Informative Path Planning for Acoustic Source Localization With Environmental Uncertainties

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***Abstract*—Source localization in the context of underwater environment has been recognized as an important but challenging research topic. Conventional methods usually require a receiver array with accurate time synchronization and a large number of elements. The feasibility of accurately localizing an underwater source by a low-cost and small underwater vehicle is greatly limited. Our previous work has successfully applied matched field processing concept to do single-vehicle underwater source localization with informative path planning. However, it requires accurate environmental knowledge of entire search space. In this paper, we focus on improving the robustness of our originally proposed approach. This improvement aims to ensure that our proposed source localization approach performs well even with the presence of environmental uncertainties. Simulation studies show that our robust method is capable of mitigating the effect of environmental mismatch in the MFP model for source localization.**

I. Introduction

For decades, source localization has been used for many military and civilian applications. For example, in the underwater domain, source localization is widely applied in search & rescue, subsea operations, and defence & coastal security.

The global positioning system (GPS) is a mature satellite-based navigation system using radio frequency signals. Unfortunately, electromagnetic waves are severely attenuated in an underwater environment due to high permittivity and conductivity of water [1], [2]. GPS is unable to effectively locate a device underwater. Therefore, people use acoustics for reliable underwater source localization. A common strategy for underwater acoustic source localization is to use beamforming with a hydrophone array. As an alternative, one can also locate a source by measuring the received intensity over the entire search space.

The former utilizes geometry to triangulate the source. Such hydrophone arrays tend to be large. For example, in [3], a 16-element vertical line array (VLA) with 3.75 m inter-element spacing is deployed to locate a source 230 m away from the VLA. A sizable surface vessel is required to carry such a hydrophone array. As a result, the implementation complexity and cost are high.

The second approach is to measure the intensity over the entire search space to locate the position with the strongest received intensity. This is the conventional way to search for the wreckage of an aircraft crashed into the sea. In the absence of multipath propagation and focusing due to changes in sound speed, acoustic signal intensity decreases monotonically with propagation range. The black box of an aircraft could be efficiently localized using gradient ascent to find the maximum intensity. However, the acoustic signal in an underwater environment experiences complicated multipath propagation. The received signal intensity fluctuates significantly because of constructive and destructive interference. Under such conditions, the intensity pattern has several local maxima and gradient ascent performs poorly. The source may only be localized by surveying the received intensities over the entire search space, effectively a brute-force search. Although the implementation complexity is much lower compared with the hydrophone array method, this method is extremely inefficient.

To cope with limitations of current methods, our previous work [4] proposed a single-vehicle underwater acoustic source localization method based on the matched field processing (MFP) technique [5]. It locates the source through a single moving receiver and trajectory of the receiver is adaptively planned to maximize the localization efficiency. However, the MFP model is very sensitive to environmental uncertainties, i.e., environmental parameter mismatches between the actual search space and propagation model. Such a mismatch significantly degenerates the localization performance. In this paper, we focus on mitigating the impact of environmental mismatch to the MFP model, so as to maintain a robust localization performance even in an uncertain environment.

In the literature, we can find some works on lowering the effect of environmental sensitivity in the conventional MFP model. In [6], the uncertain parameters were addressed in the matched field processor design. In [7], the focalization concept was proposed in which the uncertain underwater environment is regarded as a lens to do focusing. The uncertain environmental parameters are included as additional unknowns in the search space. The source position is localized by minimizing a high-resolution cost function which applies ray theory, wave theory, empirical orthogonal functions and simulated annealing. In [8], an ocean acoustic inversion method was established to globally search for the set of parameters which could minimize the mismatch between the measurements and modeled replica fields at all receiver positions. By taking reference from early works, we address this issue by including the distribution of uncertain environmental parameters in our source localization iterating process. The localization result is thus produced by considering the current distribution of uncertain environmental parameters.

The rest of the paper is organized as follows. In Section II, the problem formulation and proposed method are described. Section III presents simulation studies in order to validate our proposed method. Finally Section IV concludes the paper. Table I lists symbols used in this paper.

TABLE I
SYMBOLS USED IN THE PAPER.

Symbols	Description
$\boldsymbol{x}$	source location
i	time step
$\mathcal{Y}_i$	a collection of measured information
$\boldsymbol{w}$	receiver location
z	measured field
$\boldsymbol{\theta}$	environmental parameter set
η	convergence threshold of source location entropy
a	next move
$\mathcal{A}(\boldsymbol{w}_i)$	all feasible moves at location $\boldsymbol{w}_i$
$\bar{Z}(\boldsymbol{x}, \mathcal{Y}_i, \boldsymbol{w})$	expected modeled replica field over all candidate environmental parameter sets
$Z(\boldsymbol{\theta}, \boldsymbol{w}, \boldsymbol{x})$	modeled replica field
$\mu(\mathcal{Y}_i, \boldsymbol{w})$	expected modeled replica field over all candidate environmental parameter sets and source locations

II. PROBLEM FORMULATION AND METHOD

In order to localize a static underwater acoustic source by deploying a single low fidelity receiver, we use the MFP concept as the fundamental localization technique. The conventional MFP technique performs underwater source localization task by comparing the modeled replica fields with the measurements made at individual receiver positions from the receiver array. We first assume that the environment is quasi-static. The modeled replica field is obtained from an underwater propagation model which could accurately model the signal propagation behavior in an underwater environment if all required model parameters are precisely known. Furthermore, in order to localize signal source through a single receiver, we essentially need to take advantage of a moving receiver to spatially sample the fields at different receiver positions such that multiple sets of representative and unique field information could be captured as a replacement of the information acquired by a receiver array.

At any step i, the propagation model is able to produce a set of accurate replica fields at current receiver position $\boldsymbol{w}_i$ by placing the transmitter at all candidate source positions $\boldsymbol{x}$ if the underwater environment is precisely known. We make an assumption that the ground truth modeled replica field differs from the measurement by random noise.

By applying the MFP technique to match all modeled replica fields with current measurement z_i, the distribution of source location is updated based on Bayes' Theorem as

$$\begin{aligned} f(\boldsymbol{x}|\mathcal{Y}_i) &= f(\boldsymbol{x}|\mathcal{Y}_{i-1} \cup (\boldsymbol{w}_i, z_i)) \\ &= \frac{f(\boldsymbol{x}, \mathcal{Y}_{i-1} \cup (\boldsymbol{w}_i, z_i))}{f(\mathcal{Y}_{i-1} \cup (\boldsymbol{w}_i, z_i))} \\ &= \frac{f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}) f(\boldsymbol{x}|\mathcal{Y}_{i-1})}{\int f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}) f(\boldsymbol{x}|\mathcal{Y}_{i-1}) d\boldsymbol{x}}, \end{aligned} \tag{1}$$

where $\mathcal{Y}_i$ represents the collection of the measurements z and the corresponding receiver locations $\boldsymbol{w}$ up to step i.

However, if any environmental parameter in the propagation model is uncertain, the modeled replica fields would be inaccurate, causing significant degradation in localization performance. To handle the environmental uncertainties in the MFP model, we add the uncertain environmental parameters $\boldsymbol{\theta}$ into the Bayesian update process in (1). Unlike the case where the environment is accurately known, now we need to generate the replica fields corresponding to all possible environments at each step i and apply the MFP technique to the entire set of replica fields. The distribution of source location is inferred by finding the marginal distribution of source location. And (1) then becomes:

$$\begin{aligned} f(\boldsymbol{x}|\mathcal{Y}_i) &= \int f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_i) d\boldsymbol{\theta} \\ &= \int f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1} \cup (\boldsymbol{w}_i, z_i)) d\boldsymbol{\theta} \\ &= \int \frac{f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}, \boldsymbol{\theta}) f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1})}{f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1})} d\boldsymbol{\theta} \\ &= \int \frac{f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}, \boldsymbol{\theta}) f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1})}{\int\int f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}, \boldsymbol{\theta}) f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1}) d\boldsymbol{\theta} d\boldsymbol{x}} d\boldsymbol{\theta}. \end{aligned} \tag{2}$$

The above derivation is analytically complicated, therefore we discretize the uncertain parameters and candidate source positions for the sake of simplification in simulation. Equation (2) becomes:

$$\begin{aligned} f(\boldsymbol{x}|\mathcal{Y}_i) &= \sum_{\boldsymbol{\theta}} f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_i) \\ &= \sum_{\boldsymbol{\theta}} f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1} \cup (\boldsymbol{w}_i, z_i)) \\ &= \sum_{\boldsymbol{\theta}} \frac{f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}, \boldsymbol{\theta}) f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1})}{f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1})} \\ &= \sum_{\boldsymbol{\theta}} \frac{f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}, \boldsymbol{\theta}) f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1})}{\sum_{\boldsymbol{x}} \sum_{\boldsymbol{\theta}} f((\boldsymbol{w}_i, z_i)|\mathcal{Y}_{i-1}, \boldsymbol{x}, \boldsymbol{\theta}) f(\boldsymbol{x}, \boldsymbol{\theta}|\mathcal{Y}_{i-1})}. \end{aligned} \tag{3}$$

Intuitively we can consider which path the receiver should take to improve localization efficiency. It turns out that moving to a nearby location where the information gain is maximized, after sampling at that new position, provides us an effective path planning policy. The uncertainty of the location after making a measurement is reduced to the measurement uncertainty. To find the nearby location which results in maximum information gain is equivalent to finding the nearby location with the largest prior uncertainty of the measured field. Do note that this approach is *greedy*. The expected weighted variance over all uncertain environmental parameters is used as an effective measure of the prior uncertainty. Therefore, the next movement a follows the policy:

$$a_i = \arg \max_{a \in \mathcal{A}(\boldsymbol{w}_i)} \sum_{\boldsymbol{x}} f(\boldsymbol{x}|\mathcal{Y}_i)(\bar{Z}(\boldsymbol{x}, \mathcal{Y}_i, \boldsymbol{w}) - \mu(\mathcal{Y}_i, \boldsymbol{w}))^2, \quad (4)$$

where:

$$\bar{Z}(\boldsymbol{x}, \mathcal{Y}_i, \boldsymbol{w}) = \sum_{\boldsymbol{\theta}} f(\boldsymbol{\theta}|\boldsymbol{x}, \mathcal{Y}_i) Z(\boldsymbol{\theta}, \boldsymbol{w}, \boldsymbol{x}), \quad (5a)$$

$$\mu(\mathcal{Y}_i, \boldsymbol{w}) = \sum_{\boldsymbol{x}} f(\boldsymbol{x}|\mathcal{Y}_i) \bar{Z}(\boldsymbol{x}, \mathcal{Y}_i, \boldsymbol{w}), \quad (5b)$$

where $\mathcal{A}(\boldsymbol{w}_i)$ constitutes all feasible moves for the vehicle at location $\boldsymbol{w}_i$. $Z(\boldsymbol{\theta}, \boldsymbol{w}, \boldsymbol{x})$ is the modeled replica field at location $\boldsymbol{w}$ by assuming the source is at location $\boldsymbol{x}$ and environmental parameter set used in propagation model is $\boldsymbol{\theta}$. $\bar{Z}(\boldsymbol{x}, \mathcal{Y}_i, \boldsymbol{w})$ denotes the expected modeled replica field over all uncertain environmental parameters $\boldsymbol{\theta}$ when source is at location $\boldsymbol{x}$ and receiver is at location $\boldsymbol{w}$ based on all collected data $\mathcal{Y}_i$. $\mu(\mathcal{Y}_i, \boldsymbol{w})$ is the expected modeled replica field at receiver location $\boldsymbol{w}$ over all candidate source locations and environmental parameter sets by considering the collected information $\mathcal{Y}_i$. Fig. 1 shows a flow chart of our proposed source localziation algorithm.

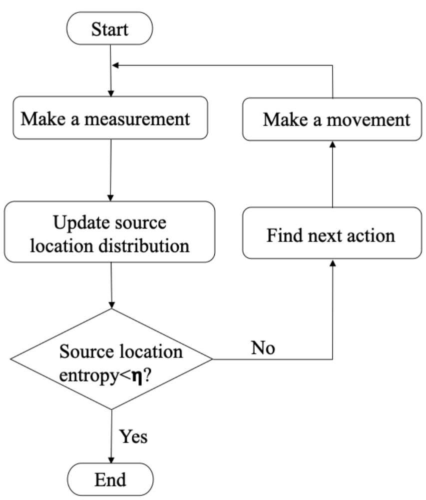


Fig. 1: Flow chart of the proposed localization approach.

III. Simulation Studies

We demonstrate our proposed idea through simulation in a two-dimensional range-independent underwater environment with 1 km range, sandy seabed and constant sound speed profile. We aim to localize a 1 kHz acoustic pinger lying on the seabed at the center of the search space. It has a bandwidth of 100 Hz and source power of 150 dB re 1 μPa. Fig. 2 shows the constructive and destructive interference pattern of the modeled field over the simulated environment.

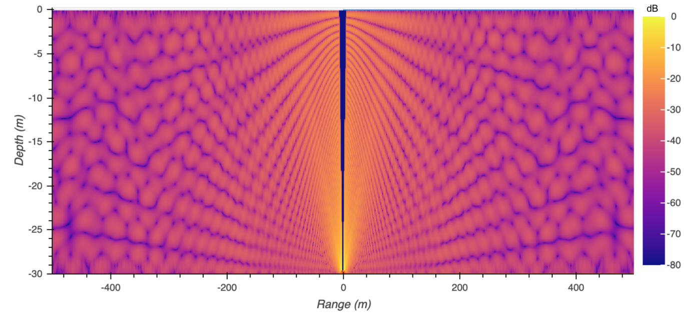


Fig. 2: Modeled field pattern over the simulated environment.

We make use a holonomic autonomous underwater vehicle (AUV) equipped with a single hydrophone to provide the mobility of the receiver. The Bellhop propagation model [9] is adopted to generate the modeled replica fields. The measurement is simulated by adding random Gaussian instrument noise with the standard deviation of 15 dB re 1 μPa to the modeled field to simulate low fidelity acoustic measurements. We also consider ambient noise with spectral level of 50 dB re $\mu\text{Pa}^2/\text{Hz}$ for 1 kHz signal based on Wenz curve [10]. The AUV initially starts at a depth of 15 m and range of 200 m from the source. We compare the localization performance of our proposed *adaptive* path planning policy with two other naive path planning policies, which we term as *straight* policy and *random* policy, over 100 Monte Carlo runs. The straight policy moves the AUV in a straight horizontal direction with constant depth. The random policy allows the AUV to move in a random directions at each step. We assume that the AUV moves 1 m at each time step for all policies. Fig. 3 shows 15 m sample paths planned by the three path planning policies. The source location is finalized when its entropy falls below a threshold η. And it is determined based on the maximum a posteriori rule.

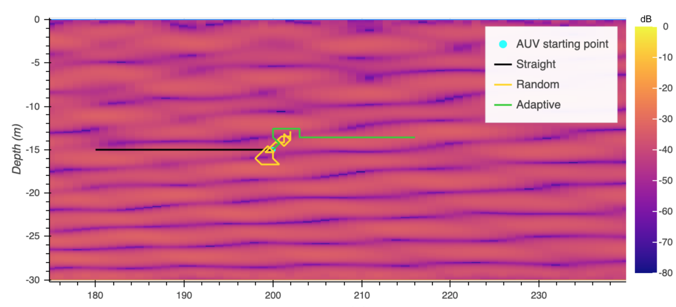


Fig. 3: 15 m sample trajectories planned by each of the three policies.

A. With accurate environmental knowledge

We start with considering the scenario that we have full knowledge of the environment. In this way, the environment can be accurately modeled and the received signal can be predicted accurately. To evaluate the localization efficiency of the three policies, here we set the threshold η to 0.1. We use average number of steps required to make the source location entropy converge below 0.1 bits over 100 Monte Carlo runs as a measure of localization efficiency.

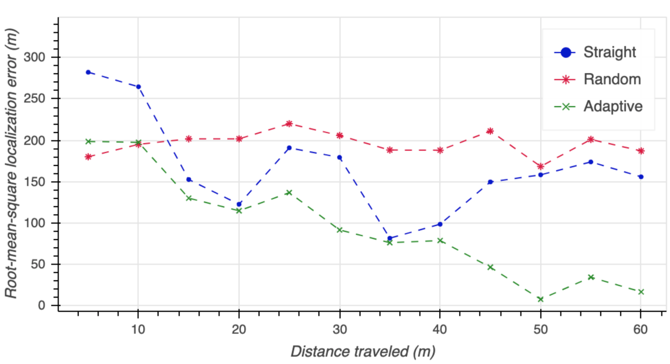
TABLE II
10%-TRIMMED AVERAGED CONVERGENCE STEPS OF SOURCE LOCATION ENTROPY OVER 100 MONTE CARLO RUNS

Policy	**Steps to convergence**	**No. of outliers**
Straight	50.6	1/100
Random	37.9	10/100
Adaptive	6.9	11/100

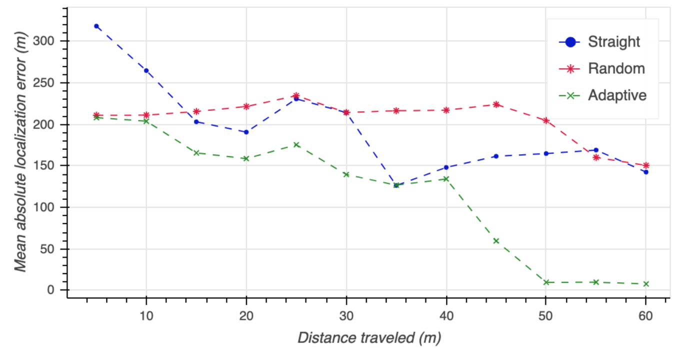
Table II shows that the adaptive policy uses the minimal time to locate the source among three policies. The result validates the superiority of proposed adaptive policy in localization time efficiency over naive policies. Once the source location entropy has converged, all policies can locate the source accurately. This result indicates that when environmental knowledge is accurately known, all of the three policies can eventually achieve errorless localization performance.

B. With environmental uncertainties

Typically, water depth and sound speed may vary over time. We consider a scenario that the average water depth is 30 m with a rough tide variation of maximal 2 m, water temperature varies within the range of 26 °C to 31 °C and salinity of seawater ranges from 3.2 % to 3.75 % [11]. Based on Mackenzie empirical equation for sound speed in ocean [12], the resultant sound speed varies from 1533 m/s to 1551 m/s. To simulate the environmental mismatch, we assume that the water depth and sound speed are uncertain. And we make an assumption that they are uniformly distributed from 28 m to 32 m and 1533 m/s to 1551 m/s respectively if no prior information is available. To investigate the effects of environmental mismatch to the localization performance for all policies, we set the water depth and sound speed in the Bellhop propagation model to 28 m and 1533 m/s when generating the modeled replica fields in our originally proposed algorithm. Whereas the ground truth values used to simulate the measurements are 30 m and 1542 m/s.

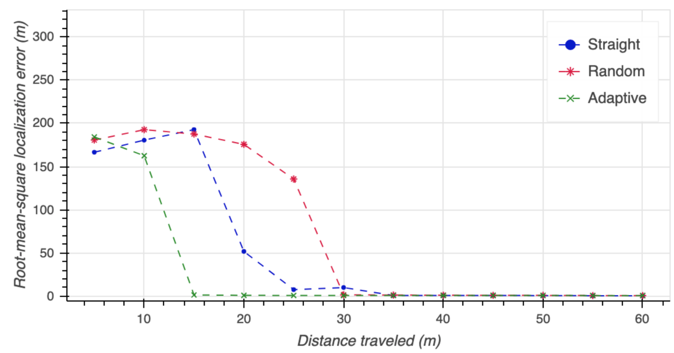


(a) Root-mean-square localization error history.

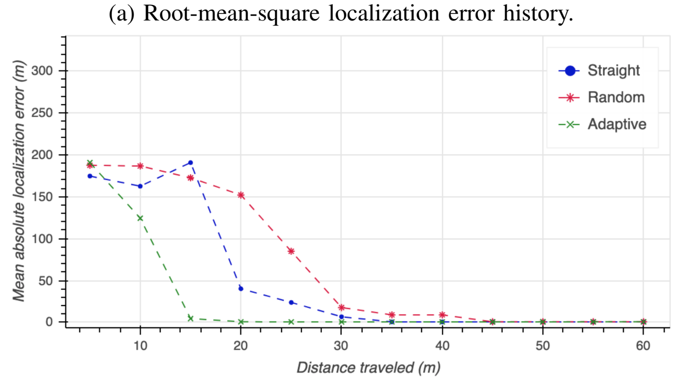


(b) Mean absolute localization error history.

Fig. 4: 10%-trimmed averaged localization performance after AUV moves 5 m to 60 m with the step size of 5 m from its initial location when using wrong set of environmental parameters in propagation model over 100 Monte Carlo runs.



(a) Root-mean-square localization error history.



(b) Mean absolute localization error history.

Fig. 5: 10%-trimmed averaged localization performance after AUV moves 5 m to 60 m with the step size of 5 m from its initial location by using robust approach over 100 Monte Carlo runs.

Fig. 4 shows the 10%-trimmed root-mean-square error and mean absolute error histories when AUV moves 5 m to 60 m with the step size of 5 m from its initial location over 100 Monte Carlo runs. It is clear that the straight policy and random policy can not converge to negligible localization error within 60 m. Whereas these two policies can errorlessly locate the source by shorter paths when environmental knowledge is known. Although the adaptive policy is able to localize the source, it is slow to converge in the face of environmental uncertainty. These observations demonstrate that the original localization approach is not capable of handling the environmental mismatch.

We then implement the robust source localization algorithm in the same simulated environment. The average localization performance is shown in Fig. 5. Compared with the localization performance shown in Fig. 4, we see that all of the three policies can locate the source correctly with much shorter time although some of the environmental parameters are not accurately known. The degradation in localization performance caused by environmental mismatch has been mitigated by using the robust approach.

IV. Conclusion

In this paper, we presented a robust single-vehicle underwater acoustic source localization algorithm which mitigates the effect of environmental mismatch in the MFP model. By incorporating the uncertain environmental parameters into the update process of source location distribution, it assures that our originally proposed localization method can perform well even the completed environmental knowledge is lacking. By applying the robust method in the scenario of environmental mismatch, the localization error is significantly reduced and it converges much faster than using our originally proposed method. The proposed algorithm is thus shown to be robust to cope with environmental uncertainties in the MFP model. Future research will focus on developing a globally optimal path planning policy. And we will further extend the single-vehicle source localization algorithm to do multi-vehicle source search for large search spaces.

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