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Multi-objective Optimization of Confidence-based Localization in Large-scale Underwater Robotic Swarms

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Abstract. Localization in large-scale underwater swarm robotic systems has increasingly attracted research and industry communities' attention. An optimized confidence-based localization algorithm is proposed for improving localization coverage and accuracy by promoting robots with high confidence of location estimates to references for their neighboring robots. Confidence update rules based on Bayes filters are proposed based on localization methods' error characteristics where expected localization error is generated based on measurements such as operational depth and traveled distance. Parameters of the proposed algorithm are then optimized using the Evolutionary Multi-objective Optimization algorithm NSGA-II for localization error and trilateration utilization minimization while maximizing localization confidence and Ultra-Short Base Line utilization. Simulation studies show that a wide localization coverage can be achieved using a single Ultra-Short Base Line system and localization mean error can be reduced by over 45% when algorithm's parameters are optimized in an underwater swarm of 100 robots.

Keywords: Underwater Swarm Localization, Confidence Values, Multi-objective Optimization.

1 Introduction

Seventy-one percent of the earth's surface is covered by water and it is commonly believed that we know more about the space than deep oceans. Spatial information in various offshore applications such as deep-sea oil and gas exploration, environmental monitoring, geological and ecological research must be collected alongside the data modality of interest. These marine missions can be achieved by means of underwater Distributed Autonomous Robotic Systems (DARS) such as a swarm of Autonomous Underwater Vehicles (AUVs). Various localization technologies for underwater DARS have been actively investigated for a decade. Localization algorithms can be classified into three main categories based on systems mobility, namely stationary, mobile and hybrid localization algorithms, and each main category can be classified into two sub-categories namely centralized and distributed localization algorithms [1].

Cheng *et al*. in [2] have investigated the distributed stationary sequential Underwater Positioning Scheme (UPS) in which four stationary anchor nodes or robots (accurately localized) are required to localize an ordinary node and in [3] the Enhanced Underwater Positioning Scheme has been introduced in which a maximum waiting time for anchor nodes to broadcast their beacons was introduced. All ordinary nodes in both localization algorithms have to be within the communication range of anchor nodes. Sabra and Fung have proposed a fuzzy logic based dynamic localization plan that requires users to specify the fuzzy rule base that capture human expert knowledge on the best performing localization methods under various operational conditions [4]. A large-scale hierarchical localization approach has been investigated in [5] for stationary underwater sensor network. In addition, Zhou *et al*. in [6] extended the algorithm in [5] and introduced a hierarchical localization approach for mobile underwater sensor network in which underwater sensors predict their mobility patterns. The main concept behind a hierarchical localization approach is that a successfully localized ordinary node with high precision can serve as a reference node for neighboring nodes localization. Both [5] and [6] considered a simple approach to regulate the promotion of ordinary nodes to reference nodes. They introduced the concept of confidence value which is associated with the localization process and a predetermined confidence threshold. Confidence values of localized ordinary nodes in [5] were solely dependent on the localization error. The major drawback of this algorithm is that it is not always possible to measure localization error in underwater missions. However, the confidence values in [6] are calculated by simply averaging the participating reference nodes' confidence values and considering the error in range measurements. Bhuvaneswari *et al*. in [7] proposed a confidence discount rule based on the number of time steps since last localization and a high but arbitrarily defined confidence threshold. A computationally expensive quality of trilateration-based localization scheme in 2-dimentional space has been introduced in [8] where reference nodes are selected based on geometric relationship of their positions and ranging errors. The authors in [8] focused only on localization by trilateration and considered the scenario in which a node has to select 3 reference nodes for localization based on their quality-of-trilateration score.

Ultra-Short Base Line (USBL) is the most commonly adopted localization method in industry due to its flexibility as it does not require artificial landmarks to be deployed on the seafloor and it only requires a single surface vessel for operation. However, the maximum number of underwater targets that can be simultaneously localized by USBL is very limited (up to 10 using the most advanced technology) [9]. Different localization methods including trilateration and dead reckoning are employed when USBL is not available in hierarchical localization. Sabra *et al*. introduced a confidence-based underwater localization scheme [10] in which three common localization methods, namely USBL localization, trilateration and dead reckoning were adopted. They have shown by numerical simulation that a swarm of 100 nodes can be tracked using a single USBL system, range measurement sensors and communication modems.

In this paper, the confidence-based underwater localization algorithm introduced in [10] that harnesses a single USBL system and common proprioceptive sensors for

large-scale swarm localization is summarized. The confidence threshold and node density are key parameters to the confidence-based localization algorithm's performance, so they are optimized in this paper for accuracy enhancement using an Evolutionary Multi-objective Optimization algorithm through extensive simulation. Each underwater robot or node[1] in the swarm is associated with a scalar confidence value which measures the localization estimate precision using a belief function. Confidence values are updated and monitored through the proposed algorithm in which confidence update rules based on localization error characteristics and Bayes filters are employed. Nodes with high confidence can be employed as references for neighboring ordinary nodes localization using trilateration.

The remainder of this paper is organized as follows. Section 2 briefly explains the proposed algorithm and formulates the multi-objective optimization problem for finding the optimal confidence threshold and node density through simulation. Section 3 shows how to employ localization method's error characteristics in confidence update rules and multi-objective optimization in localization accuracy improvement. Moreover, the algorithm's performance is compared for both optimized and arbitrary non-optimized parameters. Finally, section 4 concludes this paper and discusses possible extension of this work.

2   Confidence-based Localization Algorithm

In this section, confidence-based localization algorithm for a swarm of mobile underwater sensor nodes is presented. The proposed algorithm aims at improving localization coverage and localization estimate accuracy by promoting high-precision localized ordinary nodes to reference nodes based on their confidence values. The confidence value of a node is dynamically updated by the proposed confidence update rules.

2.1   Confidence Update Rules

Define δ_i^t as a confidence value, which is between 0 and 1, associated with the $i\text{-}th$ node at time t. It measures how confident the current localization estimate of the node is using a belief function. The certainty of a node being at a certain position can be considered as a belief (state of knowledge) and it can be represented as a conditional probability distribution [11]. A belief can be easily calculated by the Bayes filter algorithm [11]. If a node has a confidence value of 1, its current localization estimate is certain. On the other hand, the current localization estimate of a node is completely unreliable if its confidence value is 0. Initially it is set to 1 as nodes are deployed from a known position. The confidence value of node i (δ_i^t) is dynamically updated in each localization step. Any localization method can be integrated in the proposed algorithm by implementing confidence value update rules based on a localization method's error characteristics. Different update rules of the confidence value are implemented based

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[1]   The term "node" and "AUV" are used interchangeably in the manuscript.

on a designated localization method's expected localization error, instead of its measured error. In contrast to terrestrial localization, localization estimate error in the underwater environment cannot be measured unless a sophisticated localization system is employed such as Long Base Line (LBL) which require artificial landmarks to be deployed on the seafloor in advance.

If the confidence value of node i (δ_i^t) drops below a pre-defined confidence threshold (x_1) and the USBL is available, then node i will be localized by USBL and its confidence value is updated (boosted) based on its previous confidence value $\{\delta_i^{t-1} \propto \hat{p}_i^{t-1} : \hat{p}_i^{t-1} = $ estimated position at time $t-1\}$ and measurements $\{z_t = $ operational depth$\}$ which can be accurately acquired by a depth sensor. The node's confidence value (δ_i^t) is updated as follows

$$\delta_i^t = bel(\hat{p}_i^t) \tag{1}$$

$$bel(\hat{p}_i^t) = \eta\, p(m_t|\hat{p}_i^t)\, bel(\hat{p}_i^{t-1}) \tag{2}$$

where η is a normalization term and $p(m_t|\hat{p}_i^t)$ represents the probability of a node being at the estimated position $\hat{p}_i^t$ based on measurements m_t which is the operational depth z_t when a node is localized by USBL. In other words, the probability of an estimated position being matched with an expected position is related to the expected error derived from a localization method's error characteristics.

If USBL is not available (when it is localizing 10 other nodes simultaneously), then three conditions will be checked (refer to step 9 in Algorithm 1) prior to performing Time of Arrival (ToA) based trilateration [12] where J is the number of neighboring nodes and l_d is the minimum bounding box's dimensions formed by neighboring nodes $j = 1, 2, ..., J$. We solve ToA-based trilateration least squares problem using Particle Swarm Optimization (PSO) [13]. In literature, it has been usually solved by Gauss-Newton algorithm, but we have obtained more accurate results through PSO as Monte-Carlo simulation has been conducted to show that PSO always gives more accurate results with faster convergence in solving ToA-based trilateration least squares problem. Confidence value (δ_i^t) is updated, in this case, based on neighboring nodes confidence values (δ_j^t) and their estimated positions ($\hat{p}_j^t$), the estimated position of node i ($\hat{p}_i^t$) and range measurements (r_{ij}) between node i and its neighboring nodes ($j = 1, 2, ..., J$):

$$\delta_i^t = \frac{\sum_{j=1}^{J} \delta_j^t \left(1 - \frac{\left|\,|\hat{p}_j^t - \hat{p}_i^t| - r_{ij}\,\right|}{|\hat{p}_j^t - \hat{p}_i^t|}\right)}{J} \tag{3}$$

Equation (3) considers the undiscounted confidence value of a neighbor node j if the distance between node i and j through their estimated positions ($\hat{p}_i^t$) and ($\hat{p}_j^t$) perfectly matches the corresponding range measurement (r_{ij}).

Node i location will be tracked using dead reckoning when neither USBL nor trilateration method can be adopted. Confidence value (δ_i^t) is discounted based on its previous confidence value $\{\delta_i^{t-1} \propto \hat{p}_i^{t-1}\}$ and measurements $\{w_t = $ traveled distance

since the last USBL or trilateration localization} using Equations (1) and (2) with $m_t = w_t$.

Table 1 depicts the localization process of node i in which USBL system (at most ten nodes can be localized simultaneously) [9], trilateration or dead reckoning localization is selected for every localization period Δt based on its confidence value δ_i^t.

***Table 1.** Algorithm 1: Confidence-based localization*

1:	**Procedure** (Node i localization)
2:	$\boldsymbol{\delta_i^{t=1} = 1}$
3:	**for** t = 1+Δt : Δt: t$_{\text{end}}$
4:	**if** $\delta_i^t \leq x_1$
5:	Request USBL localization
6:	**if** request granted
7:	Use USBL
8:	Update $\delta_i^t \leftarrow (\hat{p}_i^{t-1}, z_t)$
9:	**elseif** $\min\limits_{j=1:J} \delta_j^t \geq x_1 \,\&\, J \geq 4 \,\&\, \min\limits_{d=1:3} l_d \geq 1$
10:	Use Trilateration
11:	Update $\delta_i^t \leftarrow (\delta_j^t, \hat{p}_j^t, \hat{p}_i^t, r_{ij})$
12:	**else**
13:	Use Dead reckoning
14:	Update $\delta_i^t \leftarrow (\hat{p}_i^{t-1}, w_t)$
15:	**end if**
16:	**elseif** $\delta_i^t > x_1$
17:	Use Dead reckoning
18:	Update $\delta_i^t \leftarrow (\hat{p}_i^{t-1}, w_t)$
19:	**end if**
20:	**end for**
21:	**end Procedure**

2.2   Parameters Optimization

In the proposed algorithm, a pre-defined confidence threshold (x_1) is set in promoting an ordinary high precision localized node to a reference node. However, determining a universal confidence threshold that suits different AUV deployment scenarios is laborious and nearly impossible. In addition, as far as ToA-based trilateration localization method is concerned, a minimum Node Density (x_2) in the swarm should also be carefully maintained.

It has been commonly assumed that the optimized parameters on random walkers may suit various deployment scenarios. Therefore, we have assumed correlated and uncorrelated random walker models [14] to govern the mobility of nodes in a confined region. The impact of confidence threshold and node density on localization performance have been investigated through extensive simulation. Four performance metrics were considered, namely mean localization error, mean confidence value, USBL utilization and ToA-based trilateration utilization.

Our objectives are to minimize both localization error $\{f_1(x)\}$ and ToA-based trilateration utilization $\{f_2(x)\}$, due to its high demand of on-board computational power, while maximizing confidence value $\{f_3(x)\}$ and USBL utilization $\{f_4(x)\}$ as it is the most reliable localization method adopted. There is no single optimum solution in the parameter space that simultaneously optimizes these four irreconcilable objectives in Equation (4). However, a set of optimal solutions that provides a trade-off among objectives seems ideal to this multi-objective optimization problem:

$$\begin{cases} \min f_1(x_1, x_2) \\ \min f_2(x_1, x_2) \\ \max f_3(x_1, x_2) \\ \max f_4(x_1, x_2) \end{cases} Subject \; to \begin{cases} l_1 \leq x_1 \leq u_1 \\ l_2 \leq x_2 \leq u_2 \end{cases} \tag{4}$$

where x_1 is the confidence threshold, x_2 is the node density, l_i and u_i ($i = 1, 2$) are their lower and upper bounds respectively. Node density (x_2) is defined as the expected number of nodes in a node's neighborhood and thus it can be varied by nodes' communication range.

Multi-objective optimization using Evolutionary Algorithms (EAs) is a promising method in design optimization for various applications [15]. Due to the flexibility of Evolutionary Algorithms (EAs) and its wide spread applicability, Evolutionary Multi-objective Optimization (EMO) has become a popular approach [15]. The nature of population-based search algorithms allows EAs to return multiple optimized solutions among objectives called Pareto Optimal solutions [16]. Pareto Optimal solutions are the elitists population in the last generation in which selecting one solution over another requires sacrificing one objective and gaining another [16]. There are many algorithms dedicated to choosing the Pareto Optimal set, that is, a set of non-dominated diverse solutions. The Fast and Elitist Multi-objective Genetic Algorithm (NSGA-II) is a robust and efficient algorithm introduced by Deb *et al.* to find the Pareto Optimal set based on Non-dominated Sorting and Crowding Distance [17].

A solution is said to dominate another when it is not worse in all objectives and better in at least one objective. The crowding distance is simply a measure of how close a solution is to another. Longer distances are associated with higher scores, and thus the diversity is ensured in a Pareto Optimal set. Interested readers are referred to [17] for details on Non-dominated Sorting and Crowding Distance Assignment procedures.

3   Simulation

In this section, error characteristics of localization methods used in our simulation are employed to generate a localization method's expected error and thus, confidence values are updated as in Equations (2) and (3). Moreover, simulation settings, parameters and results of algorithm's parameters optimization and localization estimates are provided. The importance of the confidence threshold and the node density optimization is emphasized in this section by comparing the proposed algorithm's performance in an optimized case and an arbitrary non-optimized case.

3.1 Error Characteristics for Confidence Update

When USBL localization method is adopted, the expected error for localization estimate can be generated based on its error characteristics. According to the datasheet of a given USBL system, in 1000 m depth 63% (1 Drms) of total errors are within 2.7 m radius [9]. We assume that the localization estimate error of the given USBL system follows a Gaussian distribution given by

$$\varepsilon_U \sim \mathcal{N}(\mu, \sigma^2) \tag{5}$$

where μ = 2.7 m and σ = total error (1Drms) depicted from the relationship in [9]. The error in USBL localization estimate can be predicted based on the operational depth. We calculate the probability $p(m_t|\hat{p}_i^t)$ in Equation (2) as follows

$$p(z_t|\hat{p}_i^t) \propto \frac{1}{\Gamma(\kappa)\Theta^\kappa} \varepsilon_U^{\kappa-1} e^{\frac{-\varepsilon_U}{\Theta}} + \tau \tag{6}$$

where ε_U is the USBL expected localization error, τ is a damping factor, κ and Θ are Gamma distribution parameters. A damping factor (τ) is crucial for the probability stability, the higher the value of τ the less-likely the confidence value is to fluctuate. Exponential distribution is a special case of Gamma distribution but using Gamma distribution provides us with one more degree of freedom in penalizing the expected error. It is worth mentioning that there is no need to have an expectation of a node's position as we can directly have an expectation of the error by its operational depth.

Equation (3) is used to calculate the confidence value of node i when ToA-based trilateration is adopted. Based on existing underwater range measurement technologies [18] we assume that the range measurement between two arbitrary neighboring nodes i and j (r_{ij}) follows a Gaussian distribution with mean equal to real measured range and standard deviation of 2% of the mean.

In case none of the available localization methods is adopted, a node's location is tracked using dead reckoning. Confidence value (δ_i^t) is then updated based on equation (2). We assume a low cost and low power consumption sensor suite consists of an Attitude-Heading Reference System (AHRS) and pressure gauge employed in each node with a typical dead reckoning accuracy of 30% of traveled distance [19]. We calculate the expected error of dead reckoning localization as follows

$$\varepsilon_D = w_t \phi : \phi \sim \text{uniform}(\alpha, \beta) \tag{7}$$

$$p(w_t|\hat{p}_i^t) \propto \frac{1}{\Gamma(\kappa)\Theta^\kappa} \varepsilon_D^{\kappa-1} e^{\frac{-\varepsilon_D}{\Theta}} \tag{8}$$

where ε_D is the dead reckoning expected localization error, α is related to the number of dead reckoning navigation steps (reset to 0 when USBL or trilateration is adopted) and β is the maximum drift of dead reckoning navigation (i.e. 30%). Thus, the width of the probability density function of ϕ is decreasing when time progresses.

3.2 Simulation Settings

Suppose 100 identical mobile sensor nodes are randomly distributed on a surface of a confined region of 100 m x 100 m x 100 m. Each node is equipped with a depth sensor with accuracy of 0.01% [20], AHRS with a typical dead reckoning accuracy of 30% [19] of the traveled distance, a USBL transponder and a short-range communication modem. Assume a USBL localization system, hull mounted on a surface vessel, capable of localizing 10 nodes simultaneously is deployed [9]. Correlated and uncorrelated random walker models [14] are employed to govern the mobility of the nodes. Table 2 summarizes key parameters of simulation and Evolutionary Multi-objective Optimization NSGA-II [17] used in confidence-based localization algorithm optimization.

Table 2. Simulation Parameters

| Parameter	Value
Endurance Time	1000-time steps
Swarm Size	100 Nodes
Initial Confidence Value	1
Max Simultaneous USBL Localized Nodes	10
Max Dead Reckoning Drift	30%
Node's Communication Range	[5, 55] m
Confidence Threshold	[0, 1]
NSGA-II Population size	1000
NSGA-II Max Generation No.	500
NSGA-II Non-dominated Fraction	0.02

Notice that we consider measuring distances in the objectives space (Pareto Front) instead of variables space for Crowding Distance as the computed distances of solutions in variables space might be very small although their corresponding Pareto Front distances are not.

3.3 Results and Analysis

The proposed algorithm performance with respect to the four aforementioned performance metrics has been investigated through more than 200 simulations in which the confidence threshold was varied from 0 to 1 with an increment of 0.05 and nodes' communication range were varied from 5 m to 55 m with an increment of 5 m. This represents node density ranging from 0 to 40, interested readers are referred to [10] for the four objective function surfaces, namely mean localization error, ToA-based trilateration utilization, confidence value, and USBL utilization.

The fitness function of each objective has been built based on data fitting models of the objective function surfaces in [10]. The evolutionary multi-objective optimization method NSGA-II is then employed to find the optimized Confidence Threshold (x_1): $0 \leq x_1 \leq 1$ and Node density (x_2): $0 \leq x_2 \leq 40$. The upper bound of x_2 (40) is equivalent to a node's communication range of more than 50% ($\approx$ 55 m) of a de-

ployment region's dimension (i.e. 100 m). Figure 1 reveals the Pareto Front (Pareto Optimal set score in objectives space) and Fig. 2 shows the corresponding Pareto Optimal set. Figure 3 shows the score of the four objectives of four dominant optimal solutions in the proposed deployment scenario.
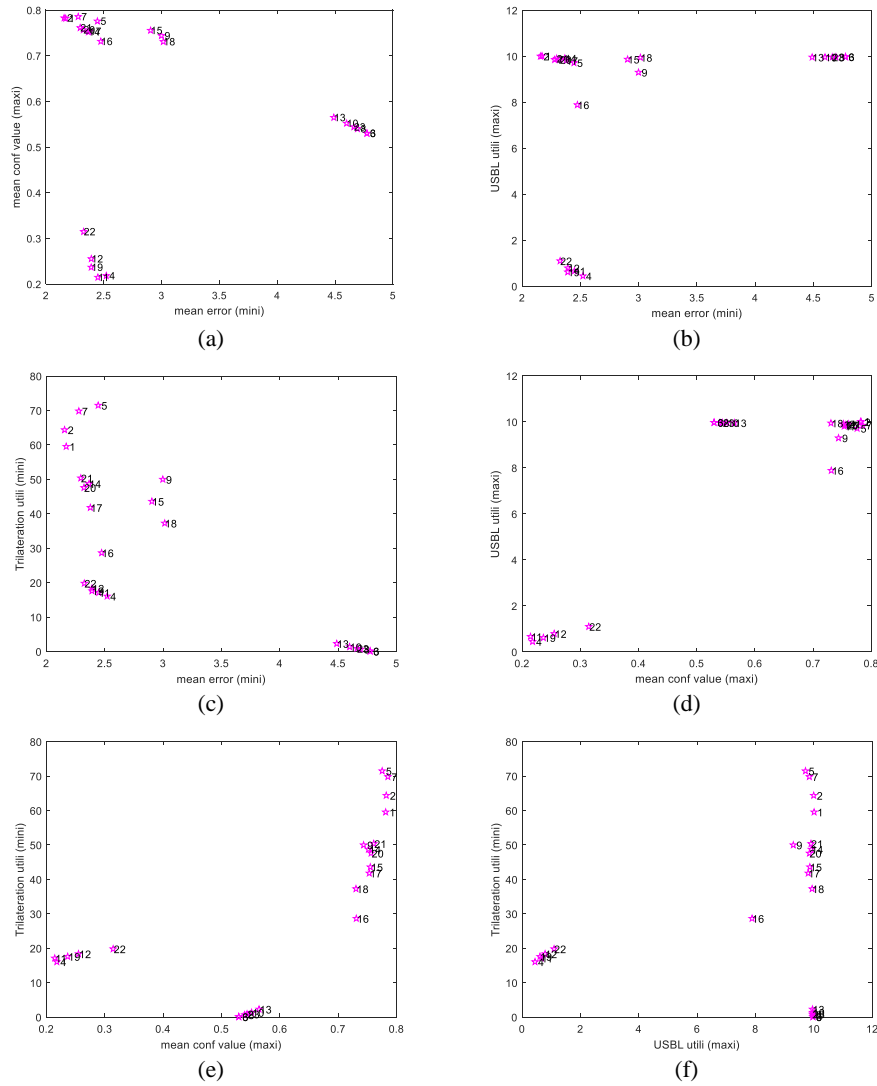
Fig. 1. The score of Pareto Optimal set, Pareto Front, in (a) mean error and mean confidence value (b) mean error and USBL utilization (c) mean error and ToA-based trilateration utilization (d) mean confidence value and USBL utilization (e) mean confidence value and ToA-based utilization (f) USBL utilization and ToA-based utilization. The solutions in Pareto front are numbered from 1 to 23.
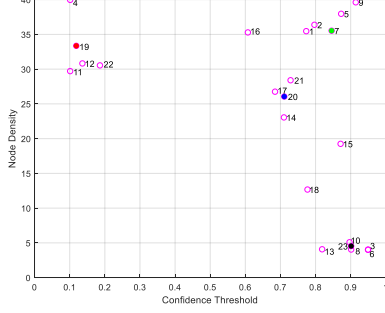
Fig. 2. The corresponding Pareto Optimal set of Pareto Front (in Confidence Threshold and Node Density). Four selected optimal solutions are represented by filled colored circles.
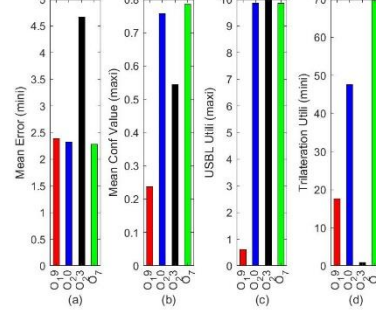
Fig. 3. The score of four selected optimal solutions in the four objectives (a) mean error (b) mean confidence value (c) USBL utilization and (d) ToA-based utilization.

A decision maker now has the option to choose any of the solutions in the Pareto Optimal set in Fig. 2 based on application requirements or objectives priorities. It can be noticed that the optimal solutions in Fig. 2 can be grouped into 4 clusters. We therefore select a single solution in each cluster in the Pareto Optimal set to emphasize each cluster's score in the Pareto Front. The selected four optimal solutions (colored) are 19, 20, 7 and 23, as shown in Fig. 2.

Solution 7 (O_7) minimizes the mean error in Fig. 3a while maximizes mean confidence value in Fig. 3b and USBL utilization in Fig. 3c but it does not minimize trilateration utilization in Fig. 3d. Although O_{23} minimizes trilateration utilization in Fig. 3d, it maximizes the mean error in Fig. 3a. However, O_{19} outperforms O_{20} in minimizing the trilateration utilization in Fig. 3d by around 30%. O_{20} outperforms O_{19} in maximizing both USBL utilization and mean confidence value; hence O_{19} suggests mostly dead-reckoning localization. Therefore, we select the set of optimal parameters represented by O_{20}. It is worth mentioning that O_{19} can provide optimal parameters for our deployment scenario given the relatively small deployment region we consider. From Fig. 2, O_{20} suggests a Confidence Threshold of 0.7109 and Node Density of 26 (communication range of 45 m).

Fig. 4 below shows histograms of localization estimate error and confidence value of a single node in a swarm of 100 nodes over 1000 localization period in an arbitrarily selected non-optimal case where confidence threshold (x_1) is 0.9 and Node density (x_2) is 6.35 (25 m communication range) and in the selected optimal case (O_{20}). Figure 5 depicts the traces of localization error, confidence value and the adopted localization method in each localization period of the same node presented in Fig. 4 over a time window of 150 localization period in both cases.
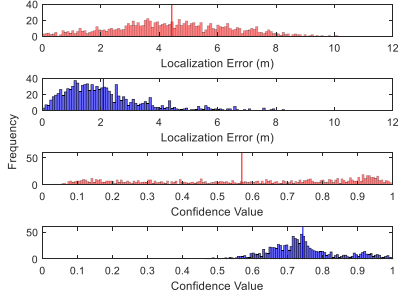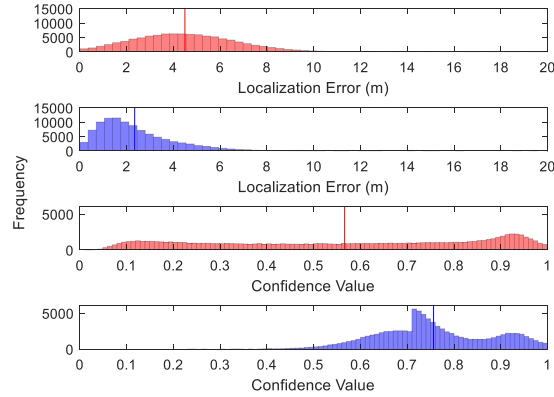
Fig. 4. Histograms of localization error and confidence value of a single node in both a non-optimal case (red) and the optimal case (blue) over 1000 localization period with mean localization error of 4.42 m and 2.08 m and mean confidence value of 0.56 and 0.74 in the non-optimal and the optimal cases respectively.
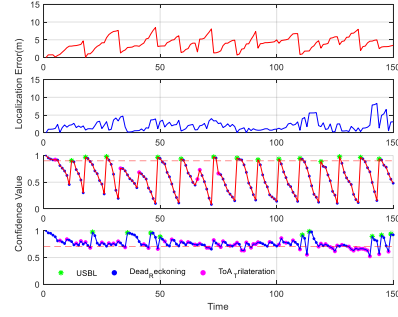
Fig. 5. Traces of typical localization errors and confidence values of a single node over the first 150 localization period in the non-optimal case (red) and the optimal case (blue). The red dashed horizontal lines represent confidence thresholds.

When both Confidence Threshold (x_1) and Node Density (x_2) are optimized, the node presented in Fig. 5 (the optimal case) was considered as a reference node for 62.9% (629 localization period) of the total running time (1000 localization period). In contrast, when confidence threshold and node density were arbitrarily set to 0.9 and 6.35 respectively (a non-optimal case), the node presented in Fig. 5 was considered as a reference node for only 18% (180 localization period) of the total running time. Consequently, mean localization error and mean confidence value have been improved by 52.94% and 32.14% respectively when confidence threshold and node density are optimized as shown in Fig 4. More nodes can become reference nodes for trilateration with sufficiently high confidence in the optimized case. In addition, standard deviations of both localization estimate error and confidence value in Fig. 4 have been improved by around 30.15% (from 1.99 to 1.39) and 65.5% (from 0.29 to 0.10) respectively.

Figure 6 shows histograms of the localization estimate error and the confidence value of all nodes in the swarm (i.e. 100 nodes) in the pre-mentioned non-optimal case and in the suggested optimal case (O_{20}).

Fig. 6. Histograms of localization error and confidence value of 100 nodes in both the non-optimal case (red) and the optimal case (blue) over 1000 localization period. The mean localization error in 10^5 localization period is equal to 4.48 m and 2.34 m with mean confidence value equal to 0.56 and 0.75 in the non-optimal and the optimal cases respectively.

Figure 6 reveals an improvement of 47.7% in localization mean error, 27.3% in localization error standard deviation and 33.92% in the mean confidence value in the swarm (10^5 localization period) when algorithm's parameters (confidence threshold and node density) are optimized.

4   Conclusion and future work

In this paper, an optimized confidence-based algorithm is proposed for large-scale underwater swarm localization. Confidence threshold and node density are key parameters for the proposed algorithm. Confidence threshold and node density are obtained and optimized through extensive simulation in which random walker models are applied so that the optimized parameters could suit various deployment scenarios. In future work, an ordinary node will be promoted to a reference node in a certain cluster of nodes based on a voting mechanism instead of a pre-defined confidence threshold so there is no need for extensive simulation to optimize a confidence threshold.

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