

UNDERWATER TERRAIN AIDED NAVIGATION BASED ON ACOUSTIC IMAGING

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Underwater terrain aided navigation is applicable to underwater vehicles during long missions. It relies on a prior known ocean bathymetric map and collected in-situ sonar data to determine the position of the vehicle. The performance of the navigation system depends on the sea floor characteristics and algorithms that are used to match those two sets of data. In this paper, a novel idea is proposed for treating bathymetric maps and in-situ sonar data as images. A variety of existing algorithms developed for image processing can then be applied to obtain position fixes. Texture features extraction, image interpolation and image registration were tested using available bathymetric data and synthesized sonar data collected in-situ. Simulation results indicate that the chosen image analysis methods are capable of providing robust position fixes in suitable cases. The image characteristics extracted from the underwater terrain data are shown to be rotation and scale invariant. As the resolution of multi-beam bathymetry sonars keeps improving with technology advances, the use of image analysis techniques facilitates underwater terrain aided navigation for a wide range of new applications will expand.

INTRODUCTION

In many applications, precise navigation is required to operate autonomous underwater vehicles (AUVs). Since GPS is not available underwater, AUVs depend on autonomous navigation particularly for long-lasting and extended missions. In order to achieve this, navigation methods using geophysical characteristics have been proposed as a supplementary means for the inertial navigation system (INS) [1]. For an AUV equipped with multi-beam bathymetric sonar, terrain aided navigation (TAN) techniques can be applied [2, 3].

Underwater TAN (or UTAN) is a relatively new approach [4, 5, 6]. Similar to terrain-based navigation systems, UTAN has two basic requirements. Firstly, the AUV should be equipped with a digital terrain map (DTM) of suitable resolution. Secondly, the actual

area where UTAN will be used must have some degree of depth variations for precise estimation of the fixes. UTAN avoids not only the costly pre-deployment of underwater transponders but also the cable connection between the AUV and its surface base platform. Multi-beam bathymetry sonar is an excellent system for UTAN, as it can cover a large area below the AUV (swath) and provide 3D underwater terrain information in real time. A multi-beam bathymetry sonar, RESON 7125 [7] data, were used for this paper.

This paper investigates the possibility of using image analysis methods in the underwater terrain matching process. Underwater terrain data collected by multi-beam bathymetry sonar can be treated as images to extract the texture features in order to characterize the terrain uniquely. Image texture analysis can be successfully used to detect texture features even for a relatively flat bottom.

Section I of the paper contains the explanation of how to convert the multi-beam bathymetric measurements into images as well as the method used for texture extraction. It also gives a detailed description of the underwater terrain matching method in which some adjustments to the texture features are made to improve their resolution. Section II evaluates the performance of the proposed UTAN implementation using actual bathymetric data as well as synthesized in-situ data. Finally, some conclusions and suggestions for future work are given in Section III.

1. IMAGE ANALYSIS METHODS

In this paper, bathymetric data collected a previously by a multi-beam system from a surface vessel were used as the surface reference data (SRD). Those data present water depth at the footprint of each beam together with its position in the 2D plane. A subset of the SRD will subsequently be used to synthesize multi-beam data collected by the AUV traveling along a given trajectory. The data collected by the AUV is called multi-beam navigation measurement (MNM) and it must be related to SRD. This will involve errors associated with sound speed uncertainty, angular and scale distortions, as well as noise; all affect errors of fixes [8].

A. Image Interpolation

The widely used gridding methods [9] were not used in this paper because they would suppress high-frequency information, including texture features, thereby producing a low resolution image. Instead, DTM was constructed using all bathymetric measurements available. Since the measurements points are unevenly distributed, interpolation techniques are needed to calculate the missing points to form a continuous underwater terrain image.

Biharmonic spline interpolation, called V4 interpolation, uses the method documented in [10]. Fig. 1 shows the interpolation result with V4 interpolation in a 3D model as well as a contour plot. This contour plot illustrates that the underwater terrain model obtained by V4 interpolation provides the naturally appearing bottom topography. Based on this, the V4 interpolation method was chosen as the tool for underwater terrain image construction. The process of reconstruction means that each point in the 3D model corresponds to a pixel in the underwater terrain image, and the gray level of each pixel represents the depth value of the corresponding 3D point.

B. Texture Feature Extraction [vertical space]

Regional characteristics of images were used to describe different images in the

matching process between the in-situ image and the DTM. The goal is to find the fixes of the AUV in an actual area.

Many regional characteristics are invariant in rotation, position and scale. This can be used to reduce noise effects. The classical texture analysis tool, using a gray level co-occurrence matrix (GLCM), extracts texture information such as direction, interval, amplitude and rate of variation [11]. Furthermore, GLCM's quadratic statistic is used more often than GLCM itself. Barald [12] suggested that only four parameters are actually needed, namely energy (E), contrast (I), correlation (C) and inverse difference moment (L). Those four parameters were chosen in this paper for discriminating texture patterns in underwater terrain images.

Tab. 1 presents the four GLCM statistical parameters for each underwater terrain image constructed from three 3D underwater terrain models shown in Fig. 2 in four directions, 0°, 45°, 90° and 135°, respectively. It can be concluded that contrast is the most useful parameter in underwater terrain discrimination, whereas inverse difference moment and energy stand in 2nd and 3rd place, respectively. This ranking is helpful to weight their contribution in the matching process.

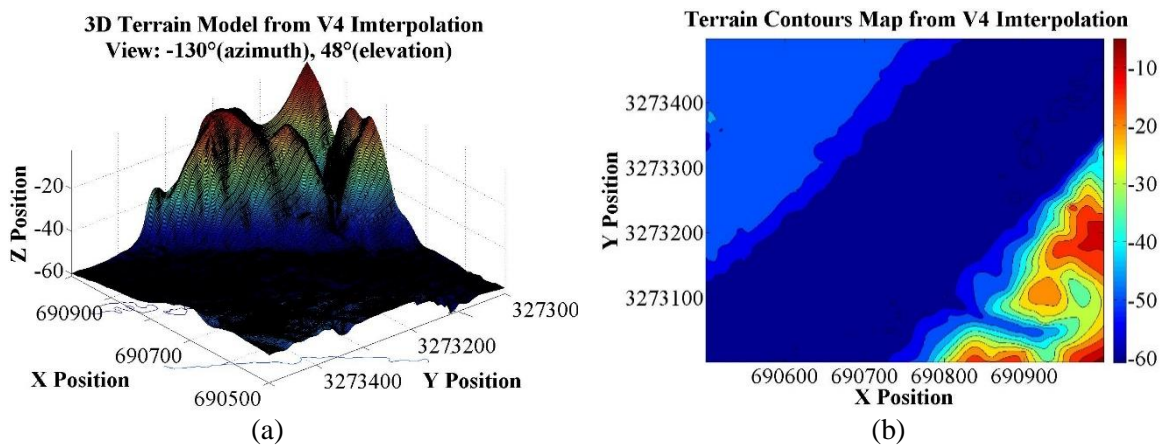
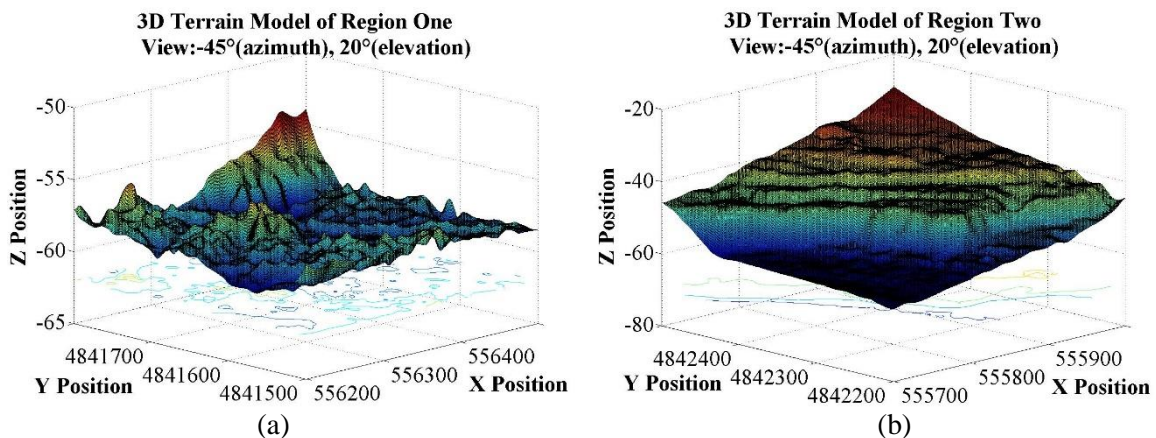


Fig. 1. V4 Interpolation results in 3D terrain models and contour maps.



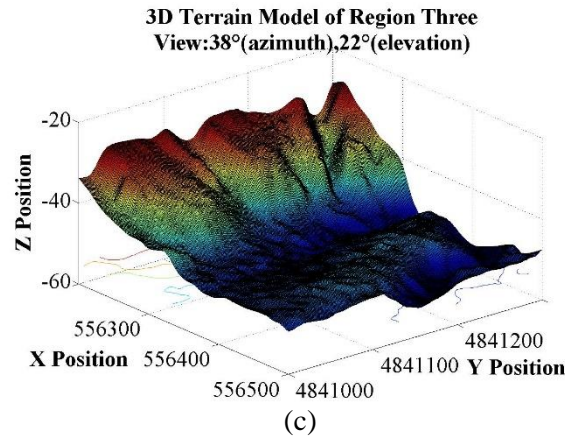


Fig. 2. Underwater Terrain Images of 3 Different Areas.

Tab. 1. GLCM statistical parameters of Fig. 2.

		Contrast (<i>I</i>)	Correlation (<i>C</i>)	Energy (<i>E</i>)	Inverse Different Moment (<i>L</i>)
0°	Fig. 3(a)	3.3239	0.99759	0.0024814	0.57189
	Fig. 3(b)	1.0728	0.99988	0.0028712	0.74266
	Fig. 3(c)	2.2751	0.99978	0.0025847	0.60234
45°	Fig. 3(a)	7.3179	0.99468	0.0019583	0.50251
	Fig. 3(b)	0.73543	0.9999	0.0029343	0.7871
	Fig. 3(c)	3.3465	0.99966	0.0026503	0.61333
90°	Fig. 3(a)	4.3119	0.99692	0.0024666	0.55739
	Fig. 3(b)	0.89196	0.9999	0.0030837	0.7715
	Fig. 3(c)	1.7071	0.99978	0.0035397	0.71568
135°	Fig. 3(a)	7.5319	0.99456	0.0017228	0.47477
	Fig. 3(b)	2.8707	0.99972	0.002177	0.63286
	Fig. 3(c)	4.2873	0.99949	0.002019	0.55528

C. Adjustments [vertical space]

The performance of UTAN depends not only on the characteristics used in the matching process, but also on terrain navigability. Parameters responsible for terrain navigability are derived from depth measurements including mean and standard deviation of the depth data, roughness, entropy, difference entropy and correlation coefficient of the bottom, and they reflect the inherent quality of an actual area with respect to dispersion, degree of concentration and smoothness. These terrain navigability parameters are often used to determine the relationship between terrain types and their impact on the success or failure of navigation. The definitions of the parameters listed above are available in [13] and [14], and their values from the terrains shown in Fig. 2 are presented in Tab. 2.

The four texture parameters are added to the six terrain navigability parameters to form an underwater terrain feature column vector. To address the possible different contributions of each component, suitable weights are applied. The weights, namely $\alpha_1, \alpha_2, \dots, \alpha_{10}$, are used to differentiate each corresponding element and the feature vector is defined as (1).

$$\vec{F} = [\alpha_1 E, \alpha_2 I, \alpha_3 C, \alpha_4 L, \alpha_5 \bar{z}, \alpha_6 \sigma, \alpha_7 r, \alpha_8 R, \alpha_9 H_f, \alpha_{10} H_e]^T \quad (1)$$

Here, the weight vector was selected based on a subjective assessment of the results obtained by simulations.

Tab. 2. Terrain Navigability Parameters of Fig. 2.

Parameters	Value		
	Fig. 2a	Fig. 2b	Fig. 2c
Mean of Depth (\bar{z})	-58.3976	-46.403	-45.6234
Standard Deviation of Depth (σ)	0.70528	7.2319	7.5353
Terrain Roughness (r)	0.46094	3.4228	3.4668
Terrain Entropy (H_f)	16.4575	16.4402	16.4367
Terrain Difference Entropy (H_e)	15.9522	16.1374	16.1251
Terrain Correlation Coefficient (R)	0.98904	0.997495	0.99678

2. RESULTS OF SIMULATIONS

Three different test results using bathymetric data from a lake are presented. The data was post-filtered to eliminate the outliers. The resolution of the underwater terrain images constructed from the area of interest (AOI) is 500×500 pixels, corresponding to the area of 500×500 meters. AUV position was given a priori and the in-situ data were simulated in each run. A smaller area around the AUV position was scanned over the AOI to simulate in-situ data modified with added white noise. The simulated data were used to calculate the AUV's position estimation (fix).

The UTAN algorithms run recursively until the whole AOI is continuously scanned. The best position estimates are used as fix updates for INS. Among common correlation algorithms, mean square difference (MSD) [15] performs well, so that it was chosen in the following tests to represent the correspondence between the in-situ image and the DTM.

The weights of each underwater terrain parameters selected and used in this section are shown in Tab. 3.

Tab. 3. Weight of Terrain Parameters Used in Simulation.

Parameters	E	I	C	L	\bar{z}	σ	r	R	H_f	H_e
Weights	1	10	10000	10	0.1	1	1	1	0.1	0.1

Fig. 3 shows the matching results in a contour format. For this simulation, white noise was added to the data in order to investigate the noise effect. The ratio of signal power / noise power (SNR) was 10dB. The in-situ data are truncated to form a window aligned with the DTM. This window is then scanned from left to right and from top to bottom in ten pixel steps over the DTM area to determine the degree of the match.

The five distinct windows in Fig. 3 are the top five in similarity ranking among all of the scans. The region within the yellow dotted rectangle is the true AUV location area for which the algorithm is searching. The AUV fix is at the center point of this region. Each of the five local windows covers the fix point, which proves that the proposed terrain features vector is capable of detecting the correct location of the AUV. One of the windows matched the true area exactly, so that its black edge coincide with the yellow dotted line of the true area. In all cases, the SNR must be limited to a certain maximum level which depends on the given terrain area in order to provide reliable results.

Similarly, Fig. 4 shows another matching result. In this simulation, the local area is given a 20° anti-clockwise rotation with respect to the DTM in order to investigate the effect of rotation. White noise at 10dB SNR is added to the in-situ data.

It can be seen that all the windows cover the true position of the AUV, which indicates the robustness of the method with respect to rotation.

The result shown in Fig. 5 demonstrates the effect of the window size. A 5° anti-clockwise rotation and white noise at 10dB SNR were added to the in-situ data. The size of the window was reduced from 100×100 to 50×50 pixels. The searching strategy and step size were the same as in the previous simulations.

The best five windows scattered badly with a window size of 50×50 pixels since there was not enough information contained in these limited points. This performance indicates that the underwater terrain information needed by the method has a certain minimum threshold which depends on the underwater terrain type. However, to investigate this limitation, a database consisting of different kinds of underwater terrain data is required.

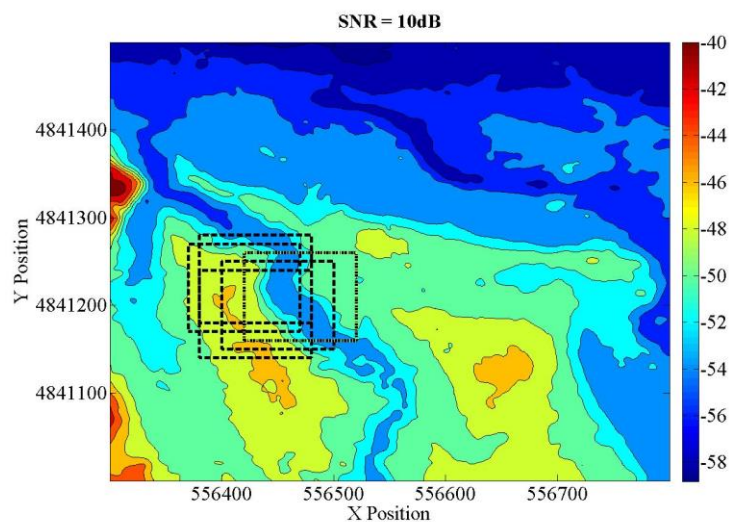


Fig. 3. Terrain Matching Result with Noise.

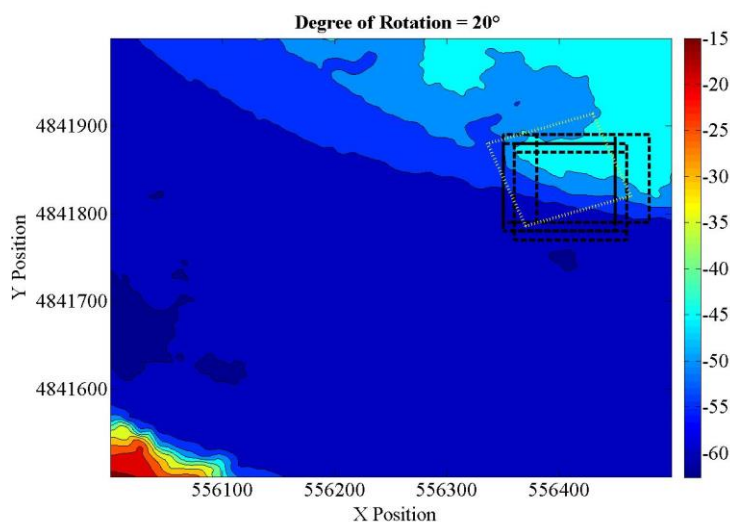


Fig. 4. Terrain Matching Result with Rotation.

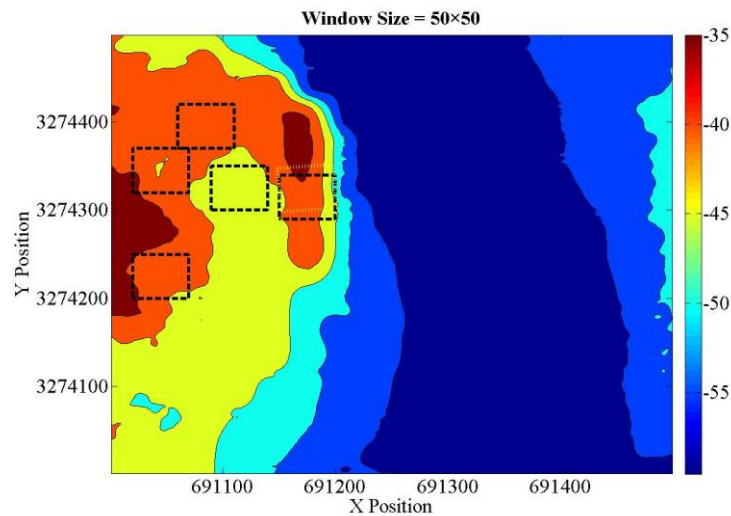


Fig. 5. Terrain Matching Result with Small Window Size.

3. CONCLUSION

The research described in this paper indicates that the selected image analysis methods are suitable for UTAN combined with multi-beam bathymetry sonar data collected in-situ. In the three simulations performed, the matching algorithm succeeded in approximating the position window of the AUV. The GLCM algorithm was used to analyze the underwater terrain images. Terrain navigability parameters were used to supplement the GLCM in order to account for the information pertaining to specific terrain categories. The terrain samples used in this paper established the efficacy of the proposed matching method. However, in case of insufficient information offered by the AOI map, an evaluation for underwater terrain distinctiveness will be required for an actual application. If the planned route of the AUV passes through regions of poor resolution, this could prevent reliable navigation.

In addition to texture features, other image characteristics may also exist in underwater terrain images taken from areas with relatively flat terrain. As a result, involving image analysis methods in UTAN broadens the use of this navigation concept. When planning the route of the AUV, one can determine in advance whether a certain area is suitable for obtaining reliable position fixes. In areas with slight terrain variations but abundant image features, image analysis based navigation methods might provide help to the INS. For example, sidescan sonars could provide a different view of the sea bottom at a higher resolution than that of multi-beam bathymetry sonars. Using such additional data will require developing new image processing methods.

To further the research of the utilization of image analysis in UTAN, more tests are needed with in-situ AUV data. Such measurements from sea trials will enrich the database and enhance the prospects of feature extraction.

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