A New Local Feature Descriptor for SAR Image Matching

Tao Tang, Deliang Xiang, and Yi Su
College of Electronic Science & Engineering, National University of Defense Technology, Changsha, China

Abstract— Because of the weather- and illumination-independent characteristics, Synthetic Aperture Radar (SAR) has been playing a more important role for target recognition. Local stable feature descriptors in SAR image matching have been a interesting field in recent years. A new local feature extraction method like Scale Invariant Feature Transformation (SIFT) is proposed in this presentation, in which Local Gradient Ratio Pattern Histogram (LGRPH) based on SAR image similarity are taken as local feature descriptor from the neighbourhood of key points. Firstly, we extract the keypoints in difference of guassian (DoG) scale pyramid like many modified SAR-SIFT methods. Secondly, in the neighbour of kepoints, the local gradient ratio pattern histogram (LGRPH) is computed individually. Finally, the similarity is obtained by utilizing K-L discrepancy to measure the distance of LGRPH. Experimental results based on synthetic and real SAR images demonstrate that the proposed approach is robust to the speckle noise and local gradient variation in SAR images.

1. INTRODUCTION

It is important to evaluate the similarity of image or targets in remote sensing images acquired by different time or angles or sensors for image registration, change detection and image interpretation. Nowadays, local invariant feature descriptors or local stable feature descriptors has been utilized methods in optical and SAR image due to their robust similarity and repeatness, among which SIFT is the most popular one. SIFT [1] was put forward to be widely used for local feature matching in optical image and is not proper for SAR image which has different imaging mechanism and coherent speckle noise. Thereby many modification of SIFT were introduced, such as SIFT-OCT [2], SIFT+ISEF-OCT [2], SAR-SIFT [3], ISIFT [4], which have obtained good performance in SAR image. Their main contribution is as followed: (1) Abandoning the first octave of DoG pyramids, then starting keypoints detection from the second octave. It equals that SAR image should filtered by Gaussian filter, with image details and speckle smoothed. (2) The Gaussian filter was taken place of with infinite symmetric exponential filter(ISEF) [2] and bilateral filter (BF) [5] to build scale space in SAR image, while decreasing the influence of speckle towards keypoints and maintaining image details. (3) Size of the support region that is the neighbourhood of keypoints is modified from single region of size 16×16 to multiple regions in size 16×16, 24×24, and 32×32. Descriptor computed from multiple support regions could handle the mismatching error better than using only one support region [6]. All these methods should detect keypoints in coarse scale in SAR image avoiding disturbance of keypoint location and descriptor accuracy from coherent speckle, and achieve better performance of matching coherence of local feature in SAR image.

All the presentations mentioned above focus more on overcoming keypoints disturbance of speckle noise, little on local feature descriptors. While dealing with multiple noise in SAR image rather than optical image, the descriptor of SIFT is not robust which is calculated with the image gradient. A novel local feature descriptor method is proposed in this presentation, in which keypoints are located in the second octave like SAR-OCT. Then a new similarity measurement suitable for SAR image named Local Gradient Ratio Pattern Histogram (LGRPH) [7] are taken as feature descriptor for the neighbourhood of key points. Symmetry Kullback-Leibler Divergence (SKLD) [8] is used to measure the similarity of local descriptor. Experiments show that this algorithm is robust against coherent speckle noise and local gradient turbulence in SAR images, which is useful for SAR image matching and registration.

2. LOCAL FEATURE DESCRIPTOR

In SIFT-like methods mentioned above, dominant orientations for constructing local feature descriptor is computed from intensity gradient of neighbourhood around keypoints. It is not inadaptable to SAR image processing because of multiplicative speckle noise. Orientations is sensitive to local image gradient variation, which makes local descriptors invalid in matching the same local blob in different SAR image. Then local gradient ratio is proved to have ability to endurance the speckle [7]. In this paper, local gradient ratio pattern histogram (LGRPH) is proposed for local feature descriptor for SAR image matching, which takes not only the pixel ratio feature but also the local gradient information into consideration.

In LGRP implementation [7], the Euclidean distance between the neighbour pixel intensity and centre pixel intensity is calculated and regarded as the gradient value of the former. Then the gradient ratio pattern (GRP) of the neighbour pixel is obtained, namely the ratio of the gradient value and the initial intensity of the neighbour pixel, as described in (1). The GRP of the centre pixel is regarded as the average GRPs of the neighbourhoods. After that, the LGRP operator is calculated at the centre pixel by evaluating the binary differences of the GRP values of a small neighbourhood, as described in (2) and (3)

$$G_{ratio}(I_p) = \frac{|I_p - I_c|}{I_p} \tag{1}$$

$$\overline{G_{ratio}(I_c)} = \frac{1}{P}\sum_{p=1}^{P} G_{ratio}(I_p) \tag{2}$$

$$\mathrm{LGRP}_{P,R}(I_c) = \sum_{p=0}^{P-1} s\left(G_{ratio}(I_p) - \overline{G_{ratio}(I_c)}\right) 2^p \tag{3}$$

where I_c is the centre pixel intensity and I_p is the neighbour pixel intensity. P is the number of neighbour pixels, R is the neighbour radius. $G_{ratio}(I_p)$ is the GRP of I_p and $\overline{G_{ratio}(I_c)}$ is the average GRPs of neighbour pixels, i.e., the GRP of I_c. $s(\cdot)$ is a sign function, which is defined as

$$s(x) = \begin{cases} 0 & x < 0 \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

The histogram of the LGRPs is named as LGRPH. For an $N \times M$ image, LGRPH is calculated as

$$\mathrm{LGRPH}(k) = \sum_{i=1}^{N}\sum_{j=1}^{M} f(\mathrm{LGRP}_{P,R}(I_{i,j}), k) \quad k \in [0, K] \tag{5}$$

where

$$f(x, y) = \begin{cases} 1 & x = y \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

K is the maximum LGRP and k is the number of bins.

We have proved that the pixel ratio measurement is robust to multiplicative noise in SAR image. Figure 1 shows how to compute LGRP value. Integrating the measurement into GRP, we can conclude that LGRPH is also insensitive to SAR image speckle. Figure 2 shows LGRPH robust with different local gradient variations, which means that the proposed feature is robust to image gradient variation and can well distinguish the background and target.

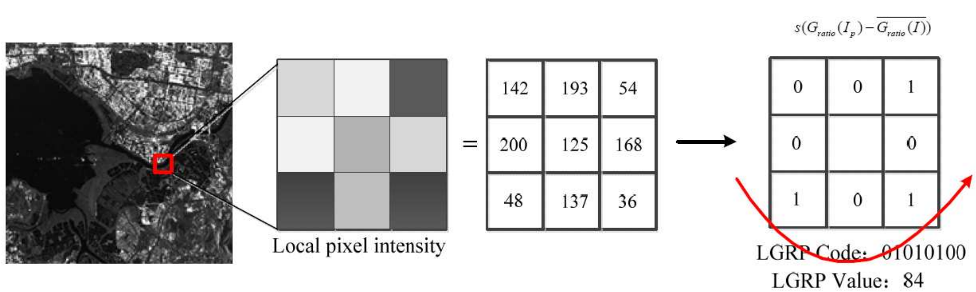

Figure 1: Calculating process of LGRP value. Red: Counter-clockwise coding.

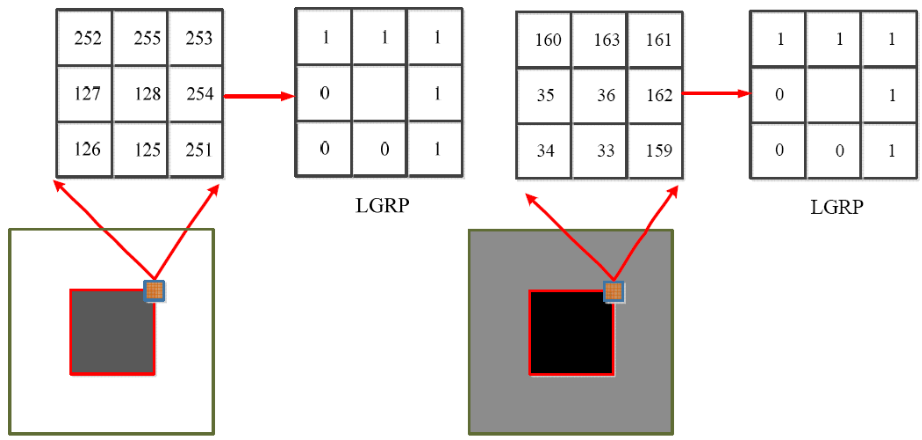

Figure 2: The stability of LGRP on local gradient variation.

3. MATCHING MESUREMENT OF LOCAL DESCRIPTORS

During matching section in SIFT, two sets of local feature descriptor around keypoints could be established correspondence by a matching strategy according to popper descriptor measurements. Similarity measure plays a key role in pattern recognition, the test pattern should be compared with the template pattern and a similarity value is obtained as the recognition criterion. Since we can extract the LGRPH vector from neighbourhood of any keypoint in SAR images, in this paper, Symmetry Kullback-Leibler Divergence (SKLD) is used to measure the similarity of two different sets of LGRPH vector. For two LGRPH vector H and Q, SKLD is defined as

$$\mathrm{SKLD}(H,Q)=\sum_{n=1}^{N}p_n\log\left(\frac{p_n}{q_n}\right)+\sum_{n=1}^{N}q_n\log\left(\frac{q_n}{p_n}\right) \tag{7}$$

where p_n and q_n are the feature vectors of H and Q, N is the feature dimension. Since the similarity ranges from 0 to 1, SKLD should be mapped as a rational normalized relativity. Using Gaussian function, we define the similarity as

$$Similarity=\exp\left(-\frac{[\mathrm{SKLD}(H,Q)]^2}{\sigma^2}\right) \tag{8}$$

where σ is the parameter which controls the width of Gaussian function and the relation between feature divergence and similarity.

After similarity being computed, keypoints matching whose descriptor is named LGPRH is concerned in this paper. Different SAR image matching would turn into different local keypoints sets matching through local feature descriptor and proper correspondence strategy. We choose Random Sample Consensus (RANSAC) to estimated the transformation parameters from established local descriptors correspondence.

4. LOCAL FEATURE EXTRACTION AND MATCHING IN SAR IMAGE

For SAR image matching, this paper proposes a local feature extraction method including three parts like SIFT: (i) keypoints detection and localization; (ii) local feature description; (iii) keypoints matching. In the first step keypoints are detected and located by DoG detector of SIFT skipping the first octave of the scale space pyramid. In the second step LGRPH is used as local descriptor detailed in Section 2. In the last step similarity measurement and correspondence of keypoint sets form reference and test SAR image are computed to realize SAR image matching. Figure 3 shows the whole method processing procedure.

5. EXPERIMENT RESULT

In this section, real SAR image with different imaging direction is used to test performance of the proposed method and SIFT and SIFT-OCT.

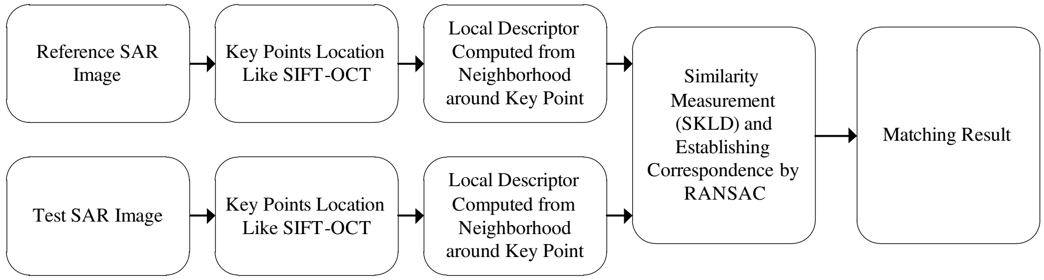

Figure 3: SAR image matching with proposed method.

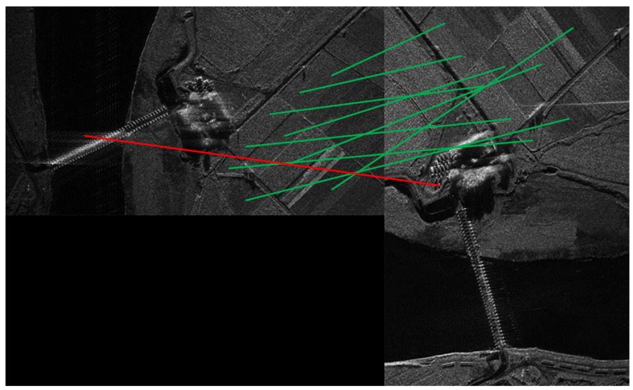

Figure 4: Matching of different SAR image. Green: correct matching. Red: error matching.

The left image and right image were imaged from different directions by airborne SAR in 2013, with the resolution $1\,\mathrm{m} \times 1\,\mathrm{m}$. Table 1 shows the result of experiment using test method and traditional methods.

According to the experiment result, the proposed method can detect correct matching pairs much more than compared methods. It shows that LGRPH is a stable local descriptor and similarity matching strategy is proper. The computation load of proposed method is nearly to SIFT, but more than SIFT-OCT. It is to save computation time that the first octave is skipped in scale space to overcome speckle noise in SIFT-OCT and the proposed method, while computation of LGRPH costs more time than orientation assignment in SIFT.

Table 1: Result of our method and other methods.

Method	**SIFT**	**SIFT-OCT**	**Proposed Method**
Matching pairs/all keypoints num.	**1/338**	**39/64**	**10/64**
Correct matching pairs	0	6	9
Computation time (second)*	11.434	8.653	12.247

The computer is equipped with AMD X2 255 (3.1 GHz CPU) and 2G RAM.

6. CONCLUSION

A new local feature descriptor named LGPRH is introduced for SAR image matching in this paper. Then a SIFT-like method is presented in which LGPRH takes place of the orientation assignment as local descriptor in SIFT. The local image intensity and gradient information are both taken into consideration in this method. Since LGRPH is insensitive to multiplicative speckle noise, LGRPH is adapted to the images with gradient variation which is the common phenomenon in real SAR images and significantly influences matching performance. The experimental results show that the proposed method has a high matching rate. Future work will focus on accuracy of keypoint detection and location and adaptability of this local descriptor on SAR images with various disturb conditions, such as the images with distortion, serious shadow. And more experiments using larger real data sets will be done for further validation.

REFERENCES

1. Lowe, D., "Distinctive image features from scale-invariant keypoints," *International Journal of Computer Vision*, Vol. 20, 91–110, 2004.
2. Schwind, P., S. Suri, P. Reinartz, and A. Siebert, "Applicability of the SIFT operator to geometric SAR image registration," *Int. J. of Remote Sensing*, Vol. 31, No. 8, 1959–1980, 2010.
3. Dellinger, F., J. Delon, Y. Gousseau, J. Michel, and F. Tupin, "SAR-SIFT: A SIFT-like algorithm for application on SAR images," *Proc. IGRASS 2012*, 3478–3481, Munich, 2012.
4. Ren, S., W. Chang, and X. Liu, "SAR image matching method based on improved SIFT for navigation system," *Progress In Electromagnetics Research M*, Vol. 18, 259–269, 2011.
5. Wang, S.-H., H.-J. You, and K. Fu, "An automatic method for finding matches in SAR images based on coarser scale bilateral filtering SIFT," *Journal of Electronics and Information Technology*, Vol. 34, No. 2, 287–293, 2012.
6. Fan, B., C. Huo, C. Pan, et al., "Registration of optical and SAR satellite images by exploring the spatial relationship of the improved SIFT," *IEEE Geoscience and Remote Sensing Letter*, Vol. 10, No. 4, 657–661, 2013.
7. Yuan, X., T. Tang, D. Xiang, et al., "Target recognition in SAR imagery based on local gradient ratio pattern," *International Journal of Remote Sensing*, Vol. 35, No. 3, 857–870, 2014.
8. Li, L., C. S. Tong, and S. K. Choy, "Texture classification using refined histogram," *IEEE Transactions on Image Processing*, Vol. 19, No. 5, 1371–1378, 2010.