Extracting Method of Control Point Pairs for Remote Sensing Image Based on Regional Matching

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Abstract

Remote sensing image registration is the basis of remote sensing image mosaic and fusion, while extracting appropriate control point pairs have great significance to establish the mapping relationship for registration of two remote sensing images. An automatic extracting method of control point pairs is proposed. Firstly, it determines the common areas of two images and divides them into blocks uniformly. The corresponding blocks of the two images are marked with the same sequence number to establish the one-to-one regional matching relation. Then, for each block, the multi-scale Harris corner detection method is adopted to detect image features which are described by feature descriptors of SIFT algorithm. Finally the regional matching strategy is performed to match the features. Experiments show that the proposed method can extract control point pairs with reasonable distribution and high precision, and these point pairs conduct to improve the precision of remote sensing image matching.

Keywords: *Remote Sensing Image, Control Point Pair, SIFT Algorithm, Harris Operator*

1. Introduction

Remote sensing image registration is essential to image mosaic and fusion, and widely used for map updating, environment change prediction, geographic data integration, and so on. While, as one of the key technologies for image registration, extracting appropriate control point pairs have great significance to establish the mapping relationship of two remote sensing images. Most of image registration methods consist of four steps [1-2], feature detection, feature matching, transforming model estimation, image resample and transformation. The most common approach to image registration is to extract some well-defined control point pairs in both reference and referenced image, and then to compute parameters of the transform model. The main difficulty lies in choice of control point pairs. This paper will focus on the feature detection and matching to acquire appropriate control point pairs.

Image registration as one of the most important issues in remote sensing is studies by many scholars. Leila M.G. Fonseca, *et al.*, [3] mainly presented a comparative study of some image registration methods, emphasized in particular techniques for multi-sensor image data. Le Yu, *et al.*, [4] proposed multi-source remote sensing registration technique which performs a preregistration process that coarsely aligns the input image to the reference image by automatically detecting their matching points by using the scale invariant feature transform(SIFT) method and an affine transformation model. Once the coarse registration is completed, it performs a fine-scale registration process based on a piecewise linear transformation technique using feature points that are detected by the Harris corner detector. Image registration is broadly divided into two approaches [5], one is area-based methods and the other is feature-based methods. The feature-based methods usually use the operator like Moravec, Harris, Forstner, Canny, SUSAN and SIFT algorithm or using different wavelet bases [6] to extract image features, the SIFT algorithm shows excellent performance [7, 8] when encounter the geometric distortion, illumination changes, resolution difference, fuzzy, rotation and image compression. Xiaoming Li, *et al.*, [9] introduced SIFT to the field of remote sensing image registration, and used RANSAC algorithm to remove the feature point pairs which has match errors. Yu chen, *et al.*, [10] reprocessed the results which were obtained by the SIFT algorithm by using mahalanobis distance and then improved the accuracy of the feature points. Yan Guo, *et al.*, [11] proposed a registration control point filtering method based on distribution of quality that make the control points are distributed more evenly and thus reduce the registration error. Xiliang Ni, *et al.*, [12] proposed an improved SIFT image registration algorithm, it made two images match points distribute more evenly and improved the speed of image matching significantly. Martin Stommel [13] reduced curse of dimensionality in histogram-based object recognition through using Hamming distance on binary SIFT descriptors.

SIFT algorithm can extract a large number of feature points from a small range of image. These feature points have the invariability of scale and rotation. But because the different sensor might cause inconsistency of light degree, resolution and so on, for some remote sensing image, such as medium or low resolution remote sensing image, SIFT algorithm is difficult to confirm relevant parameters, it can extract only a few feature points which are distributed unevenly. However Harris [14] can extract a large number of corners that cover over full image, but these corners are sensitive to rotation and scale. Considering the advantages of both SIFT and Harris, this paper try to hybrid them to find a solution to extract control point pairs of remote sensing images with reasonable distribution and high precision.

2. Procedure of extracting method

In order to extract reasonable distribution and high precision control point pairs between the reference and referenced remote sensing images, the extracting procedure of control point pairs is shown in Figure 1, and the processing steps are as follows:

① Common region Checking

The geographical scope of two remote sensing images may be different, and generally no control point pairs exist if two images have no common geographical scope. If two images have common regions, then the second step goes on.

② Block division

Common region between two images are divided into block uniformly, and the corresponding blocks which have the same geographic range are given the same sequence number. Block division is beneficial to the following regional matching and can reduce the computation cost to some extent.

③ Feature detecting and description

In order to extract much more features with scale and rotation invariability, two blocks which have the same sequence number are selected to building their multi-scale space, then features are detected in each block by Harris corner detecting method and described by SIFT feature descriptor.

④ Feature matching

Features of corresponding block in two images are matched according to the regional matching strategy. For each block, the ratio of the nearest neighbor and second-closest neighbor is computed based on the feature matching method of SIFT algorithm. If the ratio is less than a threshold, the corresponding feature pair will be selected as the control point pair.

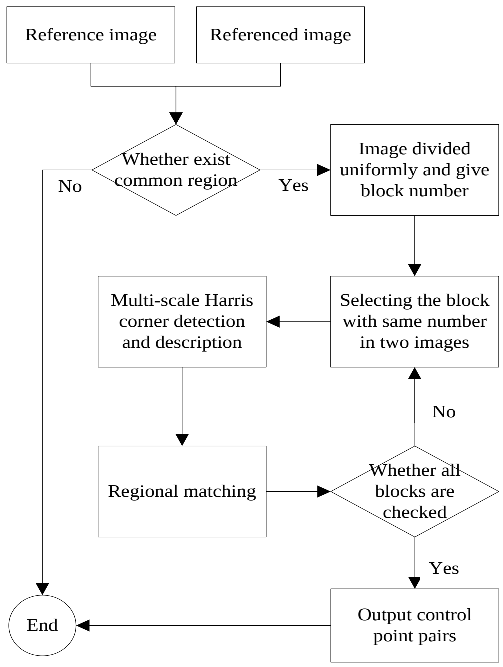

Figure 1. Workflow of the extracting method

3. Implementing Technologies

3.1. Remote sensing image division

To simplify the regional matching, the latitude and longitude are analyzed first to check whether the common areas exist between the reference and referenced image. If there are common areas exist, then divide them into blocks. Assuming that the number of block is $p*q$, the image with the size $P*Q$ will get $(P/p) * (Q/q)$ blocks. For each block, a unique sequence number is assigned and make sure that the blocks which have similar geographic range get the same number. So that, the i-th block in the reference and referenced image are referred to as A_i and B_i respectively.

3.2. Multi-scale Harris corner detection

3.2.1. Multi-scale space building: Harris operator can extract a lot of corners in remote sensing image, but the corners can not adapt to scale changes. In order to ensure these corners to be scale invariant, the multi-scale space theory [15] is introduced into the Harris corner detection method.

The multi-scale space theory is proposed firstly in field of computer vision. Its purpose is to simulate multi-scale features of image, and express the multi-scale and the relationship of different scales. Gaussian pyramid [7] is a valid expression of multi-scale structure. In Gaussian pyramid, many images are defined as an octave, every image in the octave is defined as an interval, the first interval image of the first octave is the original image, the first image of next octave is achieved through the third interval image from the bottom of the front octave by down sampling. The different scale image, $L\left(x,y,k^i\sigma\right)$, in octaves are acquired using formula 1 through the convolution operation in input image , $I\left(x,y\right)$, and Gaussian function, $G\left(x,y,k^i\sigma\right)$.

$$L\left(x,y,k^i\sigma\right)=G\left(x,y,k^i\sigma\right)*I\left(x,y\right) \ . \qquad (1)$$

$$G\left(x,y,k^i\sigma\right)=\frac{1}{2\pi(k^i\sigma)^2}e^{-\left(x^2+y^2\right)/2(k^i\sigma)^2} \ . \qquad (2)$$

Where * is the convolution operation, *(x,y)* is the point in image, $k^i\sigma$ is scale factor, the smaller $k^i\sigma$ is, the more detail feature of the image has, the larger $k^i\sigma$ is, the more general feature of the image has. $k=2^{1/s}$, s is the total intervals of an octave.

3.2.1. Harris corner detection with scale invariability: After creating the multi-scale space and the multi-scale relationship, corners in every scale will be detected by using Harris operator. The corner on image whose scale is $k^i\sigma$ is detected using formula 3.

$$R\left(k^i\sigma\right)=\det\left(M_{k^i\sigma}\right)-m\left(trace\left(M_{k^i\sigma}\right)\right)^2 . \qquad (3)$$

where , $M_{k^i\sigma}$ is a symmetric matrix as following $\begin{bmatrix} L\left(x,y,k^i\sigma\right)_x^2 & L\left(x,y,k^i\sigma\right)_x*L\left(x,y,k^i\sigma\right)_y \\ L\left(x,y,k^i\sigma\right)_x*L\left(x,y,k^i\sigma\right)_y & L\left(x,y,k^i\sigma\right)_y^2 \end{bmatrix}$, $L\left(x,y,k^i\sigma\right)_x$ and $L\left(x,y,k^i\sigma\right)_y$ respectively represent gradient at x , y direction of point*(x,y)* on the scale image $L\left(x,y,k^i\sigma\right)$, $trace\left(M_{k^i\sigma}\right)$ is the trace of matrix $M_{k^i\sigma}$, the empirical value of m is in the range[0.04,0.06], * is the convolution operation, $\det\left(M_{k^i\sigma}\right)$ is the determinant of matrix $M_{k^i\sigma}$.The concrete steps of Harris corner detection with multi-scale space theory is as follows.

① Build multi-scale images of reference and referenced image using formula 1.

② Extract Harris corners on the image whose scale is $k^i\sigma$ using formula 3.

③ Filter out pseudo-corner in multi-scale space. Compare each corner of current and smaller scale images, if both images have this corner, it will be saved, otherwise, delete this corner.

3.3. Describing Harris corner by SIFT feature descriptor

In order to achieve rotational inflexibility, SIFT feature descriptor is used to describe Harris corner. Computing gradient magnitude, *m(x,y)*, and orientation, *θ(x,y)* of pixel point*(x,y)* in every scale space based on formula 4 and 5.

$$m(x,y)=\sqrt{\left(L(x+1,y)-L(x-1,y)\right)^2+\left(L(x,y+1)-L(x,y-1)\right)^2}\ . \tag{4}$$

$$\theta(x,y)=\tan^{-1}\left(\left(L(x,y+1)-L(x,y-1)\right)/\left(L(x+1,y)-L(x-1,y)\right)\right)\ . \tag{5}$$

To achieve rotational inflexibility, firstly calculate gradient orientation histogram of the sample window whose center is the corner, secondly choose the peak of the histogram as the corner direction, thirdly coordinate axis are rotated to the direction of the corner before describing the corner. Choose the $M * M$ sample window whose center is this corner, divided it into $m*m$ small window, so $(M/m)^2$ small windows are generated. Then calculate the eight direction ($0^0, 45^0, 90^0, ...360^0$) of the first small window, get eight gradient value in gradient histogram. Eight gradient values which are sorted based on direction are the first to eighth elements of the corner's feature vector. Then compute the second small window's eight direction gradient values, they are also sorted based on direction and as 9th to 16th elements of the corner's feature vector. In proper sequence, $(M/m)^2$ small windows make up $(M/m)^2 * 8$ element feature vector for each corner. Generally M = 16, m = 4, it can form a 128 dimensional vector.

3.4. Regional matching

The classic SIFT feature matching algorithm use the Euclidean distance and calculate the distance ratio of the closest neighbor and the second-closest neighbor feature points between the reference and referenced image, and determine the final control points by checking whether the ratio exceed a certain threshold. In SIFT algorithm, the threshold was 0.8. During the calculation, the algorithm needs to traverse the entire image feature points. However, the correct control points will be present in the same geographic area. To reduce the amount of computation, the regional matching strategy is utilized by searching only the local feature points of the reference and referenced image.

① Define search ranges of the feature points in two images' blocks which defined as A_i and B_i.

② Calculate the distance ratio R_i of the closest neighbor to the second-closest neighbor feature points one in block A_i and all in block B_i.

③ If R_i is less than a certain threshold, then accept the corresponding matching points as control point pairs. The threshold is in the range of 0.4 to 0.8. The smaller the threshold value, the less number of extracted control point pairs, but more stable.

4. Experiment and analysis

Most of the related research give the comparison charts of remote sensing images before and after the registration [4-10]. The experiments focus on the extracting of control point pairs in the registration process and compare the performance with reference 9. The experiments are performed on three groups of remote sensing images which are low, medium and high resolution images. The implementing environment is Microsoft Visual Studio 2010, Intel (R) Pentium (R) CPU 1.87GHz memory size 2.00G Windows 7 Ultimate. The corresponding feature point pairs whose ratio of the closest neighbor and second-closest neighbor is less than 0.7 are selected as matched point pairs. Duplication matching or many-to-one matching are regarded as incorrect. The matching rate is the ratio of the total number of correct matching points to the total number of matching points.

4.1. Low resolution remote sensing image

The low resolution remote images are from http://earthexplorer.usgs.gov/, reference image comes from AVHRR satellite shooting in Jun 28th, 1989 which the resolution is 1km, referenced image also comes from AVHRR satellite shooting in Sep 13th, 1989 which the resolution is 1km. Use the algorithm in reference 9 and the proposed method respectively to extract control point pairs, and the result shown as Figure 2 and Figure 3. In Figure 2, there are 39 feature points in left image and 5 in right. In Figure 3, the total number of feature points in left image is 185 and 87 in right. Experimental results are shown in table 1.

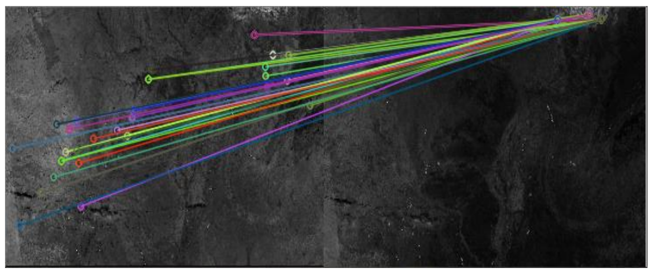

Figure 2. Extraction result of algorithm in reference 9 for low resolution remote sensing image

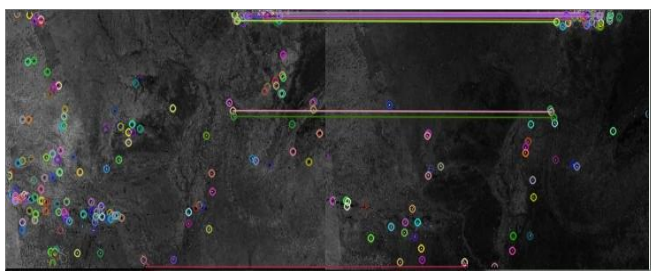

Figure 3. Extraction result of the proposed method for low resolution remote sensing image

Table 1. Comparison of registration results for low resolution remote sensing image

	algorithm in reference 9	the proposed method
total number of matched point pairs	18	37
total number of correct matched point pairs	5	12
total number of incorrect matched point pairs	13	25
matching rate	27.77%	32.43%

4.2. Medium resolution remote sensing image

Medium resolution remote images are from http://ids.ceode.ac.cn/query.html. The reference image is the one with resolution of 30m and size of 543*519 which captured by LANDSAT-5 satellite on October 7th, 2008. And the referenced image is the one with resolution of 30m and size of 549 * 521 which captured by LANDSAT-5 satellite on May 14th, 2007. Use the algorithm in reference 9 and the proposed method respectively to extract the control point pair and the results are shown in Figure 4, Figure 5 and Table 2. In Figure 4, the total number of feature points in left image is 92, and in right one is 191. While in figure 5, the total number is 179 in left image and 1267 in right one.

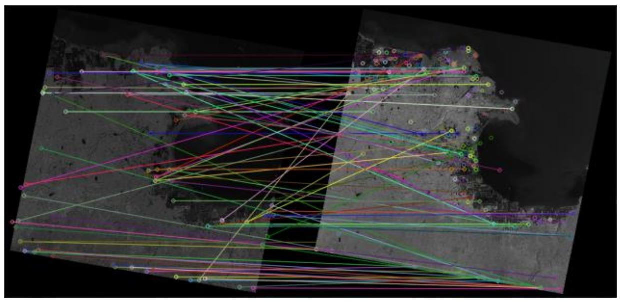

Figure 4. Extraction result of algorithm in reference 9 for medium resolution remote sensing image

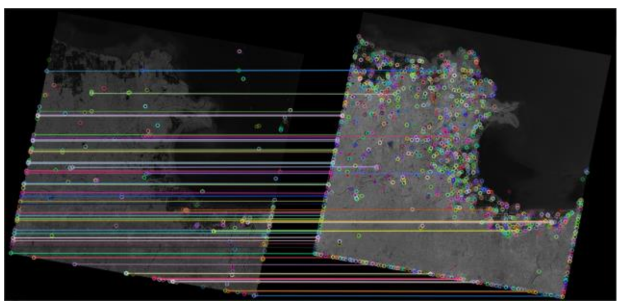

Figure 5. Extraction result of the proposed method for medium resolution remote sensing image

Table 2. Comparison of registration results for medium resolution remote sensing image

	algorithm in reference 9	the proposed method
total number of matched point pairs	92	120
total number of correct matched point pairs	53	78
total number of incorrect matched point pairs	39	42
matching rate	57.6%	65%

4.3. High resolution remote sensing image

High resolution remote images come from http://earthexplorer.usgs.gov/. The reference image is a high resolution image with the resolution of 4m and size of 620*605 taken in May, 2001 by IKONOS satellite. The referenced image is another high resolution image with the resolution of 4m and size of 620*605 taken in August, 2004 by IKONOS satellite. Then, extracting the image control point pairs by the algorithm mentioned in reference 9 and the proposed method respectively, the results are showed in Figure 6, Figure 7 and Table 3.There are a total of 1,193 feature points in left image of Figure 6, a total of 818 feature points in right image of Figure 6.Moreover, a total of 2301 feature points are showed in left image of Figure 7 and 1896 feature points are showed in right image of Figure 7.

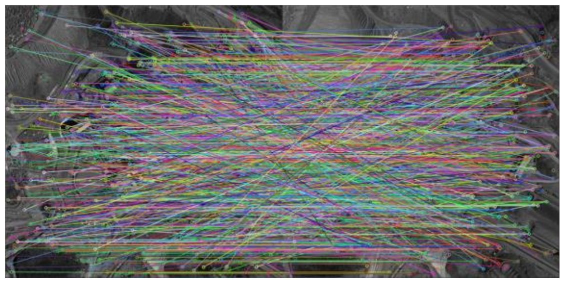

Figure 6. Extraction result of algorithm in reference 9 for high resolution remote sensing image

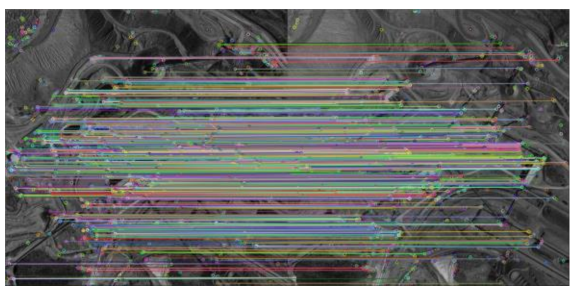

Figure 7. Extraction result of the proposed method for high resolution remote sensing image

Table 3. Comparison of registration results for high resolution remote sensing image

	algorithm in reference 9	the proposed method
total number of matched point pairs	932	898
total number of correct matched point pairs	686	675
total number of incorrect matched point pairs	246	223
matching rate	73.6%	75.17%

The above three charts show that the proposed method can not only extract more reasonable distributed control point pairs, but also gain higher matching rate.

5. Conclusions

An extracting method of control point pairs for remote sensing image is proposed based on regional matching. This method detects image feature by Harris corner detecting approach with multi-scale space theory, it can acquire more scale invariance corner. The corner is described using the SIFT feature descriptor to ensure the rotation invariability. The regional match strategy is used to not only reduce the computation of feature point matching, but also make the control point pair distribution reasonable. This method is beneficial to improve the accuracy of remote sensing image registration.

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References

[1] B. Zitova and J. Flusser, “Image registration methods: a survey”, Image and Vision Computing, vol. 21, no. 11, **(2003)**, pp. 977-1000.
[2] M. V. Wyawahare, P. M. Patil and H. K. Abhyankar, “Image Registration Techniques: An overview”, International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 2, no. 3, **(2009)**, pp. 11-28.
[3] L. M. G. Fonseca and B. S. Manjunath, “Registration Techniques for Multisensor Remotely Sensed Imagery”, Photogrammetric Engineering & Remote Sensing, vol. 62, no. 9, **(1996)**, pp. 1049-1056.
[4] L. Yu, D. Zhang and E. -J. Holden, “A fast and fully automatic registration approach based on point features for multi-source remote-sensing images”, Computers & Geosciences, vol. 34, **(2008)**, pp. 838-848.
[5] Q. Su, H. Cheng and W. Sun, “Overview of Remote Sensing Image Registration Methods” Infrared Technology, vol. 31, no. 10, **(2010)**, pp. 1-6.
[6] J. Lim, Y. Kim and J. Paik, “Comparative Analysis of Wavelet-Based Scale-Invariant Feature Extraction Using Different Wavelet Bases”, International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 2, no. 4, **(2009)**, pp. 29-38.
[7] D. Lowe, “Distinctive Image Features from Scale-invariant Keypoints”, International Journal of Computer Vision, vol. 60, no. 2, **(2004)**, pp. 91-110.
[8] K. Mikolajczyk and C. Schmid, “A Performance Evaluation of Local Descriptors”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 10, **(2005)**, pp. 1615-1630.
[9] X. Li, L. Zheng and Z. Hu, “SIFT Based Automatic Registration of Remotely-sensed Imagery”, Journal of Remote Sensing, vol. 10, no. 6, **(2006)**, pp. 885-892.
[10] Y. Chen and Q. Liu, “The Unmanned Aerial Vehicles Remote Sensing Image Registration Based on SIFT Algorithm and Mahalanobis Distance”, Geomatics & Spatial Information Technology, vol. 32, no. 6, **(2009)**, pp. 50-53.
[11] Y. Guo, Y. -f. Gu, Z. -w. Guan and Y. Zhang, “Method for Selecting Control Points for Remote Sensing Image Registration Based on Distribution Quality”, Journal of South China University of Technology (Natural Science Edition), vol. 38, no. 12, **(2010)**, pp. 50-55.
[12] X. -l. Ni, L. Ding, T. Jiang and S. -s. Hu, “A Remote Sensing Image Registration Algorithm by Obtaining Uniform Control Points Based on Invariant Feature” Science of Surveying and Mapping, vol. 36, no. 2, **(2011)**, pp. 70-72.
[13] M. Stommel, “Binarising SIFT-Descriptors to Reduce the Curse of Dimensionality in Histogram-Based Object Recognition”, International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 3, no. 1, **(2010)**, pp. 25-36.
[14] C. Harris and M. Stephens, “A Combined Corner and Edge Detector”, Manchester: Proceedings of the 4th Alvey Vision Conference, **(1988)**, pp.147-151.
[15] T. Lindeberg, “Scale Space Theory: A Basic Tool for Analyzing Structures at Different Scales”, Journal of Applied Statistics, vol. 21, **(1994)**, pp. 224-270.

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