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Dynamic Localization Plan for Underwater Mobile Sensor Nodes using Fuzzy Decision Support System

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***Abstract*—Underwater mobile sensor node localization is a key enabling technology for several subsea missions. A novel scalable underwater localization scheme, called Best Suitable Localization Algorithm (BLSA), is proposed to dynamically fuse multiple position estimates of sensor nodes using fuzzy logic, aiming at improving localization accuracy and availability along the whole trajectory in missions. Numerical simulation has been conducted to demonstrate significant improvement in localization accuracy and availability by using the proposed fuzzy inference system. The proposed method provides a cost-effective localization system by harnessing all available localization methods on-board.**

Keywords—Underwater mobile sensor nodes; deep water localization; dynamic localization plan; Fuzzy decision support system; fuzzy logic.

I. INTRODUCTION

Underwater Wireless Sensor Networks (UWSNs) localization has attracted researchers' interest for decades, due to the wide variety of offshore applications such as deep sea exploration, environmental monitoring, geological and ecological research, and samples collection [1] [2]. In an UWSN application, a swarm of sensor nodes are deployed to communicate and collaboratively achieve various predefined tasks underwater through acoustic communications. In order to successfully complete assigned missions, locations of individual sensor nodes must be known and tracked during operation for spatial information related applications.

A large number of underwater localization algorithms have been proposed, each has its own merits and limitations which make each algorithm suits certain marine applications and underwater operating conditions but not all. Around fifty underwater localization algorithms have been proposed since 2006 [3] [4]. In general, localization algorithms can be classified into three categories based on operation depth, namely near surface, mid-water, and near seafloor localization algorithms. Underwater vehicles are either umbilically connected to sea surface vehicle [5] or periodically rise and dive [6] so that nodes location can be obtained by means of GPS when they are close to sea surface.Simultaneous Localization and Mapping (SLAM) based on seafloor landscape features [7] and Doppler Velocity Log bottom track (DVL) based on seafloor relative velocity of underwater vehicle [8] are commonly employed to achieve near seafloor nodes localization. DVL water track or Acoustic Doppler Current Profiler (ADCP) and Inertial Navigation System (INS) can be used as aiding sensors in dead reckoning method to navigate in the mid-water column [9]. Conventional acoustic localization systems such as Long Base Line (LBL), Short Base Line (SBL), and Ultra-Short Base Line (USBL) are commonly used in industry to localize nodes in the mid-water column. USBL does not require any artificial landmarks on the seafloor and a single Unmanned Surface Vehicle (USV) or ship is deployed for operation. Since USBL is more flexible and has less limitations than those in LBL and SBL, it is the most commonly adopted method in industry. To the best of our knowledge, the highest localization accuracy achieved by commercially available USBL system (aided with high grade INS) is at 0.06% of slant range [10]. It can localize only one underwater target at a time and its cost is high. Other USBL systems have lower localization accuracy of around 0.13-0.27% of slant range but support simultaneous tracking of four to ten underwater targets [11]. However, there is no single localization method that is able to maintain high accuracy and availability when some underwater vehicles descend from sea surface to seafloor in deep sea exploration. Multiple localization systems are installed on them so that unavailable localization method can be replaced by other available methods when needed. This paper investigates how to dynamically fuse estimates from multiple localization methods in order to improve localization accuracy and availability throughout a deep sea mission.

This study is primarily motivated by the need for an autonomous ocean bottom seismic sensors deployment method for saving human effort and cost. Seismic imaging is being used in oil and gas industry in either fossil fuel exploration or productivity enhancement of an existing onshore or offshore oil field. Four-dimensional and three-dimensional seismic survey currently represent a significant percentage of overall seismic surveys [12]. Ocean bottom seismic sensors can provide relatively high resolution 3D and 4D seismic images of sub-seafloor. Recent developments in these sensors have heightened the need for reliable and cost-effective deployment method. Ocean bottom seismic sensors are deployed in deep oceans using Remotely Operated Vehicles (ROVs) equipped with a robotic arm and driven by on board crew. This is very costly and time consuming deployment method and it cannot be applied when it comes to large number (in thousands) of nodes. Therefore, there is a need for an autonomous seismic sensor node deployment system that can overcome the limitations of the current deployment method.

This paper proposes a novel underwater localization scheme called **B**est **S**uitable **L**ocalization **A**lgorithm (BSLA) to dynamically fuse multiple position estimates of sensor nodes for better localization accuracy along the whole trajectory using fuzzy decision support system. The necessity to this approach extends beyond the high cost of high-quality USBL localization system and the large number of newly introduced and not commonly adopted localization algorithms. This approach provides research and industry communities with a flexible tool that significantly helps in selecting the best localization plan given the cost and accuracy requirements for different subsea applications.

The remainder of this paper is organized as follows. Section II briefly presents a literature review of two localization methods that are considered in BSLA and their error characteristics. Section III describes in details how BSLA works and gives examples of linguistic fuzzy rules involved. Following that, the effectiveness of BSLA is demonstrated by simulating a common deployment scenario of ocean bottom seismic sensors. Moreover, a comparison in localization errors before and after using BSLA is provided in section IV. Finally, section V concludes this paper and discusses some of future directions.

II. LITERATURE REVIEW

In [13], authors proposed a localization scheme called **L**arge-scale **L**ocalization scheme with **N**o **P**rediction (LLNP) for large-scale underwater sensor network. . In addition authors in [14] extended the work proposed in [13] and introduced a new localization scheme called **S**calable **L**ocalization scheme with **M**obility **P**rediction (SLMP). In this section, LLNP and SLMP are briefly reviewed.

Authors in both hierarchical LLNP and SLMP schemes considered scenarios of 3-dimentional **U**nderwater **W**ireless **S**ensor **N**etwork (UWSN) consists of anchor nodes with high communications capability and ordinary nodes. At least four localized surface buoys are considered in both schemes; they can only be contacted by anchor nodes due to their high communication capability. Distances among nodes are estimated in both schemes using technique such as time of arrival (TOA). Fig. 1 shows the deployment scenario of underwater wireless sensor network assumed in both schemes.

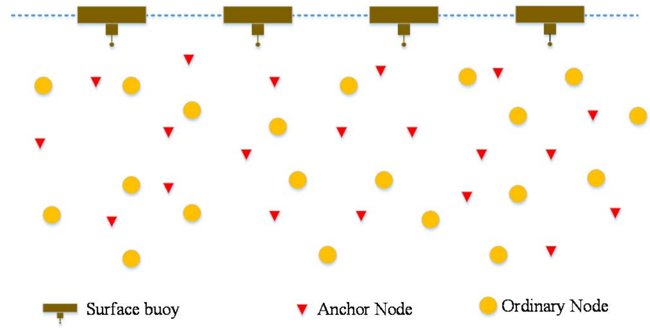

Fig. 1. *Underwater Wireless Sensor Network*

In LLNP, authors assumed that anchor nodes are localized by contacting surface buoys. Ordinary node localization process is elaborated in Fig. 2. During ordinary node localization process, each node maintains a counter of broadcasted localization messages ***n*** with a pre-defined threshold of ***N*** and a counter of reference nodes to which the distance is known ***m*** with a threshold of 4.

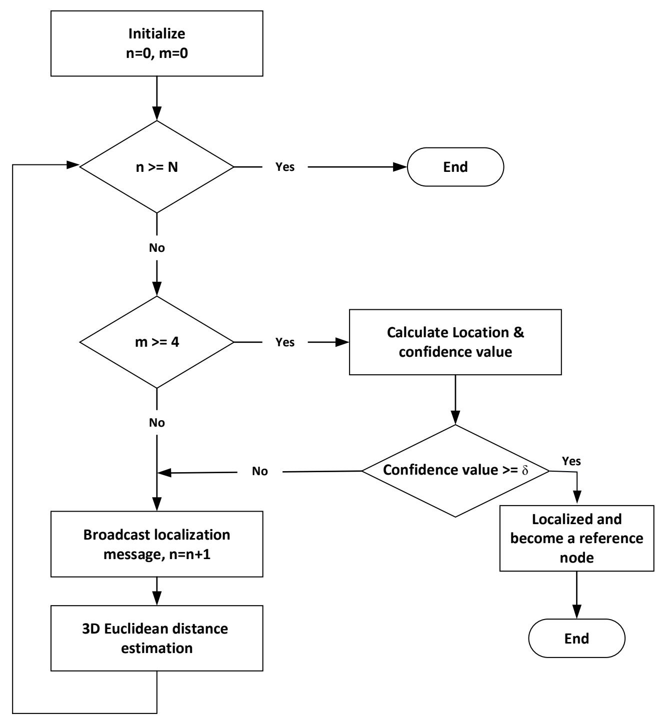

Fig. 2. *Ordinary Node Localization Process in LLNP [13]*

Given that the confidence value of any anchor node is set to 1 and δ is the confidence threshold which controls the possibility of a localized ordinary node to become a new reference node. Authors successfully demonstrated that the proposed scheme outperforms the recursive scheme proposed in [15] and the Euclidean scheme proposed in [16]. Fig. 3 shows the average normalized localization error with node density. Authors defined the node density as the expected number of nodes that lies in a node's communication range.

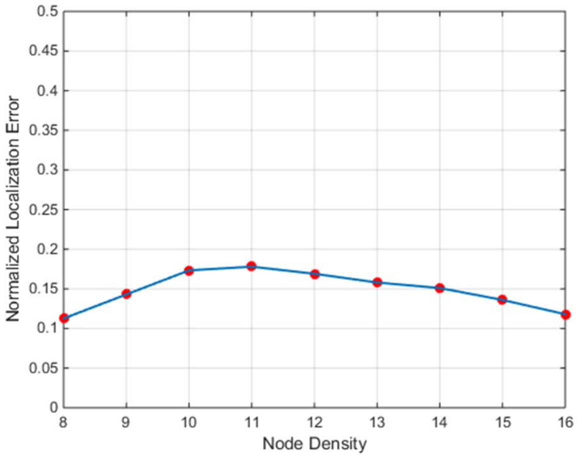

Fig. 3. *Relationship between the normalized localization error to the node's communication range and the node density in LLNP [13]*

Based on the group movement properties of underwater objects, author presented an extended version of LLNP, called the SLMP scheme in [14]. Some hydrodynamics research showed that underwater objects move in semi-periodic manner [17] [18]. The SLMP is one of the very few algorithms investigated the impact of nodes location history on its next location. Likewise, anchor nodes are assumed to be localized by contacting four or more surface buoys. However, both anchor nodes and ordinary nodes attempt to predict their mobility pattern based on a linear prediction method [19] and nodes mobility patterns are exchanged among nodes. Ordinary node localization process in SLMP is to a great extent similar to that in LLNP except the linear mobility prediction part. Interested readers can refer to [14] for more details. Fig. 4 shows the average normalized localization error with node density in SLMP under the same simulation sittings to those in LLNP.

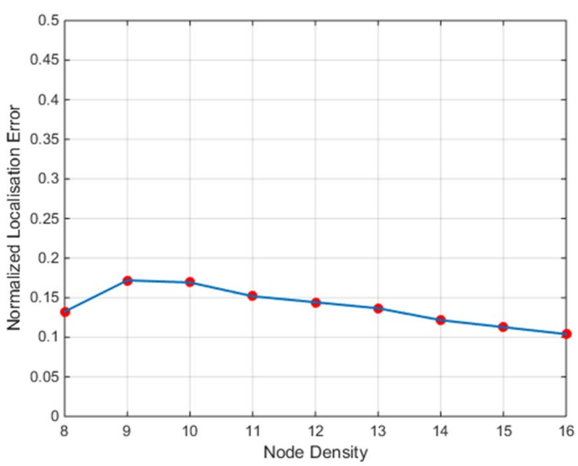

Fig. 4. *Relationship between the normalized localization error to the node's communication range and the node density in SLMP [14]*

III. Best Suitable Localization Algorithm

In this section, Best Suitable Localization Algorithm approach using fuzzy decision support system is explained in detail. The proposed BSLA scheme aims at improving both localization accuracy and availability by dynamically fusing multiple localization estimates using fuzzy logic. We validate our approach based on stochastic localization error models of four selected localization methods.

Assume we have $\boldsymbol{n}$ underwater localization methods. Each method can localize an underwater mobile sensor node at a certain zone of ocean's layers (e.g. near sea surface) with best accuracy. Mobile sensor nodes are assumed to descend from sea surface to seafloor. This approach allows each mobile sensor node to either select a single localization method or to combine two or more localization methods to improve both localization accuracy and localization coverage along the whole trajectory based on fuzzy inference system. Fuzzy logic based method is adopted in information fusion in underwater localization because human expert knowledge can be easily captured using if-then rule construct. Moreover, the impreciseness of expert knowledge can be easily modelled and processed using fuzzy inference.

Fig. 5 illustrates four decision support elements (input variables) of this approach, namely operation depth $\boldsymbol{\mathcal{D}}$, USBL availability $\boldsymbol{\mathcal{U}}$, node's battery level $\boldsymbol{\mathcal{B}}$ and number of localized neighbouring nodes $\boldsymbol{\mathcal{G}}$. When a certain node needs to be localized, variable inputs will determine the Best Suitable Localization Algorithm $\boldsymbol{\mathcal{BSLA}}$ (output variable) to be adopted based on the constructed fuzzy rule base. Each localization algorithm is represented by a fuzzy set $\boldsymbol{L_i}$, $\boldsymbol{i} = \boldsymbol{1}, \cdots, \boldsymbol{n}$. The output could either be a single localization method or a weighted combination between multiple localization methods for better localization accuracy along the whole predefined trajectory.

Number of localized neighbouring nodes input represents either number of anchor nodes or localized ordinary nodes lie within the communication range of a node. USBL availability input is crucial in cases such as the given USBL system cannot localize more than a single underwater target at a time or a USBL maximum updating rate does not suffice mission's requirments. We assume that a node's battery level follows a typical discharging curve of a lithium battery cell.

Four different localization methods are used in BSLA approach and they are: Ultra-Short Base Line (USBL) [11], Large-scale Localization scheme with No Prediction (LLNP) [13], Scalable Localization scheme with Mobility Prediction (SLMP) [14] and Inertial Navigation System aided by Doppler Velocity Log (INS/DVL) [20]. Each localization method is represented by a disjoint triangular fuzzy set on the universe of discourse.

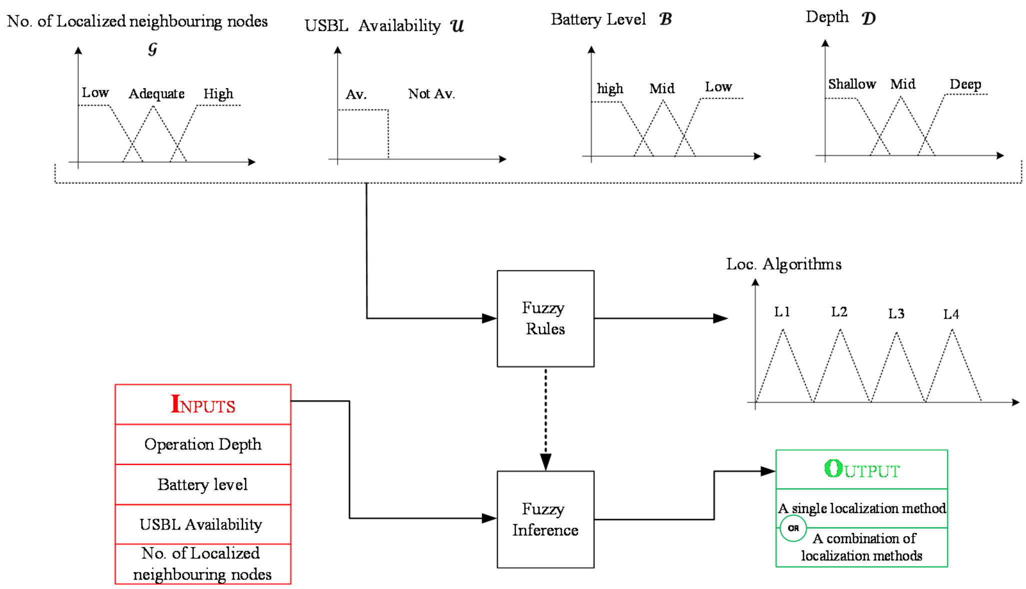

Fig. 5. *Best Suitable Localization Algorithm approach (Decision-making)*

One example of a linguistic fuzzy rule with four inputs and one output:

IF $\boldsymbol{\mathcal{D}}$ is ***Mid-water*** AND $\boldsymbol{\mathcal{U}}$ is ***Available*** AND $\boldsymbol{\mathcal{B}}$ is ***High*** AND $\boldsymbol{\mathcal{G}}$ is ***Adequate*** THEN $\boldsymbol{\mathcal{BSLA}}$ is $\boldsymbol{L_2}$.

Inputs' fuzzy sets shown in Fig. 5 have been determined based upon either its features as in $\boldsymbol{\mathcal{U}}$ and $\boldsymbol{\mathcal{B}}$ inputs or output localization algorithms working conditions as in $\boldsymbol{\mathcal{D}}$ and $\boldsymbol{\mathcal{G}}$ inputs. Fuzzy rules in BSLA are designed in a way that prioritizing input variables differently in each ocean's layer. For example, in deep ocean's layer (near seafloor), battery level is a crucial element. Given that USBL is the most power consuming method. In this case, if the battery level is low, the USBL will never be used.

IV. SIMULATION

In this section, the performance of BSLA is evaluated using numerical simulations.

A. Localization Error Models

Due to the lack of technical details of the sensor involved in all actual localization methods and the operating environment characteristics including seafloor landscape and water current model, stochastic localization error models are constructed based on literature in testing the proposed BSLA scheme in simulation. These error models are applied to emulate the localization error generated by the corresponding localization methods when sensor nodes are traversing underwater.

A relatively accurate USBL localization system can simultaneously localize up to 10 underwater targets with accuracy of 0.27% 1 Drms of slant range [11]. Fig. 6 shows the relationship between the total error in meter 1Drms of an accurate USBL system and the depth of an underwater target (blue curve). Fig. 6 reveals that in 1000 m depth 63% (1Drms) of total error are within 2.7 m radius. Localization accuracy of another USBL system is shown in Fig. 6 (red curve) which supposedly follow the same pattern of Ranger USBL but with offset error of 7.3 m. The red curve presumably suggests 63% of USBL accuracies are within 10 m radius in 1000 m depth. We assume that the localization error of a USBL system follow a Gaussian distribution. The localization error in USBL $E_U \sim \mathcal{N}(\mu, \sigma^2)$ where μ = 2.7 and 10 for Ranger USBL and Inaccurate USBL, respectively and σ is fitted to the curves shown in Fig. 6.

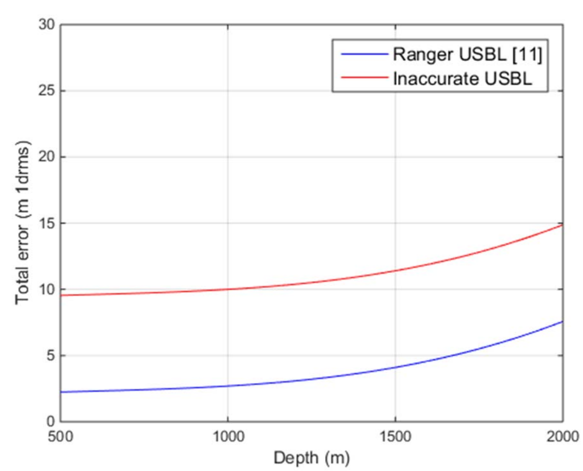

Fig. 6. *The localization error of Ranger USBL and Inaccurate USBL with water depth*

We assume that error characteristics of LLNP and SLMP are normally distributed with the aforementioned error data points of LLNP and SLMP in Figs. 3 and 4, respectively. Mean values and standard deviations to be 2% of error data points. $E_L \sim \mathcal{N}(\mu, \sigma^2)$ where μ is the localization error depicted in Figs. 3 & 4 and σ = 0.02 x μ. This assumption has made based on existing underwater distance measurement technologies [21].

In [20] authors presented a simulation results of an AUV navigation performance obtained using different data fusion methods of INS aided by DVL. Fig. 7 presents the root mean square errors of the velocity vector and the attitude error of an AUV navigates with a velocity of 2 m/s along a classic lawn mower trajectory using a tightly coupled INS/DVL. We presume that the attitude and the velocity error follows a Gaussian distribution over a sliding time window of 25 seconds.

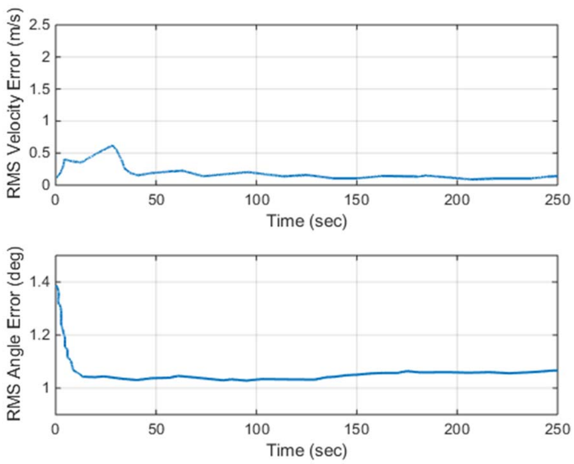

Fig. 7. *RMS of the velocity and the attitude errors using tightly coupled DVL/INS [20]*

B. *Example Scenario*

Suppose there are 50 mobile sensor nodes each of them equipped with a depth sensor, an IMU (with a 3D accelerometer, a 3D gyro, and a 3D magnetometer), USBL transponder, and a 300 kHz DVL (has a range of ~200m). Their home position is somewhere close to sea surface and need to be deployed on predetermined seafloor positions at a depth of around 3km. Assume we have a USBL localization system, which can only track one underwater node at a time with low-accuracy (e.g. 1% of slant range), hull mounted on a surface vessel.

Assume that $\boldsymbol{n}$ = 4, where $\boldsymbol{L_1}$ represents USBL localization system with total localization error suggested in the previous section in Fig. 5 (inaccurate USBL), $\boldsymbol{L_2}$ represents LLNP [13], $\boldsymbol{L_3}$ represents SLMP [14] and $\boldsymbol{L_4}$ represents DVL/INS [20]. The fuzzy rule base employed in simulation is shown in the Appendix.

C. *Simulation Settings*

A simple two-dimensional dynamic model has been assumed to govern the AUV's mobility. Its governing equations are:

$$\dot{\mathcal{X}} = \mathcal{V} \sin\theta$$
$$\dot{\mathcal{Y}} = \mathcal{V} \cos\theta$$
$$\dot{\theta} = \mathcal{V}\mu$$

where $(\mathcal{X}, \mathcal{Y})$ are AUV's position coordinates, θ is AUV's heading, $\mathcal{V}$ is the commanded forward speed and μ is the commanded turn curvature.

Table I. summarizes simulation and navigation parameters used to produce the results in this paper.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Endurance Time	14 min
Time Step	1 sec
AUV Velocity	5 m/s
DVL Range	200 m
Seafloor Depth	3000 m
Node's Communication Range	20 m
Anchor Nodes Density	50
USBL Updating Rate	1 sec

Anchor nodes are randomly deployed with a density of 50 nodes per 100 m^2 and assumed to be perfectly localized. Anchor node density and node's communication range parameters are intended to be identical to those assumed in both LLNP and SLMP. Therefore, the presented localization error of LLNP and SLMP shown in Figs. 3 and 4 respectively can be fairly and reasonably used.

Velocity and attitude errors using a tightly coupled DVL/INS shown in Fig. 7 are affected the most by AUV velocity. AUV velocity has been assumed to be 2 m/s in the simulation carried out in [20] to produce the results shown in Fig 7. As shown in table I., AUV velocity in this simulation is set to 5 m/s. Despite the mismatched velocities, the velocity and attitude errors can still be used to validate BSLA approach. The errors are overestimated when higher velocity is assumed.

Fig. 8 shows an example of a predefined path of a mobile sensor node descending from its home position (40 m below sea surface) to its destination at the seafloor. All nodes are supposedly launched from the same home position and passing through the same Way Point 1 shown in Fig. 8. The Way Point 1 is at a depth in which the bottom track DVL can successfully work.

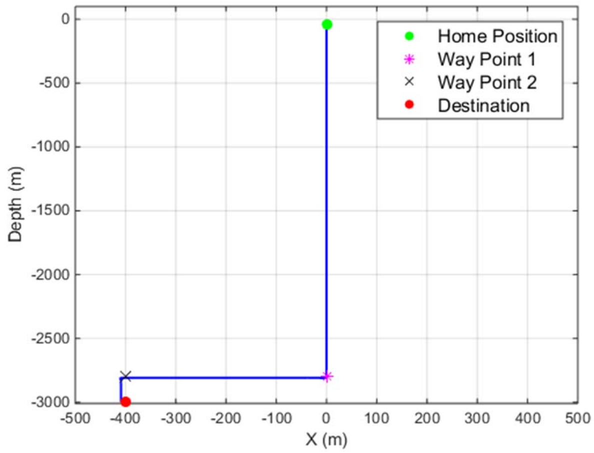

Fig. 8. *An example of a predefined trajectory*

D. Results and analysis

The localization performance of each method including BSLA is obtained through five trial trajectories. Each of them has a different destination and is presented in terms of mean errors and standard deviation of estimated positions along the whole trajectory. Moreover, the unavailability of each approach along the whole trajectory is also presented as it is a significant localization performance element.

The performance of each approach in localizing a single underwater node are plotted in Fig. 9. It is observed from Figs. 9a and 9b that LLNP and SLMP have the most accurate position estimations but only around 30% of node's locations were estimated using either LLNP or SLMP, as shown in Fig. 9c. As it was expected, USBL was able to estimate node's position at any time instant with high localization error.

On the other hand, node's positions were estimated using BSLA approach have lower localization error than that in the USBL and higher than that in LLNP and SLMP but it was available along the whole navigated trajectory. Fig. 10 shows a comparison among all localization methods. Each performance element is presented on a radius line and normalized to its highest value so that the least accurate and the most unavailable localization approach would have an equilateral circumscribed triangle.

It is clear that LLNP and SLMP have almost an identical performance and the localization using DVL/INS has the highest mean error and the highest unavailability which was expected since DVL does not work unless it is being close to the seafloor.

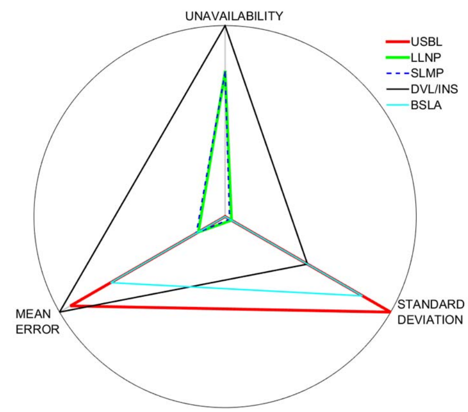

Fig. 10. *Normalized performace of five localization approaches in localizing a single underwater node*

In the second set of simulations, positions of three identically equipped underwater nodes are estimated using the five localization methods. The localization performance in terms of mean errors, standard deviation and unavailability are depicted in Figs. 11a, 11b and 11c, respectively. Fig. 12 compares three elements localization performance in the five localization methods. Compared with localization accuracy in USBL and DVL/INS, BSLA notably improved localization accuracy of around 23-30%. It is discernible that BSLA has improved localization accuracy and was the best approach in term of availability.

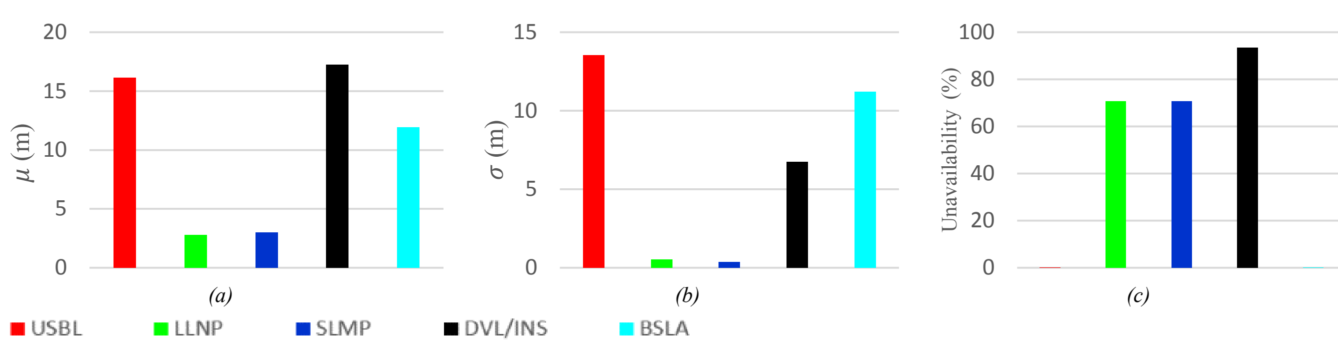

Fig. 9 . *Performace of five localization approaches in localizing a single underwater node (a) mean error (b) error standard deviation (c) localization approach unavailability along the whole pre-defined trajectory*

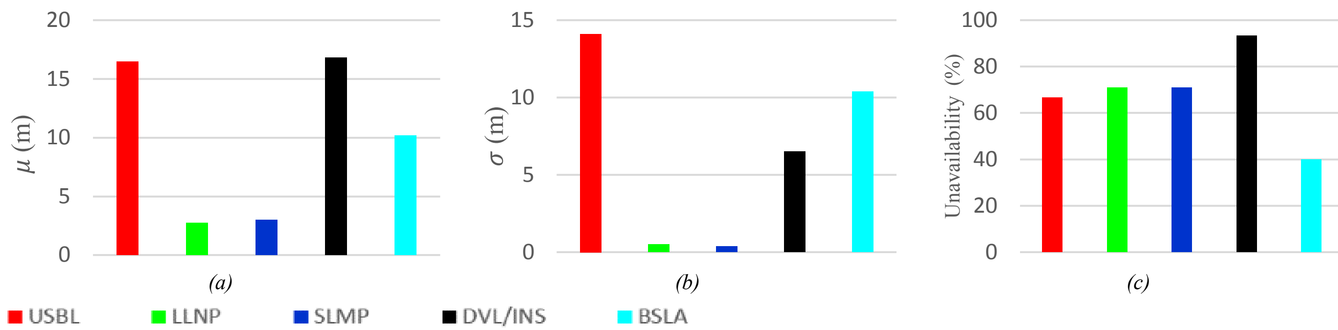

Fig. 11 . *Performace of five localization approaches in simultaneously localizing three underwater nodes (a) mean error (b) error standard deviation (c) localization approach unavailability along the whole navigated trajectory*

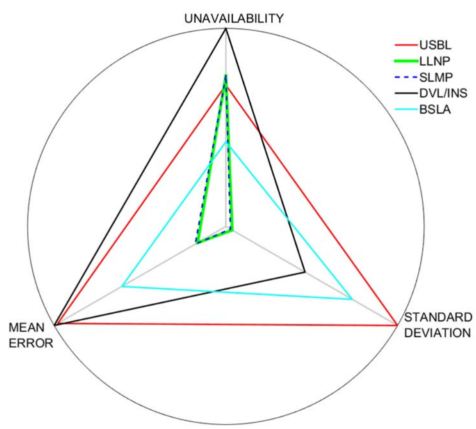

Fig. 12. *Normalized performace of five localization approaches in simultaneously localizing three underwater nodes.*

V. CONCLUSION AND FUTURE WORK

In this paper, Best Suitable Localization Algorithm (BSLA) for underwater mobile sensor nodes localization is proposed so that the localization performance elements are improved by dynamically fusing multiple location estimates of available localization methods based on a fuzzy decision support system. Results show that the presented approach improves both the localization accuracy of around 23-40% and the availability of around 70 % when three underwater nodes are simultaneously localized.

In the future, we are planning to conduct a study investigates time instants in which BSLA was not available. For example, in case BSLA is not available in certain periods simple dead reckoning can track node locations until other sophisticated localization method become available. Thereafter a simultaneous localization of large number of underwater mobile sensor nodes should be carried out. We look forward to generalizing this approach so new localization algorithms can be easily integrated based on their error characteristics by expanding the fuzzy rule base. We also look forward to testing the proposed approach on a 3D physics-based high fidelity underwater robotic simulator.

APPENDIX

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *High* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_3.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *High* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *Adequate* THEN $\mathcal{BSLA}$ is L_2.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *High* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_1.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *Mid* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_3.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *Mid* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *Adequate* THEN $\mathcal{BSLA}$ is L_2.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *Mid* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_1.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *Low* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_3.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *Low* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *Adequate* THEN $\mathcal{BSLA}$ is L_2.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{B}$ is *Low* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_1.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{U}$ is Not *Available* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_2.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{U}$ is Not *Available* AND $\mathcal{G}$ is *Adequate* THEN $\mathcal{BSLA}$ is L_2.

IF $\mathcal{D}$ is *Shallow* AND $\mathcal{U}$ is Not *Available* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_3.

IF $\mathcal{D}$ is *Mid-water* AND $\mathcal{U}$ is *Available* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_1.

IF $\mathcal{D}$ is *Mid-water* AND $\mathcal{U}$ is Not *Available* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_2.

IF $\mathcal{D}$ is *Mid-water* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_3.

IF $\mathcal{D}$ is *Mid-water* AND $\mathcal{G}$ is *Adequate* THEN $\mathcal{BSLA}$ is L_2.

IF $\mathcal{D}$ is *Deep* AND $\mathcal{B}$ is *High* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_3.

IF $\mathcal{D}$ is *Deep* AND $\mathcal{B}$ is *Mid* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_3.

IF $\mathcal{D}$ is *Deep* AND $\mathcal{B}$ is *Low* AND $\mathcal{G}$ is *High* THEN $\mathcal{BSLA}$ is L_4.

IF $\mathcal{D}$ is *Deep* AND $\mathcal{G}$ is *Adequate* THEN $\mathcal{BSLA}$ is L_4.

IF $\mathcal{D}$ is *Deep* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_4.

IF $\mathcal{D}$ is *Mid-water* AND $\mathcal{U}$ is *Available* AND $\mathcal{B}$ is *High* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_1.

IF $\mathcal{D}$ is *Deep* AND $\mathcal{B}$ is *Mid* AND $\mathcal{G}$ is *Low* THEN $\mathcal{BSLA}$ is L_4.

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