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Autonomous underwater vehicle optimal path planning method for seabed terrain matching navigation

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ABSTRACT

To solve the problem of existing methods of terrain matching having low precision in the areas with small eigenvalues, this work presents an Autonomous Underwater Vehicle optimal path planning method for seabed terrain matching navigation to avoid these areas. The method demonstrates high matching precision on each match area. This method has built the field map and value map that represents obstacle and matching performance, respectively, and the planning algorithm, which includes dynamic matching algorithm, cost function, search length and min-length, second-goal point and dynamic path planing algorithm, was proposed on basic of A star algorithm. Terrain-entropy and terrain-variance-entropy were introduced as criteria in the cost function to represent the matching performance. Then, joint criteria, which were calculated by a Back Propagation Neural Network, and fuzzy criteria were introduced and proved to be feasible through simulation experiments. The path planning method on the basic of fuzzy criteria, in terms of time consumption, was a more suitable method than the one based on joint criteria for the same terrain matching accuracy.

1. Introduction

As a means for humans to explore the underwater world, the Autonomous Underwater Vehicle (AUV) has gained more and more attention all over the world, and considerable progress has been made towards realizing an AUV.

Accurate navigation is a prerequisite for the success of the AUV mission (Cox and Wei, 1995). The characteristics of underwater operations make it impossible for an AUV to locate via GPS, and the error accumulation of an INS will reduce navigation accuracy to an unacceptable degree over time. Therefore, seabed terrain matching navigation (STMN) is required to correct INS errors (Paull et al., 2014; Groves et al., 2006). With the development of a wide swath bathymetry system and the creation of a wide swath bathymetry system data thinning method (Gui-Feng et al., 2013), high precision measurement of the seabed terrain becomes possible, and the STMN becomes a feasible way to solve the precise navigation of an AUV (Ziqi et al., 2015; Chen et al., 2015).

Recently, the matching algorithm of STMN has already achieved great development. Mok (Mok et al., 2013) introduced the adaptive Extended Kalman Filter (EKF) method to the STMN algorithm and proved its reliability by the simulation experiment. Donovan (2012) proposed an STMN algorithm using a particle filter and proved that it would obtain good location performance regardless of what sonar was used (Doppler Velocity Log (DVL), single beam sonar, or wide swath bathymetry system). Zhang (Zhang et al., 2014) proposed a robust STMN algorithm that can significantly reduce the interference of the outliers.

However, the richness of terrain features in terrain matching areas also has a huge impact on navigation accuracy. Therefore, using the path planning method for STMN is very important. Bar-Gill (Bar-Gill et al., 1994) presented a method that consists of information theory-based conditional entropy mapping and synthesizing minimum entropy trajectories, but in this method, the vessel can only move one grid at a time and the continuous operation of the sonar would lead to energy wastage. Serin (Serin et al., 2011) presented a 3-D path planning method using the Traveling Salesman Problem (TSP) assisted by the viewpoint entropy and Greedy N-Best View Selection techniques and proved it practical in real terrain and a road network dataset. However, this method does not take into account the changes in the terrain, and this would influence the reliability of the algorithm.

The greatest difficulty in path planning of STMN was choosing a terrain representation method to analyze the matching performance of an area. Chen (Chen et al., 2015) used Fisher criterion to analyze one such method and proved it applicable for STMN, Fairbairn (2011) proposed a terrain representation method using terrain entropy and applied it to real terrain data. However, the terrain matching performance could never be decided by just one feature. Wang (Wang et al.,

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2015) built the terrain features model using the terrain standard deviation, fisher terrain information, and terrain entropy, but the concept that the weight of each feature would change in different terrains was ignored.

In this paper, one path planning method for STMN, on the basic of an A star algorithm, is proposed. This method mainly uses terrain-entropy and terrain-variance-entropy to analyze the matching performance of an area, and the search length and dynamic matching algorithms have been proposed to reduce time consumption. In addition, the proposal of an Mean Square Deviation (MSD) threshold make it possible to distinguish the changed terrain area and take corresponding measures. The Back Propagation Neural Network (BPNN) and fuzzy methods were used to calculate the weight of entropy (criteria) in the cost function using joint criteria and fuzzy criteria, and the feasibility was proved by a simulation experiment.

2. Optimal Path Planning Method

2.1. Definition of terrain-entropy

In the 1950s, Shannon introduced the concept of entropy in information theory. Since then, entropy, which describes the expected value of the information contained in each message, has been widely used in the field of information matching and image processing (Xiao-Su and Zhang, 2008). In the field of terrain matching, entropy was defined as terrain-entropy, which described the expected value (average) of the terrain elevation contained in each area. The entropy ($H(S)$) can be defined as:

$$H(S) = -\sum_{i=1}^{n} p_i \log p_i \tag{1}$$

In region $M \times N$, terrain elevation at the point (i, j) is $h(i, j)$, and terrain-entropy HM can be defined as:

$$\begin{cases} P(i, j) = \frac{h(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} h(i,j)} \\ HM = \sum_{i=1}^{M}\sum_{j=1}^{N} P(i, j)\log(P(i, j)) \end{cases} \tag{2}$$

However, the terrain-entropy does not clearly show the features of the terrain in some special samples. For example, as shown in Fig. 1, most of the area (Area B) was flat and a smaller area (Area A) changed sharply. For this kind of terrain, Area A should be more of a concern than Area B. However, that has not been reflected in P in Eq. (2). In order to decrease the weight of flat areas in information calculations, terrain-variance-entropy was introduced, and the depth difference value $c(i, j)$:

$$c(i, j) = \frac{|h(i, j) - \bar{h}|}{\bar{h}} \tag{3}$$

was proposed to replace $h(i, j)$ in order to increase the weight of area A in information calculating. The terrain-variance-entropy HF

$$\begin{cases} P(i, j) = \frac{c(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} c(i,j)} \\ HF = \sum_{i=1}^{M}\sum_{j=1}^{N} P(i, j)\log(P(i, j)) \\ c(i, j) = \frac{|h(i,j) - \bar{h}|}{\bar{h}} \end{cases} \tag{4}$$

could clearly show the features of some of the special areas shown in Fig. 1.

In the following paragraphs, for convenience and simplification, the terrain-entropy and terrain-variance-entropy will be referred to as entropy.

Mean Absolute Difference (MAD) and MSD values are the performance metrics that measure the effect of terrain-entropy and terrain-variance-entropy. Suppose a matching unit contains $M \times N$ entropy values, where the entropy at point (i, j) is $H(i, j)$ (in priori map) and $H_S(i, j)$ (Real-time measurement of AUV).

1. MAD

$$\text{MAD} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} |H(i, j) - H_s(i, j)| \tag{5}$$

2. MSD

$$\text{MSD} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} (H(i, j) - H_s(i, j))^2 \tag{6}$$

The position where MAD or MSD is minimum is the best match location.

However, in most areas, the $HM(HF)$ values are big, and the difference between them is quite small and hard to separate, so Eq. (7) was used to make a distinction between the areas with similarly large $HM(HF)$ values.

$$H'(n) = \frac{H(n) - \min(H)}{\max(H) - \min(H)} \tag{7}$$

$$H''(n) = -\ln(\max(H') - H'(n)) = -\ln(1 - H'(n)) \tag{8}$$

In Eqs. (7) and (8), H is the raw $HM(HF)$ data, H' is the normalized data, and H'' is the processed data.

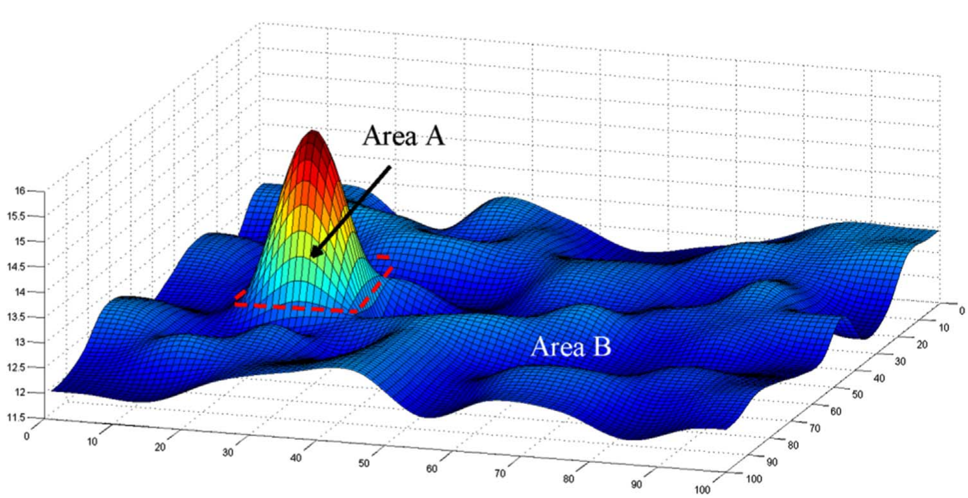

Fig. 1. Diagram of special terrain.