Confidence-based Underwater Localization Scheme for Large-Scale Mobile Sensor Networks

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***Abstract*—The absence of Global Positioning System in underwater environment predominates in the challenges of underwater vehicles navigation or sensor nodes tracking. Localization of single or few underwater vehicles has been fostered in recent years. However, online simultaneous tracking of large-scale mobile sensor network is still a very challenging research area due to the high cost and the very limited number of vehicles that can be simultaneously localized using Ultra-Short Base Line (USBL) system. We propose a confidence-based localization algorithm for large-scale underwater mobile sensor networks that employs high precision localized sensor nodes in neighboring sensor nodes localization. Numerical simulation shows that a swarm of 100 sensor nodes can be tracked using a single USBL system, range measurement sensors and communication modems.**

Keywords—underwater localization; cooperative localization; trilateration; confidence value; belief function.

I. Introduction

Deployment of large scale underwater mobile sensor networks (with more than 50 nodes) has attracted increasing attention in various underwater applications including marine seismic imaging, and marine environmental monitoring. Data acquired in these applications is location dependent and it is crucial to know the location of sensor nodes in the course of autonomous deployment and data collection. Various underwater localization methods have been proposed and they have different error characteristics, availability and operating conditions [1]. Simultaneous localization of large swarm underwater mobile sensor nodes is challenging due to the high cost of sensing systems required for single or few (i.e. less than 10) underwater vehicle navigation. Hierarchical localization approach has been employed for more than a decade [2]-[5]. The main concept behind a hierarchical localization approach is that an ordinary node can serve as a reference node (localized node with high accuracy and precision) for neighboring nodes localization using trilateration. Simple score or confidence value is employed to indicate localization estimate precision in individual sensor nodes and a node can be promoted to a reference node when its confidence value is simply above a user specified threshold [3][4]. The confidence value associated with each sensor node depends on either localization error [3] which is not always possible to be measured or range measurement errors and average of confidence values of nearby reference nodes [4][5].

This paper proposes a confidence value based localization algorithm for large scale underwater mobile sensor networks to dynamically determine the confidence value δ of each sensor node on current localization estimate and to promote a localized ordinary node to a reference node for neighboring ordinary nodes localization based on its confidence value. Sensor nodes' confidence values are updated in the proposed algorithm based on the adopted localization method's expected error.

The remainder of this paper is organized as follows. Section II explains the proposed algorithm. In section III, numerical simulation is set up to evaluate the performance of the proposed confidence value update rules. Moreover, extensive simulation results are provided to emphasize the proposed algorithm's parameters impact on selected five performance metrics. Finally, section IV concludes this paper and suggests a few future research directions.

II. Confidence-based Underwater Localization Scheme

In this section, confidence-based localization and confidence value update rules are explained.

Consider an underwater mobile sensor network with N nodes. Define the certainty of the *i-th* node at a certain position at time *t* as confidence value (δ_i^t) and it is a scalar value between 0 and 1. It measures how confident the node's current localization estimate is using a belief function. Confidence value can be considered as a belief that can be represented as a conditional probability distribution [6]. The Bayes filter algorithm [6] provides a straightforward update of beliefs in tracking sensor node location. The current localization estimate is precise when a node's localization has a confidence value of 1. In contrast, if its confidence value is 0, a node's localization estimate is completely imprecise and unreliable.

Sensor nodes are normally deployed from known positions hence their initial confidence values are set to 1. Localization methods are integrated in the proposed algorithm by implementing confidence value's update rules based on the corresponding localization method's expected error which can be derived from its error model. The confidence value of each sensor node in the network is dynamically updated in each localization step. Expected error of the corresponding localization method is used instead of measured error in implementing the confidence update rules. Localization estimate error in underwater environment cannot be easily measured unless a sophisticated and costly localization system, such as Long Base Line (LBL) [7], is employed in advance of sensor deployment.

Three common localization methods are considered in the proposed algorithm, namely Ultra-Short Base Line (USBL) [8], Time of Arrival (ToA) based trilateration [9] and dead reckoning using a low cost Attitude Heading Reference System (AHRS) [10]. Node i is considered as a reference node and can be utilized to localize other nodes using trilateration if its confidence value (δ_i^t) is higher than a pre-defined confidence threshold (λ); It is an ordinary node otherwise.

Node i is localized by USBL if its confidence value (δ_i^t) drops below a pre-defined confidence threshold (λ) and when the USBL is available. Its confidence value, in this case, is updated as shown in (1) 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.

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

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 $m_t = z_t$.

The most advanced USBL system can only localize 10 nodes simultaneously in a pipeline fashion and thus all N (N >> 10) [8] nodes in an underwater mobile sensor network can only be localized in sequential batch manner. ToA-based trilateration is adopted if USBL is not available and ToA-based trilateration conditions are achieved (refer to the blue box in Fig. 1). ToA-based trilateration's conditions are related to the neighboring nodes number, their status (ordinary or reference) and the geometry of the bounding box formed by them. We solve ToA-based trilateration least squares problem using Particle Swarm Optimization (PSO) [11]. 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. Confidence value (δ_i^t) is updated, in this case, based on J neighboring nodes ($j = 1, 2, \ldots, J$) 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 ($j = 1, 2, \ldots, J$):

$$\delta_i^t = \frac{\sum_{j=1}^{J} \delta_j^t \left(1 - \frac{\left| |\hat{p}_j^t - \hat{p}_i^t| - r_{ij} \right|}{|\hat{p}_j^t - \hat{p}_i^t|}\right)}{J} \tag{2}$$

Equation (2) considers 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}).

Dead reckoning is adopted for localization of a node when neither USBL nor trilateration can be applied or when node i is a reference node. 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 (1) with $m_t = w_t$. Fig. 1 depicts the localization process of node i in which USBL, trilateration or dead reckoning localization is selected at each localization step based on its confidence value δ_i^t.

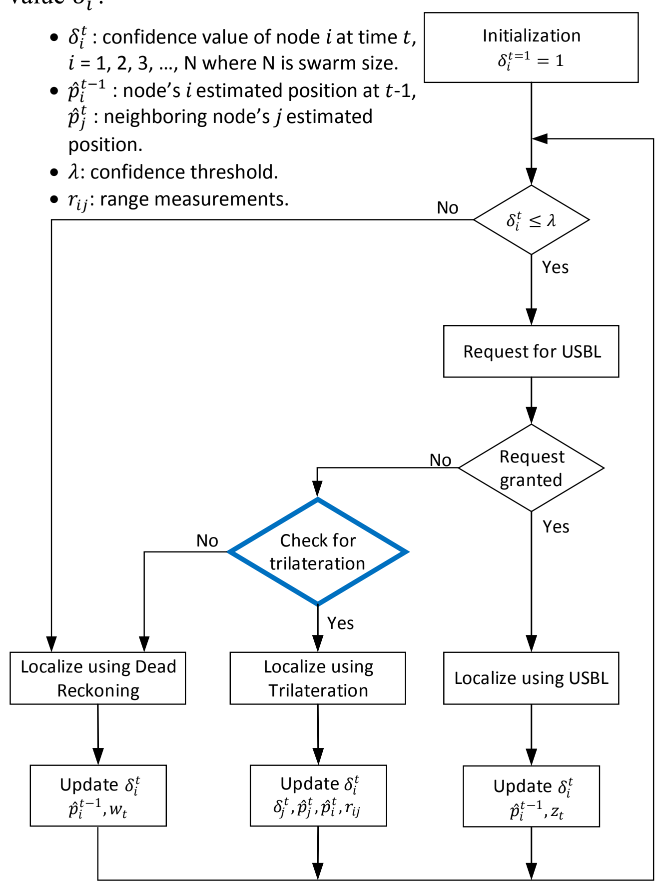


Fig. 1 Confidence-based Underwater Localization Scheme

The proposed confidence value update rules operate based on local information only and this makes it a highly distributed and scalable algorithm for underwater swarm localization. An ordinary high precision localized node is promoted to a reference node when its confidence value is above a pre-defined confidence threshold (λ). A reference node can also be demoted to an ordinary node if its confidence value is below the confidence threshold λ. A universal confidence threshold that suits different nodes deployment scenarios is nearly impossible to be set a priori of sensor node deployment. Hence we investigate confidence threshold and node density impacts on localization performance using the proposed algorithm through extensive simulation. We consider five performance metrics, namely mean localization error, mean confidence value, USBL utilization, ToA-based trilateration utilization and dead reckoning utilization to evaluate the proposed method performance.

III. Simulation

In this section, the error characteristics of localization methods considered in this paper including USBL, ToA-trilateration and dead reckoning are employed in confidence value update. Simulation settings and results are provided in the following.

A. Loclization Error Models for Confidence Update

When USBL localization method is adopted, localization estimate expected error can be generated based on its error characteristics. Fig. 2 shows the relationship between total error of USBL localization and operational depth from the datasheet of a USBL system called Ranger [8].

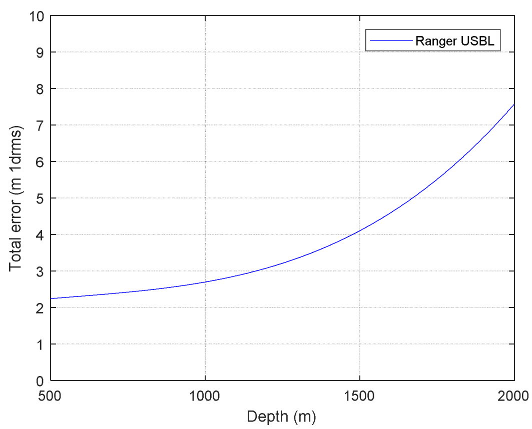


Fig. 2 Total error of USBL Ranger with operational depth. In 1000 m depth 63% (1Drms) of total errors are within 2.7 m radius.

We assume the localization estimate error of USBL Ranger follows a Gaussian distribution.

$$\varepsilon_U \sim \mathcal{N}(\mu, \sigma^2) \tag{3}$$

where μ = 2.7 m and σ = total error (1Drms) depicted from Fig. 2. 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 (1) as follows

$$p(z_t|\hat{p}_i^t) \propto \frac{1}{\Gamma(\kappa)\Theta^\kappa} \, {\varepsilon_U}^{\kappa-1} \, e^{\frac{-\varepsilon_U}{\Theta}} + \tau \tag{4}$$

where ε_U is the USBL expected localization error, τ is a damping factor, κ and Θ are Gamma distribution parameters. Exponential distribution is a special case of Gamma distribution but Gamma distribution provides an additional degree of freedom for penalizing the expected error when the expected error is high. A damping factor (τ) is crucial for the likelihood stability. The higher the value of τ, the harder the confidence value fluctuates.

Equation (2) is used to calculate the confidence value of node i when ToA-based trilateration is adopted. Based on existing underwater range measurement technologies [12] we assume that the range measurement between two arbitrary neighboring nodes i and j (r_{ij}) follows a Gaussian distribution with mean equal to the 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) is then updated based on (1). We assume a low cost and low power consumption sensor suite, that consists of AHRS and pressure gauge, is employed in each sensor node with a typical dead reckoning accuracy of 30% of the traveled distance [10]. We calculate $p(w_t|\hat{p}_i^t)$ in (1) as follows

$$\varepsilon_D = w_t \phi : \phi \sim \mathrm{uniform}(\alpha, \beta) \tag{5}$$

$$p(w_t|\hat{p}_i^t) \propto \frac{1}{\Gamma(\kappa)\Theta^\kappa} \, {\varepsilon_D}^{\kappa-1} \, e^{\frac{-\varepsilon_D}{\Theta}} \tag{6}$$

where ε_D is the expected localization error of dead reckoning, α is related to the number of dead reckoning navigation steps (it resets 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.

B. Simulation Settings

Suppose 100 mobile sensor nodes are randomly deployed on the surface of a confined region of 100m X 100m X 100m. Each node is equipped with a depth sensor with accuracy of 0.01% [13], AHRS with a typical dead reckoning accuracy of 30% [10] of the traveled distance, a USBL transponder and an omnidirectional communication modem with spherical spreading [14]. Assume a USBL localization system, hull mounted on a surface vessel, is capable of localizing 10 nodes simultaneously [8]. Correlated and uncorrelated random walker [15] models are launched to govern the mobility of the nodes. Correlated random walker model is assumed to keep the nodes in a confined region and uncorrelated random walker model is adopted to maximize region spatial coverage. We vary the expected number of nodes in a node's neighborhood (node density) by varying nodes' communication range. Table I. summarizes simulation parameters used to produce the results in this paper.

TABLE I. Simulation Parameters

Parameter	Value
Endurance Time	1000-time steps
Swarm Size	100 Nodes
Step Size	5 m

Max Number of Nodes in Simultaneous USBL Localization	10 Nodes
Initial Confidence Value	1
Max Dead Reckoning Drift	30%
Node's Communication Range	[5, 55] m
Confidence Threshold	(0,1)

Node density has been varied in our simulation through node's communication range. The following Fig. 3 shows the relationship between node density and node's communication range obtained in our simulation.

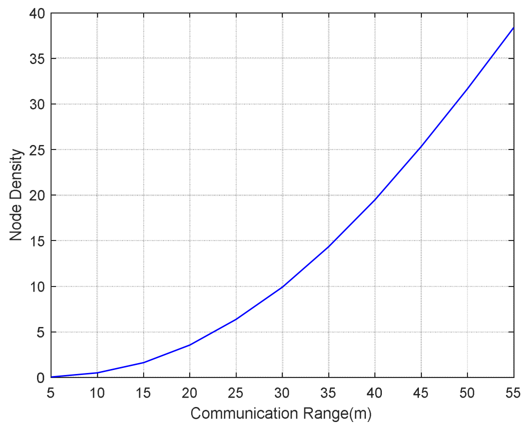
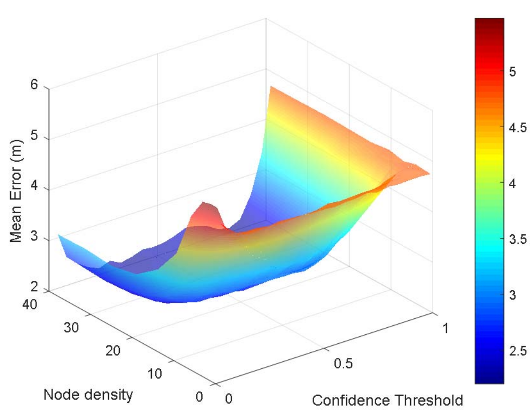


Fig. 3 The relationship between the average number of nodes in a node's neighborhood (node density) and node's communication range.

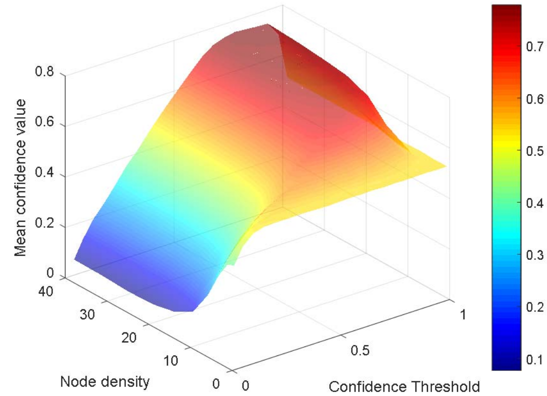
C. Results and analysis

The proposed algorithm performance has been investigated throughout the algorithm's parameters space. Confidence threshold (λ) is varied from 0 to 1 with an increment of 0.05 and nodes' communication range are varied from 5m to 55m with an increment of 5m; that represents node density ranging from 0 to almost 40 as shown in Fig. 3.

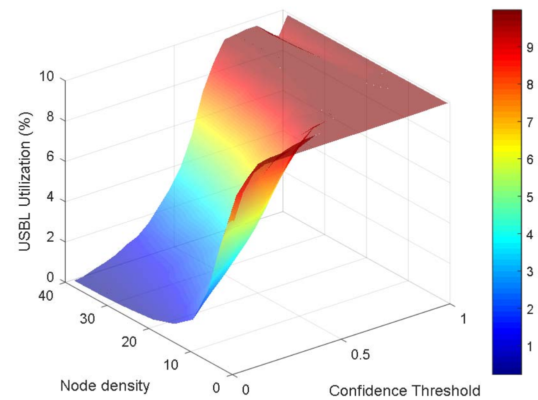
Fig. 4 shows the impact of confidence threshold (λ) and node density (varied by node's communication range) on (a) mean localization error, (b) mean confidence value, (c) USBL utilization, (d) ToA-based trilateration utilization and (e) dead reckoning utilization in a swarm of 100 sensor nodes.



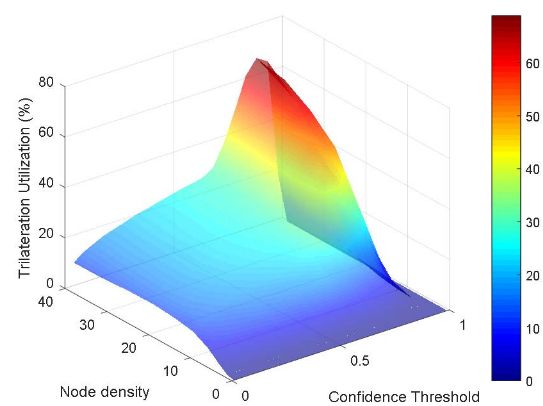
(a)



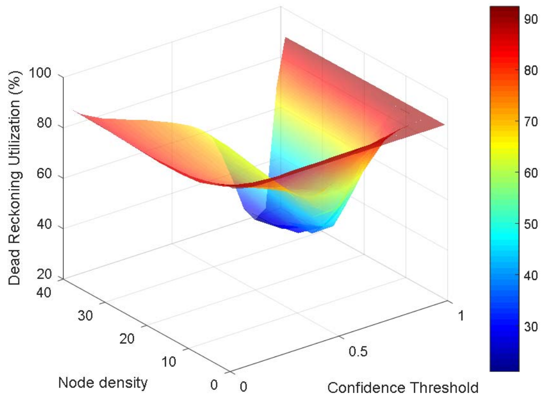
(b)



(c)



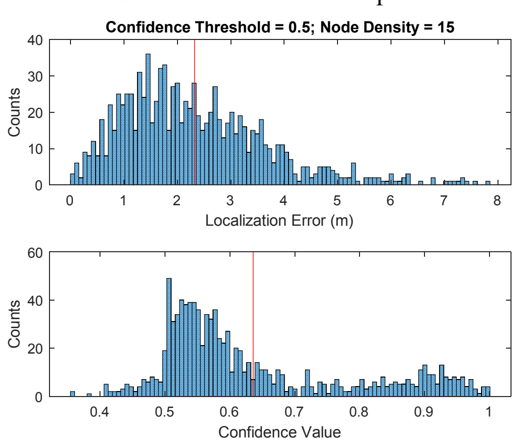
(d)



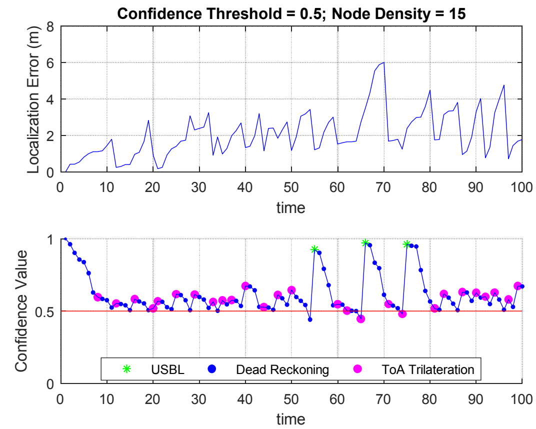
(e)

Fig. 4 The impact of confidence threshold and node density on (a) mean error (b) mean confidence value (c) USBL utilization (d) ToA-based trilateration utilization and (e) Dead reckoning utilization in a swarm of 100 nodes over 1000 localization period.

The ideal parameters (Confidence threshold and Node density) of the proposed algorithm should minimize mean error, dead reckoning utilization and ToA-based trilateration utilization due to its high computational power consumption while maximizing both mean confidence value and USBL utilization as it is the most reliable localization method considered in our simulation scenario. It can be noticed that there is not a pair of parameters (Confidence threshold and Node density) that optimizes all performance metrics at the same time. Fig. 4 shows that confidence threshold of around 0.8 and node density of around 25 minimizes both mean error in (a) and dead reckoning utilization in (e) but do not minimize ToA-based trilateration in (d). However confidence threshold of around 0.5 and node density of around 15 (communication range of 35m) seem to provide a good trade off among all performance metrics. Fig. 5 (a) shows histograms of localization error and confidence value of a single node in a swarm of 100 nodes when confidence threshold and node density are set to 0.5 and around 15 respectively. Fig. 5 (b) shows traces of localization error and confidence value of the same node presented in Fig. 5 (a) over a time window of 100-localization period.



(a)



(b)

Fig. 5 (a) histograms of localization error and confidence value of a single node in a warm of 100 nodes, the vertical red lines represent mean error (2.32m) and mean confidence value (0.63) over 100-localization period; (b) typical traces of localization error and confidence value of a single node over a time window of 100-localization period, the horizontal red line represents a confidence threshold of 0.5.

Fig. 5 (b) shows that a node's confidence value is boosted when a node is localized by USBL. Node's confidence value below confidence threshold triggers USBL localization which is associated with lower localization error and higher confidence value (e.g. when time = 65).

IV. CONCLUSION AND FUTURE WORK

In this paper, confidence-based localization scheme for large-scale underwater mobile sensor network is proposed. Confidence threshold and node density are key parameters in the proposed algorithm. Therefore, the impacts of confidence threshold and node density on mean error, mean confidence value, USBL utilization, ToA-based trilateration utilization and dead reckoning utilization are investigated through extensive simulation. Results show that a swarm of 100 sensor nodes can be simultaneously localized with mean localization error of 2.32m, error standard deviation of 1.36m, mean confidence value of 0.63 and confidence standard deviation of 0.148 by the proposed algorithm when confidence threshold and node density are set to 0.5 and 15 respectively.

In the future, the proposed algorithm's key parameters will be optimized using multi-objective optimization. Consequently, an optimized trade-off of a set of parameters will be provided so that the user will have the option to choose a set of parameters based on objectives priorities. Moreover, localization error of the proposed algorithm will be compared with other localization methods.

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