Research on Iterative Closest Contour Point for Underwater Terrain-Aided Navigation

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Abstract. In order to provide underwater vehicle high-precision navigation information for long time, the coordinate properties of underwater terrain can be used to aid inertial navigation system (INS) by matching algorithm. Behzad and Behrooz (1999) introduce iterative closest contour point (ICCP) from image registration to underwater terrain matching and provide its exact form and prove its validity with an example. Bishop (2002) proves its validity systemically. However, their research considers that the matching origin is known exactly while it is seldom satisfied in practice. Simulation results show that ICCP is easy to diverge when the initial INS error is very large (such as 3km). To overcome the drawback, two enhancements are put forward. (1) The matching origin is added into matching process; (2) The whole matching process is divided into two phases: the coarse and the accurate. The coarse matching rules include mean absolute difference (MAD) and mean square difference (MSD) which is usually applied in terrain contour matching (TERCOM). The accurate matching is the ICCP optimization. Simulation results show that the updated ICCP matches application conditions very well and it is convergent with very high precision. Especially, when INS precision is not high, the updated ICCP matching process is more stable and its precision is higher than TERCOM's.

Keywords: ICCP, TERCOM, Pattern Recognition, Map Matching, Terrain-Aided Navigation.

1 Introduction

To provide underwater vehicle high-precision navigation information for long time, the coordinate property of underwater terrain can be used to aid inertial navigation system (INS) by matching algorithm. It is called terrain-aided navigation (TAN). A TAN system shown in Fig.1 is mainly composed of INS, sonar, terrain map, and matching algorithm. The core of the system is matching algorithm. The important part of matching algorithm is map pattern recognition and the recognition correctness decides the matching precision. Different recognition methods lead to different matching algorithms, such as terrain contour matching (TERCOM), Bayes, and etc. Since sonar is a single-point sensor, the matching process is one dimension. In order to improve matching precision, a series of measured points rather than a point are

accumulated to match with map. It is a kind of correlation matching which depends on terrain fluctuation and structure. With the appearance of underwater sonar array and multi-beam sonar, it is also possible to develop two-dimension matching algorithms. This article focuses on one-dimension matching algorithm. [1-8]

Fig. 1. The Scheme of Underwater Terrain-Aided Navigation System

Iterative closest contour point (ICCP) is a common image registration algorithm. Article [9] introduces ICCP to underwater TAN and provides its principle and procedure and proves its validity with an example. Article [10] proves its validity with different application conditions further. The other articles are also based on and similar with the research of the article [9, 10]. However, it is assumed in the articles that the matching origin is exactly known while it is seldom happened in practice except that INS is accurately aligned initially. In fact, due to the difference of underwater terrain fluctuation, some regions are suitable for matching while the others are unsuitable, i.e. there are matchable and unmatchable regions. In an unmatchable region, INS alone provides underwater vehicle navigation information and its error is accumulated with running time. When vehicle has passed an unmatchable region and then enters a matchable one, it is unsuitable to consider that the matching origin is exactly known any more due to the accumulated INS error. Therefore, it is necessary to update ICCP so that it can also be applied when the initial INS error is large, such as 2~5 nautical miles. (1 nautical mile is about 1.852 kilometer.)

As to the limitation of ICCP in principle when the initial INS error is very large, two enhancements are made firstly. Then, the updated ICCP is proved by simulation. In the end, the advantages of the updated ICCP are concluded by comparison with the existed ICCP and TERCOM.

2 Principle

2.1 The Existed ICCP (It Is Called ICCP-A in the Following)[9]

The principle of ICCP-A is shown in Fig.2. There is an actual path (the heavy line shown in Fig.2) which is called ‘actual path’ and composed of the points P'_i ($i=1, 2, \dots, M$) and M is the path length. INS provides a measured path (the fine line shown in Fig. 2) which is called ‘INS path’ and composed of the points P_i ($i=1, 2, \dots, M$). At the same time, sonar provides the corresponding measured

water depth values c_i ($i=1, 2, \dots, M$) and each depth value corresponds to a contour. Due to INS error, there is difference between P_i and P_i' inevitably. The thought of ICCP is that P_i' should lie in c_i -contour and then P_i should be moved to the estimated points P_i'' ($i=1, 2, \dots, M$), which compose 'estimated path', and approached the contour with a certain rule. The approach process is realized by optimization.

Fig. 2. The Sketch of the Current ICCP Algorithm

2.2 The Enhancement I (It Is Called ICCP-B in the Following)

The principle of ICCP-B is shown in Fig.3. The only difference between ICCP-B and ICCP-A is that the matching origin is also adjusted as a point of the matching path in ICCP-B while it is not adjusted in ICCP-A. Similar with ICCP-A, we can also establish the subject of optimization as follows:

$$E = d(\mathbf{x}_1, \mathbf{a}_1) + \sum_{i=2}^M d(\mathbf{x}_i - \mathbf{x}_{i-1}, \mathbf{a}_i - \mathbf{a}_{i-1}) + K \sum_{i=1}^M d(\mathbf{x}_i, \mathbf{y}_i), \tag{1}$$

in which E is the subject or the total constrain error, $d(\mathbf{p}, \mathbf{q})$ the Euclidean distance between $\mathbf{p}$ and $\mathbf{q}$, $\mathbf{x}_i$ the estimated position of P_i'' , $\mathbf{y}_i$ the closest contour point or projection of $\mathbf{x}_i$ in c_i -contour, $\mathbf{a}_i$ the INS measured position, and K stiffness coefficient. As shown in Eq.(1), the first two items of the right side is to restrict the

Fig. 3. The Sketch of ICCP-B

estimated path in the vicinity of the INS path and the third is to make the estimated path approach to the sonar measured value contour.

Shown in Fig.4 is the influence of vehicle speed and heading errors on one-step running. ρ_i and θ_i in Fig.4 are vehicle speed and heading errors respectively. $\mathbf{b}_{i+1}$ is the unit vector along $(\mathbf{a}_{i+1} - \mathbf{a}_i)$ and $\mathbf{e}_{i+1}$ is the unit vector perpendicular to $\mathbf{b}_{i+1}$ (i.e. $\mathbf{b}_{i+1}$ rotated 90° counter-clockwise). The following equations can be expressed according to Fig.4.

Fig. 4. The Influence of Vehicle Speed and Heading Errors on One-step Running

$$\begin{aligned} \mathbf{x}_i &= \mathbf{x}_{i-1} + (\|\mathbf{a}_i - \mathbf{a}_{i-1}\| + \rho_i)(\cos \theta_i \mathbf{b}_i + \sin \theta_i \mathbf{e}_i), \quad i > 1; \\ \mathbf{x}_1 &= \mathbf{a}_1 + \rho_1(\cos \theta_1 \mathbf{b}_1 + \sin \theta_1 \mathbf{e}_1), \quad i = 1. \end{aligned} \quad (2)$$

If ρ_i and θ_i are small and the second and higher order items are ignored, Eq.(2) can be approximated as follows.

$$\begin{aligned} \mathbf{x}_i &\approx \mathbf{x}_{i-1} + \mathbf{a}_i - \mathbf{a}_{i-1} + \rho_i \mathbf{b}_i + \zeta_i \mathbf{e}_i, \quad i > 1; \\ \mathbf{x}_1 &\approx \mathbf{a}_1 + \rho_1 \mathbf{b}_1 + \zeta_1 \mathbf{e}_1, \quad i = 1, \end{aligned} \quad (3)$$

in which $\zeta_i = \|\mathbf{a}_i - \mathbf{a}_{i-1}\| \theta_i$ and $\zeta_1 = \rho_1 \theta_1$. Substitute Eq.(3) into (1) and obtain

$$E = \sum_{i=1}^M (\rho_i^2 + \zeta_i^2) + K \sum_{i=1}^M \|\mathbf{x}_i - \mathbf{y}_i\|^2. \quad (4)$$

If $\mathbf{a}_i$, ρ_i , and θ_i are known, $\mathbf{x}_i$ ($i = 1, 2, \dots, M$) can be calculated by Eq.(3). $\mathbf{a}_i$ is the INS measured position and known, so $\mathbf{x}_i$ is the function of ρ_i and θ_i . Moreover, $\mathbf{y}_i$ can be decided by $\mathbf{x}_i$, so it is the implicit function of ρ_i and θ_i .

It is a nonlinear optimization problem in $\{\rho_i, \theta_i\}$. The simplex method, which does not require the gradient, can be used to solve the minimization problem.

2.3 The Enhancement II (It Is Called ICCP-C in the Following)

It is known by comparing Fig.1 with 2 that ICCP-B is more adjacent to the practice than ICCP-A. However, it can be deduced that ICCP-B is still based on the following two hypotheses.

- (1) The vehicle actual position is in the vicinity of the INS measured position.
- (2) The vehicle actual position is in the vicinity of the sonar measured contour.

The hypothesis (2) is the basis of matching and can be satisfied if sonar's error is low enough. However, the hypothesis (1) can not be satisfied if the initial INS error is much large, which may lead to the divergence of ICCP-B. If a coarse matching is implemented before ICCP is applied, a coarse matched path, which should be closer to the actual path than the INS path, will be obtained. In the following accurate matching, the INS path is substituted with the coarse matched path and the following procedure is same as ICCP-B.

Mean square difference (MSD) and mean absolute difference (MAD), two of TERCOM matching rules, are applied here to construct the coarse matching. The two rules are expressed in Eq.(5) and (6).

$$J_{\text{MAD}}(x, y) = \frac{1}{M} \sum_{i=1}^M \left[\left| h_t(i) - h_m(i) - (\bar{h}_t - \bar{h}_m) \right| \right], \quad (5)$$

$$J_{\text{MSD}}(x, y) = \frac{1}{M} \sum_{i=1}^M \left\{ \left[h_t(i) - h_m(i) \right] - (\bar{h}_t - \bar{h}_m) \right\}^2, \quad (6)$$

in which $J_{\text{MAD}}(x, y)$ and $J_{\text{MSD}}(x, y)$ are the MAD and MSD values at the point (x, y) , $h_t(i)$ the water depth of the i -th point in the estimated path in map, $h_m(i)$ the water value of the i -th point in the sonar measured path, $\bar{h}_t$ and $\bar{h}_m$ the mean value of the estimated and sonar measured paths respectively.

If the point at which the minimum MAD value is obtained is same as the point at which the minimum MSD value is obtained, the path at the point in map is the coarse estimated path. Otherwise, the absolute differences between the paths at the minimum MAD and MSD value points and the sonar measured path are calculated. The path with a smaller difference is decided as the coarse estimated path.

Up to now, the coarse matching is completed and the coarse estimated path, which substitutes for the INS measured path in the following accurate matching, is obtained. The accurate matching is same as ICCP-B. This is ICCP-C which is composed of the coarse and accurate matching phases.

3 Simulations

The main simulation conditions are listed in Table 1 and sonar error model is shown in Table 2. The 3-D image of a map is shown in Fig.5. The map is a 473×473 square grid and the grid distance is 58 meters. Its origin is $(0^\circ, 0^\circ)$. The simulation origin is $(0.03976^\circ, 0.151599^\circ)$ and vehicle sails along longitude from west to east. The path

length M is 10 points. The compared object is matching error. In Table 1, g is gravity acceleration and 0.02° longitude (or latitude) error is about 3.149km. In Table 2, h is water depth.

Shown in Fig.6 are the simulation results of ICCP-A, ICCP-B, ICCP-C, and TERCOM.

Fig. 5. The 3-D Image of the Map

Table 1. The Main Simulation Conditions

Vehicle	Initial Longitude and Latitude Errors ($^\circ$)	0.02
	Sample Step (s)	14
	Speed (m/s)	4
Gyroscope	X-axis Bias ($^\circ/\text{h}$)	0.001
	Y-axis Bias ($^\circ/\text{h}$)	0.001
	Z-axis Bias ($^\circ/\text{h}$)	0.001
	X-axis Random Walk ($^\circ/\text{h}^{1/2}$)	0.001
	Y-axis Random Walk ($^\circ/\text{h}^{1/2}$)	0.001
	Z-axis Random Walk ($^\circ/\text{h}^{1/2}$)	0.001
Accelerator	X-axis Bias (g)	1×10^{-5}
	Y-axis Bias (g)	1×10^{-5}
	Z-axis Bias (g)	1×10^{-5}
	X-axis Random Walk ($\text{g} \cdot \text{s}^{1/2}$)	1×10^{-5}
	Y-axis Random Walk ($\text{g} \cdot \text{s}^{1/2}$)	1×10^{-5}
	Z-axis Random Walk ($\text{g} \cdot \text{s}^{1/2}$)	1×10^{-5}

Table 2. Sonar Error Model

Depth (m)	Error
0~10	0.1m
10~100	$0.4\% \times h$
100~300	$0.6\% \times h$
300~1000	$0.8\% \times h$
1000~8000	$1\% \times h$
>8000	Not Workable

(a) ICCP-A and ICCP-B; (b) ICCP-B and ICCP-C; (c) ICCP-C and TERCOM; (d) TERCOM and ICCP-C with low-precision INS

Fig. 6. The Comparison of Simulation Results

It is known from Fig.6 (a) that the ICCP-B matching error is smaller than the ICCP-A's about 800m. The result proves that adjusting the matching origin with other points of the estimated path simultaneously in ICCP-B matches the condition that the initial INS error is very large (about 3.149km), but the optimization process is very difficult to converge. In programming, there is a threshold value for iterated times, i.e., when iterated times is larger than the threshold value, the optimization is terminated and the current path is put out. The path is just a local suboptimum usually. In fact, the latter part of the ICCP-B simulation shown in Fig.6 (a) is divergent and the

INS path is put out. The result shows that ICCP-B is also easy to diverge and its matching error is still too large to be used.

Shown in Fig. 6 (b) is that ICCP-C converges quickly and its matching error is reduced sharply and the convergent error is about as low as 200m. The result proves that the introduction of the coarse matching shrinks the searching window of the following accurate matching remarkably, which makes the accurate matching applied in the vicinity of the actual path and easy to converge. The enhancement is more effective.

Shown in Fig. 6 (c) is that the matching results of ICCP-C and TERCOM are similar except that ICCP-C's precision is higher than TERCOM's in some segments. The results show that the two algorithms' results are very good under the conditions.

Shown in Fig. 6 (d) are the matching results of ICCP-C and TERCOM under the other simulation conditions. The only differences between the conditions include all gyroscope bias and random walk values changing from 0.001 to 0.01 and all acceleration bias and random walk values changing from 1×10^{-5} to 1×10^{-4} . That is, the INS' precision here is much lower than the former. The results show that ICCP-C's matching precision is higher than TERCOM's. The main reason is that there is the optimization further in ICCP-C after the coarse matching and the estimated path is moved closer to the actual path by the optimization. There is no such adjusting procedure in TERCOM so that its matching result is easy to be influenced by the shape of the INS path. Especially, when INS' precision is low, there is much large difference between the INS path and the actual path, which will lead to much large miss-matching in TERCOM. The results prove that ICCP-C is more applicable than TERCOM due to the existence of optimization.

The results show that ICCP-C is the effective fusion of ICCP-B and TERCOM. Firstly, the MAD and MSD rules in the coarse matching can reduce the following accurate matching scope and decrease the chance of miss-matching sharply, which benefits improving matching precision and increasing the convergence speed; secondly, the optimization in the accurate matching can promote matching precision further and the advantage of the existence of the optimization is more obvious especially when INS' precision is low.

4 Conclusions

By analyzing the current ICCP, i.e. ICCP-A, and the application conditions, two enhancements are put forward.

- (1) Add the matching origin into matching process and construct the updated algorithm ICCP-B.

- (2) Construct the coarse matching by referring the MAD and MSD rules from TERCOM. The accurate matching is same as ICCP-B. The updated algorithm ICCP-C has two matching phases: the coarse and the accurate.

The simulation results prove the following points.

- (1) The two enhancements are effective and ICCP-C's precision is highest under the same simulation conditions.

- (2) The enhancement that adding the matching origin into matching process makes the updated ICCP, i.e. ICCP-B, is more coincident with the application conditions

than ICCP-A and is beneficial to improving matching precision, but ICCP-B is still easy to diverge due to the local suboptimal rather than the global optimal path is found when the initial INS error is large (such as 3km).

(3) The convergence speed and matching precision of ICCP-C are improved sharply due to the introduction of the coarse matching. Compared with TERCOM, ICCP-C's application scope is larger and its matching precision is higher especially when INS' precision is low. The main reason is that the existence of the coarse matching makes the optimization applied in the vicinity of the actual path, which matches the application conditions, and the optimization can improve the matching precision further. When the shape of the estimated path is much different from the shape of the actual path due to the low INS precision, the advantage of the existence of the optimization in ICCP-C is more prominent.

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