Registration of Optical and SAR Satellite Images by Exploring the Spatial Relationship of the Improved SIFT

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***Abstract*—Although feature-based methods have been successfully developed in the past decades for the registration of optical images, the registration of optical and synthetic aperture radar (SAR) images is still a challenging problem in remote sensing. In this letter, an improved version of the scale-invariant feature transform is first proposed to obtain initial matching features from optical and SAR images. Then, the initial matching features are refined by exploring their spatial relationship. The refined feature matches are finally used for estimating registration parameters. Experimental results have shown the effectiveness of the proposed method.**

***Index Terms*—Optical and SAR image registration, remote sensing, scale-invariant feature transform (SIFT), spatial consistent matching (SCM), synthetic aperture radar (SAR).**

I. Introduction

IMAGE registration refers to the task of aligning two or more images of the same scene taken under different imaging conditions, such as at different times, by different sensors, from different viewpoints, etc. It is an inevitable problem required by many remote sensing applications, including image fusion, change detection, map updating, and so on. Optical and synthetic aperture radar (SAR) images are taken by two types of very different sensors, i.e., the passive optical sensor and the active SAR sensor. Since these two types of sensors have very different imaging principles, their images have different appearances (cf. Fig. 2) and reveal different characteristics of the imaged area. Thus, the fusion of these two types of images can lead to a better interpretation of the imaged area. Meanwhile, in many situations (such as some emergent events) only SAR images are available since SAR sensors can work in both day and night and see through fogs and clouds. In these cases, combining the information of the historical optical images and the currently captured SAR images is significantly important for analyzing the imaged area. Therefore, the fusion of optical and SAR images is both desirable and indispensable in many applications, making the registration of optical and SAR images a core and inevitable problem.

In the literature, methods for optical and SAR image registration can be generally classified into two categories: intensity-based method and feature-based method. The intensity-based method finds the geometric transformation between optical and SAR images by optimizing a similarity measure between the two images. Widely used measures include mutual information [1], cluster reward algorithm [2], and cross-cumulative residual entropy [3]. The feature-based method usually estimates the geometric transformation between images by establishing reliable feature matches. Pan *et al.* [4] used the control points of contours parameterized with nonuniform rational B-splines for multisensor (SAR–optical and optical–DEM) image registration. Huang *et al.* [5] introduced the shape context, which was first proposed for shape and object recognition, for SAR and optical image registration. There are also methods incorporating both intensity- and feature-based techniques [6]. Despite all of this promising work, the registration of optical and SAR images remains a challenging open problem.

In this letter, a novel feature-based method for the automatic registration of optical and SAR satellite images is proposed. First, an improved version of the scale-invariant feature transform (SIFT) is introduced so as to improve its performance in matching optical and SAR satellite images. SIFT is improved in three aspects: keypoint detection, dominant orientation assignment, and support region selection. Then, the obtained initial matches are refined by exploring their spatial relationship. Finally, some spatial consistent matches are obtained for estimating transformation parameters used in image registration. Since the proposed method effectively explores the spatial relationship between features which is not influenced by different sensors, it is competent to the problem of optical–SAR image registration as shown by our experiments (cf. Fig. 3).

The rest of this letter is organized as follows. Section II gives a detailed description of the proposed method, followed by experiments in Section III. Then, it is concluded in Section IV with some discussions.

II. Proposed Method

The framework of our proposed method is shown in Fig. 1. First, the improved SIFT features (see Section II-A) are extracted from the optical and SAR images, respectively. Second, an initial set of matching features is obtained by K nearest neighbor (NN) (KNN) matching. Finally, setting each of the top n matching features as the seed to obtain a set of spatial consistent matches (see Section II-B) for estimating

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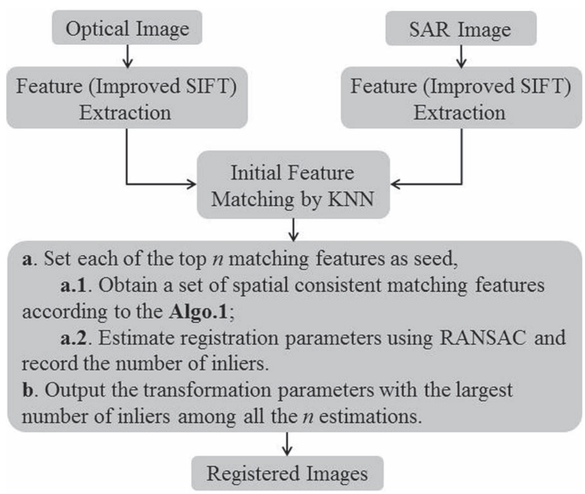

Fig. 1. Framework of the proposed method.

transformation parameters and outputting the estimated parameters with the largest number of inliers, the outputted transformation parameters are used to produce the registered images. Details will be elaborated in the following sections.

A. *Improved SIFT*

SIFT [7] has been widely used for obtaining corresponding points. Briefly speaking, it contains three major steps. First, a Gaussian image pyramid is constructed by convolving the image with Gaussian filters at different scales and then obtaining a series of difference of Gaussian (DoG) images by subtracting adjacent Gaussian images. Second, keypoints are detected by searching extremal values in the DoG pyramid, followed by the process of subpixel localization and unstable keypoint elimination. Third, dominant orientations are calculated for keypoints, and then, descriptors are constructed based on gradients in the local image patches aligned by dominant orientations. Due to the intrinsic difference between optical and SAR sensors, SIFT usually fails to match optical and SAR images. Therefore, in order to improve the performance of SIFT in matching optical and SAR satellite images, several modifications of SIFT are introduced in this letter.

1) Construction of DoG Pyramid: Due to the properties of SAR imaging process, there are many speckles in SAR images which deteriorate SIFT for keypoint extraction, i.e., extracting many unrepeatable keypoints. These keypoints cannot be detected repeatedly in the corresponding optical images. In the view of feature matching, a large amount of outliers will adversely make the matching task hard to be achieved as the matching space is contaminated by many noises. Recent works [8]–[10] have found that most of these unrepeatable keypoints are detected in the first octave. Therefore, the first modification is to detect keypoints started from the second octave.

2) Dominant Orientation Assignment: In SIFT, dominant orientations are assigned to keypoints for constructing descriptors in order to be rotation invariant. Fan *et al.* [11] have made the following observations: 1) The computed dominant orientation is not stable enough and adversely affects the matching performance of the constructed SIFT descriptor, and 2) SIFT is robust to in-plane rotation up to 20°. Therefore, the matching performance of the SIFT descriptor can be significantly improved by a more accurate estimation of dominant orientation or just skipping the dominant orientation assignment when the matching images do not have rotation transformation. In most of real applications, the available satellite images are usually rectified so that their top is the north of the Earth. Thus, the orientations of optical and SAR satellite images are coarsely aligned, i.e., the rotation error between them is very small. It means that, in the problem of registration of optical and SAR satellite images, the step of dominant orientation assignment can be skipped, thus not only speeding up the descriptor construction but also significantly improving the matching performance of SIFT. A similar modification was also used by Suri *et al.* [8] for effective multisensor SAR image matching.

3) Multiple Support Regions: In SIFT, one single support region of size 16×16 is used for descriptor construction. Intuitively, the more the support regions used for a constructing descriptor, the more distinctive the constructed descriptor would be. In other words, a constructing descriptor using multiple support regions could handle the mismatching problem better than a constructing descriptor using only one single support region. Therefore, our proposed improved version of SIFT uses multiple support regions to construct the descriptor. Specifically, three nested support regions in sizes of 16×16, 24×24, and 32×32 are used for descriptor construction. First, a descriptor is computed from each of the three support regions, and then, the three computed descriptors are concatenated together to construct the final descriptor.

B. *Spatial Consistent Matching (SCM)*

For the input optical and SAR satellite images, two sets of features can be obtained by the improved SIFT introduced in Section II-A. The traditional feature-based method usually establishes feature correspondences by a matching strategy according to descriptor distances. Popular matching strategies include the NN matching, the NN distance ratio (NNDR) matching [12], and the dual matching (DM) [10]. RANdom SAmple Consensus (RANSAC) is used to estimate the transformation parameters from the established feature correspondences. However, due to the large differences between optical and SAR images, the matching features obtained by NNDR or DM usually contain a large amount of outliers as shown in Table II, further resulting in the failure of RANSAC. Here, we adopt a different approach. First, KNN (K is set to 25 in our experiments) matching is used to obtain an initial set of matching features, denoted as $\mathcal{M} = \{(F_i^o, F_i^s, s_i), i = 1, 2, \ldots, N\}$, in which (F_i^o, F_i^s, s_i) denotes a matching feature and s_i is its matching confidence. The superscripts "o" and "s" refer to the features of the optical and SAR images, respectively, and N is the number of initial matching features. Without loss of generality, $\mathcal{M}$ is sorted in descending order of confidence. Since the initial set of matching features contains many one-to-many matching features and a large amount of outliers, it is refined by imposing the spatial consistent constraint. Finally, the refined matching features are used for parameter estimation.

The utilized spatial consistent constraint is the low distortion constraint, which was widely used in the computer vision community when matching challenging images [13]. It means that the geometric relationship between matching features should not change too much across images. Given two matching features (F_1^o, F_1^s) and (F_2^o, F_2^s), the low distortion constraint indicates the following: 1) The angle between the horizontal axis and the line passing from F_1^o to F_2^o in the optical image (denoted as $\theta(F_1^o, F_2^o)$) does not deviate too much from that of F_1^s and F_2^s in the SAR image (denoted as $\theta(F_1^s, F_2^s)$), and 2) the ratio of $\overline{F_1^o F_2^o}$ and $\overline{F_1^s F_2^s}$ does not deviate too much from the scale ratio of the optical image and the SAR image.[1] This constraint can be formulated as follows:

$$|\theta(F_1^o, F_2^o) - \theta(F_1^s, F_2^s)| < t_\theta \tag{1}$$

$$\left|\overline{F_1^o F_2^o} / \overline{F_1^s F_2^s} - \alpha\right| < t_s \tag{2}$$

where α is the estimated scale ratio of the optical image and the SAR image which can be computed from a seed matching feature. t_θ and t_s are two thresholds controlling sensitivity on deformations. The larger they are, the more the robustness to inter-image distortions, but incorrect matching features are more likely to be considered as spatial consistent. They are set to 5° and 0.2 according to experiments.

Given a set of initial matching features $\mathcal{M} = \{(F_i^o, F_i^s, s_i), i = 1, 2, \ldots, N\}$ and one seed matching feature (F^o, F^s) which is obtained from $\mathcal{M}$ automatically according to its matching confidence, we can obtain a set of consistent matching features by gradually adding a matching feature which is spatial consistent with the currently obtained matching features. The procedure is outlined in Algorithm 1.

Algorithm 1 Spatial Consistent Matching (SCM)

Input:
A set of matching features $\mathcal{M} = \{(F_i^o, F_i^s, s_i), i = 1, 2, \ldots, N\}$, one seed matching feature (F^o, F^s).

Output:
A set of SCM features $\mathcal{M}'$.

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Initialization: compute scale ratio α from (F^o, F^s), set M' = {(F^o, F^s)}.
for i from 1 to N do
   Count the number of matching features in M' which are
   consistent with (F_i^o, F_i^s) according to the constraint (1)
   and (2), denoted as m.
   if m > 0.95 × size(M') then
      Add (F_i^o, F_i^s) to M'.
   end if
end for
return M'
```

Although Hasan *et al.* [14] have used spatial analysis on SIFT keypoints for multispectral remote sensing image registration, the success of their method largely relies on NNDR. This is because their method needs to use NNDR matches to calculate a coarse affine transformation, and the inlier matches are used to get more matches by spatial analysis. Unfortunately, as can be seen from our experimental results listed in Table II, NNDR usually fails to obtain enough correct matches when matching optical and SAR images. The proposed SCM works well in cases that NNDR and DM fail, demonstrating the advantage of the proposed method.

C. Parameter Estimation

According to multiview geometry, images of a plane captured by two cameras at different viewpoints are related by a homography. Since satellite images are captured at a long distance from the Earth, the heights of buildings in the Earth can be ignored compared to the distance between the Earth and the satellite. Therefore, satellite images can be regarded as captured from a plane approximately. As a result, we take the eight parameters of a homography as the transformation parameters.[2] RANSAC is used to estimate these parameters from the spatial consistent matching features.

In order to avoid the risk that the selected seed in Algorithm 1 is actually wrong, the steps of SCM and parameter estimation are repeated n times by setting each of the top n initial matching features (with the highest matching confidences, i.e., the smallest descriptor distances) as seed, and the parameters with the largest number of inliers are used to produce the final registered images. This procedure is outlined in Fig. 1, and n is set to 10 in our experiments.

III. Experiments

In this section, we conducted experiments to validate the effectiveness of the proposed method in a laptop with 2.5-GHz CPU and 2-GB RAM. As shown in Fig. 2, two unregistered optical and SAR image pairs are used for evaluation. In order to show the effectiveness of each modification to SIFT, four methods were evaluated.

1) SIFT: It refers to the original SIFT method.
2) SIFT-M1: It refers to the feature extraction method by applying the first modification (see Section II-A1) to SIFT. It is also known as SIFT-OCT [9].
3) SIFT-M2: It refers to the feature extraction method by applying the first two modifications (see Section II-A1 and A2) to SIFT.
4) SIFT-M3: It refers to the feature extraction method by applying all the three modifications (see Section II-A) to SIFT.

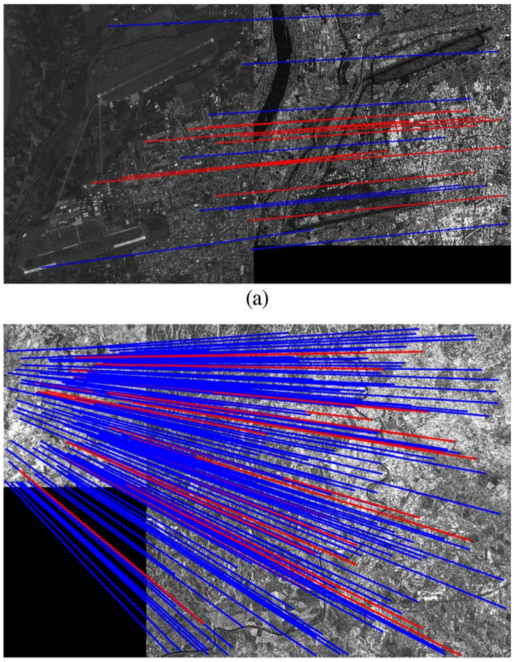
Note that, while SIFT-M1 and SIFT-M2 have been proposed for SAR image registration [8], [9], SIFT-M3 is first proposed in this letter to further increase its distinctiveness. In addition to the proposed SCM strategy, two kinds of popular matching strategies were also evaluated.

1) NNDR [12]: It is the widely used matching strategy along with SIFT. The keypoint is matched according to the ratio of its NN distance and its second NN distance.
2) DM [10]: It is based on the NNDR matching strategy, but double check is adopted. For a keypoint in the optical image F_i^o and its NNDR match F_j^s in the SAR image, (F_i^o, F_j^s) is accepted as a match only if F_i^o is also F_j^s's NNDR match in the optical image.

The numbers of detected keypoints with various tested methods are listed in Table I. It can be seen that the number of detected keypoints reduced to less than 25% (SIFT versus SIFT-M1) by applying the first modification to SIFT. As later shown by matching results, most of the keypoints detected in the first

[1] $\overline{F_1^o F_2^o}$ is the distance between F_1^o and F_2^o in the optical image, and $\overline{F_1^s F_2^s}$ is the distance between F_1^s and F_2^s in the SAR image.

[2] When the terrain height is so large that the considered region cannot be approximated as a planar one, other more complicated transformation models can be incorporated.



(a)

(b)

Fig. 2. Two unregistered pairs of optical and SAR satellite images acquired over (a) Pingtung (Taiwan) and (b) Rome (Italy), respectively. As can be seen, there are significant differences in their appearances, making their registration a challenging problem. (a) Left is a 825 × 924 optical image (band 1 of SPOT 5; pixel size is 10 m), while the right is a 850 × 798 SAR image (Radarsat-1; pixel size is 10 m). (b) Left is a 628 × 718 optical image (band 1 of Landsat Thematic Mapper; pixel size is 30 m), while the right is a 1606 × 1470 SAR image (ERS-2; pixel size is 12.5 m). The keypoint matching results of our proposed method [11 correct matches among 19 matches for (a) and 26 correct matches among 165 matches for (b)] are superimposed on images, in which the red lines indicate correct matches and the blue lines indicate incorrect ones.

TABLE I
NUMBER OF DETECTED KEYPOINTS

Image Pair		SIFT	SIFT-M1	SIFT-M2 or SIFT-M3
(a)	optical	5113	1122	868
	SAR	8926	2231	1786
(b)	optical	11113	2553	2076
	SAR	59207	9916	7991

octave are unrepeatable or hard to be matched. By skipping dominant orientation assignment, the number of keypoints further reduced to about 80% (SIFT-M1 versus SIFT-M2 or SIFT-M3) since there may exists several dominant orientations for one keypoint.

Table II gives the matching results and running times of various modifications of SIFT combined with different matching strategies. The matching results are given in the form of correct matches/obtained matches. NNDR and DM were evaluated with two thresholds: 0.95 and 0.85. The ground-truth transformations of the tested image pairs are calculated by four manual selected point correspondences. If one point transformed by the ground-truth transformation lies in 3 pixels of its matching point, then they are considered to be a correct match. From Tables I and II, we have the following observations.

1) Although SIFT detected four times more number of keypoints than SIFT-M1, the precision of the obtained matches is less than that of SIFT-M1. It indicates that most of the keypoints detected in the first octave are unrepeatable or hard to be matched.

TABLE II
MATCHING RESULTS AND RUNNING TIMES (CORRECT MATCHES/OBTAINED MATCHES AND RUNNING TIME) OF VARIOUS MODIFICATIONS OF SIFT (SIFT, SIFT-M1, SIFT-M2, AND SIFT-M3) COMBINED WITH DIFFERENT MATCHING STRATEGIES (NNDR, DM, AND SCM). SEE TEXTS FOR DETAILS

	SIFT	SIFT-M1	SIFT-M2	SIFT-M3
Image Pair (a)				
NNDR (0.95)	2/1518, 29.0s	1/369, 2.9s	1/280, 2.3s	2/129, 4.0s
DM (0.95)	1/467, 32.9s	1/138, 3.1s	1/105, 2.4s	2/43, 4.1s
NNDR (0.85)	1/111, 29.0s	1/37, 2.9s	1/21, 2.3s	1/4, 4.0s
DM (0.85)	1/24, 29.3s	1/11, 2.9s	1/6, 2.3s	1/1, 4.0s
SCM	0/32, 32.2s	0/5, 3.2s	8/19, 2.6s	**11/19**, 4.3s
Image Pair (b)				
NNDR (0.95)	1/2817, 385.0s	1/711, 17.1s	3/588, 12.4s	5/320, 19.5s
DM (0.95)	0/1673, 398.2s	1/396, 18.0s	2/363, 13.2s	4/156, 20.4s
NNDR (0.85)	0/120, 384.8s	0/45, 17.1s	1/39, 12.4s	0/4, 19.5s
DM (0.85)	0/71, 385.3s	0/25, 17.2s	0/22, 12.5s	0/2, 19.5s
SCM	0/39, 415.9s	0/7, 18.4s	22/142, 15.1s	**26/165**, 23.2s

2) When the matching strategy is the same, the performance rank of all the evaluated descriptors is as follows: SIFT-M3 > SIFT-M2 > SIFT-M1 > SIFT. It means that each of the three modifications has some effectiveness in improving the descriptor's distinctiveness. The first modification mainly aims to remove unstable keypoints, while the latter two modifications are focused on improving distinctiveness.

3) Compared with NNDR and DM, our proposed SCM not only obtains much more number of correct matches but also has much higher matching accuracy. With SIFT or SIFT-M1, SCM does not obtain any correct match maybe because of their poor distinctiveness, which results in most of the matches in the initial matching set used for SCM being incorrect ones. Therefore, the second and third modifications are critical for improving SIFT's matching performance in the problem of optical and SAR image registration.

4) The proposed SCM is relatively fast, and most of the running time of our proposed method (SIFT-M3 + SCM) is used for obtaining initial matching features as NNDR and DM do. It is worth to note that the running time of our method is much less than the original SIFT matching method since many unstable keypoints are eliminated.

The registration results of the two tested image pairs by our proposed method (SIFT-M3 + SCM) are shown in Fig. 3, and the quantitative results are listed in Table III. Note that these two image pairs cannot be registered successfully by NNDR- or DM-based methods due to their poor matching performance as given in Table II. Therefore, the quantitative results of these methods are not reported. In addition to the widely used measure of root mean square, some recently proposed quantitative measures [15] are also evaluated. The control points used for parameter estimation in our method are used for calculating these measures, i.e., the inliers after RANSAC; please refer to [15] for details about these measures. There are 12 control points used for image pair (a) and 23 control points for image pair (b).

IV. CONCLUSION AND DISCUSSION

This letter aims to solve the problem of registration of optical and SAR satellite images. In order to improve SIFT's

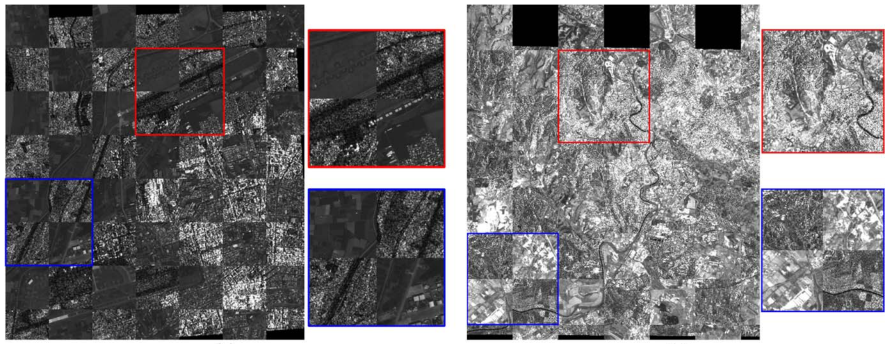

(a) (b)

Fig. 3. Registration results of our proposed method (SIFT-M3 + SCM). They are shown by chess images with alternate patches from the optical images and the registered SAR images. For each chess image, two local regions are shown in the right for a better checking of the registration accuracy.

TABLE III
QUANTITATIVE RESULTS OF THE PROPOSED METHOD (SIFT-M3 + SCM). SEE TEXTS FOR DETAILS. *: UNIT IS PIXEL

Image Pair	RMS_{all}^*	RMS_{LOO}^*	$BPP(2)$	S_{kew}	S_{cat}
(a)	2.44	2.05	0.42	0.65	0.999
(b)	2.37	2.01	0.52	0.17	0.999

performance in matching optical and SAR satellite images, three modifications are introduced. By exploring the spatial relationship of matching points, a novel matching strategy named SCM is proposed to obtain reliable matching points from an initial set of matches generated by the KNN matches of the improved SIFT. Experimental results have demonstrated the effectiveness of each modification to SIFT as well as the superiority of the proposed matching strategy. The proposed method can register the two tested pairs of optical and SAR satellite images successfully, which cannot be registered by previous methods. We have also tested the proposed method on some more images and found similar performance.

Since the spatial relationship of matching features is explored by means of the low distortion constraint in the proposed method, it is not robust to large image distortion. Fortunately, in most of real applications, the available satellite images usually contain longitude and latitude information and are coarsely aligned such that the top of the image is the north of the Earth. These images do not have large distortion. Therefore, the proposed method is extremely suitable for satellite image registration. In cases that the aforementioned information is unfortunately unavailable, a coarse registration can be first applied to downsampled optical and SAR images by a previous method, and then, the proposed method can be applied to the coarsely registered images for fine registration. Note that, for downsampled optical and SAR images, their appearance differences are not as significant as the original ones because only the large-scale information remains in the downsampled images. Thus, a coarse registration can be obtained by previous methods. However, a fine registration of the coarsely registered images with original resolution cannot be obtained by previous methods due to large appearance differences, while the proposed method does it well.

As discussed earlier, one disadvantage of the proposed method is that the utilized low distortion constraint restricts its direct use for registering images with large distortion. Future work will include incorporating more general spatial constraint for dealing with large distortion and combining segmentation for reliable feature matching, whose effectiveness has been shown with optical image registration [16].

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