RESEARCH ON SAR IMAGE MATCHING TECHNOLOGY BASED ON SIFT

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ABSTRACT:

Image matching is one of the key technologies in remote sensing image fusion and navigation. Image matching of Synthetic Aperture Radar (SAR) is a process to find relationship of pixels in many SAR images, which directly involves and affects the application of SAR image in many areas such as mapping, integrated navigation and image fusion. In order to improve the searching speed in matching, pyramid strategy is used. Considering the characteristic of low S/N ratio in SAR image, curvelet is introduced in preprocessing SAR images. 1,For the great metamorphoses between SAR images, direct Scale Invariant Feature Transform (SIFT) is used in matching of destination image and referenced image which are similar with each other in greyscale. 2, edge extraction is implemented in SAR images acquired at different times and on different orbits by using Canny operator, and then SIFT key points is extracted to match the images. Combined with correlation coefficient controlling method, error matching points are wiped off and good result is acquired.

1. INTRUDUCTION

Image matching is to make use of image data acquired by sensor and compare it with referenced image to obtain corresponding object position in referenced image. Image matching is very important in computer vision, image fusion, and object recognition and tracing.

There are severe speckle noises in SAR image and these noises have more disturbances on image processing and recognition than regular noises do and become a big obstacle in applications of SAR image, such as auto recognition and matching. In this paper, Curvelet method was introduced to denoise the SAR image. In 2D image processing that uses wavelet transformation, separated transformation cores are used to implement wavelet transformation horizontally and vertically independently. The local module maximum of parameter of transformation can only show that the position where wavelet coefficient appears is across edge, but can not express the along edge information, which makes traditional wavelet transformation restricted in 2D image processing. To solve this problem, Donoho put forward Curvelet transformation, of which anisotropism is very suitable to express the edge effectively.

Because of difference of emission source location, azimuth and height in SAR, there are rotations, zooming and metamorphoses in different SAR images. Even SAR images that obtained in one source location in different time have great difference in grayscale. These differences, which differ from traditional optical image, make it difficult to find correspondence points in SAR image of same source. Correlation coefficient matching is not able to match to ideal position, either, and as the increase of window size, the computing speed decreases obviously, which makes it hard to apply to real-time matching. In this paper, scale-invariant feature transformation was introduced to matching of SAR images of same source.

The early work of Lowe (1999) extended the feature to void the effect of scale, which also overcome the effect caused by different views and image distortion. David G.Lowe (2004) summarized the existing feature detecting methods based on invariant technology and put forward an operator which describes the local feature of image－SIFT operator. This operator maintains invariant in scale space, image zooming, rotation and even affine transformation. Afterward, Y.Ke improved this operator by replacing histogram with PCA in describing sub-parts.

2. FILTER PROCESSING OF SAR IMAGE

2.1 The Characteristic of SAR image

Comparing with traditional optical image, SAR image, which is obtained by processing echo signal, has its own features and cannot be applied to matching directly. The projection style of radar image is different from that of optical image and the image points are recorded according to the distance between object and center of antenna. So, the geometry proposition of SAR does not fit for the vision habit of human. Comparing with ortho-image, SAR image has larger distortion and stretching than optical image. SAR emits coherent waves and when these waves touch the object, the overlap of random scattering signals of each scatter unit on the scatter plane will cause coherent speckles. Speckle noise presents the sharp change of grayscale and its effect is larger than other noise, so it has serious impact on feature extraction, image matching and object recognition on SAR image.

In order to solve these problems, SAR image should be pre-processed before matching. Pre-procession of image includes contrast enhancement and denoising of SAR image. Contrast enhancement of image can adopt partition linear transform to guarantee that image is not distorted. In this paper, curvelet is introduced to denoise the SAR image.

2.2 The basic theory of curvelet transformation

Curvelet transformation develops from wavelet transformation, but overcome the inner limitation of wavelet in expressing direction of edge in image. Candes (1998) put forward Ridgelet transformation and implemented Radon transformation on image, which is to map one dimensional singularity of image, such as line in the image to a point in Radon domain, and then detect the singularity of point by one dimensional wavelet and thus solve the problem in 2D image when using wavelet transformation. However, most edges of natural image are curve lines, and it is not very effective to analyze the whole image only by single scale Ridgelet, so images need to be divided into blocks to make lines in each block are similar with beelines, and then implement Ridgelet transformation on each block. Because Ridgelet has great redundancy, Donoho put forward curvelet: firstly, decompose the image into subbands, and then adopt different blocks to subband image with different scales, at last analyze the each block by using Ridgelet. The frequency bandwidth width and length satisfy the relation width = length. This kind of dividing mode makes the curvelet transformation has fierce anisotropism, and this anisotropism increases exponentially as scale decreases. Researches show that when using finite coefficients to approach a C^2 continual curve line, the speed of curvelet is far larger than that of Fourier transformation and Wavelet transformation. In another way, curvelet is the sparsest way of presenting these curve lines. Anyway, curvelet combines the anisotropism of Ridgelet transformation and multi-scale of wavelet transformation, so its appearance is a milestone in 2 dimensional signal analyzing.

The main steps of curvelet transformation are:

(1)subband decompotion:

$$f \to (P_0 f, \Delta_1 f, \Delta_2 f, \cdots).$$

(2)smooth partitioning:

$$\Delta_2 f \to (w_Q \Delta_s f)_{\ Q \in Q_s},$$

Where, w_Q presents smoothing function sets in binary block

$$Q = [k_1/2^s, (k_1+1)/2^s] \times [k_2/2^s, (k_2+1)/2^s]$$

(3)Renormalization:

$$g_Q = 2^{-s}(T_Q)^{-1}(w_Q \Delta_S f), \quad Q \in Q_S,$$

Where, $(T_Q f)(x_1, x_2) = f(2^S x_1 - k_1, 2^S x_2 - k_2)$.This step reverts each block to unit scale.

(4)Ridgelet analysis:

$$\alpha_\mu = \langle g_Q, \rho_\lambda \rangle, \quad \mu = (Q, \lambda),$$

Where, ρ_λ is the function that composes the orthonormal basis.

Ridgelet function with double variables is defined as:

$$\psi_{a,b,\theta} = a^{-1/2}\psi((x_1\cos\theta + x_2\sin\theta - b)/a)$$

Where, ψ is the wavelet function, a is scale factor of Ridgelet variable, b is position parameter of Ridgelet-, θ is the direction of Ridgelet transformation. We can see that Ridgelet function is invariable along ridgeline $x_1\cos\theta + x_2\sin\theta = c$ (c is constant), but in vertical direction of ridgeline, it is changing curve line of wavelet function.

For an integrable single-variable function $f(x)$, the form of Ridgelet transformation is :

$$R_f(a,b,\theta) = \int \psi_{a,b,\theta}(x) f(x)dx$$

Rewrite Ridgelet transformation to be:

$$R_f(a,b,\theta) = \int R_f(\theta,t) a^{-1/2}\psi((t-b)/a)dt$$

The equation above indicates that Ridgelet transformation the one dimensional wavelet analysis on slice of Radon transformation, where azimuth θ is fixed and t is the parameter that is analyzed.

2.3 Digital implementation of Curvelet transformation

According to theory above, Starck put forward a digital implementation of Curvelet transformation, of which main steps are:

① Subband decomposing. Decompose image into different subbands by using àtrous wavelet.

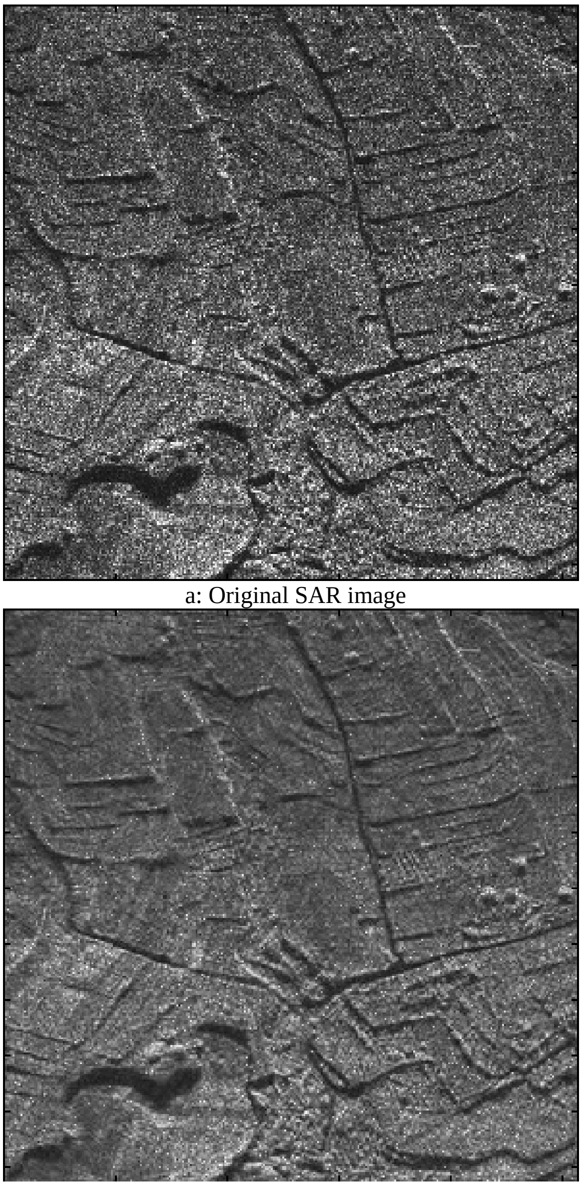
②Blocking. Each subband is processed with window, and the size of window doubles every two subbands.

② Digital Ridgelet analysis. Implement Ridgelet transformation on each block, among which 2 dimensional Fourier transformation, transformation from orthogonal coordinate to pole coordinate, and one dimensional inverse Fourier transformation and one dimensional wavelet transformation on corresponding lines.

Digital inverse Curvelet transformation is just the inversion of these steps.

2.4 Experiment on denoising SAR image

The result proves that the processing effect of Curvelet transformation is better than traditional method. The setting of threshold often gets rid of good coefficients of wavelet, so the effects on edge and texture details are not satisfying. In this paper, logarithmic transformation is firstly implemented on original SAR image, then the speckle noise become similar with Gauss additive noise. After preprocessing, Curvelet transformation is implemented on image, and hard threshold processing in implemented, and at last denoised image is obtained by executing Curvelet inverse transformation and exponential transformation.



a: Original SAR image

b: Denoised SAR image by Curvelet

Figure 1 Effect of denoising SAR image by Curvelet

3. SAR IMAGE MATCHING BASED ON SIFT

3.1 The basic steps of point feature matching of SAR image of same source

1,Build a image pyramid. Match the image of pyramid top.

2,Detect feature points. The feature points are usually local maximum of grayscale change, and sometimes are even of no intuitive meaning to vision. But in certain angle or scale, there is rich information that is useful in image matching.

3,Build eigenvector to describe feature points. The choosing of feature space determines which characteristics take part in matching and which characteristics are neglected. Because there are great metamorphoses in SAR images, and also rotations and distortions, the feature descriptor of feature point should not be invariable so as to guarantee the least effect caused by antenna or echo.

4,Implement feature matching on image to obtain candidate matching points. This can be based on the similarity of eigenvectors, and distance functions can be used to measure the similarity of feature, such as Euclidean distance, block distance or mahalanobis distance.

5,According to the construction of image pyramid, make the homologous points on the top correspond to those on the bottom.

6,Eliminate the error points. Mistakes are inevitable, no matter what feature descriptor and similarity measurements are used. And the own characteristics of SAR image will increase the possibility of errors. The main work of this step is, according to imaging characteristics of geometrical image or SAR image, POS data, correlation coefficients control, to get rid of the error in candidate points. In image matching of SAR image from same source, correlation coefficients computation can be performed and when the result is less than the threshold, this point can be eliminated.

3.2 SIFT of SAR image

For image matching and recognition, SIFT features are first extracted from a set of reference images and stored in a database. A new image is matched by individually comparing each feature from the new image to this previous database and finding candidate matching features based on Euclidean distance of their feature vectors.

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3.2.1 Build scale-space

The scale space of an image is defined as a function:

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

Where * is the convolution operation in x and y, and $G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)} / 2\sigma^2$,(x,y) is the space coordination, σ is the scale coordination. $I(x, y)$ is an input image.

To efficiently detect stable keypoint locations in scale space, we use scale-space extrema in the difference-of-Gaussian function convolved with the image, $D(x, y, \sigma)$, which can be computed from the difference of two nearby scales separated by a constant multiplicative factor k:

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \end{aligned}$$

3.2.2 Detection of scale-space extrema

Maxima and minima of the difference-of-Gaussian images are detected by comparing apixel (marked with X) to its 26 neighbors in 3x3 regions at the current and adjacent scales (marked with circles).

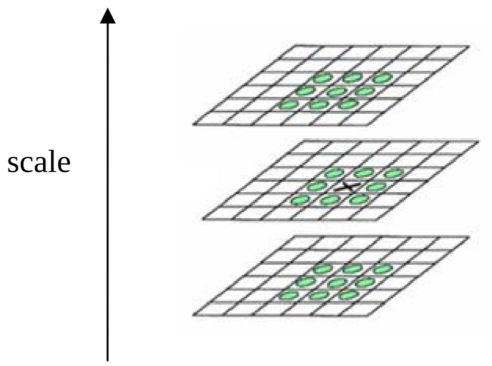


Figure2: Detection of scale-space extrema

In order to detect the local maxima and minima of $D(x, y, \sigma)$, each sample point is compared to its eight neighbors in the current image and nine neighbors in the scale above and below. It is selected only if it is larger than all of these neighbors or smaller than all of them.

3.2.3 keypoint localization

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 orientation, $\theta(x, y)$, is precomputed using pixel differences:

$$m(x,y)=\sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2}$$
$$\theta(x,y)=\alpha\tan2((L(x,y+1)-L(x,y-1))/(L(x+1,y)-L(x-1,y)))$$

3.2.4 descriptor representation

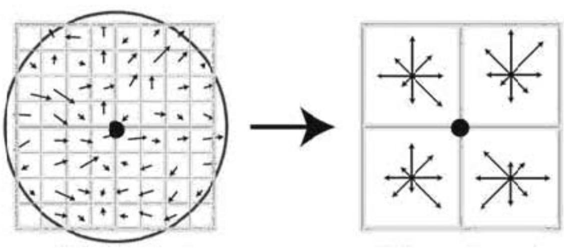


Image gradients　　　　Keypoint descriptor

Figure 3 descriptor representation

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, as shown on the left. These are weighted by a Gaussian window, indicated by the overlaid circle. These samples are then accumulated into orientation histograms summarizing the contents over 4x4 subregions, as shown on the right, with the length of each arrow corresponding to the sum of the gradient magnitudes near that direction within the region. This figure shows a 2x2 descriptor array computed from an 8x8 set of samples, whereas the experiments in this paper use 4x4 descriptors computed from a 16x16 sample array.

When SIFT eigenvectors of two images are generated, we will use Euclidean distance of eigenvectors of key points to measure similarity of key points in two images. Get certain key point in image1, and find in image2 two key points that are nearest in Euclidean distance. Among these two points, if quotient of the nearest distance divided by sub-nearest distance is less than given threshold, then these two matching points are accepted. Decreasing the threshold will decrease the SIFT matching points but will be more robust.

3.2.5 Improvement of control error matching in SAR image.

When matching keypoints, in a cluttered image, many features from the background will not have any correct match in the database, giving rise to many false matches in addition to the correct ones. The correct matches can be filtered from the full set of matches by identifying subsets of keypoints that agree on the object and its location, scale, and orientation in the new image. The probability that several features will agree on these parameters by chance is much lower than the probability that any individual feature match will be in error.

In this paper, the method of removing false matching points is:
(1)Rough location is completed with the support of SAR images POS data. We can locate one SAR image to reference SAR image approximately with POS data. When the distinction location of key points pairs more than the rough location locate by POS, the key points will be removed.

(2)Correlation coefficient control wrong match. Correlation coefficient, is the standardization of covariance function, equal to Covariance function divided by the variance of two signals. The correlation of $g(x, y)$ and $g'(x', y')$ is:

$$\rho(p,q)=\frac{C(p,q)}{\sqrt{C_{gg}C_{g'g'}(p,q)}}$$

The first thing In dealing with SAR images is to determined threshold. ρ_0 . We excavate an certain size of window both in the neighbours of keypoints a_i in target image, and the neighbours of keypoints b_i in the reference image, extracted by SIFT. For example, we excavate two windows with key points centered, of which size is 50×50, and compute the correlation coefficients ρ_i , store the values and shift to next key point a_{i+1} of real-time image. After computing all the coefficients of key point centered windows in real-time image, rank all the coefficients $\rho_1, \rho_2, \ldots, \rho_n$ (where n is the number of matching points that detected by SIFT) from maximum to minimum and set the threshold

$$\rho_0=(\rho_{max}-\rho_{min})\times k+\rho_{min}$$

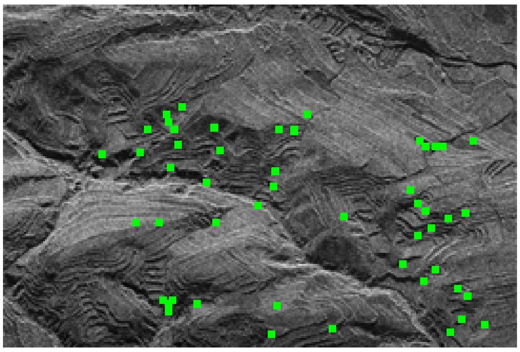
Where, ρ_{max} is the maximum in all the ranked correlation coefficients and ρ_{min} is the minimum, and k is a constant, in this paper, k=0.2. When the correlation coefficient is less than threshold, give up the detected matching points, otherwise keep these two points.

4. RESULTS AND ANALYSIS

Airborne SAR images acquired with different geometric parameters have been taken to experimentation. In order to examine the stability of different sales of this matching algorithm in the article, lots of image pairs covering different physiognomy areas have been experimented with SIFT matching algorithm.

In this experimentation, the SIFT algorithm has been used directly for image pairs with resemble gray contrast between the target image and the reference iamge. But for the SAR image pairs acquired at different times and different orbit, Canny algorithm has been used to extract edge features before the SIFT key points were extracted to match.

4.1 Results of experimentation:



a The key points of the target SAR image.
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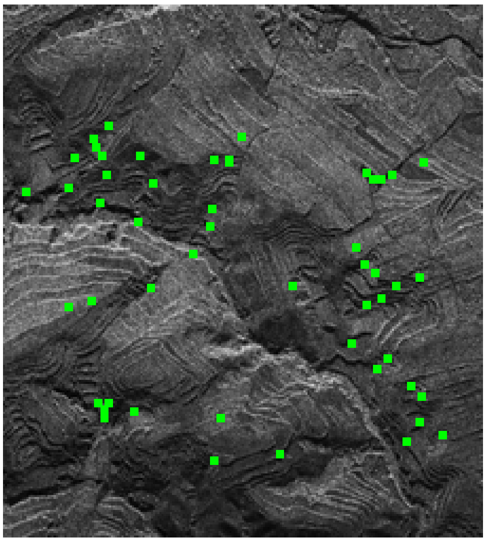
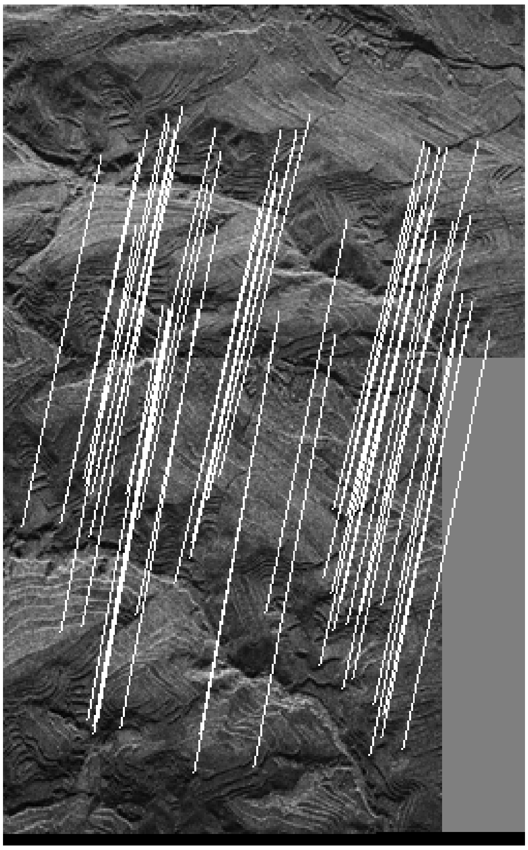


b The key points of the DOM reference SAR image.



c The result of matching points connected lines(The up-half image is the target SAR image, and the down-half image is the DOM SAR image. Both sides of lines represent corresponding match points).

Figure 4 The result of SAR images matching.

4.2 Results analysis

The flat land, the terraced field, the mountainous region and the residents, each of which include ten groups, have been taken to experiment in the article, with different SIFT threshold. If the matching error of corresponding feature points is less than 3 pixels, we consider the matching result right. Matching probability can be defined with expressions:

$$p = N / M ,$$

where: N-number of right matching points
M-number of all corresponding points.

	M	N	threshold	p（%）
flat	85	82	0.77	96
terr	112	112	0.6	100
moun	56	54	0.82	96
resi	130	123	0.6	94
All	383	371		97

Table 1 The results of different physiognomy matching

From the experimental results we can see that the matching probability of terraced field is highest. And the matching probability in resident area is inferior. As a whole, matching probability of this method is very high: 96%.

The average time of matching with target SAR images of 128×128, and reference SAR images of 256×256 is 1.23s, obviously the matching speed is very quick.

5. CONCLUSION

Curvelet, as a kind of new multi-scaling transform, already demonstrated the huge potential in the traditional image's denoising, also get good process in the SAR image's speckle denoising. The SIFT algorithm, introduced in this article, has solved the problem of locating between SAR images with distorts. For the differentia from high resolution Optical image, a further control error method has been proposed in the matching, which reduce the number of unstable correspondence key points. The superiority of this matching method applied in SAR images has been affirmed from the statistical angle.

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