Path Planning for Multipoint Seabed Survey Mission Using Autonomous Underwater Vehicle

Yang An[1,2], Gaofei Xu[1,2], Chunhui Xu[1], Hongyu Zhao[1], Jian Liu[1,*]
1.State Key Laboratory of Robotics
Shenyang Institute of Automation, CAS
Shenyang, China
2.University of Chinese Academy of Sciences,
Beijing, China
E-mail:{anyang, xugaofei, xchh, zhy, liuj }@sia.cn

***Abstract*—This paper focuses on the problem of seabed survey mission with multiple target points distributed in large scale area. To complete the survey with AUVs in minimum cost, a two-step procedure using greed strategy is presented. In the first step, the locations of so-called anchor points are found by executing k-means algorithm iteratively. In the second step, an ant-cycle system is used to find out the optimized order of access from each anchor point to target points nearby. Simulation is also implemented to prove the validity of the algorithm.**

Keywords—Autonomous Underwater Vehicles; Path planning; Multipoint seabed survey; K-means clustering; Ant colony algorithm

I. INTRODUCTION

With the growth in demand of marine resources, seabed survey is paid more attention recent years. In the application of seabed survey and exploration, Autonomous Underwater Vehicles (AUVs) with obstacle avoidance sonar and side-scan sonar provide the capability of surveying large areas of sea floor. Researchers made numerous voyages to find out resources such as sulfide, minerals.

When the data of temperature, salinity, magnetism and topography is sent to marine geologists , taking advantage of abundant domain knowledge, they can pinpoint some points which need more observations or sample collections. The target points of the second-round observation can distribute discretely in a large area .With the increase of AUV endurance, it is possible to survey multiple target points in a single dive . In order to further enhance the efficiency, multiple AUV in the same type may also be used in a mission. For these reasons, a global plan in voyage level is necessary to make the work more efficient.

Several works are done in path planning of area coverage in small area around single target point [1] and in path planning of getting the target points through current or bypass obstacles [2]. However, few studies in AUV path planning which is used in voyage level and large scale area. And fittingly in the problem of planning school bus routing, the framework of it is value to reference although there are a lot of difference.

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The core sub-problems of school bus routing problem (SBRP) are bus stop selection (students are assigned to stops), bus route generation, and route scheduling[3]. These sub-problems are highly interrelated and they cannot achieve optimum simultaneously. So, in practice they are treated separately and sequentially by strategies as the allocation-routing-location (ARL) strategy [4] and the location-allocation-routing (LAR) strategy [5]. Due to the goal of SBRP is to plan the order of access from school to clusters of students which are defined as the bus stops and the goal of the seabed survey is to reach every target point exactly. Neither of strategies is applicable to the scene of multipoint seabed survey mission.

In this paper we present an algorithm by greedy strategy to decompose the path planning problem in two steps. By using k-means clustering iteratively and ant colony algorithm, path is planned for multipoint seabed survey mission. Simulation is also implemented to prove the validity of the algorithm.

II. GENERAL PROCEDURE

The goal of the algorithm is to find out the optimized path with minimal energy consumption to access all target points distributed discretely in a large area. According to the actual situation, the model is simplified as :

- The endurance of AUV is measured by hours.
- The workload of every target point include survey and sampling .
- AUV maintain its speed during the entire mission.
- AUV have limited capacity of samples.

Due to the limited endurance of AUV and the maximum number of samples which AUV can carry, not all target points can be reached. According to the greedy strategy, a workflow is set as below: The support vessel voyage to a planned position which called anchor point in this paper, release the AUV to survey target points nearby. Monitoring and waiting at the anchor point for recovery. And then voyage to next anchor point and continue the survey mission.

In this paper, the problem is solved by two steps:

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A. Planning the locations of the anchor points

In this step, the workload of every target point and the extreme distance that AUV can voyage are considered. All the potential locations are searched to find out the locations with minimum number of anchor points which can cover all target points.

B. Planning the order of access from each anchor point to target points nearby

After settling the anchor points, every target point is assigned into the nearest anchor point. In this step, order of access from each anchor point to target points for every anchor point nearby is planned considering restrictions and optimization objectives.

III. PLANNING THE LOCATIONS OF THE ANCHOR POINTS

For every target point, the location of the nearest anchor point should be satisfy:

$$2d / s + w \leq e \tag{1}$$

In equation (1), d stands for the distance between the target point and its nearest anchor point, s represents the speed of the AUV. w indicates the workload (in hours) and e stands for the endurance of AUV(in hours). By this equation we can draw the area of all potential locations of the anchor points .

Next, turning the area of the potential locations to several connected domains according to their geometric characteristics for partitioning the problem. Using inscribed rectangle of the extreme circle ($R=e\cdot s/2$, every center represents an anchor point) uniform cover every connected domain and delete all the circles with covering no target point. The centers of the remaining circles become the initial centroids of the K-means algorithm, using K-means algorithm [6] iteratively as the following pseudo code.

Algorithm 1. Pseudo code for Planning the Locations of the Anchor Points.

function ANCHORPOINTLOCATIONS (*InitialCentrods*, *TargetPoints*, *MaxLoop*)

```
Centroids ← InitialCentrods
while (1) do
    Run K-means ( Centroids ) until MaxLoop
    Draw extreme circle with center of Centroids
    if ( all TargetPoints are covered ) then
        Delete one of the nearest Centroids
    else
        Add the last deleted Centroids
        break
    end if
end while
n ← number of Centoids
i ← 1
while ( i < n+1 ) do
    Draw extreme circle with center of Centroids
    if ( all TargetPoints are covered ) then
        Delete Centroids( i )
        Run K-means ( Centroids ) until MaxLoop
        continue
    else
        Insert the last deleted Centroids to index i
        i ← i+1
    end if
end while
```

In this procedure, the *MaxLoop* is set to big enough that the progress of K-means algorithm can converge completely. Firstly, by K-means algorithm the anchor points are moved towards the target points around it. If all the target points are accessible under the restrictions of its workload and the endurance of AUV (covered by the extreme circle with the center of anchor points) then remove one of the nearest anchor points to dwindle the number of the anchor points. Repeat above step until there are target points is unaccessible when remove one more anchor points. To continue to optimize the locations, the remaining anchor points are traversed to test that if any of them can be removed as the prerequisite of ensuring every target point accessible. The output then was designated as the final locations of the anchor points.

IV. PLANNING THE ORDER OF ACCESS FROM EACH ANCHOR POINT TO TARGET POINTS NEARBY

After the planning of anchor points, every target point is assigned to its nearest anchor point. For every anchor point , the order of access from anchor point to target points nearby is planned in this section. The following restrictions and optimization objectives are considered.

- In one dive, the AUV start from and end up at anchor point.
- In one dive, the total time that AUV operate, both travelled and worked at the target points is limited by AUV endurance.
- In one dive, the number of samples that AUV sampled is limited by the capacity.
- Minimize the total distance that AUV travelled.
- Minimize the number of dives.

To solve the problem of multi-objective optimization , the ant-cycle system [7][8] is used by following steps.

Step 0 (*Initial global parameters*). Decided the *MaxLoop* as the terminal condition of the algorithm. Set the iteration count *itr* ←1. Decide the *NumberOfAnts* and set *Phe* ← 1 for initializing the pheromone matrix.

Step 1 (*Initial ants parameters*). In every iteration, Set *Route* (1) ← 0 which means put all ants at the anchor point. And *Route* records the order of access so far. Set *SetOfUnvisited* to full set, which records the index of target points which are unvisited. Set *ListOfAccessible* to empty, which records the index of the accessible target points. Set *TimeOperated* ← 0 , which indicates the total time the AUV operated so far. Set *SampleCollected* ← 0, which represents the samples that AUV already taken.

Step 2 (*Create ListOfAccessible*). For every ant, its mission start with checking every element in *SetOfUnvisited*. Creating *ListOfAccessible* by adding target point *SetOfUnvisited*(i) if it satisfies both

$$TimeOperated + Workload(i) + TimeCost\,(i) \le Endurance \quad (2)$$

$$SampleCollected + Sample(i) \le Capacity \quad (3)$$

Where *Workload*(i) expresses the workload of target point *SetOfUnvisited*(i), and *TimeCost* (i) indicates the time cost of traveling from the current position to the target point, *Sample*(i) is the binary value if the target point need to be sampled. If *Route*(end) ≠ 0, which means that the last visited position is not the anchor point, the anchor point is also added to the *ListOfAccessible.*

Step 3 (*Empty ListOfAccessible*). If *ListOfAccessible* is empty, force ant back to the anchor point, empty *TimeOperated* and *SampleCollected*, turn to **Step 2**.

Step 4 (*Decided where to go next*). Calculate the probability of visiting every target point in *ListOfAccessible* according to the following equation:

$$P(k) = \frac{Phe_{i,k}{}^{\alpha}\, RecDistance_{i,k}{}^{\beta}}{\sum_{j \in ListOfAccessible} Phe_{i,j}{}^{\alpha}\, RecDistance_{i,j}{}^{\beta}} \quad (4)$$

Which i indicates the current position, k represents the k^{th} element in *ListOfAccessible*, $Phe_{i,k}$ is the intensity of pheromone adhere to the $arc_{i,k}$, $RecDistance_{i,k}$ is the reciprocal of distance of $arc_{i,k}$. α and β are the parameters to control the influence of pheromone and distance. Decide randomly which target point to visit according the probability (The anchor point is also allowed). Add destination to the end of *Route* and remove it from *SetOfUnvisite*, renew *TimeOperated* and *SampleCollected*.

Step 5 (*Empty SetOfUnvisited*). If S*etOfUnvisited* is empty, the ant complete its mission, force the ant back to the anchor point, empty *TimeOperated* and *SampleCollected*, count *NumberOfDives*, compute total weighted distance *T* according equation (5). And start the journey of the next ant.

$$T = DistanceOfRoute \cdot NumberOfDives^{\gamma} \quad (5)$$

Where γ is the the parameters to control the influence of dives. If S*etOfUnvisited* is not empty ,turn to **Step 2**.

Step 6 (*Update pheromone*). When all ants complete their mission, record the best route R_{best} and the minimum total weighted distance T_{min} so far. Renew the pheromone matrix as :

$$phe(itr+1) = \begin{cases} (1-\rho)\, phe_{i,j}(itr) + \rho / T_{\min} & \text{if } arc_{i,j} \in R_{best} \\ (1-\rho)\, phe_{i,j}(itr) & \text{if } arc_{i,j} \notin R_{best} \end{cases} \quad (6)$$

where ρ is the pheromone evaporation coefficient to prevent the excessive accumulation. Let *itr* ← *itr* +1, continue run **Step 1** to **Step 6** until *itr* reach *MaxLoop.*

V. Simulation and Result

In order to prove the validity of the algorithm, simulation is implemented. As Fig.1 shown, the data set is generated by a Matlab program, to simulate the banding distribution of 100 target points in a 160 miles×160 miles area. About 40% of the target points are chosen randomly which need to be sampled and their workload are chosen randomly in {2,4,6,8} hours. The endurance, velocity and sampling capacity of the AUVs which participate in this simulated seabed survey mission are set as table 1: The endurance is 40 hours with speed being 1knot and capacity of take maximum 3 samples in one dive.

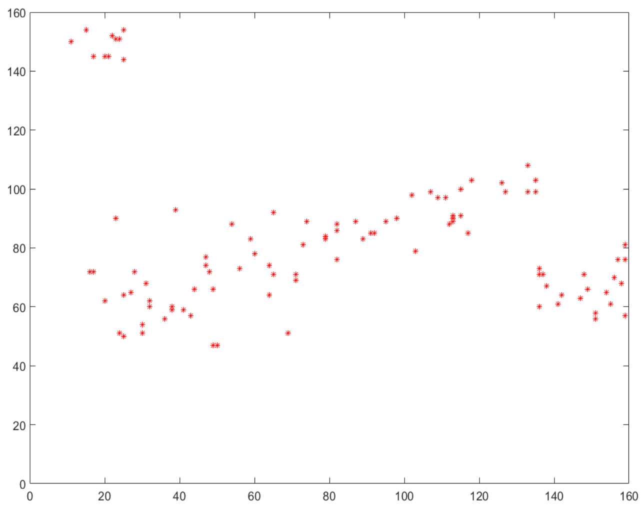

Fig.1 The data set of the seabed survey mission.

As stated above, area of all potential locations of the anchor points (colored by yellow) in Fig.2 is draw out according equation (1). Then due to the geometric characteristics, the area is divided into 2 connect domains. For the procedure is similar, we only deal with the big one below.

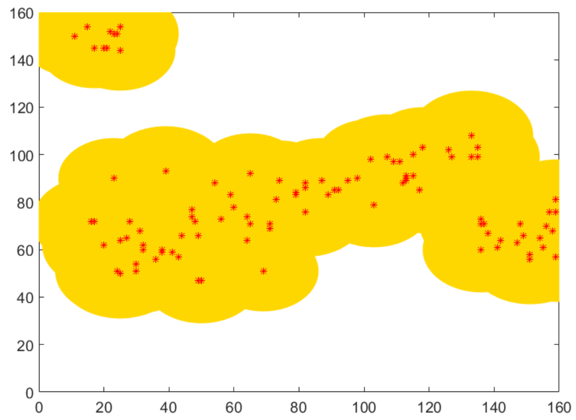

Fig.2 The area of all potential locations of the anchor points.

Next, optimizing the potential locations of the anchor points roughly to get the initial centroids of the K-means algorithm as Fig.3 shown. By the procedure of Algorithm 1 proposed in section III, the final locations of all the anchor points are settled as Fig.4 shown.

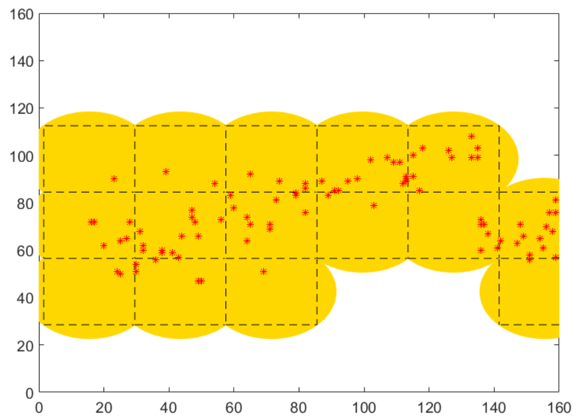

Fig.3 Locations of anchor points after rough optimization

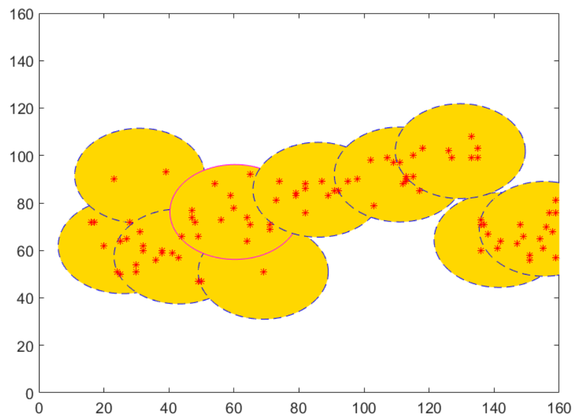

Fig.4 Final locations of anchor points

After assigning every target point to the nearest anchor point, the order of access from anchor point to target points nearby for each anchor point is planned by the ant colony algorithm described in section IV. Take the anchor point circled in violet in Fig.4 for an example. The parameters of the ant colony algorithm are set as follows:

Table 1 Parameters

parameter	**value**
s	1 knot
Endurance	40 hours @ 1 knot
Capacity	3 samples per dive
MaxLoop	500
NumberOfAnts	30
α	1
β	0.5
γ	2

The planning result is shown in Fig.5. Numbers in the figure represent the workload and '+' labels the target points need to be sampled. Fig.6 shows that the algorithm have a good global search capability.

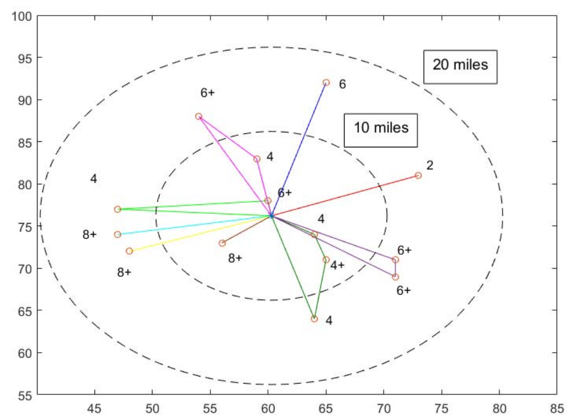

Fig.5 Order of access from an anchor point to target points nearby

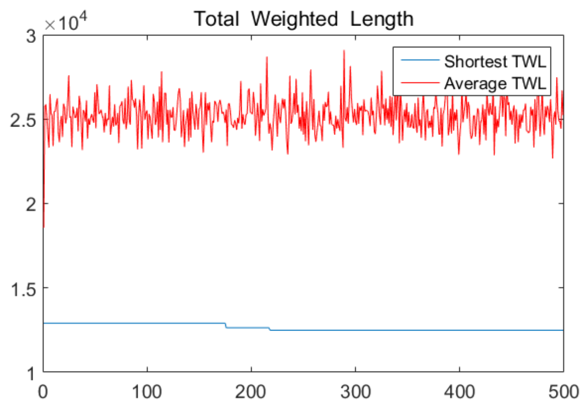

Fig.6 Total weighted length in every iteration

The access order of the anchor points is restricted by many limitations such as flow direction, direction of support vessel entering and leaving this area, other scientific missions of the voyages etc. It should be planned based on the reality, but can also be planned by the ant colony algorithm described in section IV.

VI. CONCLUSION

In this paper, we present an algorithm to minimize the cost of survey mission with multiple target points distributed in large scale area by AUVs. Simulations show that the algorithm can satisfy all constraints and is able to find feasible solution of the path planning problem. It can improve efficiency of the mission, especially when multiple AUVs in same type are used. However, due to the two sub-problems of the problem are highly interrelated, the result can not be guaranteed to be global optimal by using greed strategy. Some restrictions such as the support vessel waiting at the anchor point when AUV working may also too strict in reality. They will also be further considered in the future work.

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