Pamukkale Univ Muh Bilim Derg, 31(6), 984-992, 2025

Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi

Pamukkale University Journal of Engineering Sciences

Detecting the borders of a pool-like environment by using scanning sonar data for AUVs

İnsansız su altı araçları için tarama sonarı verilerini kullanarak havuz benzeri ortamların kenarlarını tespit etme

Hatice Hilal Ezercan Kayır[1*], *Metin Baydarakçı*[1]

[1]Department of Electrical and Electronics Engineering, Faculty of Engineering, Pamukkale University, Denizli, Türkiye.
hezercan@pau.edu.tr, mbaydarakci@posta.pau.edu.tr

Received/Geliş Tarihi: 29.01.2025 Revision/Düzeltme Tarihi: 14.02.2025 doi: 10.5505/pajes.2025.86344
Accepted/Kabul Tarihi: 18.02.2025 Research Article/Araştırma Makalesi

Abstract

This study presents a novel, cost-effective method for real-time underwater vehicle (AUV) localization in enclosed environments, pools or marinas. Traditional underwater localization techniques, often based on acoustic systems, prove costly and impractical for confined spaces. This study focuses on identifying environmental boundaries and, utilizing this information, solving the AUV's localization problem by leveraging data acquired from a 360-degree field-of-view sonar scanning sensor mounted on the AUV. Raw sonar data is processed and subsequently clustered using the K-means algorithm, enabling the identification of environmental features such as edges and corners. These identified features are then matched against a pre-existing environment map to determine the AUV's instantaneous position. Experimental results demonstrate the accuracy and reliability of the proposed approach, with small error values in corner point estimations. While the method's low computational complexity makes it suitable for real-time applications, the absence of complex and high-cost equipment requirements offers a significant advantage for daily applications. This study suggests that the proposed method has a broad application potential in AUV navigation through its iterative use.

Keywords: Autonomous underwater vehicle, Underwater localization, Scanning sonar, Data processing, Edge detection.

Öz

Bu çalışma, havuzlar veya marinalar gibi kapalı ortamlarda gerçek zamanlı insansız su altı aracı (İSAA) konumlandırması için yeni ve uygun maliyetli bir yöntem sunmaktadır. Genellikle akustik sistemlere dayanan geleneksel su altı konumlandırma teknikleri, sınırlı alanlar için maliyetli ve pratik olmadığı kanıtlanmıştır. Bu araştırma, İSAA üzerine monte edilmiş 360 derece görüş alanına sahip bir sonar tarama sensöründen elde edilen verileri kullanarak ortam sınırlarını tespit etmeyi ve bu bilgileri kullanarak İSAA konumlandırma problemini çözmeyi hedeflemektedir. Önerilen yöntem ile ham sonar verileri işlenerek kenarlar ve köşeler gibi çevresel özelliklerin belirlenmesini sağlamak üzere K-means algoritması kullanılarak gruplanır. Belirlenen bu özellikler daha sonra İSAA'nın anlık konumunu belirlemek için bilinen ortam haritasıyla eşleştirilir. Deneysel sonuçlar, köşe noktası kestirimlerindeki düşük hata değerleri ile önerilen yaklaşımın doğruluğunu ve güvenilirliğini göstermektedir. Yöntemin düşük hesaplama karmaşıklığı gerçek zamanlı uygulamalar için uygun olmasını sağlarken, karmaşık ve yüksek maliyetli ekipman gereksinimi olmaması günlük uygulamalar için önemli bir avantaj sunmaktadır. Bu çalışma, önerilen yöntemin yinelemeli kullanımı ile İSAA navigasyonunda geniş bir uygulama potansiyeline sahip olduğunu göstermektedir.

Anahtar kelimeler: Otonom insansız su altı aracı, Su altı konumlandırma, Tarama sonarı, Veri işleme, Kenar tanıma.

1 Introduction

Diving into the depths of the underwater world has long been one of humanity's greatest dreams. However, the harsh conditions of the seas, the unknown and dangerous nature of the depths, and the physiological limitations of humans have largely limited these explorations. With the acceleration of scientific and technological developments in recent years, the use of unmanned underwater vehicles (UUVs) has been increasing [1]. UUVs are widely used in both civilian and military fields, such as underwater exploration, deep-sea mining, search and rescue operations, and monitoring marine ecosystems [2]. As technology continues to advance, it is expected that UUVs will play an even more significant role in understanding underwater world [3].

Unmanned underwater vehicles can be divided into two main groups based on their operating systems: remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs) [4]. ROVs are generally connected to the outside world by a cable and are remotely controlled by an operator to perform a variety of tasks underwater. They are structurally simpler systems and do not require complex control systems. However, due to their continuous connection to the outside world, ROVs have limited maneuverability and a limited operating range [5]. AUVs, on the other hand, have no connection to the outside world. This allows them to be used in environments that are inaccessible to humans, dangerous, and lack communication capabilities. On the other hand, AUVs must be able to perceive their environment, evaluate collected data, and make decisions about their actions. Today, research is focused on developing reliable and fully autonomous AUVs with extensive maneuverability and decision-making capabilities [6].

An AUV must know where it is and what route to take to reach its target point while performing the given, predefined task. This requires accurate and real-time positioning information. In land and air vehicles, the positioning problem is solved with GPS and similar systems. However, these systems are disabled in the underwater world. In an environment where vehicles

*Corresponding author/Yazışılan Yazar

have no connection to the outside world and only acoustic and optical systems can be used to a limited extent, positioning and navigation for underwater vehicles are much more complex and challenging problems.

AUV navigation solutions are divided into three main groups [7]. Inertial navigation is based on estimating the vehicle's position and velocity using data from sensors on the vehicle [8]. The IMU sensors, a combination of gyroscope and accelerometer sensors that measure angular and linear motion variables respectively, offers a simple and inexpensive solution for inertial navigation [9]. However, as vehicle behavior become more complex and the hydrodynamic effects of water become unpredictable, large measurement errors occur in the estimated values with the IMU sensor over time. Another sensor that provides an effective solution for inertial navigation is the Doppler Velocity Log (DVL) sensor, which uses the Doppler effect [10]. In the study [10], DVL sensor measurements are processed with the Kalman Filter to obtain information about water flow, vehicle speed, and depth. In cases where the DVL sensor is integrated with the IMU sensor to tolerate the large cumulative errors caused by the IMU sensor in long-term use, despite its fast operation, effective navigation solutions are achieved [11],[12]. However, while the DVL sensor provides highly accurate position and velocity estimation [13], its high price imposes a significant cost burden on the system. For this reason, it is used more in large-scale studies rather than small-scale, low-cost systems [14].

Acoustic navigation systems use multiple acoustic wave transponders to locate underwater vehicles [15]. Based on the communication between one or more receivers/transmitters on the water surface and transponders on the AUV, its position and velocity estimates are made. While providing effective solutions for navigation and path planning, the installation cost of these systems is quite high [16]. In addition, the AUV is restricted to moving only within the system's access range.

Geophysical navigation, on the other hand, is based on systems that estimate the vehicle's position and velocity using sensors that perceive the environment and using distinctive features of the environment known as landmarks. Optical and sonar systems are the two main categories of geophysical navigation [17]. Lidar camera and IMU sensor data are combined for positioning purposes for different geometrical paths in an experimental tank environment [18]. Geophysical navigation, which is performed by processing data obtained from optical sensors, provides the highest accuracy among all methods due to providing more information about the external world [19]. It provides accurate solutions in long-term use against measurement errors [20]. However, it has disadvantages such as the complexity and time-consuming nature of image processing algorithms [21], the cost of optical sensors, and the high lighting requirements of these sensors [22]. It is very difficult to obtain healthy image data due to the turbidity and fluctuation effects encountered in the underwater environment [23]. In many studies in literature, deep learning-based methods have been used to draw precise and reliable inferences using camera images [24,25]. However, the need for a large data set and being time-consuming are the disadvantages of these approaches [26]. Bathymetric mapping method with active scanning sonars is another method used other than optical systems. Bathymetric mapping is the measurement and mapping of the depths of the seabed. Scanning sonars are successfully used for depth measurements and creating topographic maps of underwater objects [27]. Active sonars have different structures such as forward-looking sonar, side scan sonar [28] and imaging sonar [29] according to the scan angle range and settlements. The unknown contour tracking task was successfully completed with the forward-looking sonar, which is a narrow-angle sonar sensor and placed in front of the vehicle [30]. The object recognition task was performed using side scan sonar placed on the sides of the vehicle with deep learning approaches [31]. A study comparing seabed bathymetric maps obtained with sensors called multi-beam imaging sonar with reference maps has shown effective results in detecting drifts in vehicle movement [32]. For navigation, landmarks on the walls of the water tank detected using imaging sonar, which provides information about the entire surroundings of the vehicle with its wide scan angle [29]. It has been suggested to combine IMU and DVL sensors with sonar data using a particle filter for the combined use of inertial and geophysical navigation methods [33]. The most fundamental problem of geophysical navigation is the lack of sufficient and adequate landmarks to achieve successful results [34].

Generally, underwater object and obstacle detection studies are carried out using feature extraction and classification methods using optical or sonar sensor data [35]. Jian et. al. examined traditional methods based on feature extraction in this field [36]. In a study where images obtained from on-board cameras were used for edge detection and contour tracking of marina robots, Harris and Canny corner extraction algorithms were used [37]. In positioning and mapping studies in the field of robotics, methods that use distinctive features of the environment as landmarks are widely used. With the detection of landmarks, it is possible to make relative positioning according to known locations. These landmarks can be natural features of the environment, such as corner points, or they can appear as special placemarks placed by people. Hoff et. al. focused on landmarks in the environment for simultaneous positioning and mapping using side scan sonar data. In their proposed method, they first obtained a probabilistic map of the environment using the raw sonar data they processed and then detected landmarks on this map [38]. For terrestrial autonomous vehicle mapping studies, environment boundaries and obstacle edges were detected using consecutive clustering algorithms on laser scan data [39].

In this study, a method that utilizes environmental information obtained by underwater scanning sonar to determine the instantaneous position of an AUV is investigated. In this method, raw environmental data collected from the scanning sonar is initially processed and subsequently separated into groups by using the K-means clustering algorithm. This enables the rapid and highly accurate identification of edges and corner points in bounded environments such as pools and marinas. By detecting at least three edges or two corner points of the environment and comparing this information with an environment map, the AUV's instantaneous position could be determined. Because of its low computational complexity, the proposed method is suitable for real-time applications that demand speed. Additionally, as it does not necessitate complex physical equipment, it offers a low-cost system and can be readily employed in small-scale daily-life applications.

The outline of the paper is as follows: In Section 2, K-means clustering algorithm is explained briefly. Section 3 gives the details of proposed method step by step. Section 4 provides information about the application and includes experimental results. Conclusion part is in Section 5.

2 K-Means clustering

Clustering is a data analysis technique that involves grouping data points in a dataset into clusters based on their similarity. The objective of clustering is to maximize the similarity within clusters while minimizing the similarity between clusters.

K-means clustering is an unsupervised learning technique used to classify a group of data points in a dataset into a predetermined number of clusters. It is a hard-clustering algorithm that assigns each data point to exactly one cluster. Given a dataset $X = \{p_i | \, i = 1, \dots, N\}$ consisting of N data points, the K-means clustering algorithm partitions the dataset into K clusters $C = \{C_j | \, j = 1, \dots, K\}$ by minimizing the sum of squared distances between each data and its cluster centroid, as shown in Equation (1) [40].

$$arg\ min \sum_{j=1}^{K} \sum_{p_i \epsilon C_j} \|p_i - \mu_j\|^2 \quad (1)$$

This ensures that data points with high similarity are grouped together. The cluster centroid μ_j is calculated as the mean of the data points in the cluster and is given by Equation (2). The algorithm iteratively assigns data points to clusters and updates the cluster centers until convergence.

$$\mu_j = \frac{1}{|C_j|} \sum_{p_i \epsilon C_j} p_i \quad (2)$$

In the K-means clustering algorithm, determining the K value is a critical step to obtain accurate and meaningful clustering results. The K value represents how many clusters the data will be divided into, and choosing this value correctly affects the structure of the clusters. There are various approaches to determining the K value, such as the elbow method [41], the silhouette method [42], and the within-group average distance method [43]. However, the use of experimentally determined K values is also common in various applications. The K-means clustering algorithm is presented in Table 1.

Table 1. K-Means clustering algorithm.

Input : Data Set $X = \{p_i | \, i = 1, \dots, N\}$, Number of cluster K
Output: Cluster set $C = \{C_j | \, j = 1, \dots, K\}$
1. Initialize cluster representatives μ_j randomly 2. repeat 3. for $i = 1..N$ 4. Determine the closest representative μ_j for point p_i 5. $C_j = C_j \cup p_i$ 6. end for 7. for $j = 1..K$ 8. Update cluster representative μ_j 9. end for 10. until all μ_j's remain unchanged

3 Clustering-Based edge and corner detection method

In the field of AUV navigation, GPS, lidar, and radar systems are commonly used. However, due to limited bandwidth and specific frequency constraints in underwater environments, simultaneous localization and navigation processes are significantly more complex compared to those used in aerial and terrestrial vehicles. Underwater mapping and localization in high seas typically relies on acoustic communication between sensors deployed in the target area. The vehicle's position is determined based on the signals received from these sensors. However, this method is both impractical and costly for small and confined spaces like pools.

This study proposes a fast and low-cost method for real-time studies in enclosed pool environments. The method utilizes data obtained from a scanning sonar mounted on the AUV to detect the edges and corners of the pool. By comparing this information with a known map of the pool, the AUV's instantaneous position and orientation can be determined.

An underwater scanning sonar provides information about the entire environment within its detection range and scanning angle, essentially offering an image of the environment. The raw data obtained from the underwater scanning sonar is first processed to extract meaningful and real-valued information. This data is then gathered using clustering algorithms to identify the boundaries of the environment.

The underwater vehicle used in this study is a six-degree-of-freedom (6-DOF) autonomous vehicle. Figure 1 defines the axes of motion of the underwater vehicle.

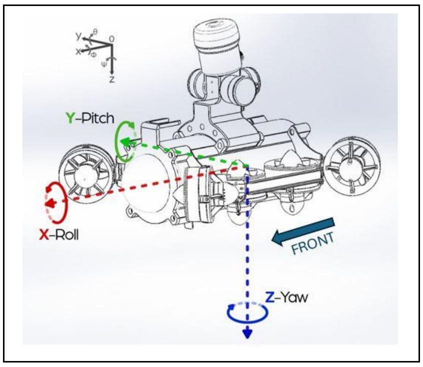

Figure 1. 6-DOF System axes definitions.

While motion planning in AUV studies is performed relative to a fixed coordinate system, the motion variable measurements such as position and velocity provided by the IMU sensor, and the environmental scanning information, are based on the local coordinate system of the vehicle. Figure 2 shows the fixed coordinate system $\{G\}$ and the moving coordinate system $\{R\}$ of the AUV. These two coordinate systems are related through a transformation ${}^{G}_{R}\mathcal{T}$, which defines the representation of frame $\{R\}$ relative to frame $\{G\}$.

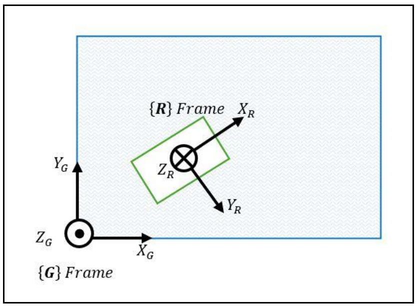

Figure 2. Coordinate frames.

The expression given in Equation (3) is valid about the transformation ${}^{R}_{G}\mathcal{T}$ that is the representation of frame $\{G\}$ relative to frame {R}.

$${}^{R}_{G}\mathcal{T} = \left({}^{G}_{R}\mathcal{T}\right)^{-1} \quad (3)$$

Step 1: Preparation

To minimize noise effects caused by reflections and echoes in the sonar scan data, the acoustic waves should intersect the pool edges as perpendicularly as possible. Therefore, the AUV's roll angle ϕ and pitch angle Θ are set to zero to prepare the vehicle for data acquisition. In this case, the transformation between frame $\{R\}$ and frame $\{G\}$is reduced to ${}^{G}_{R}\mathcal{T}\big|_{\substack{\theta=0\\ \psi=0}}$.

Step 2: Data Acquisition

A dataset is obtained by scanning the environment using an underwater scanning sonar. The sonar scan data set is defined by Equation (4), with the sonar scan angle φ_s and angular resolution σ_s.

$$\mathrm{O} = \left\{(u_i, \varphi_i) \;\middle|\; u_i = [o_{ir}]^T,\ i = 1, \ldots, \frac{\varphi_s}{\sigma_s}\ ,\ r = 1, \ldots, L\right\} \tag{4}$$

Here, φ_i represents the ith measurement direction angle, and L is a vector of length carrying the ith measurement data. Underwater scanning sonar sensors read a data series from the nearest point (o_{i1}) to the farthest point (o_{iL}) within the scanning range for each scanning direction.

Step 3: Filtering

Sonar scan data obtained, especially in underwater, contains some noisy values due to multiple reflections and echoes due to the physical structure of the environment. To obtain accurate and reliable results, these noisy components must be removed from the dataset. For this purpose, the sonar-scan data is subjected to a filter with threshold value (f_{tr}). If this threshold value is too low, it will cause noisy data to be transmitted, while if it is too high, it will result in the loss of distinctive features. This filtering process and the filtered data set are given in Equation (5) and Equation (6), respectively.

$$\mathrm{O}_n = noise\_filter(\mathrm{O}, f_{tr}) \tag{5}$$

$$\mathrm{O}_n = \left\{(u_i\ ,\ \varphi_i) \;\middle|\; u_i = [o_{ir}^n]^T, o_{ir}^n = \begin{Bmatrix} o_{ir}\ , & |o_{ir}| > f_{tr} \\ 0\ , & |o_{ir}| < f_{tr} \end{Bmatrix}\right\} \tag{6}$$

Step 4: Orientation Correction

In this step, the effect of the orientation difference between the frame $\{R\}$ and frame $\{G\}$ caused by the AUV yaw angle is corrected on the dataset. The aim is to facilitate the edge detection process in the subsequent steps. The dataset obtained after orientation correction is expressed as given in Equation (7) and Equation (8).

$$\mathrm{O}_\phi = {}^{G}_{R}\mathcal{T}\big|_{\substack{\theta=0\\ \psi=0}} (\mathrm{O}_n) \tag{7}$$

$$\mathrm{O}_\phi = \left\{\left(u_i\ ,\ {}^{G}_{R}\mathcal{T}\big|_{\substack{\theta=0\\ \psi=0}} (\ \varphi_i)\right) \;\middle|\; u_i = [o_{ir}^n]^T\right\} \tag{8}$$

Step 5: Real Coordinates Matching

The sonar scan data is read as a set of numerical values for the region from the closest point to the sonar to the farthest point within the measurement range. For each point in the dataset, the corresponding position information on the frame {R}, assigned to AUV, should be obtained. (ρ_{scan}) is the scan range of the underwater scanning sonar, and the matching coordinate values of the scan data are defined by Equation (9).

$$V = \left\{v_i \;\middle|\; v_i = \left[o_{ir}^n\ \ v_{irx}\ \ v_{iry}\right]^T\right\} \tag{9}$$

The x and y coordinates of point v_i relative to the frame $\{R\}$ are calculated using the formulas given in Equation (10a) and Equation (10b) respectively.

$$v_{irx} = \rho_{scan} * \frac{0.5 * L - r}{0.5 * L} \tag{10(a)}$$

$$v_{iry} = \rho_{scan} * \frac{0.5 * L - i}{0.5 * L} \tag{10(b)}$$

In this way, the coordinates of the physical point corresponding to each value in the dataset are obtained.

Step 6: Clustering

The coordinate-mapped dataset is clustered into K clusters using the K-means clustering algorithm. Each data point in the dataset is labeled with the cluster to which it belongs. Each cluster C_j is represented by its cluster centroid μ_j.

Step 7: Cluster Merging

Clusters that correspond to the same edge or pool boundary are merged into the same class. Given that θ_j is the angle between the cluster centroid μ_j of the C_j cluster and AUV, C_j clusters satisfying the condition $\theta_{p1} < \theta_j < \theta_{p2}$ are included in the $Edge_p$ class. The threshold values θ_{p1} and θ_{p2} are determined experimentally based on pool geometry and complexity.

Step 8: Edge and Corner Detection

Not all data points in the $Edge_p$ class represent the pool edge. Some data points may belong to obstacles in the environment, while others may be noise that have survived the filtering process. Such data points within each class must be discarded. The class center (η_p) for the $Edge_p$ class is calculated as the mean value of the class members, as expressed in Equation (11).

$$\eta_p = \frac{1}{|Edge_p|} \sum_{v_i \epsilon E_p} v_i \tag{11}$$

It is obvious that the points forming the same edge within a class will be located on a line. If the angle θ_p between the class center η_p and a point v_i in $Edge_p$ is less than a certain threshold value, this point is added to the E_p edge list, and other points are ignored. The points in the E_p list define the pth edge.

After detecting the edges, the intersection points are determined to identify the corners. A corner is the intersection of two edges. The angle between the AUV and the center of the mth edge, represented by θ_p, is calculated as in Equation (12). η_{mx} and η_{my} are x and y coordinates of η_p respectively.

$$\theta_m = atan2(\eta_{my}, \eta_{mx}) \tag{12}$$

If the pth edge and the qth edge share a common corner, θ_p and θ_q must satisfy Equation (13).

$$|\theta_p - \theta_q| \neq 180°k\ , k = 0,1,2, \ldots \tag{13}$$

Corner points are searched among the edge data that satisfy this condition. There are two possible cases:

- Case 1: If some points in the pth edge list E_p and the qth edge list E_q are in the close neighborhood of each other when considering the Euclidean distance, this clearly indicates a common corner between the two edges. The average of these points is calculated as the corner point.

- Case 2: If there are no points close to each other in the pth edge list E_p and the qth edge list E_q, this may be due to the fact that the potential corner point is outside the sonar scan range. In this case, the E_p and E_q edge lists are virtually extended by additional points starting from their midpoints up to the maximum pol edge length to estimate the corner point.

In this way, the process is completed by first determining the edges and then the potential intersection points, corners, of the underwater environment. By comparing the found corner points with the known map of the pool, the instantaneous localization information of the AUV can be obtained.

4 Experimental study and results

This section presents the experimental studies of the method by which underwater environment data, acquired by a sonar sensor, is utilized to determine environmental boundaries, specifically the edges and corners of the pool, through a clustering approach. The identified edges and corners are subsequently compared with the known pool map to ascertain the AUV's instantaneous position and orientation.

Sound Navigation and Ranging (SONAR) systems constitute a type of active sensor that operates by emitting sound waves to detect underwater objects and recording the reflections of these pulses. Scanning sonars, conversely, determine environmental characteristics by generating an acoustic wave with a wide vertical beam and a narrow horizontal beam. The distance between the sonar and the obstacle is computed using Equation (14), employing the speed of sound waves in water and the time differences between the wave's send and return.

$$\delta = v_s * (t_r - t_s) \tag{14}$$

The typical velocity of sound waves in a marine environment is $1500\,m/s$. However, this value is subject to variations depending on the water's salinity, temperature, and the sonar sensor's performance under pressure. In these experimental studies, the Ping360 Scanning Imaging Sonar sensor, manufactured by BlueRobotics, was employed. The Ping360, a mechanical sonar characterized by a $50\,m$ scanning range and a $300\,m$ depth operational range, and high-performance, is highly suitable for underwater operations due to its 360-degree scanning angle [26].

In order to test the proposed method, the AUV, that is designed and manufactured by the team comprising the authors, is utilized. This quadrotor-type AUV, with 6-DOF is equipped with 8 motors. With dimensions of $395\,mm\,x\,449\,mm\,x\,258\,mm$ and an approximate weight of $8\,kg$, this small-scale vehicle is notable for its autonomous operational capabilities. Experimental studies were carried out in a rectangular closed pool measuring $25\,m\,x\,7\,m$.

The initial phase of the test involves preparing the AUV for measurement and acquiring environmental data using the scanning sonar. Initially, the AUV's roll and pitch angles are calibrated to zero, thus preparing it for measurement. Utilizing the onboard scanning sonar, which boasts a 1-degree angular resolution, a complete 360-degree (400 grad) scan is performed to collect the necessary data. The acquired data, for each grad direction, consists of 1200 data points, with the first data point representing the nearest point and the last data point representing the farthest point within the scanning range. Each data in the $400\,x\,1200$ data set obtained for the entire surroundings takes values between $0 - 255$, depending on the perceived obstacle. Given that the studies were conducted within a small and confined pool, the scanning range was set to $5\,m$. A visualization of the acquired data set is provided in Figure 3.

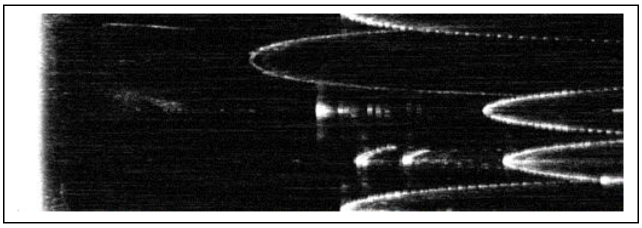

Figure 3. Scanning Sonar data visualization.

To ensure data relevance, the sonar scan data is converted to polar coordinates, resulting in a reduction of the data set size to $400\,x\,400$. The image of the data set in polar coordinates is depicted in Figure 4. The utilized scanning sonar sensor provides a grayscale representation of the environment. The white circle in the middle of the image shows the location of the AUV.

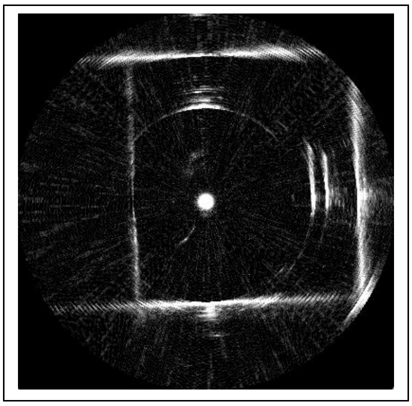

Figure 4. Scanning sonar data image.

As clearly shown in Figure 4, the sonar scan data set exhibits a substantial noise component due to multiple reflections and echoes. For successful and precise results, it is imperative to mitigate these noisy ones. Following the implementation of the filtering process designed for this purpose, the representation of the filtered data set is presented in Figure 5.

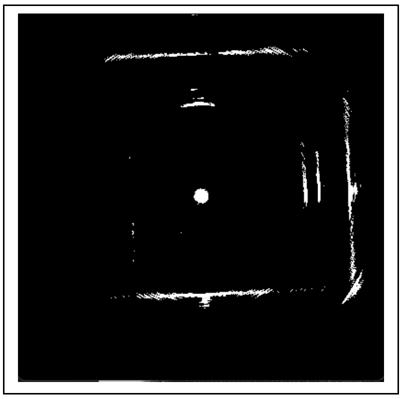

Figure 5. Filtered data image.

The obtained sonar data takes values between 0 and 255. The value of 0 means that the relevant location is empty and the value of 255 signs that there is an object in the relevant location. When the data is examined, it is seen that the noise caused by multiple reflections and echoes generally has values varying between 150 and 220. Therefore, points with values lower than 220 in the data set are canceled, and points above 220 are survived.

The sonar scan data set comprises values corresponding to the region between the point closest to the sonar and the terminal point of the scan range. These points must be transformed into real-world distance and position data, proportional to the scan range. This transformation is performed with respect to the local coordinate system, the origin of which is located on the AUV. The outcome of this transformation is shown in Figure 6. After this process, the sonar scan data is converted into coordinate values, thus reflecting the real-scale representation of the underwater environment. The location of the AUV is indicated by a red star ($*$) sign in figure.

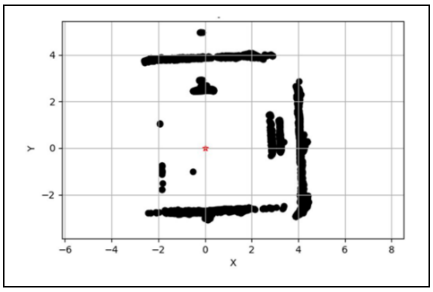

Figure 6. Coordinate frame matching data.

The second phase of the experimental studies involves performing clustering and feature extraction operations on the sonar scan data set, which has been converted to real-world distance information. For this purpose, the K-means clustering algorithm is employed to partition the data into clusters. The clustered data for a cluster count of 10 is illustrated in Figure 7. Each cluster is represented by a distinct color, and the cluster centroids are indicated by a red cross (x) marker.

There are various methods in the literature regarding the determination of the optimal number of clusters. Very small K values may cause the data not to be separated into meaningful clusters. Very large K values may lead to overfitting problems. The number of clusters to be used in this study was determined by trial and error. In the case of 6 or less clusters, the resulting cluster structure does not allow for inference.

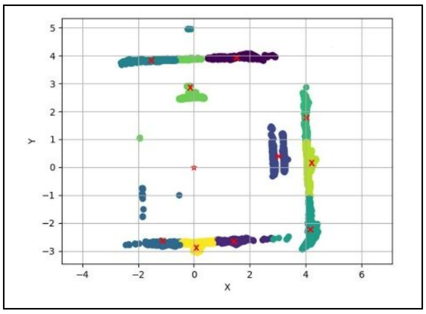

Figure 7. Clustered data.

If the number of clusters is 14 or more too many clusters are formed and the computational cost in the next steps is greatly increased. In the experiments, it was observed that cluster numbers between 8 and 11 had similar results. Considering that an AUV can detect a maximum of three edges at the same time due to the structure of the pool used in the experiments, it was concluded that choosing the number of clusters as 10 was appropriate and sufficient.

In the final stage, the obtained data clusters are evaluated, and edge information of the pool is extracted. For this purpose, the data clusters are classified using the cluster centers. Based on the information that the pool is rectangular, 120-degree scanning regions were created, and clusters whose cluster centers remained in the same scanning region were collected into the same class. The scanning regions are adjusted as shown in Figure 8.

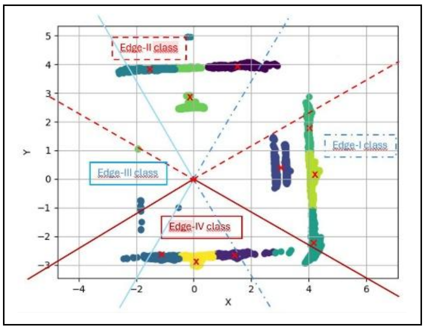

Figure 8. Cluster classification.

The points in a class that belong to an edge are added to the edge list, and the other points are ignored. As a result of this process, the points representing the edge are located as shown in Figure 9. Accordingly, three edge lists were created, which means that the three pool edges (right edge, top edge, and bottom edge) were detected.

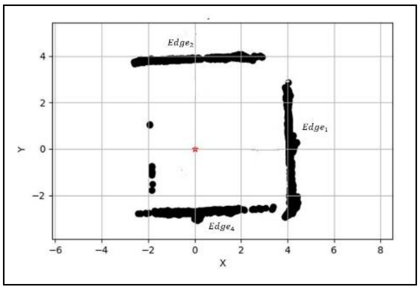

Figure 9. Detected edges.

After the edge detection is completed, the intersection points between the intersecting edges are detected as corner points. For this experimental environment, two corner points were found, one is the bottom right corner, which is the intersection point of the right edge and the bottom edge, and the other is the top right corner point, which is the intersection point of the right edge and the top edge. The detected corner points are shown in Figure 10 with a blue plus (+) sign.

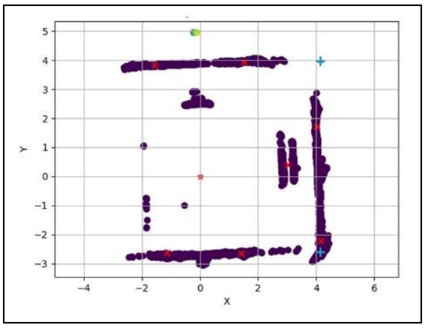

Figure 10. Detected corner points.

According to the results obtained, the top right corner coordinate values were found as $(4.154, 3.938)$ and the bottom right corner coordinate values as $(4.115, -2.689)$. These values are given in meters and according to the $\{R\}$ coordinate frame whose origin is located on AUV. In the experimental study, the AUV position at instant of sonar scan data collection was set to $(21, 3)$ and the yaw angle was set to $0°$ degrees according to the fixed coordinate frame $\{G\}$. It is assumed that the origin of the $\{G\}$ frame is placed at the bottom left corner of the pool as seen in Figure 2. Ideally, according to this position of the AUV, it is clear that the top right corner and bottom right corner coordinate values are $(4, 4)$ and $(4, -3)$, respectively. The absolute error and error percentage between these values and the estimated values obtained by the proposed method are given in Table 2.

Table 2. Actual and Estimated Values

	Coord	Top Right Corner	Bottom Right Corner	AUV position
Set Values	x	4	4	21
	y	4	-3	3
Estimated Values	x	4.154	4.115	20.864
	y	3.938	-2.689	2.692
Absolute Estimation Error	x	0.154	0.115	0.136
	y	0.062	0.311	0.308
Error Percent	x	3.85%	2.87%	6.47%
	y	1.55%	10.37%	10.26%

The difference between y-coordinates of detected corner points should be equal to the length of any of the pool edges, here it is short edge's length. The estimated edge-length is calculated as $6.627\ m$. Considering that the actual length of the short side of the pool is $7\ m$, the absolute error value of the estimation is $0.373\ m$. It can be said that the error margin of approximately 5.33% is within the acceptable error value range.

Using the estimated coordinate values of corners, the AUV position was calculated as $(20.864, 2.692)$ according to the $\{G\}$ coordinate frame. According to the estimate position, the absolute error value in the x-coordinate is $0.136\ m$ and in the y-coordinate value is $0.308\ m$. The error percentages are seen to be 6.47% and 10.27%, respectively. The values are given in Table 2.

When all the results are considered together, it is clearly seen that the estimation error values are at an acceptable level. In addition, when evaluating the results, it should be taken into account that there will be drifts in both position and orientation due to the vehicle being in operation during the experimental study.

The results obtained show that the proposed method can be used successfully in positioning and mapping studies in environments such as pools and marinas with certain boundaries. Although the detection of the edges and corners of the pool is directly dependent on the geometry of the environment, the method considered has a flexible structure. It will be possible to achieve solutions by appropriately selecting the limitations in the edge detection step for underwater environments with different geometries. It is appropriate to use the proposed method to determine the boundaries of objects and obstacles in the underwater. It can be used to solve both search tasks and obstacle avoidance problems especially in seas and rivers, which offer a different working environment than pools, because they do not have regular geometry.

In robotic research, the data obtained from the environment and IMU sensor measurements for localization, mapping and navigation problems are integrated with methods such as Kalman filter and particle filter to reach a solution. With the detection of both natural and artificial landmarks, the relative position of autonomous vehicles is achieved. Although it depends on the geometry of the working environment, it is possible to evaluate the environmental boundaries, especially the corner points, as natural landmarks due to their distinctive qualities. The method proposed in this study offers the opportunity for AUV positioning with sufficient precision and accuracy by using natural landmarks without the need for additional equipment. This opportunity allows the method to be easily adapted and used in different environments. The clustering algorithm-based structure of the method offers the opportunity for real-time operation with low computational load and easy applicability. Additionally, not needing high-cost equipment such as DVL can be considered as the biggest advantage of the method.

5 Conclusion

Underwater localization is of paramount importance in various domains, notably submarine research, underwater exploration, and the navigation of underwater robotic systems. However, this field is faced with challenges. One of the biggest problems is the ineffectiveness of conventional GPS signals underwater. Consequently, alternative underwater localization technologies are employed. Several solutions exist, including inertial navigation, acoustic navigation, and optical navigation. Acoustic localization systems deployed in open sea environments typically involve the placement of an array of receivers and transmitters on the seabed. These systems communicate with a surface station, or the underwater vehicle itself establishes a self-contained localization system using these transceivers. However, the deployment of such systems in enclosed environments incurs substantial costs.

This study has focused on more appropriate solutions as opposed to high-cost systems. In an enclosed environment, environmental data acquired from a sonar scanning sensor with a 360-degree field of view were utilized for environmental mapping and AUV localization. Initially, the raw sonar scan data was processed and subsequently classified via the K-means clustering algorithm. By identifying clusters exhibiting common characteristics with the environment map from this classified data, the boundaries of a confined underwater environment, such as a pool, were delineated. Subsequently, the intersection points of the identified edges, i.e., corner points, were estimated. Experimental results indicated that the error margins in these estimations were minimal, and the AUV localization results derived from these points were reliable. Although this study concentrated on a single localization instance, the results suggest that the proposed method can be iteratively employed for AUV navigation. The method's computational efficiency and low cost make it a viable option for real-time applications. Ongoing research is focused on integrating the method with various filtering techniques to enhance the method's robustness and adaptability.

6 Author contribution statements

In the study conducted, Hatice Hilal Ezercan Kayır contributed to the formation of the idea, following theoretical and experimental studies, evaluation of the results, and text editing and content control, while Metin Baydarakçı contributed to the literature review, system design, conducting experimental studies, and reporting the results.

7 Ethics committee approval and conflict of interest statement

“There is no need to obtain permission from the ethics committee for the article prepared”.

“There is no conflict of interest with any person / institution in the article prepared”.

8 References

[1] Mazumdar A, Lozano M, Fittery A, Asada HH. “A compact, maneuverable, underwater robot for direct inspection of nuclear power piping systems”. *2012 IEEE International Conference on Robotics and Automation*, St. Paul, Minnesota, USA, 14-18 May 2012.

[2] Ali A, Ahmed SF, Naqvi SYR, Joyo MK. “Efficient maneuvering and control of unmanned underwater vehicle (UUV)”. *Sindh University Research Journal*, 50(3D), 95-100, 2018.

[3] Xu Z, Wang Z. “Recent advances and future trends in foreign underwater navigation techniques”. *Ship Science and Technology*, 35(11), 154-157, 2013.

[4] Ali A, Ahmed SF, Kadir KA, Joyo MK. "Fuzzy PID controller for the upper limb rehabilitation robotic system". *2018 IEEE International Conference on Innovative Research and Development (ICIRD)*, Bangkok, Thailand, 11-12 May 2018.

[5] Sahoo A, Dwivedy SK, Robi PS. “Advancements in the field of autonomous underwater vehicle”. *Ocean Engineering*, 181, 145-160, 2019.

[6] Kırcı H, Yılmaz S, Yakut M. “İnsansız sualtı araçları”. *Endüstri & Otomasyon Dergisi*, 134, 24-29, 2008.

[7] Stutters L, Honghai L, Tiltman C, Brown DJ. “Navigation technologies for autonomous underwater vehicles”. *IEEE Transactions on Systems, Man, and Cybernetics*, Part C (Applications and Reviews), 38(4), 581-589, 2008.

[8] Zhou F, Han L. “A survey of multi - sensor information fusion technology”. *Telemetry, Tracking and Command*, 27, 1-7, 2006.

[9] Chang L, Li J, Chen S. “Initial alignment by attitude estimation for strapdown inertial navigation systems”. *IEEE Transactions. Instrumentation and Measurements,* 64(3), 784-794, 2015.

[10] Ribas D, Ridao P, Cufí X, El-Fakdi A. “Towards a DVL-based navigation system for an underwater robot”. *4th Workshop on European Scientific and Industrial Collaboration WESIC’03*, Miscolc, Hungary, 28-30 May 2003.

[11] Shome SN, Nandy S, Pal D, Das, SK. “Development of modular shallow water AUV: issues & trial results”. *Journal of Institution of Engineers Series C*, 93, 217-228, 2012.

[12] Kang Y, Zhao L, Cheng J, Wu M, Fan XA. “Novel grid SINS/DVL integrated navigation algorithm for marine application”. *Sensors*, 18(2), 364, 2018.

[13] Liu J, Yu T, Wu C, Zhou C, Lu D, Zeng Q. “A low-cost and high-precision underwater integrated navigation system”. *Journal of Marine Science Engineering*, 12(2), 200, 2024.

[14] Yang H, Gao X, Huang H, Li B, Jiang J. “A tightly integrated navigation method of SINS, DVL, and PS Based on RIMM in the complex underwater environment”. *Sensors*, 22(23), 94-109, 2022.

[15] Alcocer A, Oliveira P, Pascoal A. “Study and implementation of an EKF GIB-based underwater positioning system”. *Control Engineering Practice*, 15(6), 689-701, 2007.

[16] Li S, Bao G, Wu S, “A practical overview and prospect of acoustic positioning technology”. *Ocean Technology*, 24, 130-135, 2005.

[17] Yuan K, Wang H, Zhang H. “Robot position realization based on multi-sensor information fusion algorithm”. *2011 Fourth International Symposium on Computational Intelligence and Design*, Hangzhou, China, 28-30 October 2011.

[18] Yang H, Xu Z, Jia B. “An underwater positioning system for UUVs based on LiDAR camera and inertial measurement unit”. *Sensors*, 22, 5418, 2022.

[19] García CC, Rafael JB, Cufí i Solé X, Josep AIG. “Positioning an Underwater Vehicle Through Image Mosaicking”. *IEEE International Conference on Robotics and Automation*, Seoul, Korea, 21-26 May 2001.

[20] Chi W, Zhang W, Gu J, Ren H. “A vision-based mobile robot localization method”. *IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Shenzhen, China, 12-14 December 2013.

[21] Huang H, Sun D, Chen W, Mills JK. "A vision-based position control methodology to drive mobile robots towards target positions". *2005 IEEE International Conference on Robotics and Biomimetics-ROBIO*, Hong Kong, China, 5-9 July 2005.

[22] Lu H, Li Y, Serikawa S. “Computer vision for ocean observing”. *Artificial Intelligence and Computer Vision.* Switzerland, Springer International Publishing, 2017.

[23] Wang Y, Wang Q, Jin S, Long w, Hu L.” A literature review of underwater image detection”. Frontiers in Artificial Intelligence and Applications, 347, 42-51, 2022.

[24] Wang X, Sun Z, Chehri A, Jeon G, Song Y. “Deep Learning and Multi-Modal Fusion for Real-Time Multi-Object Tracking: Algorithms, Challenges, Datasets, and Comparative Study”. Information Fusion, 105, 2024.

[25] Roberts P, Helmholz P, Parnum I, Krishna A. “Image feature extraction methods for structure detection from underwater imagery”. *Remote Sensing and Spatial Information Sciences*, XLVIII-1/W2, 1067-1074, 2023.

[26] Chen J, Zhu S, Luo W. “Instance segmentation of underwater images by using deep learning”. *Electronics*, 13, 274, 2024.

[27] Ferguson J. “Under-ice seabed mapping with AUVs.” *IEEE International Conference on OCEANS 2009-EUROPE,* Bremen, Germany, 11-14 May 2009.

[28] Jalal F, Nasir F. "Underwater Navigation, Localization and Path Planning for Autonomous Vehicles: A Review”. *2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST)*, Islamabad, Pakistan, 12-16 January 2021.

[29] Westman E, Hinduja A, Kaess M. "Feature-Based SLAM for imaging sonar with under-constrained landmarks”. *2018 IEEE International Conference on Robotics and Automation (ICRA)*, Brisbane, QLD, Australia, 21-25 May 2018.

[30] Yan Z, Min X, Xu D, Geng D. “A novel method for underactuated UUV tracking unknown contour based on forward-looking sonar”. *Ocean Engineering*, 301, 117545, 2024.

[31] Wen X, Wang J, Cheng C, Zhang F, Pan G. "Underwater side-scan sonar target detection: YOLOv7 model combined with attention mechanism and scaling factor". *Remote Sensing*, 16, 2492, 2024.

[32] Morice C, Veres S, McPhail S. May 2009. "Terrain referencing for autonomous navigation of underwater vehicles *IEEE International Conference on OCEANS 2009-EUROPE,* Bremen, Germany, 11-14 May 2009.

[33] Teixeira FC, Quintas, J, Pascoal, A. "*AUV terrain-aided navigation using a Doppler velocity logger*". *Annual Reviews in Control*, 42, 166-176, 2016.

[34] Teixeira, FC, Quintas, J, Maurya, P, Pascoal, A. "Robust particle filter formulations with application to terrain-aided navigation". *International Journal of Adaptive Control and Signal Processing*, 31(4), 608-651, 2017.

[35] Jian MW, Liu XY, Luo HJ, Lu XW, Yu H, Dong JY. "Underwater image processing and analysis: a review". *Signal Processing: Image Communication*, 91, 116088, 2021.

[36] Jian M, Yang N, Tao C, Zhi H, Luo H. "Underwater object detection and datasets: a survey". *Intelligent Marine Technology and Systems,* 2, 9, 2024.

[37] Yi Y, Sun S, Junxin S. "Research on algorithms for edge detection and contour tracking of marine robots". *2023 5th International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, Dalian, China, 28-30 November 2023.

[38] Hoff S, Haraldstad V, Hogstad BR, Varagnolo D. "Side-Scan sonar based landmark detection for underwater vehicles". *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Abu Dhabi, UAE, 14-18 October, 2024.

[39] Movafaghpour MA, Masehian E. "Poly line map extraction in sensor-based mobile robot navigation using a consecutive clustering algorithm". *Robotics and Autonomous Systems*, 60, 1078-1092, 2012.

[40] Theodoridis S, Koutroumbas K. *Pattern Recognition.* 2nd ed. San Diego, USA, Elsevier Academic Press, 2003.

[41] Bishop CM. *Pattern Recognition and Machine Learning*. 1st ed. Singapore, Springer, 2006.

[42] Rousseeuw PJ. "Silhouettes: a graphical aid to the interpretation and validation of cluster analysis". *Computational & Applied Mathematics*, 20(1), 53-65, 1987.

[43] Jain AK. "Data clustering: 50 years beyond k-means". *Pattern Recognition Letters*, 31(8), 651-666. 2010.

[44] Blue Robotics Company. "Blue Robotics - Underwater ROVs, USVs, Thrusters and Sonars!". https://bluerobotics.com/ (27.01.2025).