An AUV Path Planner for Large-scale Search and Rescue based on A* Algorithm

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Abstract. For large-scale search and rescue (SAR) tasks that require complete coverage of the workspace, it is important to increase the efficiency and obtained sensor data quality. A novel path planner named SAR-A* to this problem is introduced, which takes into account the sensor performance and practical prior information. Firstly, the workspace is decomposed into plenty of hexagonal cells which are treated as waypoints for A* algorithm. Target present probability is then modeled to Gaussian distribution and the performance of the side-scan sonar (SSS) is evaluated. The proposed path planner is validated in a complex terrain scenario which proves that the SAR-A* path planner can increase confidence in locating the target quickly, and is suitable for the large-scale SAR.

1. Introduction

The maritime large-scale search and rescue (SAR) mission is a complex task that requires the use of a variety of expertise, including operational management, prior information estimated by rescue specialists, and equipment provided by governments. Applying the Autonomous Underwater Vehicle (AUV) to the SAR mission makes sense in a harsh underwater environment with strict timeliness requirements. In this work, the AUV platform equipped with a Side Scan Sonar (SSS) is used to completely cover the large-scale search area. As the core of the operating system, the SSS can create a sonar image of large areas on the seafloor effectively in a stable platform by the sound wave. This work focuses on integrating resources and information to improve the quality of sonar images while performing the SAR mission.

In all existing search approaches using an AUV, Coverage Path Planning (CPP) is a general method in a SAR mission. Most of the path planning methods like the Dijkstra algorithm, the classical A* algorithm\cite{1}, and the simulated annealing algorithm search for paths from the start point to the endpoint. Unlike classical path planning, the purpose of the CPP is to determine a feasible path that passes over all waypoints without being left out while avoiding obstacles \cite{2}. The concept of online CPP is first proposed in \cite{3} in which an optical camera was used to generate a photomosaic. The general applications are seabed geomorphology \cite{4}, mine countermeasures (MCM) \cite{5}, pipeline inspection \cite{6}, submarine archaeology \cite{7}, etc. There are diverse research emphases for CPP algorithm application such as unknown environment\cite{8}, uncertain pose\cite{9}, irregular area shapes\cite{2}, unreliable navigation\cite{10}. As to path planners applied in the CPP area, the lawn-mower (LM) algorithm, also called the boustrophedon approach, is a classical solution for complete coverage, which provides an adaptive and constant-wide path \cite{11}. To improve LM approaches for inspection from multiple views, Kapetanovic et al. proposed a SSS data-driven coverage approach that evaluated shorter length/time in
various scenarios [12]. Apart from a series of LM methods, recent studies are engaged in combining the timely information obtained by sensors with coverage path planners. The [13] presented a novel sensor-based coverage algorithm based on the Morse decomposition which resulted in encountering all waypoints. Side-scan sonar data-driven CPP algorithms are developed in [14,15], in which the information gained from side-scan sonar data is used to generate a way that coverage area. Considering both efficiency and data-related objective, a coverage path planner described in [16] collected better data through adaptively changing the track spacing. Considering the payloads of the AUV, it is apparent that most of the methods concentrate on the path planner and equipment used with less considering the cooperation with collaborators.

Based on the background and requirements mentioned above, we proposed an online path planning approach named the SAR-A* algorithm for the large-scale SAR mission. We divided the process of the mission into 3 steps: 1) decompose the task area into many hexagon grids, 2) establish the probability model of target presence and the model of system detective ability according to the practical prior information, and 3) continuously determine the next waypoint until completely covering the area. The criteria for selecting the next waypoint are a smaller turning angle, shorter distance, and higher probability of locating the target. The main contribution of this research is summed up as follows.

(a) The prior information from rescue specialists is considered and modeled as bivariate Gaussian distribution which is practical and provides reliable search evidence for path planning.
(b) The system detective ability is modeled to enhance the quality of sonar images acquired.
(c) Considering the operational constraints of the SSS, the objective function makes the AUV maintain stability without sharp turns or varying velocity.
(d) Aiming the SAR mission using an AUV, the SAR-A* algorithm is designed for purposeful search based on the classical A* algorithm.
(e) The Dubins curve is used to generate a feasible AUV trajectory.

The remainder of this article is organized as follows. Section 2 describes the problem definition and assumptions. Section 3 presents the proposed approach including the objective functions and the basic algorithm. Section 4 shows simulations and experiments designed for the proposed algorithm. The general conclusions and future work are discussed in section 5.

2. Problem Definition and Assumptions

SAR mission is a multidisciplinary operation that requires coordinated resources. Therefore, making full use of all information and decisions is essential for enhancing the practicability of the path planning algorithm. In this section, the definitions for the CPP problem and assumptions for this article are introduced.

2.1. Problem Definition

The problem stressed in this work can be defined as an AUV equipped with a SSS is assigned a mission of covering an area interested to search for a predefined target. Accordingly, there is no more than one target in the whole area.

The workspace $W$ to be covered by dimensions $L_w \times W_w$, which is defined as a large-scale open sea area. The waypoints of the path planner are obtained by dispersing the area into $N_c$ small cells $c_i$

$$W \subseteq C_{all} = \bigcap_{i=1}^{N_c} c_i$$  \hspace{1cm} (1)

Each cell is represented by its position $L_i = [x_i, y_i]^T$, where $i$ denotes the indexes of cells, $x_i$ and $y_i$ are coordinates. The AUV at constant speed $u$, and fixed altitude $h_{ref}$ decides the next waypoint meeting the objective function. The National Standards of China about the port and waterway engineering survey suggests that the height from the seabed of the platform of the SSS should be controlled at 10% of the sonar range $R_{sss}$ which corresponds to the experience. Hence, the $h_{ref} = W_z \times 10\%$, where the $W_z = R_{sss} \times 2 + W_{nadir}$ denotes the range of the SSS equipped.
With the above analysis, the online path planning work iteratively determines the eligible next waypoint by minimizing the objective function value. The objective function is described in section IV. The task is completed when all the cells are visited.

2.2. Assumptions

- **Assumptions related to the workspace.** In this work, we assumed the task area is an open area without obstacles. The terrain and hydrology in different areas are diverse, i.e., the influence of the environment on locating the target is indeterminate. The target may be in the predicted location within the search region.

- **Assumptions related to AUV.** In this work, the AUV is supposed to a point mass and moves in an x-y plane with a constant speed and altitude. It is also supposed that the energy is sufficient and navigation correct by surfacing regularly. There is no exceptional case in simulation.

- **Assumptions related to SSS.** To survey the workspace, an AUV equipped with an SSS is applied which is represented in figure 1. Generally, when performing a task, only the platform moves stably and straight the SSS can get high-quality sonar images. The blind spot of the side-scan sonar (nadir) is assumed to be compensated with an additional sonar. We suppose that the nadir can be compensated by technical means which has been successfully reached. The closer the target is to the edge, the less likely it is to be discovered. Hence, it is meant to increase the edge overlap area.

![Figure 1. 3D model of SSS System.](image)

3. Proposed Method

In this section, we propose a SAR-A* online path planner to select the next waypoint until no waypoint remains. The workspace decomposition method, related models and modified A* algorithm are essential parts of the SAR-A* path planner.

3.1. Workspace Decomposition

The hexagon decomposition shown in figure 2 is applied to generated waypoints for completely covering the workspace. The hexagon decomposition can splice any area in the right size which is the basis of the complete coverage. In addition, according to the study of [13] the confidence to identify targets decreases with the increase of lateral distance from the AUV trajectory. Especially when the lateral distance is longer than 70%Wₛ, the SSS almost can’t identify any target. Hence, the overlapped area shown in figure 3 can increase the confidence of target detection. Moreover, the hexagon decomposition provides six optional equidistance headings. As a result, the distance between cells is ignored when designing the path planning strategy.
3.2. Target Presence Model

The general prediction result of estimating the SAR scope and predicting the target trajectory has been intensively studied [17]. In this work, a predicted target location is assumed to be provided which guides the AUV to the area with greater interest. In addition, the target presence probability decreases with the distance from the predicted target position. According to this, the bivariate Gaussian distribution is used to model the presence probability. The target exists at any given cell $c_i$, denoted $p^t_{e_i}$, is given by

$$p^t_{e_i} = \frac{1}{2\pi\sigma_1\sigma_2} \exp \left( -\frac{1}{2\sigma_1^2}(x_i - \mu_1)^2 - \frac{1}{2\sigma_2^2}(y_i - \mu_2)^2 \right)$$

where $x_i$ and $y_i$ are coordinate of the hexagon cell $c_i$, $\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}$, $\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{pmatrix}$ are mean vector and covariance matrix of the bivariate Gaussian distribution. The isocontour of the bivariate Gaussian distribution is usually a rotated ellipse. Different target trajectories and locations can be reflected in the shape of the isocontours. Take figure 4 for example, the target presence probability distribution without estimated target trajectory is described in the left figure. When a horizontal estimated trajectory is assumed, the distribution can be described by the right figure.

3.3. SSS Detective Ability Model

There are many influencing factors of system detective ability such as environment, target, and sonar. The detective ability $P_D$ defines the capability of detecting and identifying the target which can be obtained by effectiveness evaluation methods. figure 5 describes a detailed analysis of the indicators that affect the system's comprehensive evaluation.

We summarize the evaluation indicators into four categories: underwater environment (En), SSS parameters (SSS), target characteristics (Tg), and AUV state (AS). The influence on detection probability $P_D$ can be expressed as $P_{En}, P_{SSS}, P_{Tg}, P_{AS}$ respectively where $P_D, P_{En}, P_{SSS}, P_{Tg}, P_{AS}$ are the probability set of grid cells. The grading level set of the object comprehensive evaluation is \{very strong, stronger, medium, weaker, very weak\}. Corresponding to the grading level set, the numerical values of those four categories can choose from \{0.2, 0.4, 0.6, 0.8, 1\}, which can be scored by subjective evaluation and expert scoring. For instance, since small targets are hard to identify, we think the too-small target has a strong influence on detective ability and the numerical value of $P_{Tg}$ is 0.2 in this case. Due to the factors of all categories are in tandem, the detective ability $P_D$, in this case, is specified according to

$$P_D = P_{En} \times P_{SSS} \times P_{Tg} \times P_{AS}$$
Factors Affecting Detective Ability

Target (Tg)
AUV State (AS)
SSS (SSS)
Underwater Environment (En)

Scale size
Distance
Target Strength
Stability
Energy
Uniform velocity
Resolution
Effective coverage radius
Range
Frequency
Seabed sediment
Turbidity
Depth
Reverberation level
Current

Figure 4. Isocontours of two bivariate Gaussian distributions in area 10 × 10 meters with $\mu_1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$, $\Sigma_1 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ and $\mu_2 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$, $\Sigma_2 = \begin{pmatrix} 3 & 0 \\ 0 & 1 \end{pmatrix}$.

Figure 5. AHP indicator system for the comprehensive evaluation of the SSS system performance.

3.4. Objective Function

In this part, three objective functions are designed as the SAR-A* objective function: shorter distance, fewer turns and higher detective confidence. The formulas used and reasons for considering such objectives are illustrated in the following. The global formula is given by the following:

$$\min f(C_a) = w_d f_d(C_a) + w_a f_a(C_a) - w_l f_l(C_a)$$

where $f$ denotes the total score, $C_a$ stands for a set of all unvisited available cells, $f_d$ is the distance from the current position, $f_a$ is the angle from the previous heading, $f_l$ is the probability of locating the target, $w_d$, $w_a$, $w_l$ are corresponding weights. The cell in $C_a$ with minimum $f$ value is chosen by the objective function iteratively. The expanded details of all components are described as follows.

3.4.1. Objective 1: Shorter distance. The first component $f_d$ guarantees the shorter distance which can make full use of resources. Take the case in figure 6(a) as an example, the next waypoint of point A is not point B while points C and D haven’t been covered yet.

$$\min f_d(C_a) = d(c_c C_a) + d(c_h C_a)$$

where $c_c$ is the current position, $c_h$ is the cell with the highest $p_e$, $d$ is the Euclidean distance.

3.4.2. Objective 2: Fewer turns. Sharp turns result in distortion of obtained images and thus decrease the performance of the mission. The second component $f_a$ helps to avoid unnecessary turns. In figure 6(b), point G is the suitable next waypoint of point F.

$$\min f_a(c_a) = \theta_a(c_c C_a)$$

where $\theta_a(c_c C_a)$ stands for the included angle between $c_c$ and each element of $C_a$. 

...
3.4.3. **Objective 3:** Higher detective confidence. The final component $f_i$ highlights the higher probability of locating the target. This component concerns the probability of locating the target $p_l$ (shown in Formula (7)) which is the product of detective ability $p_D$ and target presence probability $p_e$. Take the situation in Figure 6(c) for illustration, the next step of point $J$ prefers point $K$ since point $K$ has the largest probability of locating the target.

$$p_l(c_i) = p_e(c_i)p_D(c_i)$$  \hspace{1cm} (7)  

$$\max f_i(C_a) = p_l(C_a)$$  \hspace{1cm} (8)

**Figure 6.** The scenario prefers a higher probability of locating the target.

3.5. **Overview of the proposed approach**

This approach starts with the decomposition of the workspace into a large number of hexagon cells, complete coverage is then attained by visiting each cell. Next, the target presence probability model and detective ability model are established. Finally, A* algorithm framework combining models and objective function guides complete coverage of the workspace.

4. **Simulation Results**

To gain further insight into the proposed SAR-A* algorithm, the performance is evaluated on MATLAB in a nonuniform detective ability situation. Default setting parameters are listed in Table 1. The $L_w \times W_w$ underwater working area measuring with nonuniform detective ability is represented by hexagon grid maps shown in Figure 7,8. It is assumed that there are special areas with stronger detective ability (see light blue zonal region in Figure 7 and higher area in Figure 8) and weaker detective ability (see the wheat rectangle in Figure 7 and lower area in Figure 8). The target presence probability model is shown in Figure 9, in which the predicted target location moved up to describe the dynamic target scenario.

**Table 1.** Default parameters setting.

| Category                  | Parameters | Value  | Description              | Category                  | Parameters | Value  | Description              |
|---------------------------|------------|--------|--------------------------|---------------------------|------------|--------|--------------------------|
| Workspace                 | $L_w$      | 5000 m | Length of workspace      | Presence Probability     | $P_{En}$   | 1      | Influence of environment |
|                           | $W_w$      | 2500 m | Width of workspace       | Presence Probability     | $P_{SSS}$ | 1      | Influence of SSS         |
|                           | $W_s$      | 200 m  | Range of the SSS         | Presence Probability     | $P_{Tr}$  | 1      | Influence of target      |
| Hexagon decomposition     | $r$        | 100 m  | Hexagon cell radius      | Presence Probability     | $P_{AS}$  | 1      | Influence AUV state      |
| Gaussian Distribution     | $\mu$      | $\frac{3L_w}{4}$ | Mean vector             |                           | $w_d$      | 0.5    | Weight of the distance   |
|                           | $\Sigma$   | $\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ | Covariance matrix        |                           | $w_a$      | 0.1    | Weight of the angle      |
|                           | $r_d$      | 10 m   | The radius of AUV turns  |                           | $w_l$      | 0.4    | Weight of the probability|


Figure 7. The workspace with nonuniform detective ability is decomposed into hexagon cells.

Figure 8. The distribution of nonuniform detective ability.

Figure 9. Two perspectives of the bivariate Gaussian distribution model with $\mu = \begin{pmatrix} 3L_w/4 \\ 3W_w/4 \end{pmatrix}$ and $\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ used in the workspace.

Meanwhile, the classical lawn-mower path planner (LM), random path planner (Rnd), distance considering path planner (Dist), and path planner only considering the probability of locating the target (Pl) are performed. The Rnd planner selects random cells from available cells. The Dist algorithm gives preference to the closest cell from the current distance. The Pl algorithm prefers the cell with the highest probability of locating the target. Performance of above path planners is discussed based on the confidence of locating the target, distance traveled and the total number of turns. Figure 10 shows four snapshots of the path planning in chronological order. The generated trajectory is based on the Dubins curve which calculates vehicle positions considering the curvature constraints and prescribed tangents at each waypoint. The trends of the probability of locating the target using five methods are described in figure 11, which indicates that the proposed SAR-A* method (see green line) rapidly promotes the confidence of locating the target in 150 steps.
Table 2 displays numbers of turns and traveled distances using five methods. The traveled distance is obtained by calculating the sum of the Euclidean distance between every two waypoints. As shown in Table 2, the SAR-A* and LM have better performance in shorter distances and fewer turns. The SAR-A* algorithm has 70.12%, 69.18%, 31.72% fewer turns compared with the other four algorithms. In terms of traveled distance, the SAR-A* algorithm has 51.44%, 8.90% and 21.22% shorter distances respectively compared with the other four algorithms. Due to the nonuniform scenario, the SAR-A* path planner is more appropriate for complete coverage without prior information.

Table 2. Simulation results of number of turns and traveled distances

| Methods | Number of turns | Traveled distance(km) |
|---------|----------------|-----------------------|
| Rnd     | 425            | 207.08                |
| Dist    | 412            | 110.39                |
| PI      | 186            | 127.65                |
| LM      | 66             | 88.16                 |
| SAR-A*  | 127            | 100.56                |

The simulation result illustrated that the proposed SAR-A* path planner performs well in respect of the number of turns, traveled distance, and confidence in locating the target. One of the key advantages is combined with the predicted target location provided by rescue specialists as prior knowledge. Even if the task fails, most information can be obtained using the SAR-A* path planner.

5. Conclusion

In this research, significant effort was paid to successfully implement and test the proposed SAR-A* path planner for an AUV applied in a large-scale SAR mission. Considering the characteristics of the SAR mission and equipment, the proposed path planner generated a feasible path based on the A* algorithm framework with fewer turns, shorter distance traveled, and fast-increasing confidence in locating the target. The proposed method guarantees complete coverage, besides, the higher confidence of locating target is also obtained when the task termination or failure happens. In our future work, the multi-AUV system will be applied at the large-scale SAR mission for reducing the makespan.

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