Online Passive Localization for Underwater Swarm Vehicles using a Low-cost Acoustic Modem

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***Abstract*— We present an online underwater localization method that enables passive vehicles to localize themselves by overhearing two-way ranging (TWR) communication between an active vehicle and multiple acoustic anchors. Swarm simulations confirm the scalability of the system and show faster position updates, as well as improved accuracy compared to the active benchmark. A field experiment in a shallow water canal using the low-cost BlueROV2 underwater vehicle and ahoi modems has demonstrated the real-world applicability of the system, achieving an RMSE of approximately $0.82\,\mathrm{m}$.**

I. Introduction

Recent advances in low-cost autonomous underwater vehicles (AUVs) and affordable underwater sensors have enabled various applications, including shallow water quality monitoring [1], sewers and flooded mine operation [2], and harbor structures inspection [3]. Compared to a single vehicle, a swarm of underwater vehicles offers shared environmental awareness and enables cooperative decision-making. However, achieving accurate self-localization for individual swarm members remains a challenge, primarily due to the constraints of the underwater environment. Visual localization systems are often limited by turbidity and the lack of structures in natural underwater environments, while GNSS is infeasible underwater due to severe signal attenuation. Acoustic localization, as a well-established technique, enables long-range positioning in structureless and turbid waters such as harbors and coastal areas. It has shown great potential for low-cost swarm applications, supported by the availability of acoustic modems priced as low as a few hundred euros [4], [5].

Underwater acoustic localization is challenging in a swarm context. First, communication among swarm members should be efficient in terms of both latency and energy consumption, to support timely ranging and information sharing. The communication protocol should maintain consistent localization accuracy and update rate even as the swarm size increases. Moreover, to enable autonomous decision-making, each vehicle should be capable of self-localization without relying on a central node to compute the positions of the entire swarm. Therefore, a decentralized localization strategy is preferred, in which swarm vehicles share and fuse independent sensor measurements to enhance their localization accuracy.

In this work, we present a novel acoustic localization system for underwater vehicles swarms. This system is designed for low-cost applications and achieves cost efficiency

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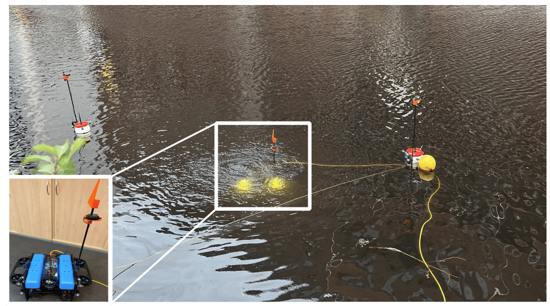


(a) A submerged ROV (remotely operated vehicle) on an underwater mission in a canal in Hamburg.

(b) Experiment on a jetty using the low-cost ahoi modems [4] in Hamburg.

Fig. 1: Real world experiments using low-cost underwater vehicle and acoustic modems.

in two key ways. First, it uses affordable acoustic modems and underwater vehicles. The availability of low-cost acoustic modems from both academic and commercial sources provides a wide selection for practical deployment [6]. For the vehicle platform, we employ compact, low-cost swarm vehicles equipped with affordable sensors. Fig. 1 illustrates a real-world experiment setup with the cost-effective BlueROV2 [7] and ahoi modems [4]. Second, we use a decentralized localization protocol that minimizes message exchanges between swarm members. Most acoustic systems rely on packet-based communication between vehicles and anchors. Passive one-way ranging (OWR) systems offer scalability for large swarms, however, they often require expensive atomic clocks [8], [9] for high-precision time synchronization, which makes them impractical for low-cost applications. Active two-way ranging (TWR) methods eliminate the need for time synchronization but suffer from message exchange overhead that increases with swarm size, leading to poor scalability and reduced localization accuracy under limited communication bandwidth.

To address these challenges, we propose a passive

TABLE I: Comparison of Different Acoustic Methods for Swarm Localization

Systems	OWR	TWR	passive TWR
Time Sync.	✓	✗	✗
Loc. Update (time)	$O(1)$	$O(n)$	$O(1)$

TWR localization system that enables each vehicle to self-localize by passively listening to transmissions from a limited number of active nodes. This approach combines the synchronization-free advantage of TWR with the scalability of passive localization. A comparison between the proposed system and aforementioned methods is shown in Table I. For an n-vehicle swarm, assuming that periodic acoustic ranging measurements are acquired (e.g. every $1\,\mathrm{s}$) and processed by the localization algorithm, the localization update time complexity for the entire swarm is shown.

In this work, the main contributions are:

1) We design and implement a scalable, low-cost ROS2-based passive swarm localization system with minimal communication overhead and no time synchronization.
2) A novel passive TWR protocol and a two-stage Extended Kalman Filter(EKF) that enable decentralized self-localization for swarm vehicles.
3) We implement swarm simulations that demonstrate improved scalability and localization accuracy over a benchmark active localization system.
4) We validate the proposed system in a real-world harbor experiment using a BlueROV2 and three buoys equipped with low-cost ahoi modems [4]. The passive localization system achieves a root-mean-square error (RMSE) of $0.82\,\mathrm{m}$.

To the best of our knowledge, this is the first passive localization system demonstrated in a real harbor environment that is scalable to large underwater swarms. Furthermore, Robot Operating System (ROS2), is integrated to enable real-time deployment. Development and evaluation are conducted using the DESERT Underwater simulation framework [10], which supports modular protocol design and includes a physical layer module for the ahoi modems [4] used in our field experiment. Benefiting from ROS2, the proposed passive localization system can be deployed online or tested using either collected field data or simulation data.

In the rest of the paper, we discuss related works in Section II followed by the design of the proposed localization protocol and ROS2 implementation of the system in Section III. Next, we present the simulation scenario with results including a comparison with the active localization benchmark in Section IV. We finally describe the real experiment evaluation of the proposed system and its results in Section V.

II. Related Works

A. Acoustic Swarm Localization

Acoustic localization offers the longest range compared to other underwater localization techniques. For low-cost applications in small-scale, nearshore environments, previous studies have demonstrated real-world feasibility within ranges of up to a hundred meters [11]–[15]. In this paper, we refer to acoustic localization methods specifically based on acoustic ranging, which involves measuring distances using acoustic signals transmitted between acoustic transducers. These methods are typically categorized into active and passive approaches, both of which rely on acoustic anchors (or referred to as beacons) or surface vehicles to provide reference positions. Among active methods, TWR is commonly used since it allows straightforward distance estimation based on the time-of-flight (TOF) without the need of clock synchronization [11], [12], [15].

In swarm localization, active methods require each vehicle to perform acoustic ranging with multiple anchors to estimate its position. The anchors can be surface buoys or vehicles. Fenucci et al. [11] present an EKF-based localization system involving surface and submerged vehicles, tested in a fresh water lake over a $50\,\mathrm{m} \times 50\,\mathrm{m}$ area. A single ecoUSB AUV runs the EKF during a $20\,\mathrm{min}$ dive. Localization is only evaluated when the AUV surfaces at the beginning and the end of the trial, showing errors of $2.2\,\mathrm{m}$ and $7.9\,\mathrm{m}$ for two communication protocols. The system targets small-networks, and scalability for larger swarms is not addressed. Behrje et al. [12] propose a method for MONSUN AUV swarms using just three messages per vehicle to localize via two surface vehicles in a V-formation. However, scalability remains limited where updating positions of five vehicles takes $7.5\,\mathrm{s}$ and no localization accuracy is reported. More recently, Busse et al. [15] develop an active TWR approach using a BlueROV2 [7] and two RTK-GPS-equipped surface buoys, achieving sub-meter accuracy in a $25\,\mathrm{m}\times 25\,\mathrm{m}$ harbor test. The vehicle polls the buoys alternately every $1\,\mathrm{s}$, but the method's scalability to larger swarms remains an open challenge due to increased communication overhead.

Our work adopts the same TWR setup as [15] but introduces a scalable solution by enabling passive vehicles to localize by overhearing TWR exchanges. Only one active vehicle performs TWR, while the rest of the swarm remains passive. This method maintains a constant position update rate regardless of the swarm size, provided all vehicles remain within acoustic range of the active vehicle and anchors.

B. Passive Localization

In passive acoustic localization, multiple vehicles can localize themselves simultaneously by eavesdropping on active acoustic communication from a small subset of the swarm. Typically, OWR is used, where vehicles listen to periodic packets sent by several anchors [16]. However, OWR relies on accurate time-of-arrival (TOA) measurements, often requiring expensive atomic clocks for synchronization. To reduce costs, we instead design a passive TWR method based on time-difference-of-arrival (TDOA), which does not require time synchronization among vehicles.

The one-way hyperbolic localization method in [17] is most similar to the idea of this work. Four transducers are deployed to periodically send acoustic signals to the

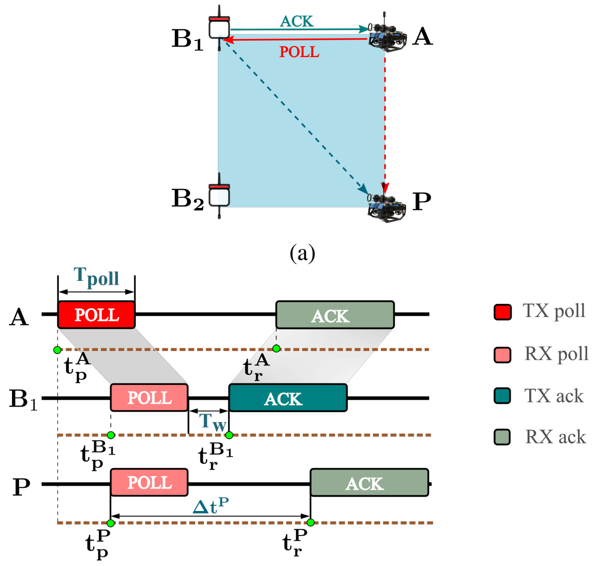


Fig. 2: Illustration of the one TWR cycle of the passive localization protocol where buoy $\mathbf{B}_1$ is polled. (a): 2D Geometry of the AUV swarm and buoys. (b): Timing of acoustic packet exchanges.

receivers, which is analogous to our passive TWR method where an active vehicle works as one moving anchor. EKF is used for deriving the receiver's position , and a water tank experiment has shown that most position errors are within $10\,\mathrm{cm}$. Another TDOA-based method is introduced in [18] for bio-inspired robot fishes. Four time-synced speakers are sending acoustic signals at the same time periodically and an initial time synchronization between the senders and receivers is required before submersion. Similarly, a water tank experiment has been conducted and the robot position is derived using acoustic pseudo-ranging technique.

Compared to the above mentioned passive methods with four fixed anchors, our setup only needs two surface buoys and one active vehicle which is actively polling the buoys. We adopt a decentralized two-step localization framework where each passive vehicle estimates the active vehicle's position based on the received acoustic packets from the TWR transmission, and then use the active vehicle as the third anchor to localize itself. Moreover, previous passive localization solutions have only been tested in small indoor water tanks, whereas we provide a low-cost implementation that is online-capable and tested in a real harbor environment.

III. Passive Localization System Overview

In this chapter, first we provide the passive localization protocol and the formulation of a two-stage EKF localization, then we introduce the ROS2 online system implementation.

A. Passive Two-way Ranging Protocol

Swarm composition: Two fixed buoys $\mathbf{B}_1$ and $\mathbf{B}_2$, an active AUV (AAUV) $\mathbf{A}$ and a passive AUV (PAUV) $\mathbf{P}$ positioned at the corners of a rectangular area. We describe here a minimal swarm setup with one passive vehicle. This protocol can be easily scaled up with multiple passive AUVs as showcased in Section IV. More buoys can be added for redundant ranging measurements.

Protocol description: The active vehicle $\mathbf{A}$ performs TWR with the buoys periodically. First, $\mathbf{A}$ sends a polling (POLL) packet to buoy $\mathbf{B}_1$, which is responded with an acknowledgment (ACK) packet after a short back-off time $\mathbf{T_w}$ (as shown in Fig. 2). After a pre-defined time interval, $\mathbf{A}$ repeats this process with buoy $\mathbf{B}_2$.

Hyperbolic constraints: During the TWR, passive vehicle $\mathbf{P}$ "overhears" the POLL and ACK exchanges, which enables it to self-localize by formulating a hyperbolic localization problem. Using the geometric and transmission timing given in Fig. 2, the hyperbolic constraint below holds at t_p^A when A initiates the polling:

$$\begin{aligned} &\overline{B_iP} - \overline{AP} \\ &= (t_{r,i}^P - t_{p,i}^P) \cdot c - T_{poll} \cdot c - T_w \cdot c - \overline{AB_i} \end{aligned} \tag{1}$$

where overlined variables are distances, T_{poll} is the POLL packet duration, T_w is the buoy's back-off time, and c is the speed of sound in water. The superscript P denotes PAUV's time frame, and i indexes the current polled buoy. We reorganize Eq. (1) as:

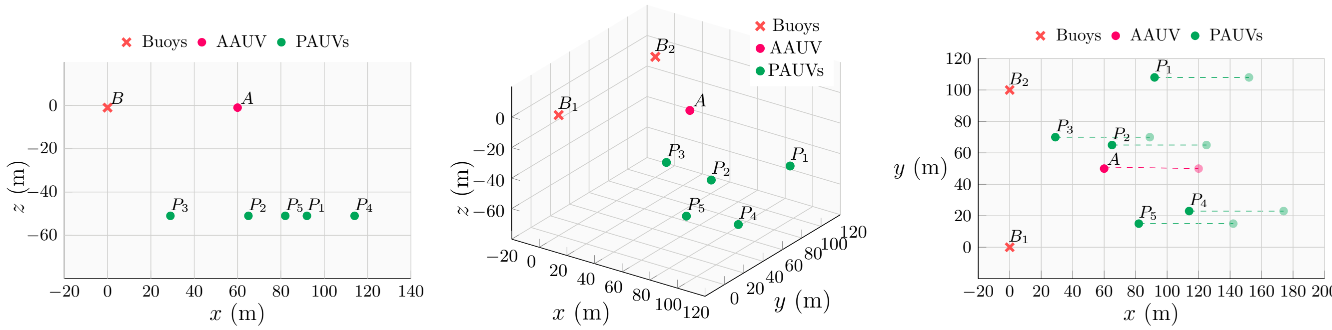
$$\begin{aligned} \Delta t_i^P \cdot \mathbf{c} = \|\mathbf{B_i} - P\| - \|A - P\| + \overline{AB_i} \\ + \mathbf{T_{poll}} \cdot \mathbf{c} + \mathbf{T_w} \cdot \mathbf{c} \end{aligned} \tag{2}$$

with the unknown PAUV position $P = (x_p, y_p, z_p)^T$, known parameters in **bold** letters which include the buoy position $\mathbf{B_i} = (x_{b_i}, y_{b_i}, z_{b_i})^T$, as well as measurements including the range measures $\overline{AB_i}$ and AAUV position A. Note that $\Delta t_i^P = t_{r,i}^P - t_{p,i}^P$ represents the TDOA measured by the PAUV, $A = (x_a, y_a, z_a)^T$ represents the AAUV position at time t_p^A, and $\overline{AB_i}$ is the range measured by the AAUV upon ACK reception, which will be included in the payload of next POLL to be sent.

B. Two-stage EKF Localization

We design a decentralized localization method where each PAUV estimates both the AAUV's position and its own using a two-stage algorithm. Two consecutive EKFs are employed: first EKF estimates the AAUV's position using the range measurement, and the second localizes the PAUV using the estimated AAUV position and the measured TDOA.

EKF is a classical technique for robot state estimation and is widely used in underwater acoustic localization [15], [17], [19]. The first EKF for AAUV localization is adopted from the work in [15], with the distinction that it is deployed on the PAUV. The second EKF builds on the result of the first and solves a hyperbolic localization problem. We formulate the PAUV EKF here. Due to the availability of depth sensors, it's a common practice for underwater localization to simplify the problem into 2D position estimation. The state vector to be estimated is $\mathbf{x} = (x,\, y,\, v_x,\, v_y)^T$. We use a linear constant velocity model as the process model. The non-linear measurement in the EKF is the TDOA measured by PAUV, which can be derived from Eq. (2) as:



(a) Front view (b) 3D view (c) Top view

Fig. 3: Swarm simulation shown from 3D (middle),front (left) and top-down (right) perspectives. Two fixed buoys B_1, B_2, an AAUV at the surface, and five PAUVs submerged. In 3c, dotted lines represent the moving trajectories of the swarm.

TABLE II: Swarm Vehicle Start and End positions

ID	Start Position	End Position
P1	(92, 108, -51)	(152, 108, -51)
P2	(65, 65, -51)	(125, 65, -51)
P3	(29, 70, -51)	(89, 70, -51)
P4	(114, 23, -51)	(174, 23, -51)
P5	(82, 15, -51)	(142, 15, -51)

$$\begin{aligned} z &= h(\hat{\mathbf{x}}_k) = \Delta t_i^P \\ &= (\hat{d}_{b_i k} - \hat{d}_{ak} + d_{b_i a}) \cdot \frac{1}{\mathbf{c}} + \mathbf{T_{poll}} + \mathbf{T_w} \\ &= \left(\left\| \begin{pmatrix} \hat{x}_k \\ \hat{y}_k \end{pmatrix} - \begin{pmatrix} x_{b_i} \\ y_{b_i} \end{pmatrix} \right\| - \left\| \begin{pmatrix} \hat{x}_k \\ \hat{y}_k \end{pmatrix} - \begin{pmatrix} x_a \\ y_a \end{pmatrix} \right\| + \right. \\ &\quad \left. \left\| \begin{pmatrix} x_{b_i} \\ y_{b_i} \end{pmatrix} - \begin{pmatrix} x_a \\ y_a \end{pmatrix} \right\| \right) \cdot \frac{1}{\mathbf{c}} + \mathbf{T_{poll}} + \mathbf{T_w} \end{aligned} \tag{3}$$

where $\hat{\mathbf{x}}_\mathbf{k}$ is the estimated state at time k, $\hat{d}_{b_i k}$ represents the distance between the vehicle's estimated position $(\hat{x}_k, \hat{y}_k)^T$ and the known buoy position $(x_{b_i}, y_{b_i})^T$, $\hat{d}_{ak}$ is the distance between the vehicle's estimated position and the estimated AAUV positon $(x_a, y_a)^T$, and $d_{b_i a}$ is the range measurement from the AAUV to the buoy. The Jacobian is computed as:

$$\mathbf{H_k} = \left. \frac{\partial h(\mathbf{x})}{\partial \mathbf{x}} \right|_{\mathbf{x} = \hat{\mathbf{x}}_k} = \tag{4}$$
$$\left[\left(\frac{\hat{x}_k - x_{b_i}}{c \cdot \hat{d}_{b_i k}} - \frac{\hat{x}_k - x_a}{c \cdot \hat{d}_{ak}} \right) \quad \left(\frac{\hat{y}_k - y_{b_i}}{c \cdot \hat{d}_{b_i k}} - \frac{\hat{y}_k - y_a}{c \cdot \hat{d}_{ak}} \right) \quad 0 \quad 0 \right]$$

C. ROS2 Implementation

We implement the passive localization system in ROS2 based on the protocol in Section III-A. The two-stage EKF in III-B is implemented as a ROS2 node. The received acoustic messages at the PAUV are published on two ROS2 topics: *pauv_poll* and *pauv_ack*, which contain the range measurement from the AAUV to the last polled buoy, and the TDOA measure Δt_i^P, respectively.

Real-world Data: We use low-cost ahoi modems [4] for the acoustic communication. A Raspberry Pi acts as the host to run the ROS2 nodes. During the sea trial described in Section V, the modems and hydrophones are deployed on floating buoys and a BlueROV2 [7]. The ROS2 drivers for the AAUV and PAUV are developed using *PyLib* (python library of ahoi modem), with the PAUV publishing the received messages on two topics at 1 Hz.

IV. Simulation with DESERT

A. DESERT Simulation

The simulation and passive TWR protocol are implemented using the underwater simulator DESERT [10]. In the simulation, the PAUV logs timestamps of received packets, the TDOA measurements and the range measurements from received POLLs. These logs are converted into ROS2 bags with two topics, *pauv_poll* and *pauv_ack*, which can be replayed and used by the localization node.

B. Simulation Scenario

To demonstrate the scalability of proposed passive localization system, we simulate a swarm of six moving AUVs. Two static buoys are positioned at $(0, 0, -1)^T$ m and $(0, 100, -1)^T$ m, which are known to all swarm members. Within the swarm, one AAUV is initially located at $(60, 50, -1)^T$ m, at the same depth as the buoys. The five PAUVs are distributed at different locations at a constant depth, as illustrated in Fig. 3. When simulation begins, all vehicles are stationary, then start moving along the positive x-axis, away from the buoys. The assumption of a constant depth is based on the use of depth sensors, which reduces the localization problem to 2D. The initial positions of all vehicles are assumed known. The swarm's initial and final positions are summarized in Table II and shown in Fig. 3c.

C. Velocity Ramping

To address the large position errors caused by abrupt speed changes noted in [15], we implement a more realistic movement model using velocity ramping. The mobility model of DESERT allows nodes to follow waypoints at a constant velocity, thus we design such velocity profile for all swarm vehicles: Initially, the swarm remains stationary for 20 s. Upon movement, a velocity ramping phase of 18 s is applied: vehicles first travel at 0.1 m/s for 1 m, then at 0.25 m/s for 2 m, before they reaching a steady cruising

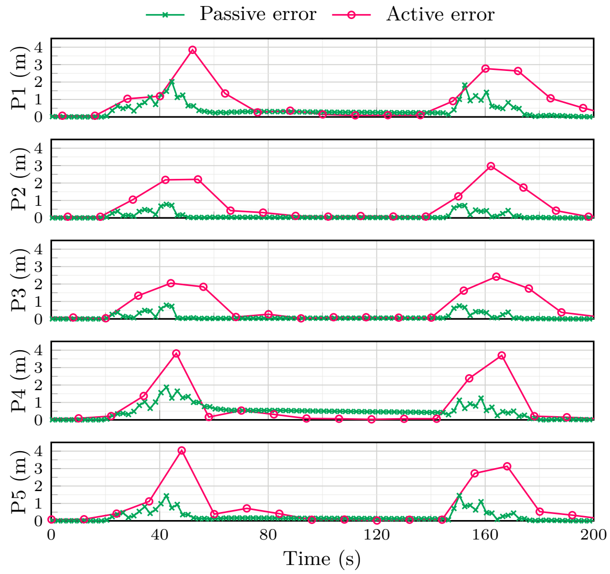


Fig. 4: Comparison of EKF position errors (euclidean distance) of the passive and active localization.

speed of $0.5\,\mathrm{m/s}$ for the majority of the mission. As vehicles approach their target positions, they decelerate using a reversed pattern and stop movement at $164\,\mathrm{s}$.

D. Protocol Parameters

We adopt the passive TWR communication protocol described in Section III-A, where the moving AAUV periodically performs TWR with the two static buoys. We choose practical parameters according to the specification of the ahoi modem that is used in the field experiment. The POLL size is $8\,\mathrm{bytes}$ containing a header and the range measurement as payload. The ACK is $10\,\mathrm{bytes}$ with the measured TOF as payload. The data rate is $200\,\mathrm{bit/s}$. The speed of sound in water is set as $1500\,\mathrm{m/s}$. The polling interval is $2\,\mathrm{s}$, consistent with our field experiment setup. This configuration supports acoustic range up to $200\,\mathrm{m}$ and enables the transmission of up to $27\,\mathrm{bytes}$ of data in each TWR cycle. The payloads of both POLL and ACK packets are configurable, allowing the exchange of additional information within the swarm. In this work, only the latest AAUV range measurement is transmitted. However, the protocol supports including other data, such as AAUV's real-time position, velocity or control commands, especially when it serves as a leader AUV of the swarm.

E. Passive localization vs. Active localization

We benchmark our passive localization method using the classic active TWR method in [15]. In the simulation scenarios all six vehicles participate in localization. For our passive method, one AAUV polls the buoys while positions of all six vehicles are updated. For the active method, each vehicle polls the buoys, resulting in an update interval that increases linearly with swarm size (as shown in Table I).

Passive Localization: An AAUV A polls buoys B_1 and B_2 alternately every $2\,\mathrm{s}$. Each PAUV updates both its own position and A's position at every POLL reception. All vehicles receive localization updates every $2\,\mathrm{s}$.

Active Localization: No designated AAUV is used. All six vehicles take turns sending POLLs to buoy B_1 every $2\,\mathrm{s}$, then repeat with buoy B_2. Each vehicle runs an EKF to update its position [15]. Due to sequential polling, each vehicle receives a localization update every $12\,\mathrm{s}$.

TABLE III: Quantitative Comparison for Swarm Localization Errors Using Passive and Active Methods

ID	**Passive** entire path (0-200 s)	**Active** entire path (0-200 s)	**Passive** steady phase (60-140 s)	**Active** steady phase (60-140 s)
P1	0.39 ± 0.40	0.88 ± 1.09	0.27 ± 0.02	0.34 ± 0.45
P2	0.11 ± 0.19	0.71 ± 0.92	0.03 ± 0.01	0.17 ± 0.14
P3	0.11 ± 0.18	0.67 ± 0.84	0.04 ± 0.01	0.11 ± 0.07
P4	0.48 ± 0.39	0.71 ± 1.22	0.50 ± 0.05	0.16 ± 0.19
P5	0.23 ± 0.30	0.76 ± 1.19	0.14 ± 0.01	0.20 ± 0.26

F. Localization Results

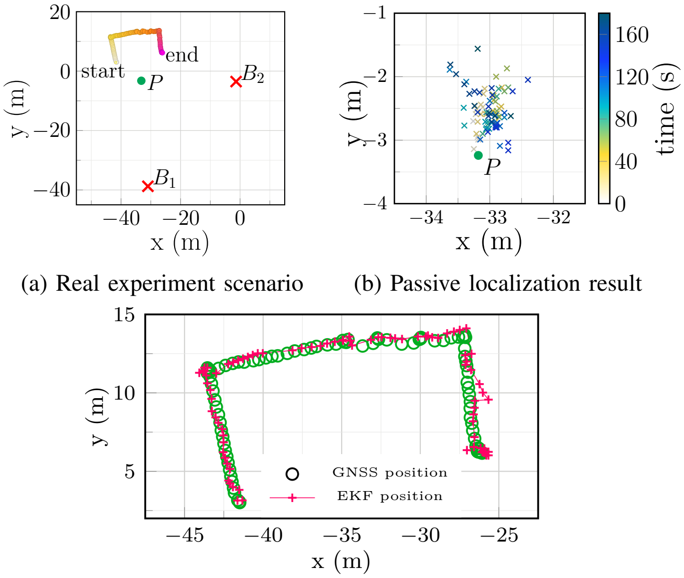
Fig. 4 compares the 2D localization errors of the passive and active methods, showing the Euclidean distance between estimated and true positions. The summary of the error evaluation is presented in Table III. As shown in Fig. 4, our passive EKF achieves a sixfold increase in update rate compared to the active EKF, resulting in smaller error peaks, particularly at the beginning and end of movement. In contrast, the active EKF exhibits large spikes due to its longer update interval (thus more outdated range measurement) and also converges slower compared to the passive EKF. Overall, the passive method has lower localization error over the entire trajectory, as reflected in Table III. To reduce the impact of transient errors caused by sudden velocity changes, we define a "steady phase" during which the vehicle moves at a constant speed and both estimates stabilize. In this phase, the passive EKF performs better for vehicles $P1$, $P2$, $P3$ and $P5$, but worse for vehicle $P4$. This discrepancy is attributed to the spatial geometry of the swarm relative to the anchors. As illustrated in the top view in Fig. 3, vehicle $P4$ is farthest from the buoys, leading to decreased accuracy in the TDOA-based system.

To further demonstrate scalability, a 16-vehicle swarm is simulated by adding ten additional passive vehicles. The position update time remains $2\,\mathrm{s}$ for the passive method but increases to $32\,\mathrm{s}$ for the active method. The passive method maintains mean errors between $0.1\,\mathrm{m}$ to $0.48\,\mathrm{m}$ across all 15 PAUVs, consistent with Table III. In contrast, the accuracy of the active method degrades significantly, with mean errors exceeding $3.54\,\mathrm{m}$ for all vehicles. These results confirm that the proposed passive localization approach provides better scalability, maintaining consistent accuracy as swarm size increases.

V. Real Experiment

A. Experiment Setup

To reduce the overall cost of the swarm localization system, this work uses the affordable BlueROV2 underwater



(a) Real experiment scenario (b) Passive localization result

(c) BlueROV2 TWR localization result

Fig. 5: Real experiment setup and passive localization results.

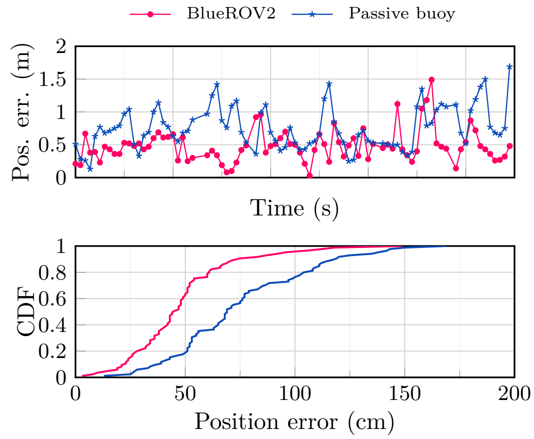


Fig. 6: Evaluation of EKF position estimation (upper plot); Culmulative Distribution Function (CDF) of position error (lower plot).

vehicle [7], low-cost acoustic modems [4] and in-house-built surface buoys [15]. A field experiment was conducted in a shallow water canal in Hamburg, Germany. The setup, shown in Fig. 5a, includes three near-static surface buoys: two serve as anchors (B_1 and B_2) with known GNSS positions, and the third acts as a passive listening node (P). The buoys are stabilized with heavy weights on the canal floor to reduce drift from currents. A BlueROV2 serves as the AAUV, following a path composed of three straight segments. All buoys and the ROV are equipped with RTK-GNSS antennas mounted on vertical masts extending above the water surface (visible in Fig. 1), providing centimeter-level ground truth positioning at $1\,\mathrm{Hz}$ for evaluation.

Each buoy carries a low-cost ahoi modem [4] mounted approximately $1.5\,\mathrm{m}$ below the water surface, while the modem on the BlueROV2 is positioned about $10\,\mathrm{cm}$ underwater. The GNSS positions of the buoys and the trajectory of BlueROV2 are shown in Fig. 5a. The experiment adopts the proposed passive localization protocol, in which the BlueROV2 sends a POLL packet every $2\,\mathrm{s}$, alternately targeting the two buoys. Each POLL includes the most recent range measurement, enabling passive localization by other nodes.

B. EKF results

We evaluate the passive localization method using the collected experimental data. The EKF position estimates and ground truth GNSS positions of the BlueROV2 are shown in Fig. 5c. The experiment lasts approximately $3\,\mathrm{min}$. The ACK packet loss rates at buoys B_1 and B_2 are $11\,\%$ and $14\,\%$, respectively, resulting in missing range measurements. On the passive buoy side, this leads to a $10\,\%$ loss of TDOA measurements. The localization system handles such losses by performing only the EKF prediction step when either range or TDOA data is unavailable. This occurred in approximately $22\,\%$ of the position updates.

Fig. 6 shows the Euclidean distance between the EKF-estimated positions and the GNSS ground truth for both the BlueROV2 and the passive buoy. The overall RMSE is $0.54\,\mathrm{m}$ for the BlueROV2 and $0.82\,\mathrm{m}$ for the passive buoy. According to the Culmulative Distribution Function (CDF), $90\,\%$ of the position errors remain below $0.74\,\mathrm{m}$ and $1.19\,\mathrm{m}$, respectively. The higher error for the passive buoy can be attributed to the combined effects of TDOA measurement error, AAUV position estimation error and range measurement uncertainty.

Compared to the active localization field experiment in [15], which employs a similar setup, our system achieves comparable localization accuracy for the active vehicle while also supporting passive localization with similar accuracy. Notably, this experiment uses only a single passive buoy, yet still demonstrates accuracy on par with the active benchmark. This suggests that, as the number of passive vehicles increases, the advantages of our passive localization system will become more pronounced, particularly in terms of scalability and accuracy.

VI. Conclusion and Outlook

In this work, we present a low-cost, online passive localization system for underwater swarm vehicles. The system uses a scalable, low-overhead communication protocol that enables efficient information exchange among swarm members. Our EKF-based passive localization method provides decentralized positioning and supports higher position update rates than the benchmark active method, leading to improved localization accuracy at larger swarm scales. The system is validated through both simulations and real-world experiments, demonstrating its advantages in scalability and accuracy. Future work will extend the real-world experiments to dynamic scenarios with passive vehicles. To further improve accuracy, IMU data can be integrated on both vehicles and buoys to correct rotation-induced misalignments between GNSS antennas and hydrophones. Additionally, replacing stationary floating buoys with surface vehicles will improve swarm mobility.

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