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Self-Adaptive Dynamic Obstacle Avoidance and Path Planning for USV Under Complex Maritime Environment

XINYU LIU[1], YUN LI[2], JING ZHANG[1], JIAN ZHENG[3], (Member, IEEE), AND CHUNXI YANG[1], (Member, IEEE)

[1]Faculty of Chemical Engineering, Kunming University of Science and Technology, Kunming 650500, China
[2]Merchant Marine College, Shanghai Maritime University, Shanghai 200135, China
[3]College of Transport and Communications, Shanghai Maritime University, Shanghai 200135, China

Corresponding author: Chunxi Yang (ycx@kmust.edu.cn)

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ABSTRACT The unmanned surface vehicle (USV) is usually required to perform some tasks with the help of static and dynamic environmental information obtained from different detective systems such as shipborne radar, electronic chart, and AIS system. The essential requirement for USV is safe when suffered an emergency during the task. However, it has been proved to be difficult as maritime traffic is becoming more and more complex. Consequently, path planning and collision avoidance of USV has become a hot research topic in recent year. This paper focuses on dynamic obstacle avoidance and path planning problem of USV based on the Ant Colony Algorithm (ACA) and the Clustering Algorithm (CA) to construct an auto-obstacle avoidance method which is suitable for the complicated maritime environment. In the improved ant colony-clustering algorithm proposed here, a suitable searching range is chosen automatically by using the clustering algorithm matched to different environmental complexities, which can make full use of the limited computing resources of the USV and improve the path planning performances firstly. Second, the dynamic searching path is regulated and smoothed by the maneuvering rules of USV and the smoothing mechanism respectively, which can effectively reduce the path length and the cumulative turning angle. Finally, a simulation example is provided to show that our proposed algorithm can find suitable searching range according to different obstacle distributions, as well as accomplish path planning with good self-adaptability. Therefore, a safe dynamic global path with better optimize performances is achieved with the help of multi-source information.

INDEX TERMS Ant colony-clustering algorithm, dynamic path planning, adaptive searching range, smoothing mechanism.

I. INTRODUCTION

In recent years, researches on Unmanned Surface Vehicles (USV) have obtained a series of important achievements in environmental sensing technologies, communication navigation technologies, intelligent sailing control technologies and lane planning technologies, etc. At present, obstacle avoidance and path planning, as an important functions guaranteeing safety of USV and efficient completion of operation tasks, have become one of important research topic in USV. Specifically, based on environmental perception of multi-source information such as radar, AIS and electronic charts, USV can plan a sailing path with optimal performance so as to complete tasks efficiently and safely. In case of complex maritime navigation environments and climate conditions, USV can not make full perception of global environmental information due to the limit in layout height and power of sensors, bad information receiving conditions and other problems, then the perception of complex environments will be limited. This can be a huge challenge for efficient and reliable dynamic obstacle avoidance planning.

Current researches on USV dynamic obstacle avoidance planning can be divided into global path planning based on maritime environmental information and local path planning

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based on sensor information. Global path planning refers to that static obstacle layout in the environment is obtained based on the given environmental information and then a suitable path from the starting point to the global target is sought with a path planning search algorithm. The path planning algorithm focuses on designing an obstacle avoidance path according to known obstacles layout in the environment so as to reach the goal with the best efficiency [1]–[4]. Algorithms of A* [5] and Dijkstra [6] are classic methods for solving optimization problem of static path planning. Based on maritime obstacle avoidance rules, Kuwata *et al.* [7] established geometric areas to divide obstacle avoidance zones and carried out the global obstacle avoidance planning of USV with the improved A* algorithm; Haiqing *et al.* [8] combined the A* algorithm with the potential field method to formulate a dual-layer global planning algorithm, accordingly an optimized path advantaged in both the effective obstacle avoidance and short voyages was obtained; however, as for irregular obstacles, boundary information of obstacles is often effectively extracted with a grid method model, so a high-quality environmental model can be obtained and path planning can be realized based on interval geometric association [9]. However, in the face of complex and time-varying maritime environments, almost all methods mentioned above do not obtain optimal performance of the planned paths, or even fail to plan. Hence, some scholars have introduced intelligent bionic algorithms to deal with these highly nonlinear path planning issues. Song *et al.* [10] proposed an improved particle swarm optimization algorithm for optimizing the path planning cost functions, with which the global smooth path planning is realized; Duguleana and Mogan [11] improved the Q learning neural network reinforced algorithm to train and optimize the multi-obstacle environmental robot scene in order to obtain the global optimal planning path. With global path planning, redundancy and losses of paths can be effectively reduced and a global optimal path can also be obtained. Regretfully, these intelligent algorithms can not judge movable obstacles and dynamic factors in a maritime environment in advance and still remain deficient in timeliness. Hence, another type of local path planning was generated. It senses external and real-time information with facilities, own sensors and equipment so as to analyze obstacle locations and make corresponding treatments [12], [13].

As for local path planning rules, it is necessary to establish a real-time planning model for path optimization. Hence, geometric correlation modeling is carried out according to surrounding obstacle space commonly. Dai *et al.* [14] designed a real-time path planning method by setting up a correlation model concerning distances and angle changes between the object and obstacle; Kim *et al.* [15] discussed USV path planning method with yaw angle converged LOS(line of sight) model. However, the planning efficiency is decreased by complex model structures and huge calculated amount. Some researchers use artificial potential field methods to simplify models in order to avoid the deficiency that artificial potential field methods can easily fall into local minimums. Montiel *et al.* [16] designed an artificial potential field method and combined it with the bacteria evolution algorithm so as to enhance planning flexibility. The better verification effects were shown through comparison with traditional potential field methods; Mousazadeh *et al.* [17] carried out standard obstacle avoidance optimization under wave interference based on searching balls and potential field functions. Due to states uncertainty of dynamic obstacles, complex scientific theories such as artificial intelligence algorithms are often applied to path planning problem. Kozynchenko and Kozynchenko [18] designed dynamic predication planning algorithm which combines neural networks and fuzzy algorithms aiming at the ship passing scene so as to carry out dynamic real-time path optimization of ships; Plessen *et al.* [19] carried out dynamic obstacle topologic modeling based on graph theories and expanded Kalman filter algorithm so as to form planning paths. In general, the local path planning algorithm is more suitable for real-time dynamic path optimization. However, it has poor overall performance of path planning because it can only obtain local information from ship equipment and cannot in advance obtain global environmental information.

Based on characteristics of global and local path planning methods, some scholars proposed several comprehensive planning algorithms with advantage complementation. Mahmoudzadeh [20] obtained global static obstacle information with an offline environmental map and then carried out dynamic obstacle avoidance and real-time path selection with particle swarm optimization algorithm, evolution algorithm and fire fly algorithm respectively; Fei *et al.* [21] carried out global path planning based on electronic chart, and then handled local path planning with potential field functions; on this basis, Tsou [22] carried out path selection of dynamic obstacle avoidance of ships with ant colony algorithm, AIS information and obstacle avoidance rules. This algorithm combines local static obstacle information and characteristics of local real-time dynamic planning model to balance advantages of global path planning and local path planning so as to realize short-distance obstacle avoidance path planning and carry out validity description through comparison with common genetic algorithms [23] in the obstacle avoidance mechanism. Meanwhile, Tsou also pointed out that if the ant colony algorithm can overcome problems such as slow convergence and low efficiency in large-scale planning problem, the large-scale, long-distance obstacle path planning will be realized.

As for USV, static environment sensing equipment mainly depends on an electronic chart. Dynamic environment sensing equipment mainly relies on radar, AIS system (ship automatic recognition system) and HD cameras. In the maritime environment with complicate interference, USV may be limited in dynamic environment sensing during performing tasks. For example, video signal collection of cameras are intervened by bad visibility; radar antennas mounted on USV are too low, the power is too low and its performance is worse than that of commercial ship radars; in case of heavy snowy or rainy weathers and maritime noise jamming, the sensing capacity of radars for small dynamic objects on the sea will be greatly limited within the considerable wide range. Although AIS system has robust fault tolerable performance for environmental interference, its signal renewal is slower. What is more, AIS is applied to business ships or parts of fishing boat with over 500t. This means that AIS does not cover all the maritime power-driven ships, so its sensing ability of dynamic objects cannot be completely enough for USV maritime obstacle avoidance tasks. Hence, when the sensing cabicity of USV for maritime dynamic obstacle is limited, how to realize large-scale maritime dynamic path planning and obstacle avoidance through full use of multi-information integration will be a huge challenge.

Hence, a self-adaptive dynamic path planning algorithm of USV with maritime environmental multi-information sensing is proposed based on an improved ant colony-clustering algorithm which can recognize complex degrees of maritime local static and dynamic obstacles in this paper. The paper makes contributions mainly in the following three aspects:

1) In order to make simulation experiments of USV dynamic obstacle avoidance more realistic, a dynamic grid simulation environment which can ensure that real-time dynamic states of a ship and dynamic obstacles are constructed based on electronic charts and AIS system. And the dynamic update mechanism of simulation environment is driven by time.

2) In order to solve dynamic path planning problems under complex maritime inference and limiting of USV sensing range, we take USV as the origin, make self-adaptive adjustment of a path search range of the dynamic obstacle avoidance algorithm within the sensitive range of radar or HD camera and selects a rational path planning range according to the complexity range of obstacles so as to make dynamic path planning effective. In this way, integration of path planning and obstacle avoidance mechanism is realized.

3) In order to enhance reliability of obstacle avoidance planning and shorten optimization time of the algorithm, the complexity of obstacle distribution is recognized by the clustering algorithm and the self-adaptive adjustment of the search range according to the complexity degree is also achieved. In this way, the problem that the classic ant colony algorithm is only applicable to problems concerning to static path planning, large calculated amount and slow solution speed is solved effectively.

II. MARITIME ENVIRONMENT MAP CONSTRUCTION BASED ON ELECTRONIC CHART AND AIS SYSTEM

In path planning issues, grid maps are often used to establish a static simulation environment [8]. In order to make the constructed maritime simulation environment more realistic, here based on the grid model, electronic charts and AIS information system, we makes static and dynamic obstacles of designated maritime areas into correspondent grid model and realizes dynamic update of the given maritime environment by time-driven manners.

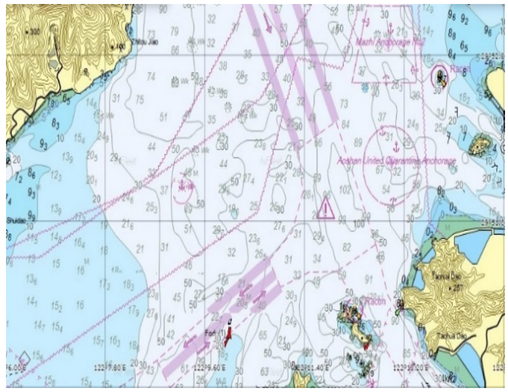


FIGURE 1. Electronic chart of a given area.

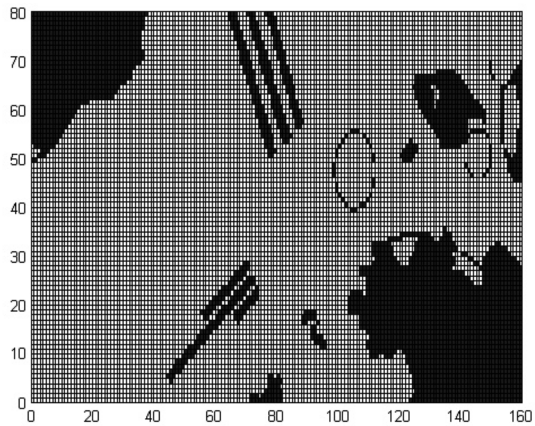


FIGURE 2. The grid map of a given area related to the electronic chart.

A. CONSTRUCTION OF MARITIME STATIC GRID OBSTACLES BASED ON ELECTRONIC CHARTS

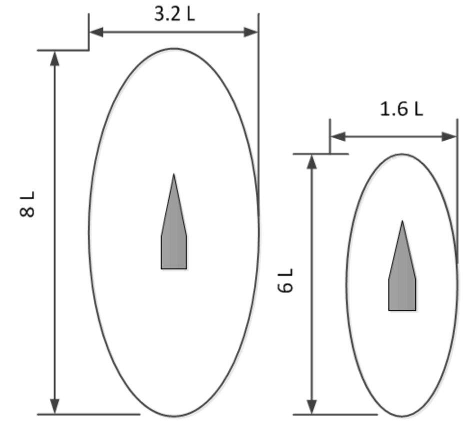
At first, local electronic charts of designated maritime areas were selected from the global electronic chart, which is shown in Figure 1.

Then, static obstacle grid maps of corresponding maritime areas were obtained through several steps including earthy yellow land information extraction and binary processing grid processing. Details of the correspondent grid map related to Figure 1 can be seen in Figure 2.

It is shown in Figure 2 that the grid map can only roughly reflect outlines of static obstacles (such as lands and islands), but they greatly decrease the difficulty in dynamic path planning. In addition, static obstacles such as highways and anchor points can be added on grid maps according to maritime traffic rules, so that reliable information can be provided for construction of highly vivid static grid simulation environments.

B. CONSTRUCTION OF MARITIME MOVABLE GRID OBSTACLES BASED ON AIS INFORMATION

According to real information of middle-sized and large ships provided by the AIS information system, specific



(a) Bygones ship field model. (b) Limited channel ship field model.

FIGURE 3. Fujii ship field model.

information such as size, speed and courses of ships sailing in the sea within a certain period can be obtained. Hence, we can construct mobile obstacles according to the information, specifically involving the following two aspects.

1) GRID CONSTRUCTION RULES BASED ON SHIP OBSTACLE AVOIDANCE MODEL

Due to volume and dynamic characteristics of ships, they need a certain time and a responding space for obstacle avoidance maneuvering. Hence, researchers have constructed a lot of collision risk models according to specific requirements, such as VCRO model [24], ship Bumper model [25] and Fujii model [26]. In order to confirm safe sizes of each ship accessible to the designated sea area, the safe scale of movable obstacles's static outlines are provided based on the Fujii ship model.

In addition, in order to consider both the convenience of grid models and timeliness of path planning, we not only takes into account sizes of ships in obstacle avoidance model, but also considers speeds of ships in designated areas. Without loss of generality, the computation formula of grid edge length is as follows.

$$L_a = \sigma L_{usv} + \bar{V}_{usv} \cdot t_s. \tag{1}$$

where L_{usv} denotes length of USV, $\bar{V}_{usv}$ denotes average ship speed of USV, t_s denotes required sailing time within a grid and σ denotes a coefficient of the Fujii obstacle avoidance model. The coefficient is 7 when the ship stays in an overtaken area or is 5 when it is in a limited channel.

According to equation (1), we can know the grid size is correlated with length, average sailing speed and real-time demands of USV. In other words, we can adjust the grid size according to busy degree, demanded sailing speed and real-time demands of maritime traffic environments and plan feasible dynamic paths under different real-time conditions and sailing speeds.

2) CONSTRUCTION OF OUTLINE MODEL OF MOVABLE OBSTACLE

For simplifying the computation, the discrete maritime environment model is obtained through discretizing the dynamic and continuous maritime environment model with given constant sample period, and then multiple relatively static maritime environmental maps satisfying real-time requirements are also obtained. Hence, movable grid obstacles are constructed according to following steps.

Step 1: An update sample period T is selected according to real-time requirement firstly. Then, times of local path planning m within an update sample period is computed. Meanwhile, the number of relative static maritime environmental maps with dynamic-static obstacle integration is determined by the ratio between the global path planning time and the sample period.

Step 2: According to number of grids passed by ships with different sizes and speeds along the courses within one update sample period, numbers of grids occupied by these ships as movable obstacles in different relatively static maritime environmental maps can be obtained.

Step 3: Numbers of grids occupied are obtained according to time and sizes of other accidental obstacles. In this way, the accurate model can be conducted for accidental obstacles with different sizes and speeds.

C. DYNAMIC UPDATE MECHANISM OF MARITIME ENVIRONMENT

After confirming static and dynamic obstacle models under the rasterized electronic chart and AIS system, it is necessary to design a rational update mechanism to ensure normal running of these models so as to vividly reflect changes of obstacles. Flow charts of the overall dynamic update mechanism are shown in Figure 4.

From Figure 4 we can see, times of local path planning m within each sample period is determined by the real-time measurement parameter for simplifying simulation. When m decreases to zero, the former static map shall be replaced with the latest static map and the new round of local path planning shall be restarted till reaching the global goal. The real-time requirements of path planning are determined by the update sample period T.

III. SELF-ADAPTIVE SEARCH MECHANISM BASED ON LAYOUT RECOGNITION OF LOCAL COMPLEX ENVIRONMENTAL OBSTACLES

In general, a USV is small and the sensing range with its carried detection devices is limited. Under simple maritime environments with good communication conditions, larger-range accurate dynamic path planning can be conducted according to multiple types of sensed information such as AIS system and electronic charts. In case of complex maritime environments with poor communication conditions, safe paths for obstacle avoidance shall be planned based on the limited sensing ability and computing ability constraints. In order to realize obstacle avoidance and path planning under

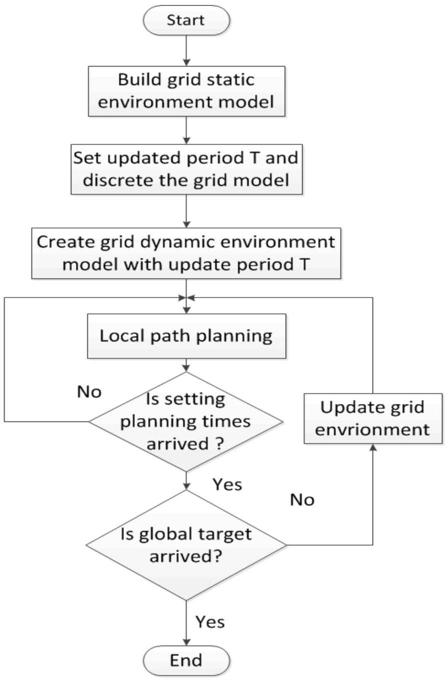


FIGURE 4. The flow chart of marine environmental renewal mechanism.

complex environments and limited sensing ability of USV, a self-adaptive search mechanism for obstacle distribution recognition in local complex environments is designed based on the clustering algorithm and combines it with an ant colony intelligent algorithm, so that the dynamic path planning under restraints of sensing range and computing ability can be realized.

At first, the maximum allowable steps N of local dynamic path planning is determined according to the sensing radius and obstacle distribution complexity. Then, in the obstacle recognition within limited steps, the occupancy ratio which is defined by percentage of obstacle grids in total number of grids within the range is usually used to measure the environmental complexity. Corresponding computing formula is as follows.

$$\delta = \frac{N_{ob}}{(2R+1)^2} \times 100\%. \tag{2}$$

where $R \in \{1, 2, \cdots, N\}$ denotes the number of step length within the planning range, N_{ob} denotes the total number of obstacle grids within the given step range.

This method is feasible when there are only a few of obstacles, but it often leads to wrong judgments when there are many obstacles which are not distributed evenly. For example, under the same obstacle occupancy ratio, path planning under gathering obstacles is generally easier than that of with scattered obstacles one. Hence, the obstacle gathering degree is proposed as a key parameter in order to judge complexity of obstacle distribution. Computation formula of obstacles is as follows.

$$N_{obc} = N_{obs} + N_{obg}. \tag{3}$$

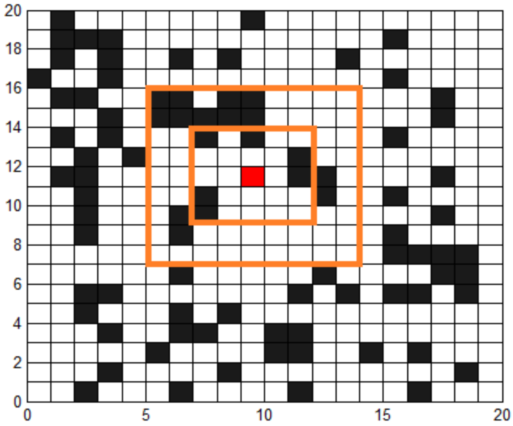


FIGURE 5. Grid obstacle map.

Equation (3) denotes that the number N_{obc} of obstacle types within the given range is equal to the sum of number N_{obg} of isolated obstacles and number N_{obs} of obstacle clusters.

As shown in Figure 5, with the red part as the center, there are two orange square frames with the 2 steps and 4 steps. There are 6 black obstacles within the 2-step frame, with the occupancy ratio of 0.24. From view of the gathering degree, there are 4 types of obstacles. In the 4-step frame, there are 19 black obstacles with the occupancy ratio of about 0.24 and 3 types of obstacles according to the gathering degree. As judged rules of the occupancy ratio rules, complexity of obstacles within the two steps length is the same; as judged rules of the obstacle types, the obstacle distribution complexity within the 4-step range is lower than that of the 2-step range. It is thus clear that obstacle distribution complexity from view of obstacle types mainly considers gathering degree of obstacles rather than simply take into account numbers of obstacles. Hence, this method can more accurately judge obstacle distribution complexity. Moreover, if there are equal number of obstacle types, the larger step range shall be selected for dynamic path planning.

Therefore the clustering algorithm is introduced for counting the gathering degree of obstacle grids within the search step automatically and the search step is selected in the principle of minimizing the obstacle types. In this way, a self-adaptive matching mode between the obstacle complexity and search step can be realized, while purposes including even computing loads, short overall path planning time and short overall planning path can be realized. The obstacle complexity recognition algorithm based on clustering algorithm can be seen in algorithm 1.

In algorithm 1, ∅ denotes a null set, $|\Phi|$ denotes number of all the null sets. At the sixth step, the number of obstacle types is equal to the difference between total obstacle types number and total null set number. The result is equal to that of equation (3).

IV. DYNAMIC CHARACTERISTIC CONSTRAINTS OF USV

While sailing on the sea surface, USV is influenced by maritime environment and its own dynamic characteristics,

Algorithm 1 Obstacle complexity recognition algorithm based on clustering algorithm

while new data exists **do**
Initialize obstacle types $N_{obc} \leftarrow N_{ob}$
Compute Euclidean distance between obstacle grids satisfied
$d(i,j) = \sqrt{(x^i - x^j)^2 + (y^i - y^j)^2},\ i,j \in \{1, 2, \cdots, M \times M\}$
Where (x^i, y^i), (x^j, y^j) denote horizontal and longitudinal coordinates of obstacles respectively.
Construct obstacle set $\varphi_s : g \in \varphi_s \leftarrow if \ \ d(g, s) = 1 \ or \ \sqrt{2}, \quad g, s \in N_{ob}$
Compute obstacle set: $\varphi_s = \varphi_s \cup \varphi_g,\ \varphi_g = \emptyset \ \leftarrow if \varphi_s \cap \varphi_g \neq \emptyset, \quad g, s \in N_{ob}$
Update obstacle types: $N_{obc} = N_{obc} - |\Phi|, \ \ \Phi = \{g \in \{1, \ldots, N_{ob}\} : \varphi_g = \emptyset\}$
end while

leading to some constraints such as difficult large-angle turning, large maneuvering radius and unnecessary energy consumption by frequent acceleration and deceleration, etc. Hence, these constraints shall be considered fully during dynamic path planning process. Here, we need to carry out dynamic path planning under uniform-speed sailing of USV and make sure that the USV does not need to make difficult actions such as reversing and large-angle maneuvering within the planned path. Hence, the problem of dynamic path planning is considered when the USV is limited in sailing visual field range and large turning angle shall be avoided along the track.

A. VISUAL FIELD RANGE CONSTRAINT OF USV

The dynamic path planning issue under the rasterized electronic chart environment and USV visual field restraining can be converted to the issue that the included the angle α which exists between the USV position coordinates (x_k^i, y_k^i) at the current moment and the position coordinates (x_{k-1}^j, y_{k-1}^j) of the previous moment and the horizontal coordinates is taken as the sailing trajectory direction, while the local target can only be selected in a sector area within a certain negative or positive angle along the sailing trajectory, so the visual field restraining problem can be solved.

Let angles β^q which exists between the current USV position coordinates and positions (x_k^q, y_k^q) of all the feasible local targets within the search step and the horizontal coordinates be taken as planned direction angles. $\theta \in [30°, 90°]$ denotes USV visual field angle restraints. The set of all the feasible local targets within the range of search steps N is Ψ, while the set of feasible local targets satisfying USV visual field constraint conditions is Λ, then one has

$$(\beta^q,\ q \in \Lambda) \begin{cases} T, & \alpha - \theta \leq \beta^i \leq \alpha + \theta, \quad i \in \Psi \\ F, & otherwise \end{cases}, \tag{4}$$

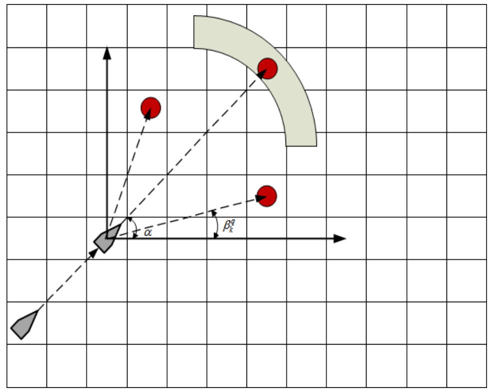


FIGURE 6. Local targets selection under visual field constraints of USV.

where the planned direction angles of all the feasible local target points satisfying USV visual field constraints can be obtained by the equation (5).

$$\beta^q = \begin{cases} 0° - \arcsin\left(\dfrac{|y_k^q - y_k^i|}{\sqrt{(x_k^q - x_k^i)^2 + (y_k^q - y_k^i)^2}}\right), \\ \quad First\ quadrant \\ 180° - \arcsin\left(\dfrac{|y_k^q - y_k^i|}{\sqrt{(x_k^q - x_k^i)^2 + (y_k^q - y_k^i)^2}}\right), \\ \quad Second\ quadrant \\ 180° + \arcsin\left(\dfrac{|y_k^q - y_k^i|}{\sqrt{(x_k^q - x_k^i)^2 + (y_k^q - y_k^i)^2}}\right), \\ \quad Third\ quadrant \\ 360° - \arcsin\left(\dfrac{|y_k^q - y_k^i|}{\sqrt{(x_k^q - x_k^i)^2 + (y_k^q - y_k^i)^2}}\right), \\ \quad Fourth\ quadrant \end{cases} \tag{5}$$

Then, relationships among the feasible local targets, the planned direction angles and the sailing trajectory angle are shown in Figure 6.

From Figure 6 we can see, feasible local targets can only be selected in a sector area within $\pm\theta$ degree, which is chosen with the USV as the origin point and the sailing track as the forwarding direction. In this way, reversing and large-angle maneuvering will be avoided during USV sailing. In addition, the searched sector area can be adjusted according to sailing speed and obstacle complexity for further approach real experimental conditions.

B. CONDITIONS CONSTRAINT OF USV MANEUVERING

When USV is moving with higher speed and larger turning angle, shipwreck accidents may take place due to bias of motion gravity center. Hence, during path planning process, it is necessary to avoid large turning angles as much as possible. Then a midpoint smoothly mechanism is proposed which can smooth turning angle along the planned path. Therefore, the path become relatively smooth and the distance between

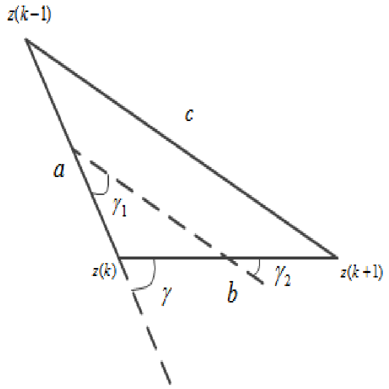


FIGURE 7. Path planning smoothing mechanism schematic.

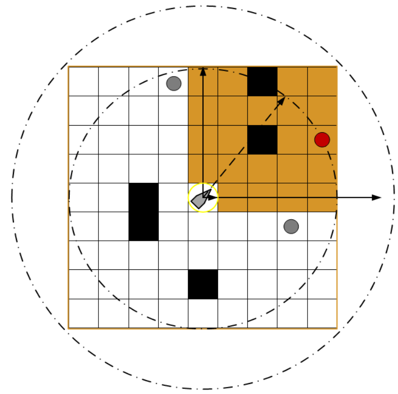


FIGURE 8. The path search range within a finite step.

starting point and ending point is also shortened. Basic principles of the midpoint smoothing mechanism method are shown in Figure 7. Three adjacent position points in the planning path are $z(k-1)$, $z(k)$, $z(k+1)$. If the turning angle on the line of these three points from a to b satisfies $\angle\gamma \geq \delta$, the smoothing mechanism will be triggered for the turning angle: with the position $z(k-1)$, $z(k+1)$ as the starting position, a straight line which passes two position midpoints $(\frac{|z(k-1)-z(k)|}{2}, \frac{|z(k+1)-z(k)|}{2})$ at the same time is generated to take the place of the original broken line, namely the dotted line in Figure 6, wherein δ denotes the angle threshold of smoothing mechanism starting. In this way, the original large turning angle $\angle\gamma$ is replaced by two relatively small turning angles $\angle\gamma_1$, $\angle\gamma_2$. Specific steps of the smoothing mechanism are be seen in Algorithm 2.

Algorithm 2 Smoothing Mechanism Algorithm of Path Planning

1: **while** new data exists **do**
2: Initialize states $z(k-1) = z(k) = z(k+1) = 0, \ k \leq -1$
3: If $k \geq 1$, compute slope k_1 of $z(k-1)$, $z(k)$ and slope k_2 of $z(k)$, $z(k+1)$
$$\begin{cases} k_1 = (y_{z(k)} - y_{z(k+1)})/(x_{z(k)} - x_{z(k+1)}), \\ k_2 = (y_{z(k)} - y_{z(k-1)})/(x_{z(k)} - x_{z(k-1)}). \end{cases}$$
4: Judgment of slope: $k = k+1$, *back to* $1 \leftarrow$ *if* $k_1 = k_2$, *continuous* $\leftarrow$ *if* $k_1 \neq k_2$
5: Compute values of a, b and c in Figure 7.
6: Compute γ and satisfy $\cos(\pi - \gamma) = (a^2 + b^2 - c^2)/2ab$
7: Under the given threshold $\delta = 25°$, if $\gamma \geq \delta$, recomputed coordinates of the new node $\frac{|z(k-1)-z(k)|}{2}, \frac{|z(k+1)-z(k)|}{2}$
8: Connect new nodes $\frac{|z(k-1)-z(k)|}{2}, \frac{|z(k+1)-z(k)|}{2}$ and delete the node $z(k)$.
9: **end while**

After smoothing process by the algorithm 2, no large turning angle will existed during the improved planning path, so relative steadiness of USV during uniform-speed railing is ensured.

V. SELF-ADAPTIVE PATH PLANNING AND OBSTACLE AVOIDANCE INTEGRATION ALGORITHM BASED ON ANT COLONY-CLUSTERING ALGORITHM

A. LOCAL PATH OPTIMIZATION BASED ON ANT COLONY ALGORITHM

The traditional ant colony algorithm is generally well known as slower convergent rate and sharp rise of calculated amount with the expansion of search areas. When the algorithm is applied to dynamic path planning of USV, it is necessary to consider constraints such as the limited search area and the path planning time. Hence, the concept of path planning with finite step length is introduced. The core idea of this method focuses on dividing the global path planning into multiple pieces of local path planning. In each local path planning, the search range, algorithm calculated amount and real-time demands of radars can be taken into full account. Specific steps are shown in Figure 8.

Let the maximum search radius is $4\sqrt{2}$ step grid length and the USV visual field restraint is $\theta = 45°$, then the local target shall be located within the square area with $\pm 45°$ of the USV sailing trajectory and the step length no more than 4. When the local target is located at the red origin point, it is necessary to assume that all the dynamic and static obstacles within this area are kept unchanged in this local path planning. Moreover the ant colony algorithm can be called for path planning of this area. The ant colony algorithm has smaller calculated amount, faster convergent rate and guaranteed real-time performance because of smaller local path planning range.

B. SETTING OF RELAY NAVIGATION POINT IN LARGE-RANGE MARITIME ENVIRONMENT

In the traditional ant colony algorithm, a heuristic function shall be set for construction of path selection updated principles. The formula is as follows.

$$Eta(i) = \frac{1}{\sqrt{(x_k^i - x_{eta})^2 + (y_k^i - y_{eta})^2}}, \quad i \in \{1, 2, \cdots, M \times M\}. \tag{6}$$

where (x_k^i, y_k^i) denotes grid coordinates of the current USV location, (x_{eta}, y_{eta}) denotes the grid coordinates of the target point, M denotes the edge length of grid map.

From equation (6) we know, the value of the heuristic function depends on the reciprocal of current Euclidean distance between the USV and the feasible grids. The larger value is corresponding to the smaller probability for the grid to be selected as the local target. When the ant colony algorithm is applied to dynamic path planning of a large-scale maritime environment, the local target nearest to the target point cannot be selected with large probability because the target point is far from the USV and the difference between heuristic function values of different local targets is not bigger enough. As a result, the dynamic path planning will spend too much time, while path optimization effect is poor generally.

Therefore, several suitable relay target points (x^j_{eta}, y^j_{eta}), $j \in \{1, 2, \cdots\}$ are added properly in the dynamic path planning area for reinforcing features of the heuristic function: During dynamic path planning of USV, the nearest relay target which in front of USV will play a role in guidance and guarantee only one targets including relay targets and the final target works at any moment during the entire path planning.

Remark 1: Relay targets can be selected along the static path planning route. Simulation testing results show that rational number of relay points and positions can effectively increase the success rate of dynamic path planning.

C. DYNAMIC OBSTACLE AVOIDANCE AND PLANNING ALGORITHM WITH ADAPTIVE SEARCHING RANGE

Through improving the traditional ant colony algorithm, the improved one can be applicable to small-range dynamic path planning. Meanwhile, for solving the inaccurate judgment problem of maritime environmental obstacle complexity, the recognition method for obstacle complexity is constructed based on the clustering algorithm. After combination of these methods, the integrated algorithm is applied to relative static maritime traffic map set obtained by electronic charts and AIS information system. In this way, the global self-adaptive dynamic obstacle avoidance and planning algorithm based on ant colony-clustering algorithm is designed. Specific running steps can be seen in Figure 9.

From Figure 9 we can see, in our proposed algorithm in this paper, the object of setting relay targets is improving the path planning rate of the ant colony algorithm. The algorithm 1 is used to obtain matching search steps according to complex degree of obstacles within a limited search range. Visual constraints are used to find a feasible local targets complying maneuvering characteristics of USV and smoothing path algorithm 2 is used to eliminate the larger turning angles which exist in the original planning path. Through combing multiple algorithms, our proposed algorithm can carry out a feasible dynamic and obstacle-avoiding path of USV in a wide range of seas.

VI. SIMULATION EXPERIMENT

Example 1: No.1 caution water area of the routing system in the Ningbo-Zhoushan core harbor area (regional range: $122.106833°E \sim 122.286833°E, 29.817667°N \sim 29.893333°N$*). Let the starting point of USV is* $(122.242364°E, 29.865524°N)$ *and the final target is* $(122.204527°E, 29.838548°N)$*. The length of USV is 30 m, the initial heading angle is* $255°$ *and the sailing speed is 9kn. The anchor point is set in* $(122.221341°E, 29.850265°N)$*. Object data information in the electronic chart is constituted of data in electronic charts. Depths of all the water areas in the electronic chart satisfies water absorbing requirements of the experiment USV. The visual angle of USV is* $\theta = 45°$ *and the maximum searching steps is* $N = 4$*.*

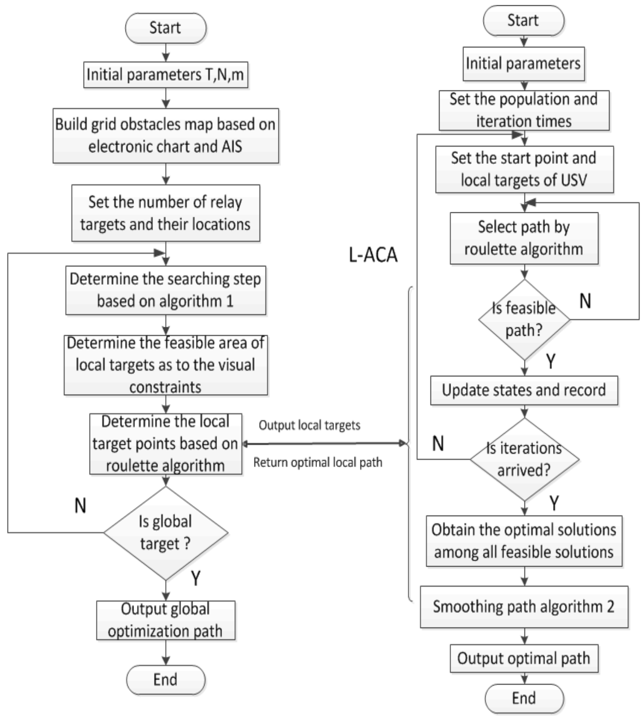


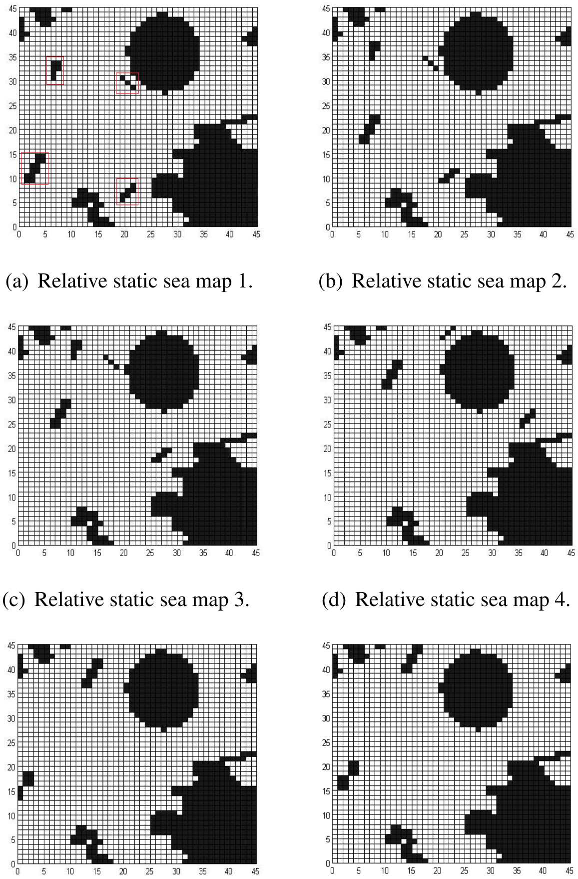
FIGURE 9. The flow chart of dynamic obstacle avoidance and planning algorithm with adaptive searching range.

TABLE 1. Parameters settings of two algorithms.

Parameters	Initial values of L-ACA	Initial values of IACS
Pheromone factor	1	1
Heuristic factor	0.7	0.7
pheromone evaporation coefficient	0.3	0.3
number of ants	10	10
maximum number of steps	10	10
search steps	1 - 4	1
number of relay targets	2	4

For comparing performances of different algorithms in the similar conditions, let initial values of related parameters in our local ant colony sub-algorithm (L-ACA) and the improved classic ant colony system (IACS) [27] as Table 1. It is notice that the classic ACS can not run properly in this dynamic environment until it is improved to a dynamic one according to the frame of L-ACA.

Obstacle information provided by the original electronic charts and AIS information system of the area is treated with grid processing. According to the dynamic obstacle

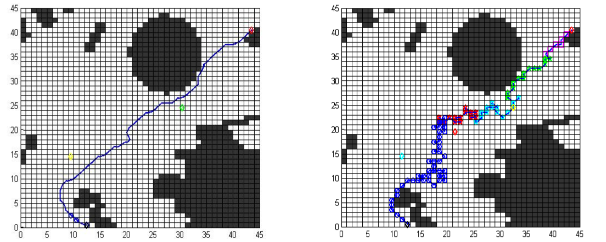


(a) Relative static sea map 1. (b) Relative static sea map 2.

(c) Relative static sea map 3. (d) Relative static sea map 4.

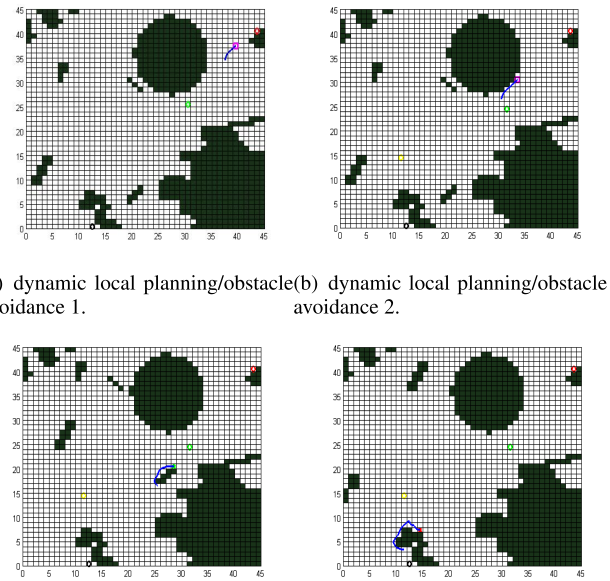
(e) Relative static sea map 5. (f) Relative static sea map 6.

FIGURE 10. Relative static sea grid map.



(a) dynamic panning map of our proposed algorithm. (b) dynamic panning map of IACS algorithm.

FIGURE 11. Composite map of dynamic path planning.



(a) dynamic local planning/obstacle avoidance 1. (b) dynamic local planning/obstacle avoidance 2.

(c) dynamic local planning/obstacle avoidance 3. (d) dynamic local planning/obstacle avoidance 4.

FIGURE 12. Decomposition grid map of the dynamic path planning algorithm based on ant colony-clustering algorithm.

updated mechanism, 6 relative static electronic charts are shown in Figure 10.

Figure 10 shows relative static grid sea maps generated according to dynamic features of movable obstacles. In Figure 10(a), obstacles in the red frame marks are corresponding locations of the ship in grids, while their outline sizes depend on size and speed of the ship. The USV will make dynamic path planning in different relative static grid sea charts as the time pass; the black round obstacles are anchor points known as maritime vital communication lines. During dynamic path planning, USV will successively pass anchor points, relay targets and finally reach the final object.

The algorithm proposed in the paper is the integrated algorithm of dynamic path planning and obstacle avoidance method, so the composite graph of successful path planning and the distribution path planning/obstacle avoidance map will be given here to illustrate effectiveness of the algorithm in path planning and obstacle avoidance. Limited to characteristics of the ant colony algorithm, path planning which is successful each time is not repeated, so composite maps are not completely corresponding with distribution graphs. Specific graphs are shown in Figure 11 and Figure 12.

Figure 11 is an overall path planning map of USV from the starting target point to the final target point. For recording the planned paths continuously, all the dynamic planning paths are drawn in the dynamic local planning/avoidance obstacle map Figure 12(d). It is shown in Figure 11(a), the overall paths planned with the algorithm proposed in the paper are successful, while no big turning angle problem appears along the whole planning path. Paths planned with the improved classic ACS algorithm is shown in Figure 11(b). The whole path planning time is about four times than that of our proposed algorithm in the paper. What is more, the overall path is longer and subject to large turning angles. In order to explain reasons for existing some curves in the overall path planning map Figure 11(a) and effects of the obstacle avoidance mechanism, Figure 12 is given here. It is shown in Figure 12 that that the clustering algorithm can select different searching steps according to obstacle distribution. From Figure 12(c) and Figure 12(d) we can see, the algorithm proposed in the paper can successfully avoid static and dynamic obstacles and realize integration of dynamic path planning and obstacle avoidance, while some curves in the planning path are generated due to obstacle avoidance maneuvering.

Remark 2: From more than 50 simulation results we know, ICAS can not match the varying complex degree of external maritime environment, which led to lower path planning success rate and spend lots of planning time. In contrast, our algorithm proposed in this paper can find suitable search steps for maritime environment with different complex degree and improve the path planning success rate greatly with much less planning time than that of ICAS.

According to analysis of simulation experiment results, we know that simulation environments of USV in obstacle avoidance and dynamic path planning are simplified greatly, if the electronic chart information and AIS system information from the actual dynamic maritime environment are converted to grid maps with the rasterized method. And then the improved ant colony-clustering algorithm is used for large-range path searching mission. In the end, obstacle avoidance and path planning are integrated and dynamic feasible paths with better performances can also be planned. At the same time, Static and dynamic obstacles in the maritime environment can be avoided accurately, while safety during USV sailing in the complex maritime environment can be ensured.

VII. CONCLUSION

With the dynamic path planning subject, the USV obtains dynamic and static information of maritime environments with multi-source devices such as electronic charts, AIS system and the mounted detection equipment and constructs a grid sea chart simulation environment with dynamic update mechanism and an intelligent integration algorithm of dynamic path planning and obstacle avoidance with short convergence time, balanced computing loads and good comprehensive performance indexes based on two intelligent algorithms including ant colony and clustering algorithms. As verified in the simulation experiment, the simulation environment of rasterized electronic chart can effectively reflect changes of dynamic and static obstacles in the maritime areas and has good real-time characteristics. The proposed ant colony-clustering algorithm can satisfy USV feature restraints and successfully use multi-source information positioning to realize self-adaptive recognition, obstacle early warning and dynamic path planning for obstacle avoidance in the designated sea areas. The algorithm has good local and global optimization performance. In the future, deep combinations of obstacle avoidance rules and the path planning algorithm will take into account as well as design of the multi-ship collision avoidance mechanism.

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