COREGISTRATION BASED ON SIFT ALGORITHM FOR SYNTHETIC APERTURE RADAR INTERFEROMETRY

Fangting Li a, *, Guo Zhang a, Jun Yan a

^a State key Library of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, 430079, China, lifangting1985@163.com, guozhang@whu.edu.cn, yanjun_pla@263.net

KEY WORDS: Coregistration, INSAR, SIFT,

ABSTRACT:

Single-look complex image coregistration is the key step of Synthetic Aperture Radar(SAR) Interferometry. The precision of the coregistration results have a direct effect on the quality of the SAR interferogram generated, thereby it will influence the accuracy of extracting DEM. In this paper, SIFT (Scale Invariant Feature Transform) algorithm will be used in Single-look complex image coregistration, and in the pilot study, experiments have provn the method is useful.

1. INTRODUCTION

1.1 Single-look complex image coregistration

Single-look complex (SLC) image coregistration is the key step of synthetic aperture radar interferometry. The precision of the coregistration results have a direct effect on the quality of the SAR interferogram generation, thereby it will influence the accuracy of extracting DEM. When accurately coregistrater the two SAR complex images from the two approaching tracks, their interferometric phase differencing images will display stripes. The changes of the stripes include the terrain undulation information. If the two images were not precisely coregistratered, the interference stripes generated will be blurred, or even no interference stripes will be generated. At present, in order to achieve sub-pixel level accuracy, the generally used coregistration method for complex image is multi-stage coregistration, the commonly used method is: the rough image coregistration based on the orbit information or on the intervention of users, which is the first stage of coregistration; image coregistration based on pixel level, which is the second stage of coregistration; and image coregistration based on sub-pixel level, which is the third stage of coregistration.

1.2 Original solutions

SLC image coregistration is to calculate the coordinate projection relationship between a master image and slave image, and then to take use of this relationship to implement coordinates transformation, image interpolation and resampling. The interference measurement requires the accuracy of image matching to be on a sub-pixel level. Therefore, the SAR image matching includes two steps - coarse and precise matching.

The coarse matching can be effectuated by using satellite orbital parameters or manually selecting a few feature points to calculate the deviation values, Δr and Δc , in direction (row of image) and in distance (column of image) between the master image and slave image. The deviation values are relatively rough values, whose accuracy is usually on pixel level. The

purpose of coarse matching is to provide an initial value for the stereo-pair pixel searching of precise matching.

The precise matching method of SLC images, firstly, samples the master image and slave image, then identifies N uniform distributed control feature points on the master image, and selects the matching window of a certain size, whose center is the control feature points. According to the deviation values of coarse matching, the precise matching method then selects a larger search window than the matching window in the corresponding position of the slave image. Based on a certain order, it moves the matching window pixel by pixel to calculate the indicator values for the two windows. The point with the best matching indicator value in the search window will be chosen as the stereo-pair point in the slave image. Through these processes, the coordinates in two images of the stereo-pair points are obtained.

According to the coarse and precise matching mentioned above, we can get N coordinate pairs of N feature stereo-pair points. The polynomial (such as third-order) model is used to simulate the coordinate projection relationship of the master image and slave image. The parameters of the polynomial model can be solved by measurements of N coordinate pairs and the least-squares algorithm. The coordinate transformation relationship of the pair-image is achieved. Finally, coordinates transformation and resampling can be carried out based on this relationship. In this way, the slave image is transformed into the space of master image, which is ready to produce the interferometry image.

The three matching method analyzed in this study are all precise matching methods. The general algorithms and the processes are all almost the same with these three methods. The only differences are the method for calculating the indicator value in the matching window and the standard of selecting the stereo-pair point. The details of these three methods will be discussed below.

(1) The coherent coefficient method uses the coherent coefficient as the indicator value. The coherent coefficient of the stereo-pair pixel of matching window and the target window

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^{*} Corresponding author.

can be calculated by formula (1). This coherent coefficient is the value of the window centre.

$$\Upsilon = \frac{\left| \sum_{i=1}^{m} \sum_{i=1}^{n} M(i,j) S^{*}(i,j) \right|}{\sqrt{\sum_{i=1}^{m} \sum_{i=1}^{n} \left| M(i,j) \right|^{2} \sum_{i=1}^{m} \sum_{i=1}^{n} \left| S(i,j) \right|^{2}}}$$
(1)

In the formula, M (i, j), S (i, j) are the plural data of the corresponding position (i, j) in two matching windows respectively. The symbol "*" represents conjugated plural. The coherent coefficient of every point in the search window can be calculated by the formula above. The point with the largest coherent coefficient is selected as the matching point.

- (2) The greatest spectrum method uses the spectrum value as the indicator value. The two matching windows are processed by interference processing to obtain the interference fringe images. The two-dimensional discrete Fourier Transformation (DFT) is processed to the interference fringe images to get the two-dimensional spectra. The greatest value of the plural absolute value of the two-dimensional spectra is the indicator value (spectra value). Finally, the point with the greatest spectra value is selected as the matching point.
- (3) The average fluctuation function of the phase difference method uses the function value (f) of the phase difference average fluctuation as the indicator value. Firstly, the corresponding pixel phase differences P (i, j) of the two matching windows are calculated, and the function value (f) of the phase difference average fluctuation is calculated by formula (2).

$$f = \sum_{i} \sum_{j} (|P(i+1,j) - P(i,j)| + |P(i,j+1) - P(i,j)|)/2$$
 (2)

Where, f is the indicator value. The point with the least f value is selected as the matching point (Lu, 2005).

2. METHODOLOGIES

2.1 SIFT algorithm

2.1.1 Keypoint detection

The first step of SIFT construction is the detection of a keypoint. The main principium: for each octave of scale space, the input image is convolved with the Gaussian function to produce the set of scale space images. And then adjacent Gaussian images are subtracted to produce the difference-of-Gaussian images (DoG). Finally, the Gaussian image is Sub-Sampled by a factor of 2. A pixel is compared to its 26 neighbors in 3 by 3 regions at the current and adjacent scales, detecting the maxima and minima of the difference-of-Gaussian images.

In addition, with the curve fitting method, the keypoint can be further processed by precise location.

2.1.2 The local image descriptor

Before the local image descriptor, one or more orientations are assigned to each keypoint location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.

Then, the local image gradients are measured at the selected scale in a region around each keypoint. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination (Lowe, 2004).

2.2 Advantages of the SIFT algorithm

Theoretically speaking, the SIFT algorithm is invariant, even for images with scale change and rotation. However, the tectonic of SIFT has been specially treated in many details. Therefore, SIFT algorithm has a strong adaptation to images with complex deformation and changes of light. At the same time, it has higher computing speed and higher positioning accuracy.

- (1) Compared to the traditional method Laplacian of Gaussian (LoG), DoG has higher computing speeds to detect the keypoint in scale space.
- (2) The precise position of the keypoint not only improves the accuracy, but also improves the stability of the keypoint.
- (3)When constructing the keypoint descriptor, we use statistical characteristics on a sub-region level as a research object, not on a pixel level, which improves the adaptability to the local deformation of images (Zhao, *et al.*, 2007).

2.3 Coregistration based on sift for insar

Some commonly used operators for describing characteristics are Sum of Squared Difference (SSD), Sum of Absolute Difference (SAD), and Normalized Cross Correlation (NCC). Directly depending on gray information of images, all these operators are sensitive to noise in the images. Thus, the robustnesses of these operators are weak during the non-linear gray transformation of images. As for a SAR image with mass speckle noise, using these operators seems to be unpractical. However, the method based on SIFT algorithm shows a characteristic of better robustness and anti-interference when transforming images in both geometric and optical aspects. On the basis of this conclusion, the SIFT operator can be applied to the registration of INSAR image processing for getting a better result. This result can also be used for further steps of interference processing. In this paper, the SIFT algorithm will be used in precise matching to improve the accuracy of matching and computing speed. The process of coregistration based on SIFT algorithm is as follows in Fig. 1.

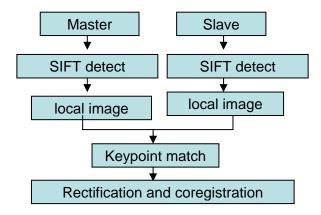


Fig.1. the process of coregistration

2.4 Keypoint detection in scale-space

Images can be expressed with different scales, and with the increasing of the scale parameter, images get smaller. In other words, a small scale is corresponds to details of image features and a large scale is for profiling characteristics.

The scale-space image is defined as the convolution of a variable-scale Gaussian with an input image

$$L(x, y, \delta) = G(x, y, \delta) * I(x, y)$$
 (3)

where (x,y) are pixel coordinates of the image and $\,\delta$ is scale factor.

DoG is computed from the difference of two nearby scales separated by the constant multiplicative factor k:

$$D(x, y, \delta) = (G(x, y, k\delta) - G(x, y, \delta)) * I(x, y)$$
 (4)

The DoG function is similar to the scale-normalized LoG.

Every keypoint has information including location, gradient magnitude and orientation. The scale of the keypoint is used to select the Gaussian smoothed image, L, with the closest scale, so that all computations are performed in a scale-invariant manner. For each image sample, L(x, y), at this scale, the gradient magnitude, m(x, y), and $\theta(x, y)$, is precomputed using pixel differences:

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$
(5)
$$\theta(x,y) = \tan^{-1}((L(x,y+1) - L(x,y-1))/(L(x+1,y) - L(x-1,y)))$$
(6)

2.5 Produce local image descriptor

A keypoint descriptor is created by first computing the gradient magnitude and orientation at each image sample point in a region around the keypoint location. These are weighted by a Gaussian window, indicated by the overlaid circle. These samples are then accumulated into orientation histograms summarizing the content over 4 by 4 subregions, as shown in Fig. 2, with the length of each arrow corresponding to the sum of the gradient magnitudes near that direction within the region. Fig. 2 shows a 2 by 2 descriptor array computed from an 8 by 8 set of samples.

2.6 Keypoint match

The best candidate match for each keypoint is found by identifiying its nearest neighbour in the database of keypoints from the master image and slave image. The nearest neighbour is defined as the keypoint with the minimum Euclidean distance for the invariant descriptor vector.

When comparing the distance of the closest neighbour to that of the second-closest neighbour, if the ratio between them is less then a threshold, we choose the keypoint as a matching point. The smaller the threshold is, the less matching points we get, and the more reliable the matching points are (Lowe, 2004).

2.7 Rectification and Registration based on TIN

In this part, we create the Triangulated Irregular Network (TIN) by the minimum distance method (Li, *et al.*, 2006) in the two images. Each of the large numbers of triangles has three tie points Xi ,Yi) ,(X' i ,Y' i) ,i = 1 ,2 ,3 ,which can be used to calculate affine parameters:

$$X' = a0 + a1 X + a2 Y$$

 $Y' = b0 + b1 X + b2 Y$ (7)

Three points can get six equations, then we can calculate a0 ,a1 ,a2 and b0 ,b1 ,b2 with which we can correct the $\triangle P'$ 1 P' 2 P' 3 on the slave image to $\triangle P1$ P2 P3 on the master image. The process of rectification is as follow in Fig. 2. (Liu, et al., 2007)

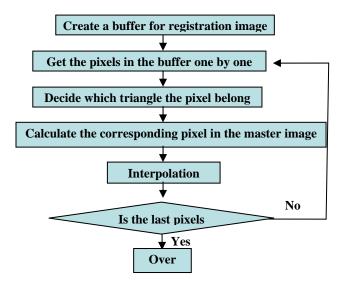
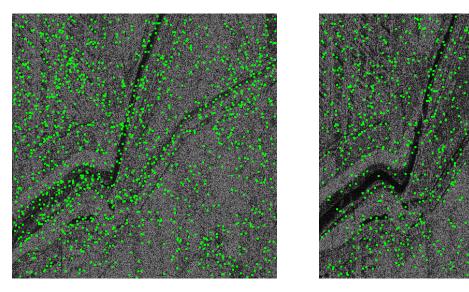


Fig.2. the process of resampling

3. RESULTS

In this paper, two ERS images of Tianjing (the obtaining time of the images are 199710190253, 199710180253) are used, one for master image and other for slave image, to test the method. SIFT algorithm was used to detect the keypoints in the images which is shown on Fig.3.

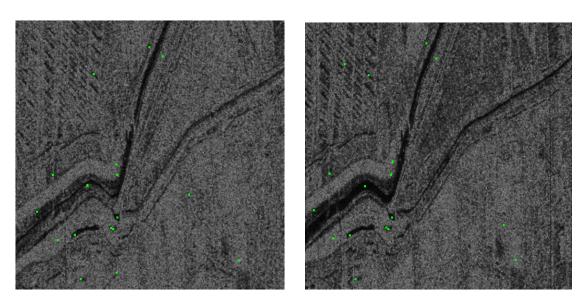
These keypoints are matched with the method above, which is shown on Fig.5. Fig.4 illustrates the matching points with the threshold of 0.75. Finally, the slave image is rectified based on TIN. The two point linked by a white line are the matching points.



keypoints on master image

Fig.3. keypoints

keypoints on slave image



matching points on master image

matching points on slave image

Fig. 4. matching points on two images

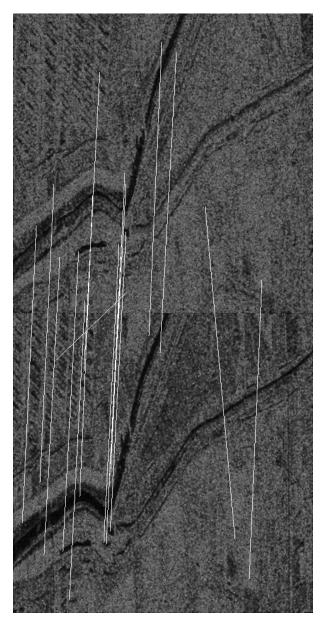


Fig.4. Keypoint match

4. DISCUSSION

In this paper, the SIFT algorithm is introduced into the coregistration for the INSAR, and the result of our experiments shows that this method can precisely detect the keypionts and choose some reliable matching points. Comparing with traditional method of coregistration for INSAR in frequency domain, this method has a higher speed.

Fig.4 illustrates that there are also few wrong matching points. We will do some research on

5. CONCLUSION

In this paper, we have presented a method based on the SIFT algorithm to solve the problem of INSAR. Coregistration is a key step in the INSAR process, and a high accuracy of coregistration has a vital effect on interference. Some

advantages when using this method are a higher speed of computation, a higher precise of matching and an anti-noise ability.

From the experiments above, we get a prospective result of coregistration in INSAR process.

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ACKNOMLEDGEMENT

The authors wish to thank open research subject of Key Laboratory of Geo-informatics of State Bureau of Surveying and Mapping (Project No.: A1721), and China International Science and Technology Cooperation Project: High-Resolution Stereo Mapping Satellite: Field Geometric Calibration and Application (Project No.: 2006DFA71570), and Commission of Science Technology and Industry for National Defense Project: Key Techniques of Data Processing for Mapping Satellite for financial support.