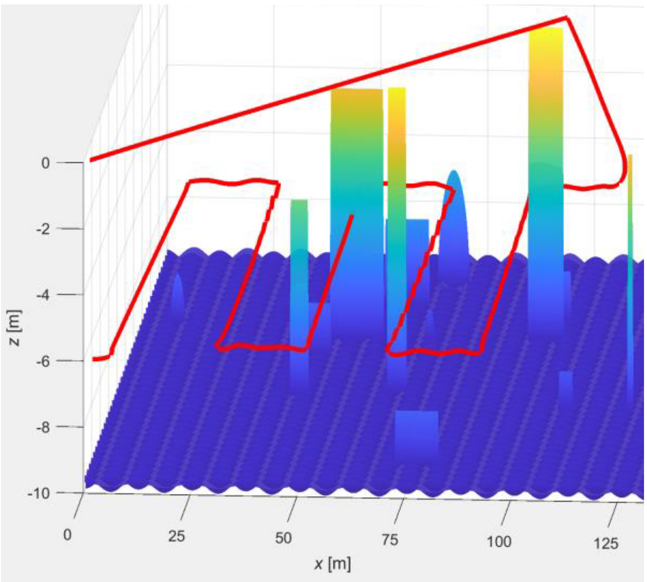

Fig. 7. AUV trajectory during benchmarking processing times for various sonar parameters

of rays contained in the longer beam compared to the shorter one.

However, taking into account the fact that the designed AUVs are designed to move along fixed trajectories close to the bottom with speeds of approx. $1 - 2m/s$, the selection of sonar viewing from 10 to 20m in the sector from ±10° to ±30° seems to make sense, i.e. it allows AUV to manoeuvre around an obstacle and/or make an emergency stop. Such a choice of parameters is not associated with an excessive increase in computational time. In addition, the choice of resolution at the level of 3.6° with a beamwidth in azimuth of 3° and the above-mentioned value of the distance gives a lack of coverage between successive beams at their ends at the level of 5-10 cm. It also does not cause a risk of not noticing the obstacle, especially since the clearance between the beams decreases as the AUV

No.	Viewing angle [deg]	Viewing distance [m]	Sonar resolut. [deg]
1	±10	10	3,6
2	±20	10	3,6
3	±30	10	3,6
4	±40	10	3,6
5	±50	10	3,6
6	±60	10	3,6
7	±10	20	3,6
8	±10	30	3,6
9	±10	40	3,6
10	±10	50	3,6
11	±10	60	3,6
12	±10	70	3,6
13	±10	10	0,9
14	±10	10	1,8
15	±10	10	3,6
16	±60	10	0,9
17	±60	10	1,8
18	±60	10	3,6

TABLE I: Variants of sonar configuration

approaches to the possible obstacle.

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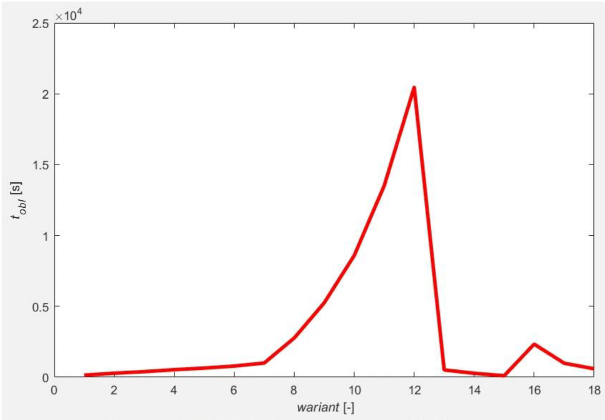

Fig. 8. AUV motion simulation processing times for 18 variations of different sonar configuration variants

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Rafał Kot. Graduated from the Military University of Technology in Warsaw with a degree in Electronics and Telecommunication Studies in 2016. He worked for almost 6 years in the Marine Aviation Base in the Polish Army where he gained experience in servicing and maintenance of aircraft in the avionics area. From the beginning of 2022, he is working at Polish Naval Academy. His main research includes underwater obstacle detection systems, path planning algorithms, and collision avoidance systems for Autonomous Underwater Vehicles.