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13—31

On the 3-D Reconstruction of Seabed Using Multiple Sidescan Sonar Images

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Abstract

This paper proposes an original method for the 3-D reconstruction of seabed from multiple sidescan sonar images. The proposed method adopts a stereo-like vision approach based on a combination of the GPS positioning and the image matching technology to correspond among multiple sidescan sonar images taken from different viewpoints, and then extract the 3-D structure information of seabed from the images according to the relation of the spatial position. This method consists of three stages of processing. First, the sidescan sonar is tracked in 3-D space. Second, based on maximum slant range, the corresponding sub-image is extracted from each sidescan sonar image. Third, the method of multi-step gray-level projective matching is applied to find the corresponding points among the sub-images. Finally, according to the spatial relation in 3-D space, the 3-D structure of seabed is estimated and reconstructed. The experiment with EdgeTech's DF1000 sidescan sonar and JRC's DGPS200 GPS is reported.

1 Introduction

Sidescan sonar plays an important role in ocean investigation, for it provides higher quality underwater acoustic images than other sensors such as optical camera [1]. One of the applications of sidescan sonar is the 3-D reconstruction of seabed [2]. As we know, getting the information about 3-D structure of the seabed is important for safe navigation, positioning of offshore installations such as oil platforms or oil and gas pipes, recognition of topographical features of the seabed etc., so it becomes necessary to find an efficient method for 3-D reconstruction of seabed.

But since typical sidescan sonar is poor for determining accurate bathymetric positions [3], its application was limited in 2-D analysis such as observation, segmentation and classification of seabed. For 3-D analysis, we usually have to deploy multi-beam sonar to obtain the bathymetric measures [4]. This technology based on beam-forming often has less spatial resolution capability, map smaller sectors, so it leads to increase the costs of investigation.

At present, several approaches are developed. Johnson and Herbert applied shape from shading techniques to reconstruct elevation maps of the seabed from sidescan sonar backscatter images and sparse bathymetric points co-registered within the image [5]. This method depends on a scattering model, so depth information was not necessary. But some of the scattering parameters have to be estimated correctly and some parameters have to be set up empirically. Zerr and Stage developed an algorithm to compute the volume information from the shadow information obtained from a sequence of sonar images [6]. Dura, Lane, and Bell extended this work to automatic 3-D reconstruction of mine geometry [7]. In these approaches, only a few sonar parameters, such as the altitude and range are needed and the computational requirements are lower. But the shadow information couldn't always be obtained.

In this paper we thus address the 3-D reconstruction problem of seabed from multiple sidescan sonar images, by a stereo-like vision approach based on a combination of the GPS positioning and the image matching technology to correspond among multiple sidescan sonar images taken from different viewpoints, and then extract the 3-D structure information of seabed from the images according to the relation of the spatial position.

In Section 2 of this paper we present a stereo-like vision model. We describe the algorithms for correspondence of the multiple sidescan sonar images in Section 3. In Section 4, we report experimental result and summarize the conclusions.

2 Stereo-like Vision Model

As we know, the range information is included in the sidescan sonar image, but sidescan sonar image does not directly convey the elevation of the seabed. Because sidescan sonar consists of one cylindrical source that creates a conic acoustic beam pattern that is symmetric around the axis of the source, and it will measure the range to the first surface it encounters within the cone and the intensity or echo of the return, however, the position of the surface cannot be localized within the cone [3].

To solve this problem, we propose a way in which given knowledge of the spatial relation of sidescan sonar imaging, if the same object on the seabed is 'seen' by the sidescan sonar from different positions, it is possible to measure its 3-D position using two or more sidescan sonar images like the stereo vision way of optical camera. We call this technique 'stereo-like vision'.

Geometrically, let us consider two coordinate systems, virtual projective plane coordinate system U-V and object space coordinate system X-Y-Z (Fig.1).

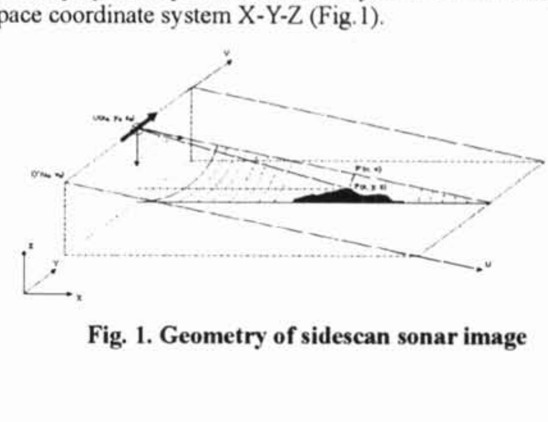

Fig. 1. Geometry of sidescan sonar image

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In the virtual projective plane coordinate system U-V, the distance in the range direction of sidescan sonar corresponds to U-axis, the distance in the azimuth direction of sidescan sonar corresponds to V-axis, and the point P' (u, v) is a projection of the echo intensity from the point P (x, y, z) on the surface of object in the object space coordinate system X-Y-Z. In the object space coordinate system X-Y-Z, X-axis and Y-axis are parallel to U-axis and V-axis respectively. Let O' (u_0, v_0) be original point of U-V and O (x_0, y_0, z_0) be original point of X-Y-Z, the relation between P' (u, v) and P (x, y, z) is ideally given as follow:

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} ((x-x_0)^2 + (z-z_0)^2)^{1/2} \\ y \end{bmatrix} + \begin{bmatrix} u_0 \\ v_0 \end{bmatrix}, \qquad (2.1)$$

where, $y = y_0$.

Now let us assume that sidescan sonar tracked along parallel course (Fig. 2).

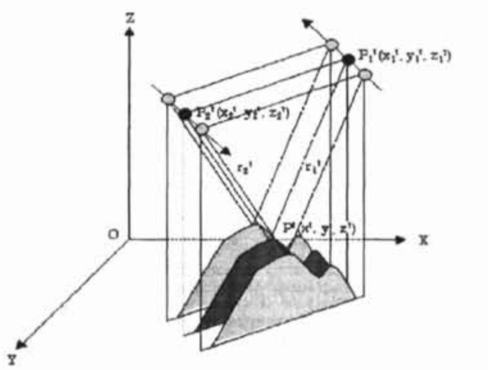


Fig. 2. A spatial series of sidescan sonar images taken at different viewpoints

We can estimate their positions in 3-D space according to the formula of spatial relation as follow:

$$r_i^2 = (x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2 , \qquad (2.2)$$

where, $i = 1, 2, \ldots, n$.

Here, i is the number of viewpoint, (x_i, y_i, z_i) is the position of viewpoint i, and (x, y, z) is the position of the point on the object surface, r_i is slant range from the viewpoint i to the point on the object surface. Since the sidescan sonar tracked along parallel course, we can consider the different (usually two) viewpoints as in same vertical plane, so formula (2.2) can be rewritten to:

$$r_i^2 = (x_i - x)^2 + (z_i - z)^2 , \qquad (2.3)$$

where, $i = 1, 2, \ldots, n$.

There is a problem remained above how to correspond the points that is same point in the real 3-D space between the different images. This is referred to as the matching problem in computer vision, which is considered a challenging task due to its difficulty. Contributing factors to this difficulty include the lack of image texture, object occlusion, and acquisition noise, which yield frequently in real imaging applications [8]. In order to solve such problems, there are a lot of methods developed over the last decades. Generally, they can be classified to two types, area-based and feature-based [9].

In this work, we developed a new method, Multi-step Gray-level Projective Matching (MGPM) with GPS Positioning, which bases on combining the positioning technology of GPS and the matching technology of the computer vision.

3 Algorithms for Correspondence

Step 1: Sensor Tracking in 3-D Space

Sensor tracking is to get a set of position data of sidescan sonar in the real 3-D space.

For horizontal tracking, a set of synthesized GPS data are used. As the GPS is not directly located on the sidescan sonar, it is possible that geometric distortions caused by movement of the sensor that do not rely on onboard navigation measurements [10]. In this work, an experiential value is set as initial layback, and then corrected by the motion estimation method introduced later.

For vertical tracking, as we know, for each impulse, the reverberated signals from the seabed right under sidescan sonar are generally the fastest. It means first bigger change of gray-level from centerline to both sides on the image will be measured. A running mean filter is used to reduce noise and an average depth is considered as the plane of seabed (Fig. 3).

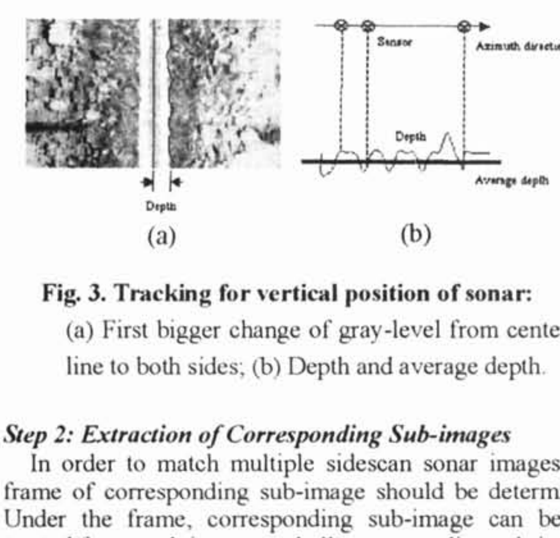


Fig. 3. Tracking for vertical position of sonar:
(a) First bigger change of gray-level from centerline to both sides; (b) Depth and average depth.

Step 2: Extraction of Corresponding Sub-images

In order to match multiple sidescan sonar images, the frame of corresponding sub-image should be determined. Under the frame, corresponding sub-image can be extracted from each image, and all corresponding sub-images can be registered each other to find corresponding points.

First, as the maximum slant range of sidescan sonar should be set up beforehand and the average depth from sidescan sonar to the bottom has been known, the maximum ground range that is covered by the sidescan sonar can be calculated according to the geometry of sidescan sonar image. The slant range image then is projected to the ground range, which the projected image is called 'ground range image'.

Second, as we know, the range direction is orthogonal to azimuth direction, so that the ground range image can be registered to a global 2-D map along the normal direction of the wake of sidescan sonar. Similarly, another overlapped sidescan sonar image can be registered too.

Third, the frame of corresponding sub-image overlapped each other can be determined and the corresponding sub-images can be extracted (Fig. 4).

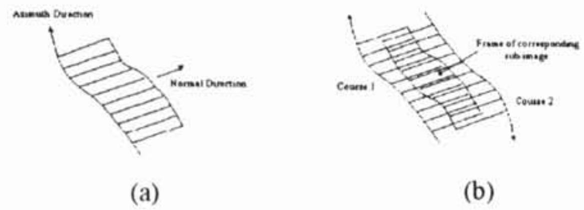


Fig. 4. Frame determination of corresponding sub-images: (a) Register to a global 2-D map; (b) Frame of corresponding sub-images.

Step 3: Multi-step Gray-level Projective Matching

A. Motion Estimation in Azimuth Direction

As explained above, the misalignment of horizontal position exists between the different images. It is difficult to directly synthesize the GPS data and the sidescan data. About motion estimation, a lot of approaches have been developed over the last decades in the several relative fields such as stereovision and analysis of image sequences [11]. In many cases the input sidescan sonar images are strongly corrupted by speckle noise [3]. Therefore, we study methods using gray-level projection to reduce the noise effect.

First, all gray-level of the pixels are projected to the azimuth direction over two images. Let gray-level of the pixel (u, v) and the range width in image f_1 be $G_1(u, v)$ and h_1, respectively. The projective distribution of number u is defined as:

$$P_{Y1}(u) = \frac{1}{h_1} \sum_{v=1}^{h_1} G_1(u, v)\,, \tag{3.1}$$

In same way for image f_2, the projective distribution of number u is defined as:

$$P_{Y2}(u) = \frac{1}{h_2} \sum_{v=1}^{h_2} G_2(u, v)\,. \tag{3.2}$$

Next, Getting a center part where larger motion estimation may be looked for from the projective distribution for each image, let P_{Y1} be as reference, shifting P_{Y2}, compare these two projective distributions (Fig. 5). The motion estimation will be found when the difference between these two projective distributions is the smallest. The difference degree D_Y is defined as:

$$D_Y = \sum | P_{Y1}(u) - P_{Y2}(u) |\,. \tag{3.3}$$

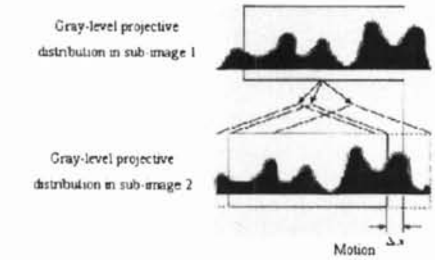


Fig. 5. Motion estimation using gray-level projective distribution

B. Extraction of Feature Points

After the motion is detected and corrected in the azimuth direction, the search area of corresponding points over two images can be limited in a smaller area along the azimuth direction to reduce the computational burden of matching. So, first, we separate the sub-images into several zones along the azimuth direction, and then use the gray-level projective distribution both along the azimuth direction and the range direction in the each zone again. We select the cross points as the feature points where there are bigger changes of the projective distribution (Fig. 6).

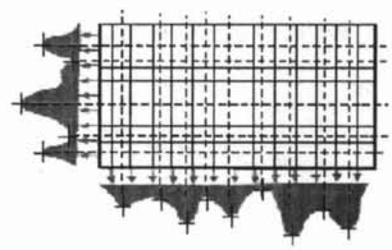


Fig. 6. Extraction of feature points

C. Mutual Matching

After selected the feature points, we match the feature points over the different images.

Since the occlusion problem exists in sidescan sonar imaging, we use a mutual matching between the different images [12]. First, let one feature point in image f_1 is as reference; search the corresponding point in the image f_2. Next, let the feature point found above step in image f_2 is as reference, search the corresponding point in the image f_1. Just only mutual matching is successful, the points are considered as confident correspondent ones (Fig. 7).

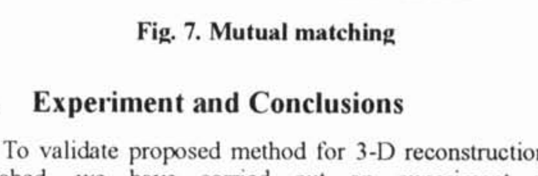


Fig. 7. Mutual matching

4 Experiment and Conclusions

To validate proposed method for 3-D reconstruction of seabed, we have carried out an experiment with EdgeTech's DF1000 sidescan sonar and JRC's DGPS200 GPS in Seto inland sea, Japan.

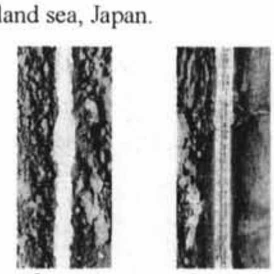
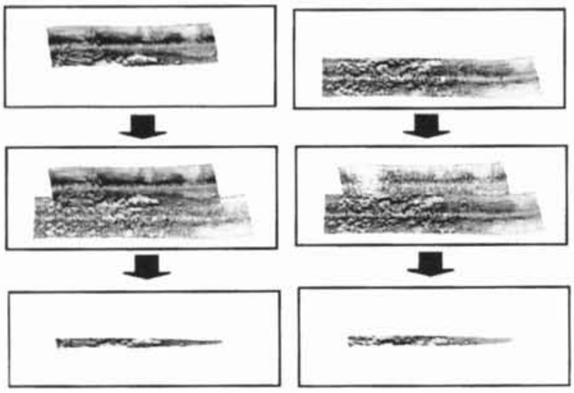


Fig. 8. A pair of input sidescan sonar images

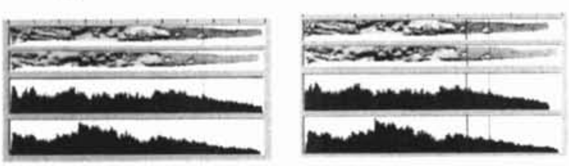
Fig.8 is a pair of input sidescan sonar images taken along a set of parallel courses.



(a) (b)

Fig. 9. Extraction of corresponding sub-images: (a) Image 1; (b) Image 2.

Fig. 9 shows a process for extraction of corresponding sub-images.



(a) (b)

Fig. 10. Result of motion estimation and correction in azimuth direction: (a) Before correction; (b) After correction.

Fig.10 shows a result of motion estimation and correction in azimuth direction using gray-level projective distribution.

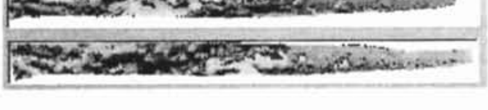


Fig. 11. Result of mutual matching

Fig.11 shows a result of feature points matching over two images.

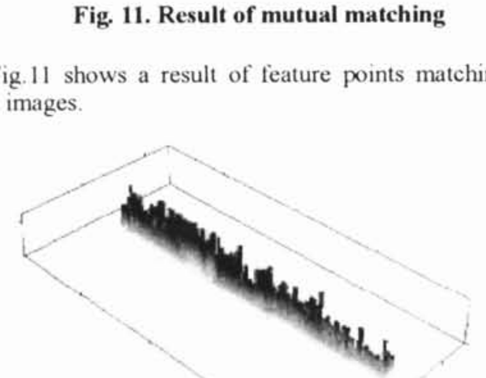


Fig.12. The 3-D reconstruction of seabed

Finally, the 3-D structure of seabed was estimated by using a pair of range data sets obtained by matching feature points over two images. Fig.17 shows the result.

In this paper, we have presented a stereo-like vision approach to the 3-D reconstruction problem from multiple sidescan sonar images, which used a combination of the GPS positioning and the image matching technology. The multi-step gray-level projective matching was applied to match the corresponding points between the corresponding sub-images. The experimental result showed the proposed method is valid.

References

[1] Japan Society for Marine Surveys and Technology, Frontier of Ocean Investigation: To Measure Ocean, 1993.

[2] Y. Lu and M. Oshima, "3-D reconstruction of the seabed using multi-view underwater acoustic images", IPSJ SIG Notes, vol. 2002, no. 84, pp. 33-40, Sept. 2002.

[3] John P. Fish and H. Arnold Carr, Sound Reflections, Lower Cape Publishing, Orleans, MA, 2001.

[4] Freddy Pohner, "Technology for mapping and inspection of the ocean seafloor," Korean/Norwegian Workshop on Ocean Mining, pp. 31-46, Seoul, 1997.

[5] A. E. Johnson and M. Herbert, "Seafloor map generation for autonomous underwater vehicle navigation," Autonomous Robots, vol. 3, 2-3, (Jun-Jul 1996), pp. 145-168.

[6] B. Zerr and B. Stage, "Three-dimensional reconstruction of underwater objects from sequence of sonar images," Pro. International conference on Image processing, vol. 3, pp. 927-930, Sept. 1996.

[7] E. Dura, D. Lane, and J. Bell, "Automatic 3D reconstruction of mine geometries using multiple sidescan sonar images," Goats 2000 Conference, (Aug. 2001).

[8] A. Arsenio and J. Marques, "Performance analysis and characterization of matching algorithms," Pro. The International Symposium on intelligent Robotic System, Stockholm, Sweden, July 1997.

[9] Takeo Kanade and Masatoshi Okutomi, "A stereo matching algorithm with an adaptive window: theory and experiment," IEEE trans. PAMI, vol. 16, no. 9, pp. 920-932, 1994.

[10] D. T. Cobra, A. V. Oppenheim, and J. S. Jaffe, "Geometric distortions in sidescan sonar images: a procedure for their estimation and correction," IEEE J. Oceanic Engineering, 17 (3), pp. 252-268, 1992.

[11] T. Huang and A. Netravali, "Motion and structure from feature correspondences: A review," Proc. IEEE, vol. 82, No. 2, pp. 252-268, 1994.