Study on Side Scan Sonar Image Matching Based on the Integration of SURF and Similarity Calculation of Typical Areas

Jianhu Zhao[1], Weiliang Tao[1], Hongmei Zhang[2], Kun Yang[3]
[1]School of Geodesy and Geomatics Wuhan University，Luoyu road 129, Wuhan city, China
taowl2003@126.com
[2]Automation Department, Wuhan University Luojia hill, Wuhan city, China
[3]Tianjin Research Institute for Water Transport Engineering, Tianjin city, China

Abstract- **In this paper, a method for side scan sonar image matching is proposed based on SURF and similarity calculating in typical areas. The process is composed of three steps of rough matching, geometric correction and accurate matching. Firstly, rough matching is implemented to get a rough matching relationship of reference image and matching image based on SURF. Then geometric correction is executed with the relationship to make the matching image have a same viewing condition with the reference image. Finally, accurate matching is implemented by similarity calculating of typical areas in two corrected images. This matching algorithm combined the merits of the regional matching and feature matching. Experiment proved that the method has advantages in speed, accuracy, reliability and invariance to geometric differences between two side scan sonar images.**

I. INTRODUCTION

Side scan sonar (SSS) system is generally used for seabed relief investigation, underwater object detection, seabed sediment analysis and so on. SSS image has high resolution and imaging quality. In order to acquire finer seabed relief image, sometimes, multi-time side scan are finished by SSS in a studied area. Thus it becomes necessary to implement the image fusion and get a new, rich-information seabed relief image, while SSS image matching should be firstly done before it. Moreover, if SSS measurement is implemented in two adjacent water areas, an image mosaic processing needs to be done so as to acquire the seabed relief image of the whole area, while the image matching is its basis. Besides, underwater topography or relief navigation becomes a hot research recently, which also needs the matching between the real-time seabed relief image and the background one so as to get the underwater vessel location. In sum, SSS image matching has widely been used in marine applications.

II. RELATED WORK

Recent researches on image matching methods can be divided into two categories. One is region matching, the other is feature matching.

Region matching methods match images with the similarity of gray scale between the regions of both images. For example, Baeza-Yates computes the similarity between two images by approximating the distance between extended region adjacency graphs which are extracted from the images in time and space linear in the number of pixels [1]. Zhang-Shu proposes an image matching method by computing structure similarity of images to medical image fusion [2]. Khalid studies the performance of a similarity measure in grayscale image matching through numerous experiments with different sizes of objects and different kind of movements between the pairs of images [3]. These methods can effectively match images under ideal condition, but often have high computational complexity, long operation time and sensitivity to circumstance noise. Besides, the invariance with respect to scale, rotation and light is hard to achieve.

Feature matching methods extract features, like entropy, corner points, edge points, and compare them to find the matching relationship of the two images. Moravec implements stereo matching with corner operator [4]. Schmid and Mohr realize the recognition of general targets using Harris detector [5]. Mikolajczyk analyzed and compared several most representative matching algorithms currently, such as correlation calculation, invariant moments, the scale invariant feature transform (SIFT) algorithm and so on [6,7]. The results show that SIFT algorithm has the best performance. Bay presents the speed up robust features (SURF) method which is better than SIFT in operation speed and required storage space, and is similar in performance [8]. Feature matching methods, such as SURF, have high matching efficiency, can resist noise, and are easy to get the invariance to scale, rotation and light with additional information on feature points. The main disadvantage of the method is mismatch problem caused by discarding distribution information of features in images.

So combined the two kinds of techniques depicted as above, a SSS image matching based on SURF and the similarity calculation of typical areas is studied and used in this paper.

III. METHODOLOGY

The SSS image matching method proposed in this paper includes three steps. First, rough matching is implemented using SURF operator, which consumes less time to find rough mapping relation in the reference image and a matching image. Then in virtue of the relationship, the geometric correction is

Supported by the National Natural Science Foundation of China (40976061) and the National High Technology Research and Development Program ("863"Program) of China (2009AA12Z311).
978-1-4244-5222-4/10/$26.00 ©2010 IEEE

done for the invariance to scale, rotation and light. Finally, the accurate matching is implemented with similarity between the typical areas of the two images, which are corrected in above operations. So the accurate relation of the matching can be achieved.

A. Rough matching based on SURF algorithm

In the work, the feature matching method is adopted to make the process efficiency. It is important to extract stable features for matching robustness when there are differences between the reference image and the matching image.

SURF algorithm takes local extremum as features in images, but the locations of these extremum will vary with the image scale. The problem is solved with the ideal of image pyramid, in which one layer is an image presentation with a fix scale, and only a point with larger gray value than its neighbors in its scale and adjacent two scales is considered as feature point.

The Hessian matrix [8] is used to determine the location and scale of feature points. If a point is represented by $\mathbf{m}=(x, y)$ in an image $I(\mathbf{m})$, and (x, y) is its coordinates, then the Hessian matrix of pixel $\mathbf{m}$ can be calculated by (1):

$$H=\begin{bmatrix} L_{xx}(\mathbf{m},s) & L_{xy}(\mathbf{m},s) \\ L_{yx}(\mathbf{m},s) & L_{yy}(\mathbf{m},s) \end{bmatrix} \tag{1}$$

Where

$$L_{xx}(\mathbf{m},s)=I(\mathbf{m})*\frac{\partial^2 g(s)}{\partial x^2} \tag{2}$$

The symbol, * , denotes the convolution operation. The $g(s)$ denotes the zero mean Gaussian function, and s is its variance, which represents the image scale. The definitions of L_{xy}, L_{yx} and L_{yy} are similar to L_{xx}.

SURF makes some measures to simplify the process. Such as the second order Gaussian filter is replaced by a mean filter [8], as shown in Fig. 1, and the convolution operation is replaced by image template integration [9] . Changing the size of the mean filter window, the layers with variant scales are formed and the image pyramid is constructed. The local extremum extracted from the image pyramid are stable keypoints.

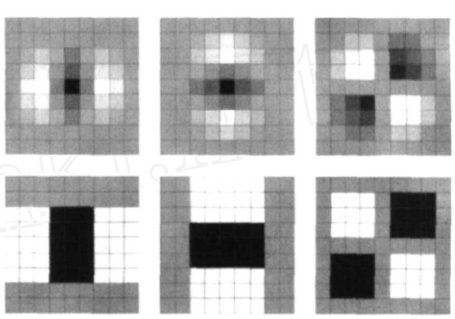

Figure 1. Principal direction searching

To assign a primary direction to a keypoint is available for the invariance to rotation. Primary direction should be determined with neighborhood information of the keypoint. So the keypoint is taken as a center, around which a circle region is enclosed with $6s$ radius. In this region, Haar wavelet responses of every point in x-, y- directions, whose size is $4s$, are calculated to achieve the point direction trend and its intensity. Sum up intensities of all points within 60° of fan-shaped window in the region mentioned above, overall intensity of a direction is achieved as shown in Fig. 2. Sliding the window with an interval of 5° until the whole region has been traversed. The direction with the largest intensity is defined the primary direction of the keypoint, such as Fig. 2(c). Usually a Gaussian function, which centers on the keypoint and has a variance of $2.5s$, is adopted to weight neighbor points before the sum operation is put in practice, so that the responses close to the feature point have great contributions, while those far to the feature point have small contributions.

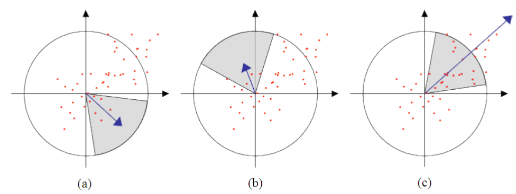

Figure 2. Principal direction searching

Achieved primary direction, keypoint and its neighborhood is rotated to the direction. So all the keypoints are compared in their primary direction, which makes the matching can resist the rotation difference between two images.

The neighborhood information of keypoints should be used to increase the matching robustness. Region Of Interest (ROV) of a keypoint is defined as a square region centered this keypoint with $20s$ length, which can be divided into 16 sub-regions with $5s$ length. In every sub-region a 2D Haar wavelet function with $2s$ size is calculated and the responses in x-, y-direction of a point are denoted wx, wy separately. So a vector $\mathbf{V}_{\text{sub}}$ can be achieved.

$$\mathbf{V}_{\text{sub}}=\left[\sum wx, \sum wy, \sum|wx|, \sum|wy|\right] \tag{3}$$

There are 16 vectors in ROV of a keypoint, which are merged into a vector with 16 × 4 dimensions. After normalized processing, the vector is treated as a keypoint descriptor, which contains the neighbor information of the keypoint and can resist the differences from scale, rotation, and contrast between two images.

Now all descriptors can be extracted from reference image and matching image and then rough matching is implemented with the nearest neighbor matching method. Some measures taken to reduce the mismatching are same with SIFT [6]. The rough matching has fast operational speed and robustness under different viewing conditions.

B. Geometric correction

According to the matching pairs, the mapping relationship between two images can be achieved. The relationship between reference image **R** and matching image **M** can be shown as (4).

$$\mathbf{M} = \mathbf{H} \times \mathbf{R} \tag{4}$$

where, **H** is a transform matrix with information of mapping relationship.

So if **H** is achieved, the relationship between images is achieved, too. In theory, three matching pairs in **M** and **R** are sufficient to resolve **H**. But considering the matching accuracy, mismatching and the distribution of matching pairs, random sample consensus (RANSAC) [10] and the least square method are combined for nonlinear optimization of the resolving processing [11].

Once the relationship is known, the matching image **M** can be adjusted to have similar view, scale and contrast with reference image **R**. The adjusting is preprocessing for next accurate matching based on similarity calculation.

C. Accurate matching based on similarity calculation

Rough matching has advantages over the operation speed and invariance to disturbance, but its shortcoming lies in its mismatching and accuracy of pixel scale in matching pairs.

The similarity calculation is introduced in the matching to compensate above shortcomings, which is implemented to abide following steps.

1) Pick up three pairs of keypoints randomly. To every pairs, a square region, which centers on the keypoint and has fixed size, is implemented segmentation from the matching image and a corresponding square region is also implemented segmentation from the reference image, which centers on the other keypoint and has larger size than it from the matching image.

2) The similarity calculation is done by sliding the matching square region on the reference one. If the maximum similarity is achieved and is more than a given threshold, the accurate matching relation of the pairs is thought to be found. Otherwise, the pairs are thought to be inaccurate or mismatching pair and another pair should be pick up to do the similarity calculation again.

3) Until three accurate pairs are located, relationship between two images can be determined by (4). Using the matrix **H**, the location of one keypoint of every pair in images can be calculated from another, which is compared with real one can verify the accuracy of matching pairs. According to the verified results of all pairs, the entire matching is verified.

4). Repeat the steps 1) ~ 3), until the result of the entire matching is accurate and meets with the matching requirement in accuracy.

IV. Experiment and Analysis

In order to verify the effectiveness of the proposed method in this paper, a side scan sonar image of 3614×7416 pixels of an experimental water area with 3-kiliometer width and 7-kiliometer length is used as a reference image, as shown in Fig. 3.

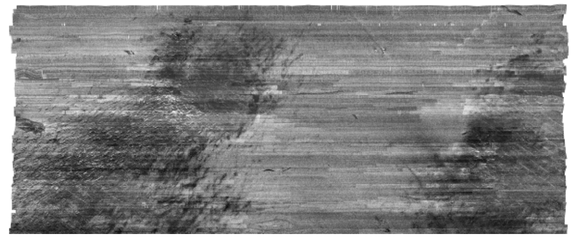

Figure 3. The seabed relief map

Different strip images of 300×50 pixels are extracted out. After the random changes of rotate, scale and contrast, these strip images are used as the real-time side-scan sonar images, namely matching images. The matching processing is implemented between the matching images and the reference image. One matching results is shown in Fig. 4. The figure is clipped and scaled to make them clear.

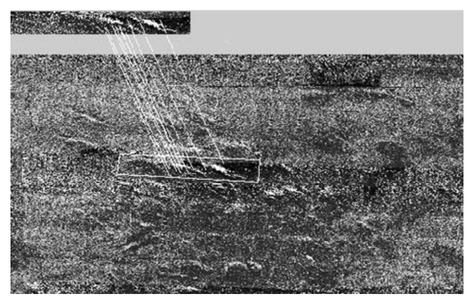

Figure 4. Rough matching result

It can be seen from Fig. 4 that the proper area in reference image is found by the rough matching. Then the integrated matching algorithm mentioned as above is implemented. The accurate mapping relationship is also acquired. In order to evaluate the method objectively, the number of matching pairs and mismatching pairs, the variance of the verifying results and real corresponding keypoints, and time consumption acquired in the experiment are listed in TABLE I.

The experiment shows that the method proposed in this paper has higher performance in consume time, matching accuracy and reliability.

TABLE I
MATCHING SPECIFICATIONS

Matching specifications	Specifications' value
matching pairs number	18
mismatching pairs number	2
Final Variance(m)	0.78
time consumption (s)	2.47

By above experiment, the following advantages of the method based the integration algorithm are found in the SSS image matching.

1) Less operational time consumption

Rough matching has higher matching speed by many simplifying measures from SURF. The algorithm implements the rough match in virtue of some keypoints extracted by SURF, and accurate match in typical areas rather than in whole image. The procedure decreases the time consumption.

2) Invariance to geometric changes

Rough matching is based on SURF whose most valuable property is invariance, so it is invariant to different viewing conditions too. Before accurate matching, geometric correction is executed based on the matching pairs, thus the effect of rotation, scale and contrast between two images are removed. Accuracy matching will not be influenced by these factors.

3) High accuracy

Rough matching is used for finding the corresponding points in the reference image according to the keypoints in the matching image, so its accuracy can reach pixel scale in ideal condition. But in the matching based on the image similarity, the point locations in reference image corresponding to the keypoints in matching image can be accurately acquired. The positioning accuracy can reach sub-pixel scale.

4). High reliability

Similarity calculation is able to distinguish the mismatching pairs and matching ones. In the matching, the iterative operation helps to find accurately appropriate matching pairs, which makes the matching relationship between two images can be determined accurately and has high reliability. Besides, the region matching uses the overall information of keypoint neighborhood area, and thus has more stable result.

V. Conclusion

In this paper, the SSS image matching based on the integration of SURF and similarity calculation of typical areas is proposed. The matching method has high operational speed and invariance to different viewing conditions by using SURF and has high accuracy and high reliability by using similarity calculating. Experiment verifies the effectiveness of the method.

Acknowledgment

This work is supported by the National Natural Science Foundation of China (40976061) and the National High Technology Research and Development Program ("863" Program) of China (2009AA12Z311). Tianjin Research Institute for Water Transport Engineering provides the seabed relief maps.

References

[1] R. Baeza-Yates and G. Valiente, "An Image Similarity Measure Based on Graph Matching," in *String Processing and Information Retrieval, 2000. SPIRE 2000. Proceedings. Seventh International Symposium on*, 2000, p. 28-38.

[2] X. Zhang-Shu and Z. Chong-Xun, "Medical Image Fusion Based on the Structure Similarity Match Measure," in *Measuring Technology and Mechatronics Automation, 2009. ICMTMA '09. International Conference on*, 2009, p. 491-494.

[3] M. S. Khalid, M. B. Malik, M. U. Ilyas, M. S. Sarfaraz and K. Mahmood, "Performance of a Similarity Measure in Grayscale Image Matching," in *Emerging Technologies, 2005. Proceedings of the IEEE Symposium on*, 2005, p. 121- 125.

[4] H. P. Moravec, "Rover Visual Obstacle Avoidance ," in *Proceedings of the 7th international joint conference on Artificial intelligence - Volume 2* , Vancouver, BC, Canada , 1981, p. 785-790.

[5] C. Schmid and R. Mohr, "Local Grayvalue Invariants for Image Retrieval," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 19, p. 530-535, 1997.

[6] D. G. Lowe, "Distinctive Image Features from Scale-invariant Keypoints," *International Journal of Computer Vision,* vol. 60, p. 91-110, 2004.

[7] K. Mikolajczyk and C. Schmid, "A Performance Evaluation of Local Descriptors," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 27, p. 1615-1630, 2005.

[8] H. Bay, T. Tuytelaars and L. van Gool, "SURF: Speeded Up Robust Features," in *9th European Conference on Computer Vision, ECCV 2006, May 7, 2006 - May 13, 2006*, Graz, Austria, 2006, p. 404-417.

[9] V. Paul, "Rapid Object Detection using a Boosted Cascade of Simple Features," in *Computer Vision and Pattern Recognition, IEEE Computer Society Conference on*, 2001, p. 511-511.

[10] Y. Min and S. Chunlin, "A Random Sampling Algorithm for Fundamental Matrix Robust Estimation," *Journal of Applied Sciences,* vol. 22, p. 178-182, 2004.

[11] Z. Ruijuan, Z. Jianqi and Y. Cui, "Image Registration Approach Based on SURF," *Infrared and Laser Engineering,* vol. 38, p. 160-165, 2009.