REGISTRATION FOR LONG-TERM MULTI-TEMPORAL REMOTE SENSING IMAGES UNDER SPATIAL CONSTRAINTS FROM HISTORICAL DATA

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ABSTRACT

In long-term multi-temporal images, the objects are very different and the feature matching is very difficult. However, in short-term multi-temporal images, the differences of objects are relatively insignificant. With the small difference, the correct matching points and the right affine transformation can be easily obtained. According to long-term multi-temporal image matching, in the range of time span we insert some historical image to reduce intervals in temporal difference. Through a series of affine transformation between neighboring temporal, the rough spatial relations between the two images can be gradually determined. Under the rough spatial constraints, the accuracy of the points matching can be significantly improved.

Index Terms— Remote sensing image, image registration, historical data, spatial constraint

1. INTRODUCTION

Registration is the basis of multi-temporal change detection. Due to the variations in viewing angle, atmospheric conditions, seasons and other factors, there exist appearance differences for objects on the same area [1]. SIFT (Scale-Invariant Feature Transform)[2] and SURF (Speeded Up Robust Features)[3] features are invariant to rotation and scaling, widely applied for remote sensing image registration. Some objects' appearance maybe very different for long-term multi-temporal images, which exacerbate the difficulty on correct matching of local invariant features. There are obvious errors on spatial relationships between false matching points. If the spatial relations are obtained, the accuracy of feature matching can be improved under the spatial constraint [4-6].

With the growing number of remote sensing satellites, more and more remote sensing images can be easily obtained. And the historical data of the same area is gradually increasing. The time interval of historical data is getting shorter and shorter. The remote sensing image pair for registration with short-term may acquire the correct matching features due to the small change of ground objects.

In the process of change detection, there are the requirements of the remote sensing image registration for long time span. In this paper, we present a registration method for long time span under spatial constraints. The methodology is described in Section 2, the results of its application to the long-term remote sensing images are illustrated in Section 3, and the discussion is presented in Section 4.

2. METHODOLOGY

I_a and I_b are remote sensing images of the same area, which token in time of T_a and T_b. The time interval between T_a and T_b is long, and it is difficult to get the correct matching features and transform due to the change of ground objects. Between T_a and T_b, there are a series of historical images $I_{a+1}, I_{a+2}, \cdots, I_{b-2}, I_{b-1}$ token in time of $T_{a+1}, T_{a+2}, \cdots, T_{b-2}, T_{b-1}$. There exists the relationship that $T_a < T_{a+1} < T_{a+2} < \cdots < T_{b-2} < T_{b-1} < T_b$.

Let us consider I_a is the reference image and I_b is the image to be registered. We choose SURF feature points as the matching feature and RANSAC[7] as the method of removing the false matching point pairs. The approach we present is demonstrated by Fig. 1. Firstly, we find and insert the historical images to form the image serial by the time of T_a and T_b from the remote sensing image database. Then, with the I_a and I_b as the start and the end, respectively. According to the number of correct matching point pairs, we choose the some image to form the registration chain. Then, the transform of pair of neighboring image in the registration chain is evaluated in order to get the transformation of I_a and I_b. Finally, between I_a and I_b we extract and match SURF points. False matching point pairs are removed by spatial relations of transformation and RANSAC. These steps will be separately described in the following subsection.

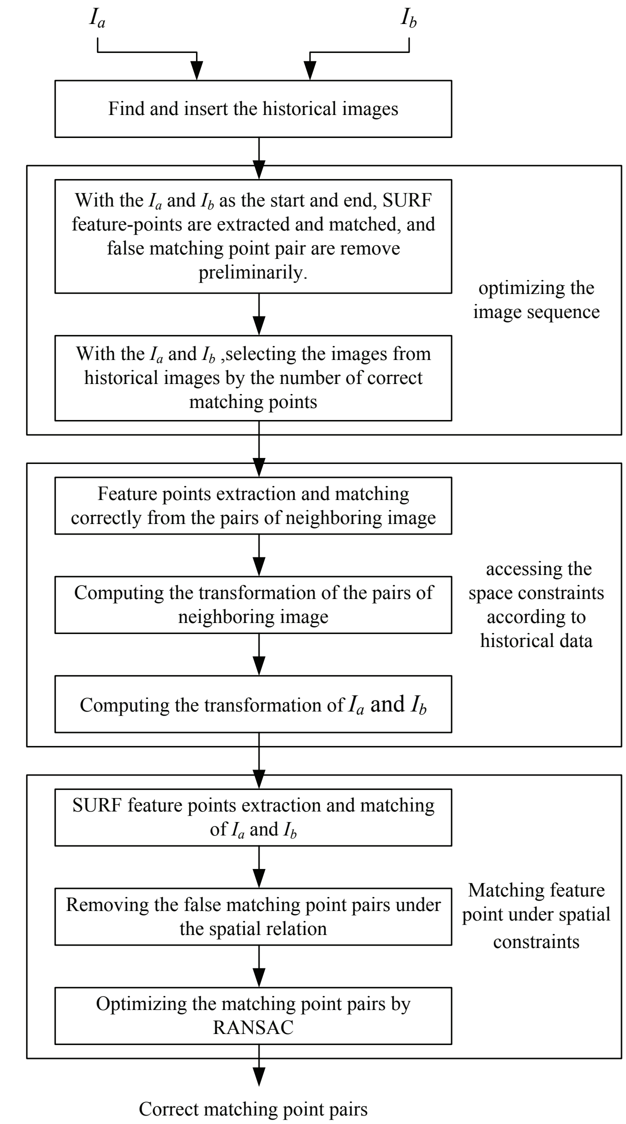


Fig. 1 Main steps of the proposed methodology

2.1. Optimizing the image sequence

Due to the influence of image quality, in the historical image sequence of $I_{a+1}, I_{a+2}, \cdots, I_{b-2}, I_{b-1}$, not all of neighboring image pairs can achieve the correct matching feature and transformation. So we choose the images with the better matching from the historical image sequence. Those images form the optimized image sequence of $I_a, I_{r1}, I_{r2}, \cdots I_{m2}, I_{m1}, I_b$ to get the relatively accurate transformation between I_a and I_b. In the serial of $I_a, I_{r1}, I_{r2}, \cdots I_{m2}, I_{m1}, I_b$, the images are added by pair of $< I_{rk}, I_{mk} > (k = 1,2,3,\cdots)$. The algorithm of adding $< I_{r1}, I_{m1} >$ can be summarized as follows:

Step1: Image $I_i (i = a+1, a+2, \cdots, b-2, b-1)$, put out from $I_{a+1}, I_{a+2}, \cdots, I_{b-2}, I_{b-1}$, and image I_a form orderly the registration image pair $< I_a, I_i >$. In the pair, n SURF points extracted and matched with SURF description. We can get C_{ai} pair of correct matched points after RANSAC. According to the C_{ai} with Formula (1), we choose the image I_p of T_p. If p is multi-results, the optimal solutions is I_p having the largest number of correct matched points and having the largest interval between T_p and T_a.

$$p = \arg \max_{i=1,2,\cdots,n} (C_{ai}) \tag{1}$$

Step2: Forming the registration image pair $< I_j, I_b >$, where $I_j (j = a+1, a+2, \cdots, b-2, b-1)$ is from $I_{a+1}, I_{a+2}, \cdots, I_{b-2}, I_{b-1}$, like Step 1, we find the I_q which is best registrated with I_b.

Step3: Adding the pair $< I_{r1}, I_{m1} > = < I_p, I_q >$ to the optimized serial $I_{r1}, I_{r2}, \cdots I_{m2}, I_{m1}$. If $q = p+1$ or $q = p+1$, end. If $q < p$, suboptimal I_p or I_q instead the optimal I_p or I_q.

The historical data subsequence $I_{p+1}, I_{p+2}, \cdots, I_{q-2}, I_{q-1}$ between I_p and I_q repeats the Step1~Step3 and gets the $< I_{r2}, I_{m2} >$. And so on down the historical data sequence, we obtain the optimized image sequence.

2.2. Achieving spatial restraint

For the optimized image sequence, we put out the image pairs $< I_a, I_{r1} >, < I_{r1}, I_{r2} > \cdots < I_{m2}, I_{m1} >, < I_{m1}, I_b >$ with neighbor time. To those $2k+1$ image pairs, we extract and match SURF feature points in order. The affine transformation $A_1, A_2, \cdots, A_{2k}, A_{2k+1}$ can be obtained with the corrected matching points. And the affine transformation A is the rough spatial constraints between I_a and I_b points.

$$A = A_1 \cdot A_2 \cdot \ \ldots \ \cdot A_{2k} \cdot A_{2k+1}$$

2.3. Matching feature points under spatial restraint

After transformation, the pixels in I_b still exist some error with the corresponding pixels in I_a. So the affine transformation A can hardly describe the spatial relationship accurately. But a certain error range e, A can depict the relations of corresponding pixels in I_a and I_b

In the process of matching the feature points (x_1, y_1) and (x_2, y_2) in I_a and I_b, we compare (x_1, y_1) and (x_2, y_2) under the spatial restraint of A and e as the formula (2). If the relationship is not satisfied, the matched points would likely to be mismatch points.

$$(x_1 \;\; y_1) \subset (x_2 \;\; y_2) \cdot A \pm e \tag{2}$$

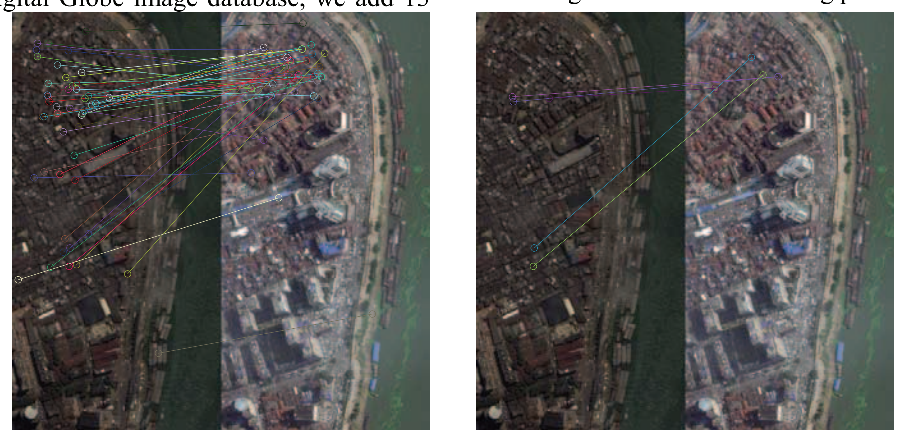
After removing lots of mismatching points by the spatial restraint, we use RANSAC refine the matched points. Now, the matched results are refined.

3. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed method was applied to multi-temporal remote sensing images covering Wuhan City in China, as shown in Fig. 2 (a) and (b). Left of Fig. 2 (a) was collected on 19 February 2003. Right of Fig. 2(a) was collected on 23 October 2014. The images are with large time span, and land changes severely. The registration results by using SURF are shown in Fig. 2 (a). We can observe that there are a lot of mismatch points. Even by using RANSAC to select the correct point pairs, there are also some mismatch point pairs, which are shown in Fig. 2 (b). Those mismatch points directly affected the correct solving of transformation model.

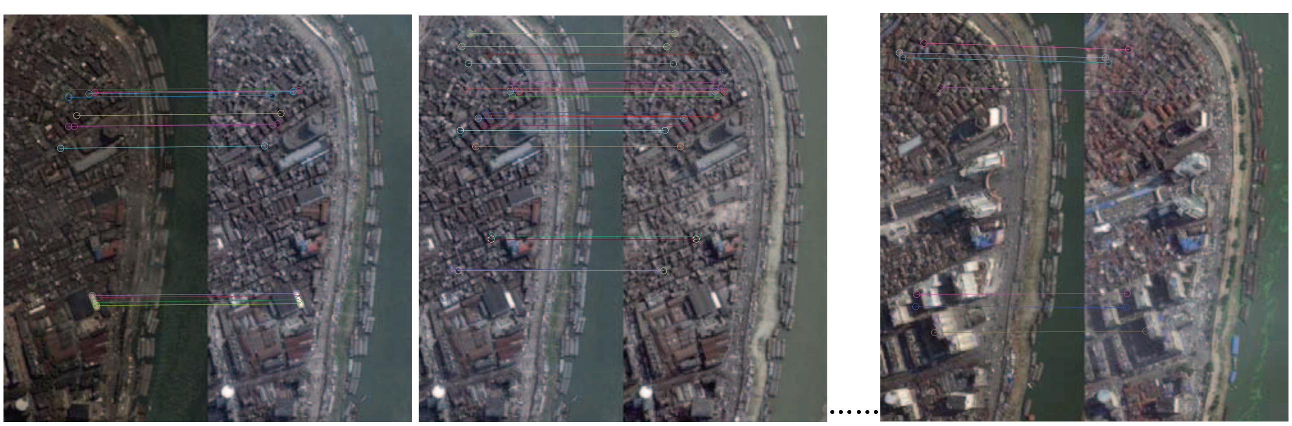
In order to improve the validity of point pairs in Fig. 2 (b), based on the Digital Globe image database, we add 13 pictures between the pictures of Fig. 2 (a) and form a image sequence of 15 temporal. After optimizing the image sequence by the number of correct matching points, we get an optimized image sequence with 7 temporal. From the optimized image sequence, we can put out 6 image pairs in which the two images are neighboring. After RANSAC, the correct matching SURF points of the image pairs are shown in Fig. 3. And the transform relationship of image pairs can be solved by the correct matching SURF points.

Based on the transform of image pairs in the optimized image sequence, we can get the transformation between the image on 19 February 2003 and the image on 23 October 2014 and obtain the spatial restrains between them. Under the spatial restrains, lots of false matching points are removed and the results are shown in Fig. 4 (a). After RANSAC, the correct matching points are shown in Fig. 4 (b). Comparing the Fig. 2 (b), the validity of point pair in Fig. 4 (b) is greatly improved. The Fig. 4 (c) shows the affine transform result of the image on 23 October 2014 according to the correct matching points.



(a) (b)

Fig. 2 (a) The results of SURF point extracted and matched in image (left) on 19 February 2003 and image (right) on 23 October 2014, (b) The results of removing false matching points in (a) by RANSAC.



(a) (b) (c)

Fig. 3 (a) The results of points matched in image (left) on 19 February 2003 and image (right) on 27 March 2003, (b) The results of points matched in image (left) on 27 March 2003 and image (right) on 27 February 2004, (c) The results of points matched in image (left) on 22 Janurary 2009 and image (right) on 23 October 2014.

(a) (b) (c)

Fig. 4 (a) The results of points matched in Fig. 2 (a) after removing the false matching points under spatial restraint, (b) The results of point pairs in (a) after deleting the false matching points by RANSAC, (c) The transform results of the image on 23 October 2014.

In order to improve the validity of point pairs in Fig. 2 (b), based on the Digital Globe image database, we add 13 pictures between the pictures of Fig. 2 (a) and form a image sequence of 15 temporal. After optimizing the image sequence by the number of correct matching points, we get an optimized image sequence with 7 temporal. From the optimized image sequence, we can put out 6 image pairs in which the two images are neighboring. After RANSAC, the correct matching SURF points of the image pairs are shown in Fig. 3. And the transform relationship of image pairs can be solved by the correct matching SURF points.

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4. CONCLUSIONS

Many remote sensing image registration methods can achieve accurately registration if the ground objects in two images are nearly same. However, for long-term multi-temporal remote sensing image, there may be many changes that it is hard to get correct matching points. By complementing the historical data and gradually estimating the affine transformation model between long-term multi-temporal images, spatial constraints under the affine transformation model can improve the correctness of the feature matching.

5. ACKNOWLEDGMENT

The research is supported by the National Natural Science Foundation of China (Grant No. 61262036, Grant No. 61462042, and Grant No. 61371143).

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