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

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INTRODUCTION

- Ultra-Short Base Line (USBL) is the most commonly adopted localization method in industry due to its flexibility. 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) [1].
- A large-scale hierarchical localization approach has been investigated in [2][3] for stationary underwater sensor network.
- 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.
- The authors in [2][3] 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 [2] were solely dependent on the localization error.
- An optimized confidence value-based localization algorithm for large scale underwater mobile sensor networks is proposed.
- To dynamically determine the confidence value of each sensor node on current localization estimate
- To promote a localized ordinary node to a reference node for neighboring ordinary nodes localization; based on its confidence value.
- The proposed algorithm harnesses a single USBL system and common proprioceptive sensors for large-scale swarm localization.

CONFIDENCE-BASED LOCALIZATION

- 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), that is a scalar value between 0 and 1.
- It measures how confident the node's current localization estimate is using a belief function (reflects the AUV's internal knowledge about its position).

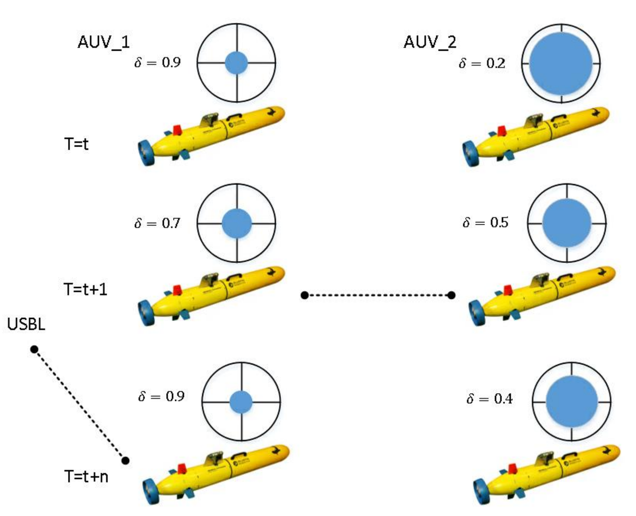

Fig. 1. An overview of confidence-value based localization in 1D

- $\delta_i^t = \eta \, p(m_t|\hat{p}_i^t) \; \delta_i^{t-1}$
- $p(z_t|\hat{p}_i^t) \propto \frac{1}{\Gamma(\kappa)\Theta^\kappa} \, {\varepsilon_U}^{\kappa-1} \, e^{\frac{-\varepsilon_U}{\Theta}} + \tau$
- $\varepsilon_U \sim \mathcal{N}(\mu, \sigma^2)$
- $p(w_t|\hat{p}_i^t) \propto \frac{1}{\Gamma(\kappa)\Theta^\kappa} \, {\varepsilon_D}^{\kappa-1} \, e^{\frac{-\varepsilon_D}{\Theta}}$
- $\varepsilon_D = w_t \phi : \; \phi \sim \text{uniform}(\alpha, \beta)$
- $\delta_i^t = \frac{\sum_{j=1}^{J} \delta_j^t \left(1 - \frac{\left| |\hat{p}_j^t - \hat{p}_i^t| - r_{ij} \right|}{|\hat{p}_j^t - \hat{p}_i^t|}\right)}{J}$
  - $\hat{p}_i^{t-1}$: node's i estimated position at t-1.
  - $\hat{p}_j^t$: neighboring node's j estimated position.
  - r_{ij}: range measurements.

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.
- 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.

OBJECTIVES:

- Minimizing localization error $\{f_1(x)\}$
- Minimizing ToA-based trilateration utilization $\{f_2(x)\}$
- Maximizing mean confidence value $\{f_3(x)\}$
- Maximizing USBL utilization $\{f_4(x)\}$

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

- l_i and u_i ($i = 1, 2$) are the lower and upper bounds of the confidence threshold and node density respectively.
- The Fast and Elitist Multi-objective Genetic Algorithm (NSGA-II) [4] finds the Pareto Optimal set based on Non-dominated Sorting and Crowding Distance to ensure the diversity in the pareto optimal set.

SIMULATION

- 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% AHRS with a typical dead reckoning accuracy of 30% 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.
- Correlated and uncorrelated random walker models are employed to govern the mobility of the nodes.

Table 1. 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

RESULTS

- The fitness function of each objective has been built based on data fitting models of the objective function surfaces. The evolutionary multi-objective optimization method NSGA-II is then employed to find the optimized Confidence Threshold (x_1): $0 \le x_1 \le 1$ and Node density (x_2): $0 \le x_2 \le 40$.

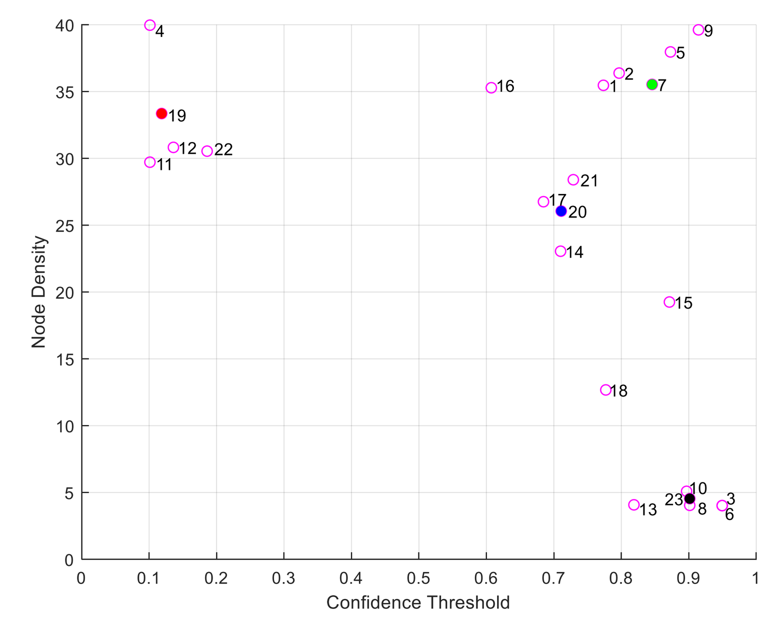

Fig. 2. The corresponding Pareto Optimal set of Pareto Front (in Confidence Threshold and Node Density). Four selected optimal solutions are represented by filled colored circles.

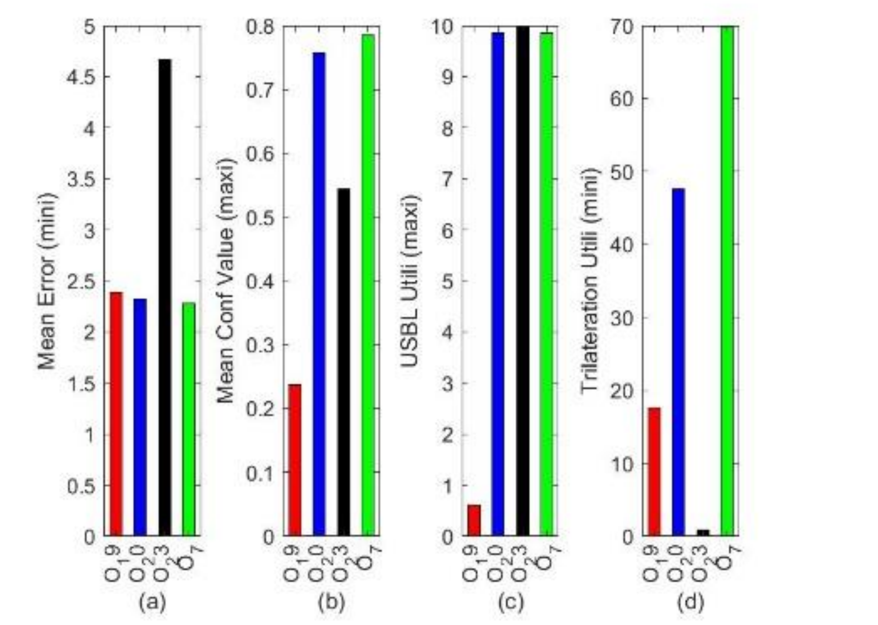

Fig. 3. The score of four selected optimal solutions in the four objectives (a) mean error (b) mean confidence value (c) USBL utilization and (d) ToA-based utilization.

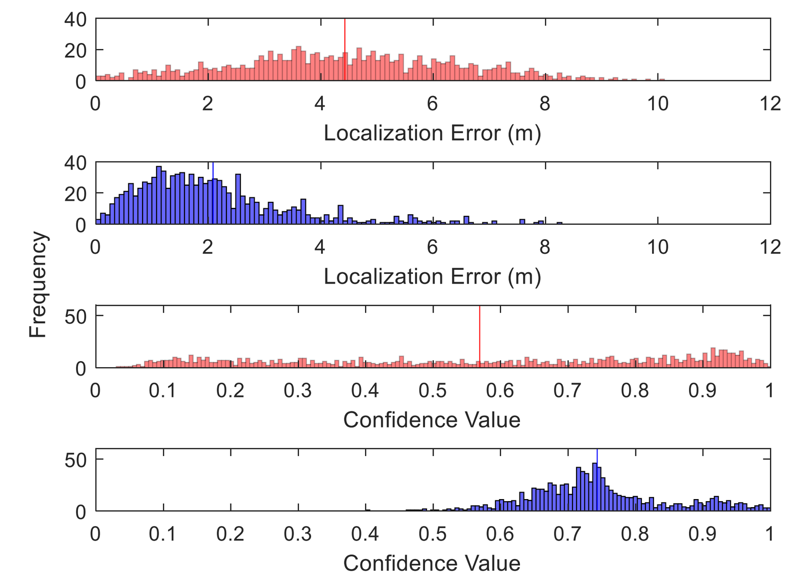

Fig. 4. Histograms of localization error and confidence value of a single node in both a non-optimal case (x_1=0.9 and x_2=6.35; red) and the optimal case (x_1=0.7 and x_2=26; blue) over 1000 localization period with mean localization error of 4.42 m and 2.08 m and mean confidence value of 0.56 and 0.74 in the non-optimal and the optimal cases respectively.

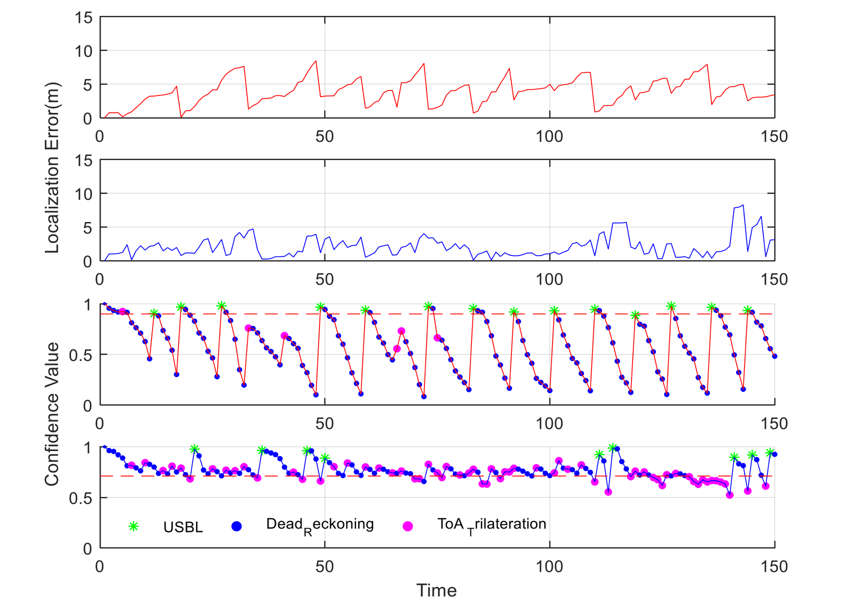

Fig. 5. Traces of typical localization errors and confidence values of a single node over the first 150 localization period in the non-optimal case (red) and the optimal case (blue). The red dashed horizontal lines represent confidence thresholds.

- 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.

CONCLUSION

- There is 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 are optimized.
- 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.

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