Bio-inspired geomagnetic navigation method for autonomous underwater vehicle

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Abstract: This paper presents a bio-inspired geomagnetic navigation method for autonomous underwater vehicle (AUV) without using any a priori geomagnetic information. Firstly, the multi-objective search problem is raised. Secondly, the geomagnetic navigation model is established by constructing a cost function. Then, by taking into consideration the biological magneto-taxis movement behavior for the geomagnetic environment stimulus, the multi-objective evolutionary search algorithm is derived to describe the search process. Finally, compared to the state-of-the-art, the proposed method presents better robustness. The simulation results demonstrate the reliability and feasibility of the proposed method.

Keywords: autonomous underwater vehicle (AUV), geomagnetic navigation, bio-inspired navigation, hex-path algorithm, evolutionary algorithm.

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1. Introduction

Autonomous underwater vehicle (AUV) has been widely used in the civilian and military applications, such as ocean data collection, laying pipelines, underwater equipment maintenance, scout, and laying mines [1,2]. At present, the navigation systems using global positioning system (GPS) and inertial navigation system (INS) have demonstrated great utility for positioning real-time navigation, mapping, and other applications [3]. However, the existing navigation systems cannot provide accurate position for the dead-reckoning error in underwater environment [4]. In the case of AUV working in complex sea environment, an effective way of navigation is indispensable for AUV.

The geomagnetic fields are everywhere at the earth surface, which can be treated as a major candidate for providing the large scale positioning cues and directional cues [5,6]. Large scale oceanic travelers such as pelagic birds are likely to rely on geomagnetic positioning cues

when other cues may be unavailable [7]. The previous homing experiment showed that geomagnetic information could help adult green turtles to return to their egg laying site [8]. The researches on animal geomagnetic navigation have provided sufficient evidence that geomagnetic information can be used as a solid source for geomagnetic navigation. Therefore, the geomagnetic fields as vector fields are being developed to provide relatively stable positioning information for AUV.

Based on the characteristics of the geomagnetic fields, numbers of methods have been proposed on the correlation matching algorithms, which include mean square difference (MSD), mean absolute difference (MAD), and iterative closest contour point algorithm (ICCP) [9–13]. However, the conventional matching techniques strongly depend on a priori geomagnetic map, which is quite challenging to implement in practice.

To overcome such issue, the bio-inspired geomagnetic navigation method is proposed, during which the real-time measured data are used. Firstly, the geomagnetic navigation problem without using a priori geomagnetic data is generalized as a multi-objective search problem. Secondly, the search algorithm based on the evolutionary strategy is introduced by geomagnetic environment stimuli.

The rest of this paper is structured as follows: in Section 2, the search problem of geomagnetic navigation for AUV is raised. In Section 3, two search strategies are proposed in terms of a movement constrain law, and the proof of convergence of the multi-objective evolutionary search algorithm is given. In Section 4, the main results and theoretical analysis are given, and numerical simulations are provided to demonstrate the effectiveness and the robustness of the proposed algorithm. Section 5 offers the concluding remarks and future work.

2. Problem formulation

Consider the kinematic model of AUV in a two-dimensional space:

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$$\begin{cases} x_k = x_{k-1} + V_k \cdot \cos \theta^k \cdot \Delta T \\ y_k = y_{k-1} + V_k \cdot \sin \theta^k \cdot \Delta T \end{cases} \quad (1)$$

where ΔT is the sample period, k is the time instant ($k = 0, 1, \dots, N - 1$), V_k is the kinematic velocity, θ^k is the heading of AUV.

2.1 Mathematical description of the problem

It is well known that the geomagnetic fields include multiple geomagnetic components [10]. The geomagnetic components can be described as follows:

$$\mathbf{B} = \{B_1, \dots, B_n\} \quad (2)$$

where $B_1, \dots, B_n$ are defined as geomagnetic components, such as the north geomagnetic field component B_x , the east geomagnetic field component B_y , the vertical geomagnetic field component B_z , the total intensity B_F , the horizontal magnetic field B_H , the declination angle B_D , and the inclination angle B_I .

From the perspective of bionics, biological magnetotaxis movement behavior is virtually the response to the geomagnetic environment stimuli. Depending on the geomagnetic information on the basis of navigation, its physical significance is that the multiple geomagnetic components could determine the only geographic location on the earth [11]. The geomagnetic navigation is the convergence process of the geomagnetic components from the current position to the target position. When the geomagnetic errors converge to zero, the AUV achieves the navigation task. Therefore, it can be considered as the multi-objective convergence process as follows:

$$\begin{aligned} \min F(\theta^k) &= (f_1(\mathbf{B}, k), f_2(\mathbf{B}, k), \dots, f_n(\mathbf{B}, k)) \\ \text{s.t. } t_i &= f(B_i^t, B_i^k, \theta^k) \end{aligned} \quad (3)$$

where $\mathbf{B}$ is the set of the geomagnetic components vector, B_i^t is the geomagnetic component of the target position, B_i^k is the geomagnetic component of the current position, and $F(\cdot)$ is the cost function.

Therefore, the bio-inspired geomagnetic navigation problem can be summarized as the multi-objective search problem.

2.2 General regularized cost function

The bio-inspired geomagnetic navigation is caused within the magnetotaxis, and the difference error of the geomagnetic components between the current position and the target position is considered as the stimulus. Then, the introduced cost function can describe a change in the difference error of the geomagnetic components, wherein the cost function of the i th geomagnetic component is followed as

$$f_i = (B_i^t - B_i^k)^2, \quad i \in n. \quad (4)$$

Considering the different magnitudes and units of the geomagnetic components, the cost function is normalized as follows:

$$F(k) = \sum_{i=1}^n \frac{f_i(\mathbf{B}, k)}{f_i(\mathbf{B}, 0)} = \sum_{i=1}^n \frac{(B_i^t - B_i^k)^2}{(B_i^t - B_i^o)^2} \quad (5)$$

where $\mathbf{B}^o = (B_1^o, B_2^o, \dots, B_n^o)$ are the geomagnetic components of the starting position.

The cost function shows the nonlinear characteristic of geomagnetic fields in Fig. 1. The distribution of the cost function demonstrates polyhedron, including convex and concave.

Fig. 1 Change of the cost function in geomagnetic fields

The purpose is that the cost function can converge to the optimal value in the searching process, and the search vector θ^k is bound to converge to the optimal vector θ^* , which can be expressed as

$$\lim_{k \rightarrow \infty} F(\theta^k) \rightarrow 0. \quad (6)$$

Based on the above description, the bio-inspired geomagnetic navigation problem of AUV could be generalized as the multi-objective search problem by using the cost function to explore and exploit the geomagnetic information.

Consequently, the problem of geomagnetic navigation for AUV above is reduced to a multi-objective search problem, when the cost function is convex and a global unique solution can be found.

3. Multi-objective evolutionary search algorithm

A bio-inspired navigation method is investigated, which is based on a simple assumption that a homing animal only perceives the variation of the geomagnetic field to reach its home.

As one of the animal instincts, the evolutionary behavior was first proposed by Alcock in 1993 [14]. He described

the evolutionary causes of behavior for animals. Here, we extent the concept and an action of behavior will be produced when animals are affected by external stimuli.

The evolutionary algorithm (EA) is to simulate the nature evolution process based on a heuristic search algorithm [15]. This paper makes use of the idea of the evolutionary strategy to update the navigation parameters, which is based on the Darwinian theories of natural selection and survival [16,17]. This process is inspired from animals' navigation behaviors, which can determine the way accurately without map or instruments. The movement of individual animals from one place to another is an evolutionary feature of their lives [18]. The magneto-taxis search strategy based on multi-objective of geomagnetic components is virtually the response to the geomagnetic environment stimuli [19].

Hence, by utilizing the evolution of animals behaviors, the EA is employed for searching the geomagnetic space. In the algorithm, each possible solution is defined as the individual, whereas a set of individuals is defined as the population. In this paper, the sample within the population is considered as the behavior solution of the multi-objective search problem, then the evolutionary process overcomes the convergence from the real solutions to the target solutions by virtue of the magneto-taxis.

The search algorithm has to perform two tasks. It must calculate the variation of geomagnetic components by measuring the real-time geomagnetic data, and it must make the AUV towards the target position.

The search algorithm is raised as follows:

(i) Population initialization. Generate randomly a number of N initial individuals in the population space Q , which is defined as $Q = \{\theta_j | j = 1, 2, \dots, N\}$, θ can be expressed as

$$\theta = \{\theta_1, \theta_2, \dots, \theta_m\} \quad (7)$$

where $m = 2\pi/\Delta\theta$, $\theta_j = \Delta\theta \times i$, $i \in [1, m]$.

(ii) Individual selection. Select randomly a heading sample from the population as the movement direction of AUV, then the probability of the selected sample can be written as

$$p(\theta_j) = \frac{1}{N}. \quad (8)$$

When performing the present number of iteration k , the probability of the selected individual θ_i can be obtained as

$$p(\theta_j^k) = \frac{\sum_{j=1}^N \delta_j(\theta_j = \theta_i)}{N}. \quad (9)$$

(iii) Individual updating rules. When $F(k) \leq F(k-1)$ means AUV closing in the target solution, the selected in-

dividual θ_j is better and should be saved in the population. When $F(k) > F(k-1)$ means AUV keeping away from the target solution, the selected individual θ_j is bad and should be replaced. The goal is to keep the superior heading with higher probability in the sample, as shown in Fig. 2. The rules are shown as follows:

$$\begin{cases} \theta_j^k = \theta_i, & F(k) \leq F(k-1) \\ \theta_j^k = \Delta\theta \times i, & F(k) > F(k-1) \end{cases} \quad (10)$$

Fig. 2 Selecting and updating of the heading

(iv) Terminate condition. If the search algorithm meets the termination condition, which can be expressed as

$$\begin{cases} |F(\theta^{k+1}) - F(\theta^k)| < \varepsilon \\ F(\theta^{k+1}) < \delta \end{cases}, \quad (11)$$

then the search algorithm will terminate; otherwise, go to (ii) above.

In the following discussion, we work on the convergence analysis of the proposed search algorithm. Reference [20] proved the convergence of the best individual preservation strategy in the EA. On that basis, it is essential to prove the convergence of the evolutionary search in this paper.

Theorem 1 Considering the best individual preservation strategy, the selection of the individual is required by the operating behavior of maximum probability $\lim_{k \rightarrow \infty} p(\theta_j^k) \rightarrow 1$, then

$$\lim_{k \rightarrow \infty} F(\theta^k) \rightarrow 0. \quad (12)$$

Proof Let $p(\theta_1, \theta_1, \dots, \theta_j)$ be the probability of the sample $(\theta_1, \theta_1, \dots, \theta_j)$. The probabilistic change of the individual is generated in (10) at the k th step. If $F(k) \leq F(k-1)$ with $\theta_j^k = \theta_i$, we can get

$$\Delta p(\theta_i^k) = p(\theta_i^{k+1}) - p(\theta_i^k) = \frac{1}{N} \quad (13)$$

else $F(k) > F(k-1)$ with $\theta_j^k = \Delta\theta \times i$, we can get

$$\begin{aligned} \Delta p(\theta_j^k) &= p(\theta_j^{k+1}) - p(\theta_j^k) = \\ \beta(k) - \beta(k)p(\theta_i^k) &= \beta(k)(1 - p(\theta_i^k)) \end{aligned} \quad (14)$$

wherein $0 < p(\theta_j^k) < 1$, $0 < \beta(k) < 1$, so $\Delta p(\theta_j^k) \geq 0$.

According to (13) and (14) above, the frequency of the selected individual θ_j^k is gradually increased as

$\lim_{k \rightarrow \infty} p(\theta_j^k) \rightarrow 1$, which means that it has bigger probability of individual θ_j^k , we can get

$$\lim_{k \rightarrow \infty} F(\theta^k) \rightarrow 0. \quad \square$$

4. Simulation results

To verify the effectiveness of the proposed search algorithm, numerical simulations are implemented in Matlab.

4.1 Simulation setup

World Magnetic Model (WMM2010) is used to provide the real time geomagnetic data as the geomagnetic sensor [21]. Simulations have been carried out based on the three physical fields: the north magnetic field B_x , the east magnetic field B_y , and the total intensity B_F , which are retrieved in real time from the WMM2010 model. In the simulations, we choose a rectangular area from (15N, 120W) to (55N, 80W). In the scenario, the starting position is located at (40N, 115W), and the goal is located at (20N, 90W), where the values of three geomagnetic components for the starting position are as follows:

$$(B_x^o = 21\,423nT, B_y^o = 5\,005nT, \text{ and } B_F^o = 51\,604nT),$$

the target position is as follows:

$$(B_x^t = 27\,065nT, B_y^t = 4\,927nT, \text{ and } B_F^t = 41\,613nT),$$

and the red square “□” stands for the starting position, and the red triangle “▽” for the target position, respectively. Here, $N = 50$, $\Delta\theta = 30$, $\varepsilon = 0.5$, $\delta = 0.001$, $m = 500$ m, $V_k = 5$ m/s.

4.2 Simulation results

To demonstrate the effectiveness and efficiency of the proposed algorithm, this article gives a comparison of different methods.

4.2.1 The algorithm based on hex-path

The 2-dimensional version of the hex-path algorithm is used, with respect to the orientation estimation. It is worth noting that the mentioned hex-path algorithm is different from the previous hex-path algorithm which was put forward by Russell [22]. The previous hex-path algorithm searches the odor source which occurs with the increasing of odor concentration, but the geomagnetic navigation process is based on the error decrease of the cost function to acquire more information of the target geomagnetic components.

Here, the hex-path algorithm is firstly introduced to solve the searching problem of the geomagnetic navigation. In this algorithm an AUV traces out a path through a

hexagonal grid and at each junction, and it chooses either a left or right turn based on geomagnetic sensor reading taken one and two junctions previously. The AUV moves forward a fixed distance m , then turns to one of two new headings. The change of headings for k step is either $+60^\circ$ or -60° , depending on the geomagnetic sensor reading taken at $k-1$ and $k-2$. As shown in Fig. 3, the AUV trajectory can be viewed as a path through a hexagonal grid. The choice of turning direction is explained in the following description of the hex-path algorithm:

```
repeat {
    if the cost function at  $k-2 >$  the cost function at  $k-1$  and rotation direction at  $k-1$  is anticlockwise or
    the cost function at  $k-2 <$  the cost function at  $k-1$  and rotation direction at  $k-1$  is clockwise
    then rotate clockwise  $60^\circ$  and move forward  $m$ 
    else rotate anticlockwise  $60^\circ$  and move forward  $m$ 
}
```

Fig. 3 AUV path produced by the hex-path algorithm

4.2.2 Results comparison

Comparative studies between the proposed algorithm and the hex-path algorithm are performed to evaluate the effectiveness of the proposed method.

In Fig. 4, two navigation paths show AUV can reach the goal within two different search strategies. From the simulation shown in Fig. 4, the traveling path of the hex-path algorithm is able to reach the goal slowly, following a zigzag route. In the initial stage, the heading of AUV is selected randomly. Then, the change of headings after k step is either $+60^\circ$ or -60° depending on the geomagnetic sensor reading at $k-1$ and $k-2$. The search result of the hex-path algorithm presents fluctuates greatly.

Based on the multi-objective evolutionary search algorithm, a self-adjusting search behavior will occur by the geomagnetic stimuli. Fig. 4 illustrates the moving trajectory of the evolutionary search algorithm, where the heading is updated continuously depending on the cost function at k and $k-1$. The range of headings for the population

is an evolving process. Therefore, the search result of this algorithm presents a good global search capability.

Fig. 4 Geomagnetic navigation within two different search strategies

4.3 Performance evaluation of the search strategies

4.3.1 Convergence analysis

Fig. 5 illustrates the convergence property of two different search algorithms, from which we can see that the step number is 650 for the evolutionary search algorithm, and 1 050 for the hex-path algorithm, respectively. The results derived in this paper reveal that each algorithm could converge to a stable state. However, the transition of convergence time is shorter for the multi-objective evolutionary search algorithm than the hex-path algorithm, where the number of iterations in 400 is tending towards stability for the evolutionary search algorithm. The analysis results confirm the convergence characteristics of the two different search algorithms according to the given parameters.

Fig. 5 Convergence curves of the cost function

The same cost function shows the convergence state after different iterations, 1 050 for the hex-path algo-

rithm and 650 for the evolutionary search algorithm, which presents early convergence (before 1 000 iterations). Therefore, the simulation example shows that the evolutionary search algorithm has better convergence behavior than the hex-path algorithm.

4.3.2 Robustness

The similarity in the number patterns of the cost function shows the robustness of the two methods mentioned above. Fig. 6 and Fig. 7 illustrate the steady states of the three geomagnetic components, from which we can see that the efficacy and cost effectiveness of the two algorithms are observed and compared. In the hex-path algorithm, the convergence curves of three geomagnetic components present strong variations in their approach, but the variation difference is very small in the multi-objective evolutionary search algorithm. Furthermore, significant chattering happens at the end of the convergence state in the hex-path algorithm.

Fig. 6 Three components convergence curves in the hex-path algorithm

Fig. 7 Three components convergence curves in the evolutionary search algorithm

From the simulation results, it can be concluded that the proposed evolutionary search algorithm is capable of realizing the evolutionary search process with better robustness than the hex-path algorithm.

4.3.3 Analyzing paths

This section aims at providing a comprehensive framework to analyze the structure of geomagnetic navigation and search problem for AUV. To better compare the capabilities of the two algorithms, the trials about 50 times are performed respectively in the same scenario. This is clearly illustrated in Fig. 8 where two box plots show the time responses for two successful navigation methods, where the histogram 1 represents the data statistics of the evolutionary search algorithm, and the histogram 2 represents the data statistics of the hex-path algorithm. From these results we can see that the average iteration steps are 720 for the evolutionary search algorithm and 900 for the hex-path algorithm, respectively. It has been proven that the hex-path algorithm has good ability to search for the goal, but suffers from slow searching speed in the iterations.

Fig. 8 Data statistics in two cases

Therefore, the running time should be considered in the application. The multi-objective evolutionary search algorithm is more suitable for geomagnetic navigation than the hex-path algorithm, with respect to rapid convergence and good global search capability.

4.4 Discussions

The simulations show that the navigation task can be successfully carried out with the magneto-taxis. In the imitation, the priori geomagnetic information is not required, only depending on three axial magnetic sensors to read the values of geomagnetic components for the current position.

Comparing the difference between two search algorithms mentioned in this paper, (i) there is no population in the hex-path algorithm, but it is indispensable for the multi-objective evolutionary search algorithm; (ii) the selection

of the direction has different ways; (iii) the hex-path algorithm only relies on the cost function at $k - 1$ and $k - 2$. In conclusion, the hex-path algorithm indicates the search process of the zigzag route at the expense of running time.

In realistic navigation applications, an AUV often works in complex and unknown environments, wherein geomagnetic anomaly and ocean current will easily make the search algorithm trapped in local minimum. These deserve further investigations in the future work.

5. Conclusions

This paper provides a novel search method for achieving geomagnetic navigation of AUV without using a priori knowledge. Firstly, the bio-inspired geomagnetic navigation can be attributed to a multi-objective search problem. To settle the problem, the geomagnetic navigation model is established by constructing a cost function. Then, the multi-objective evolutionary search algorithm is proposed in this paper. Finally, the numerical simulations are provided to demonstrate the effectiveness and the convergence properties of the proposed methods.

Compared with the hex-path algorithm, the proposed evolutionary search algorithm is capable of realizing the multi-objective search, and has better robustness. Moreover, the migrating sea turtles are believed to perform long distance navigation using geomagnetic cues [23]. The actual routes strongly resemble the above simulated trajectories from the multi-objective evolutionary search algorithm. Therefore, the simulation result shows the validity of the proposed algorithm for the bio-inspired geomagnetic navigation.

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