SAR Image Matching Based on SIFT Keypoints and Multi-Subregions Information

Wentao Lv, Wenxian Yu, Junfeng Wang, and Kaizhi Wang
Department of Electronic Engineering
Shanghai Jiao Tong University

***Abstract*—Conventional image matching methods hardly consider the location relationships between matching points, reducing the reliability and accuracy of matching results. A novel matching mode based on SIFT (scale-invariant feature transform) keypoints and multi-subregions information is proposed in this paper. The new strategy breaks the isolation between matching points, also inhibits the deficiency caused by differences in gray for SAR (synthetic aperture radar) images. The experimental results show that the proposed algorithm is effective and robust.**

Keywords-image matching, SIFT keypoints, multi-subregions, location constraint

I. INTRODUCTION

Image matching is an important task of SAR images interpretation. Previous researches had promising performance in this field. The book [1] expounded the detailed procedure of template matching method and its application for SAR images. Ronald G.Caves *et al* [2] adopted a template matching method based on matching map features in SAR images. Reference [3], the paper proposed a matching algorithm called algebraic template matching to improve the quality of traditional template strategies. In order to acquire much higher efficiency of matching measures, Richard Tate *et al* [4] developed fast template matching methods using VHDL.

In most cases, those methods based on template matching mainly rely on gray-scale principle, hence, the effectiveness was always impaired when used for SAR images, due to big difference in gray caused by different imaging mechanisms. To overcome this weakness, many feature-based matching approaches were developed. The correlative applications were provided in [5]-[8]. In [5], the paper employed a hierarchical strategy, including normalization, shape matrix estimation and geometrical invariant constraint algorithm, to formulate matching problem as a model based on feature. G. Oller *et al* [6] used the edge strength map to construct radar grammetric chain and then develop a matching module. A hierarchical filtering strategy for affine invariant feature detection, which was based on information entropy and spatial dispersion quality constraints, was provided for image matching in [7]. A probabilistic framework-multiscale generative models known as dynamic trees-was proposed for the matching of image regions in [8].

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Recently, scene matching methods based on scale-invariant features transform (SIFT) have revealed promising results [9]-[11]. Ref.[12]-[14] introduce the applications of SIFT in image registration. For SAR images from different sensors, however, the number of SIFT keypoint incorrect matches increases rapidly and the correct registration rate declines. This arises because SAR images differ from each other in imaging mechanism so as to give significant differences, even inverse for grey-level values at the same areas of SAR images. Another reason is that most current matching algorithms only build one-to-one relation for a pair of matching points, omitting the correlations between all matching points.

In reality, the location constraints principles between these points are critical factors for SAR image matching. To register these kind of image pairs, we propose a location restriction criteria derived from keypoints and subregions for SIFT matching to reduce the incorrect matches. To take advantage of the constraint relations between matching points, in this paper, we design a novel model based on SIFT keypoints and multi-subregions information. We first establish location constraints of keypoints in the four subregions, then introduce a mapping mode to correct matching deviations. Throughout the new mapping relation, we locate the matched points onto the corresponding positions.

The remainder of this paper is organized as follows. Section II describe the strategy of constraint relations between keypoints, followed by some experimental results and comparison with other matching methods are provided in section III, and finally we conclude this paper.

II. THE PROPOSED LOCATION CONSTRAINT MATCHING STRATEGY

In this section, we describe the location constraint strategy in detail. The entire algorithm consists of seven processes.

Step-1. As we know, the matching happened in a large range easily causes a whole deviation. The matching result would be improved throughout setting constraint relations between many smaller areas. Thus, we divide the whole real image I_{rl} into four subregions: $I_{rl} = \{I_m \mid m = 1,2,3,4\}$. The dipartition is shown in Figure.1.

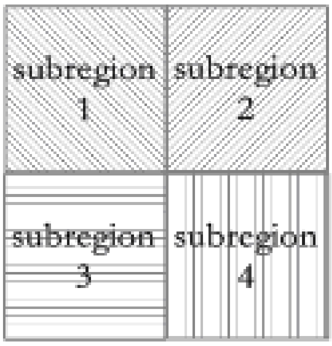

Figure 1. dipartition of real image

Step-2. We extract all SIFT keypoints from the four subregions. Each SIFT keypoints is described by a vector: $v = \{v \mid I_m = (f, \sigma, x, y)\}$. Here, f is the 128-element feature vector; σ denotes scale and (x, y) represents the spatial coordinate of the keypoint. Figure.2 shows all SIFT keypoints in the four subregions of a real image. The red points denote the SIFT keypoints.

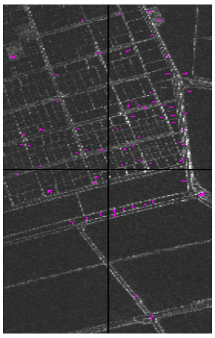

Figure 2. SIFT keypoints information

Step-3. We establish the location constraint relations of keypoints in all four subregions: $S(v_i \mid I_m, v_j \mid I_n) = \bigcup_{m \le n \le 4} (v_i \leftrightarrow v_j)$, $1 \le i \le num(I_m)$, $1 \le j \le num(I_n)$, $num(I_m)$ and $num(I_n)$ represent the total number of keypoints in I_m and I_n , respectively. Figure.3 illustrates the concrete constraint relations between all SIFT keypoints and their corresponding center points.

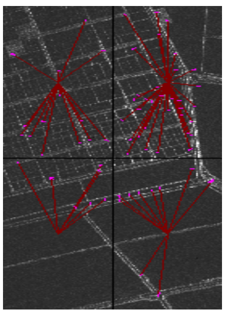

Figure 3. location constraint relations of all keypoints

As can be shown in Figure.3, each keypoint not only has a specific correlation expression with the center of subregion, but also has multiple constraints with other keypoints via center points of subregion. Based on these constraints, we can correct location deviations in the reference image.

Step-4. Implement SIFT matching and recording the relations of matching points: $M = \{p_{rl}(i), p_{rf}(i)\}$, $1 \le i \le num(pairs)$. p_{rl}, p_{rf} represent real and reference SAR images, respectively.

Step-5. By introducing a mapping function: $f: S \to M$, $S = S1 \cup S2$, we have $M \overset{f}{=} M1 \cup M2$. Then we calculate the distance $d = \| S - M \|_2$. Here, $| S - M \|_2 = [(S1 - M1)^2 + (S2 - M2)^2]^{1/2}$. Through multiple iterations, we finally have the mapping mode: $\{f' : S \to M' \mid d = min\}$.

Step-6. Based on the mapping mode, we can correct the corresponding coordinates: $M' = \{M \mid f'\} = \{p_{rl}(i), p'_{rf}(i)\}$.

Step-7. Finally, we output the four center points p_c and target region: $\{Region, p_c\} = \{I_{rf} \mid M'\}$. I_{rf} denote the reference image.

The entire flow chart of the proposed algorithm lists in Figure.5.(Page.3)

III. EXPERIMENTS AND DISCUSSION

A set of SAR images, from the same sensors and different sensors, are selected to evaluate the effectiveness of our algorithm. Parts of the matching results are provided in Figure.6 (Page.4) and Figure.7 (Page.4), where images (a),(b),(c),(d) and (e) represent original SAR images, location distribution of SIFT keypoints, traditional SIFT matching algorithm, the proposed method and the matching area, respectively.

The two images in the first group (Figure.6) are both airborne SAR images, but with different scales. The two images (Figure.7) in the second group: the left image is airborne image with 5-meter resolution, and the right image is RADARSAT-1 image.

Discussion: From Figure.6 and Figure.7, it shows that the proposed method attains the more accurate results compared with traditional SIFT algorithm. The proposed measure can correct all matching errors by constraint relations as well as output matching area if only three pairs of matching points are obtained. The results also demonstrate that SIFT algorithm has excellent performance in SAR image matching, even for SAR images with variant scales or from different sensors, which many registration approaches based on template matching fail to work [15].

To statistically demonstrate the effect of the proposed approach, we calculate the correlation coefficients of matching points and plot the values in Figure.4.

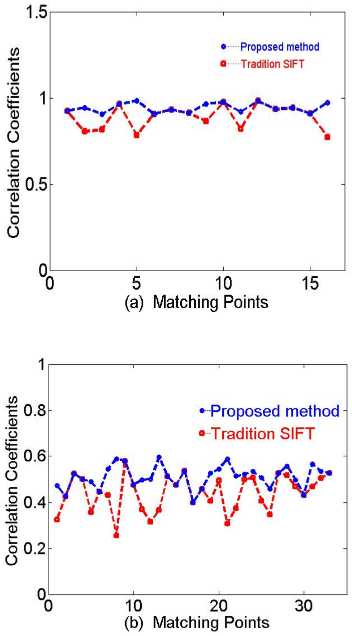

Figure 4. correlation coefficients of matching points

As can be seen, for the proposed method, the curves have the larger values as well as the smoother fluctuations. Even for the SAR images with complex disturbance, the values in (b) are still robust.

IV. CONCLUSION

In this paper, we have proposed a novel algorithm based on SIFT and multi-subregions. Due to the establishment of location constraints and mapping relations, the proposed strategy can obtain better performance in SAR images matching compared with other matching algorithms. Also, the matching results can serve as a preprocessing of some further processing such as image fusion and stitching.

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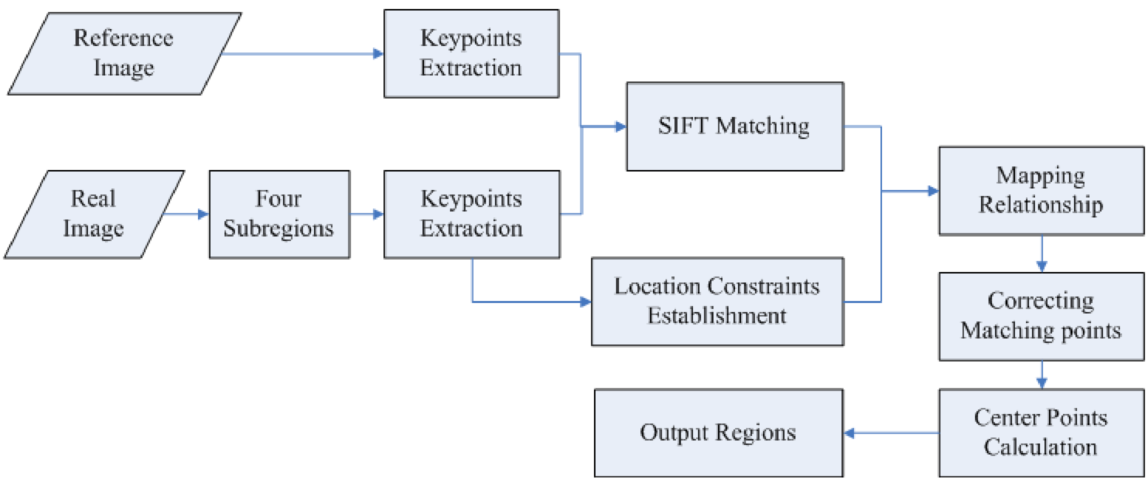

Figure 5. the entire procedure of the propose algorithm

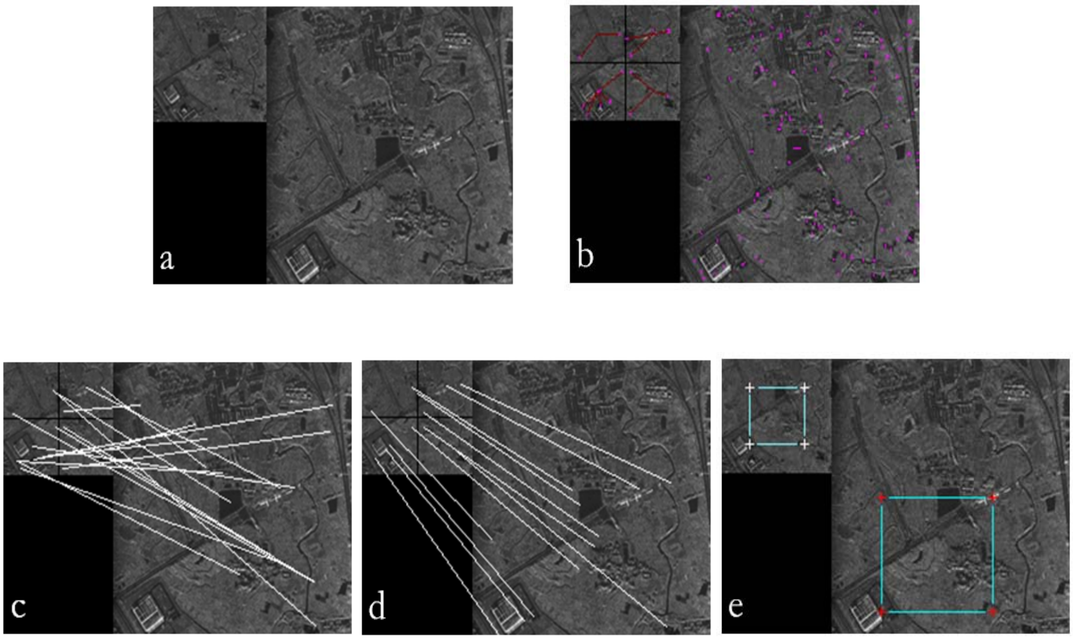

Figure 6. the results of the first set of SAR images

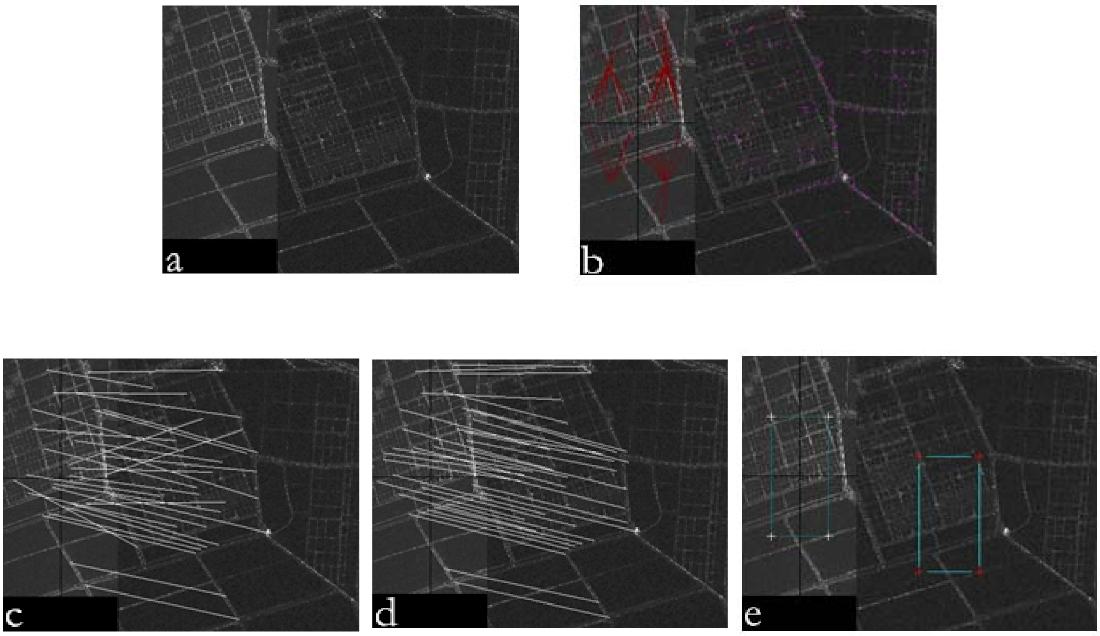

Figure 7. the results of the second set of SAR images