2011 International Conference on Computer Science and Information Technology (ICCSIT 2011)
IPCSIT vol. 51 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.V51.44

An Improved SIFT Feature Matching Algorithm Based on Maximizing Minimum Distance Cluster

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Abstract. Due to the invariance of image scale, rotation, illumination, SIFT(Scale Invariant Feature Transform) algorithm has been widely applied in image registration. However, the existence of noise and similar surface features causes the mismatch points, and there are always too many matching points detected, which leads to uneven distribution in the whole image. In order to solve this problem, this paper proposed an improved SIFT method, which based on the original SIFT feature extraction and maximum of minimum distance clustering. This algorithm can select out uniformly distributed matching points from a large number of matching points detected by the SIFT algorithm, achieving the secondly accurate feature point matching. The experiments show the improved SIFT algorithm can successfully locate multi-source remotely-sensed imagery to realize a more accurate matching to specific target.

Keywords: SIFT, Automatic Registration, Maximum of Minimum Distance Cluster

1. Introduction

Image feature extraction and matching technology is an important component of computer vision and digital image processing, and plays an important role in target detection, object recognition, three-dimensional reconstruction, image registration, image understanding and etc., so it has become the focus of the research of image processing [1]. But due to the image translation, rotation, scale change caused by the external conditions such as illumination, occlusion and the influence of different sensor imaging angle, imaging time, it is quite hard to detect the target objects in the feature extraction and matching. To solve these problems, David G. Lowe proposed a scale invariant feature transform (SIFT) matching algorithm. The algorithm can effectively maintain invariance to the translation, rotation, scale and illumination change, moreover, maintain a certain degree of stability and adaptability [2, 3]. However, a large number of feature points extracted by SIFT include many mismatched points, and the uneven spatial distribution can also affect the accuracy of further geometric correction.

In response to these problems, this paper proposed a modified SIFT feature matching algorithm, using the original SIFT algorithm to extract a large number of feature matching points, then combining the principle of maximum of minimum distance cluster we can further select the matching points of uniform spatial distribution in order to achieve the second accurate matching. The second to fifth part of this paper will analysis the principle of the optimized SIFT algorithm theoretically, and the sixth part shows how this algorithm will be implemented with the multi-source remote sensing data and experimental results will also be analyzed and discussed in detail. The last part is the conclusion.

2. SIFT feature matchign theory

2.1. SIFT Feature Matching Pricinple

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SIFT, proposed by D.G.Lowe in 1999, perfected in 2004, is a Feature-based matching algorithm, and it can extract the local features near real-time, these features were contemplated to be highly distinctive and invariant to image scale and rotation. It can complete high-speed, accurate match from the massive feature database.

2.2. SIFT Feature Matching steps

a) Scale-space extrema detection

The input image is convolved with Gaussian kernel and down-sampled to produce the set of scale space pyramid images. Then adjacent Gaussian images are subtracted to produce the difference-of- Gaussian(DoG) scale space.

For each point in DoG scale space, compare it with surrounding points in the same and adjacent layers(total 26 neighbors), the maxima and minima will be detected as candidate interest points.

b) Keypoint location

By fitting three-dimensional quadratic function the interpolated location of the maximum can be estimated to determine precise positioning coordinates and scale. After the computation of the Hessian matrix(2.4) we can further remove the points with low contrast or the unstable edge points to obtain accurate positioning as a key point of the extreme points.

c) Orientation assignment

The direction parameters of each key point can be determined by computing the gradient direction of the neighboring pixels. To be specific, we use gradient direction histogram to gain the gradient direction. Thus, each key point has been tested fully, up to now there are 3 properties for every key point, that is, location, scale and direction, which can determine a region of SIFT features in the next step.

d) Keypoint descriptor

For any one of the key points, take the neighborhood 16 pixels by 16 pixels round the center of the key point, then this neighborhood will be evenly divided into 4*4 sub-regions, calculated for each sub-region gradient direction histogram(histogram equalization is divided into eight directions).Then, 4*4 sub-regions of the 8-direction gradient histogram sorting order according to its location, thus constituting a 4*4*8=128 dimensional vector, called SIFT descriptor. The idea of neighborhood joint direction has greatly enhanced the ability of anti-noise algorithm, and also it provides better fault tolerance for the match with the characteristics of location error.

3. maximum of minimum distance cluster

3.1. maximum of minimum distance cluster principle

The basic idea is to select the object as far as possible as the initial cluster center to get a good data set division. The aim is to avoid initial cluster seeds too close from each other, the appearance of too many cluster seeds at the same class or the bad situation of no seeds at the small cluster. Using this algorithm can guarantee the distance between the new cluster center and the already found center as far as possible [4].

3.2. maximum of minimum distance cluster flow

1) Suppose there are n objects, Set Sn={x1, x2, ... , xn}.Take any object, such as x1, put it as the cluster center of the first class, there are Z1=x1;

2) Find the furthest object from Z1 in the set Sn as the cluster center, call it Z2;

3) Compute the distance between each remaining object in the set Sn and the selected object(Z1, Z2), and let the smaller value being as min(di1,di2);

4) Compute the maximum of min(di1,di2), let it being as max(min(di1,di2)), corresponding to the object Z3;

5) Similarly, compute the distance between each remaining object in the set Sn and the selected object(Z1, Z2,Z3), and let the smaller value being as min(di1,di2,di3);

6) Similarly, compute the maximum of min(di1,di2,di3), let it being as max(min(di1,di2,di3)), corresponding to the object Z4;

7) Repeat the step 5) and 6) until all the cluster centers have been found;

8) In practical implementation, delete the two points with nearest distance in the preliminary computing results, re-looking for the maximum of the minimum distance. After several iterations, the experimental result can be optimized to reach a high accuracy.

4. Consistency detection

With the influence of imaging posture and projection center, some areas may appear a kind of distortion or deformation, which may lead to the error matching. Experiments show that these errors cannot be removed in the fine matching, and its presence will affect the reliability of the registration results.

Consistency detection principle is based on the fact that any line segment before or after the transformation has the same ratio as that of the transform. The matching points by the precise matching composite the set of {ai} and {bi}, respectively include n corresponding matching points. And the ratio of line segment is aiaj/bibj, the total number of these line segments is n*(n-1)/2. When the matching result is accurate to model requirement, the ratio is close or almost the same. So this step is the check links to verify the positioning accuracy of the matching points selected.

5. Optimized SIFT feature matching algorithm

Due to the noise and surface similarity, the accuracy of image matching can decrease in the original SIFT algorithm. In order to reduce the mismatched points and eliminate the redundant points, this paper proposed an optimized matching algorithm blow.

First, by using the original SIFT algorithm to extract a large number of matching points as initial candidate feature points. Then establish kd-tree data structure according to the feature points and its feature vector in the image. By doing this we can greatly improve the searching speed. Meanwhile, limit the relative displacement between feature points less than two pixels, which can ensure the ratio of the nearest neighbor and the second nearest neighbor at a large scale. This step accomplished the coarse matching.

Second, with the application of maximum of minimum distance cluster algorithm, select matching points from the above matching points detected to find spatial farthest cluster center, so it can form the most uniform spatial distribution of matching points. This step can largely improve the accuracy for the next geometric correction.

Last, according to the principle of consistency test, compute the line segments composited by precise matching points. If the ratio of the corresponding line is similar, it shows that the further-selected matching points can meet with the registration precision; we can call them consistency data.

6. Multi-source remote sensing image experiments

This part applies the original SIFT algorithm and the optimized SIFT algorithm in two pair of remote sensing images, one is based on the remote sensing image of the same source, same time, but different resolution, the other is based on the remote sensing image of different source, different time, but the same resolution. Li Xiaoming[5] claimed that realistic objective data without theoretical reference data, lack a quantitative evaluation method, so the evaluation of the experimental results usually applied the visual judgments.

6.1. image registration with different resolution

Figure.1 shows the registration result with the method of the original SIFT algorithm in the satellite SPOT5 remote sensing imagery in somewhere of Shanghai city. One is the panchromatic image with the resolution of 2.5 m, the other is the multi-spectral image with the resolution of 10 m. When using kd-tree searching in the given area in the reference image, the number of candidates is set at 250, and the NN/SCN is set at 0.5,the consequence is that a total of 413 matching points has been detected, of which 354 points are correct, that is to say, the correct matching rate is 85.7%; Figure 2 reflects the registration result with the method of the optimized SIFT algorithm with the same imagery. It can be found that the distribution of the matching points selected is quite uniform and the precision is also quite high. With the help of optimized maximum of minimum distance cluster algorithm, we can find six matching points of the best uniform in the space distribution (The corresponding selected matching points marked by colored circle).Because the geometric correction of rational function only needs 6 points. After the consistency test, all the matching points selected by this algorithm meet with the requirements of the visual judgments. These two images reflect how the optimized SIFT algorithm work in the situation of rich surface features information and small differences. These two images reflect the optimized SIFT algorithm performs as well in the situation of quite different surface objects.

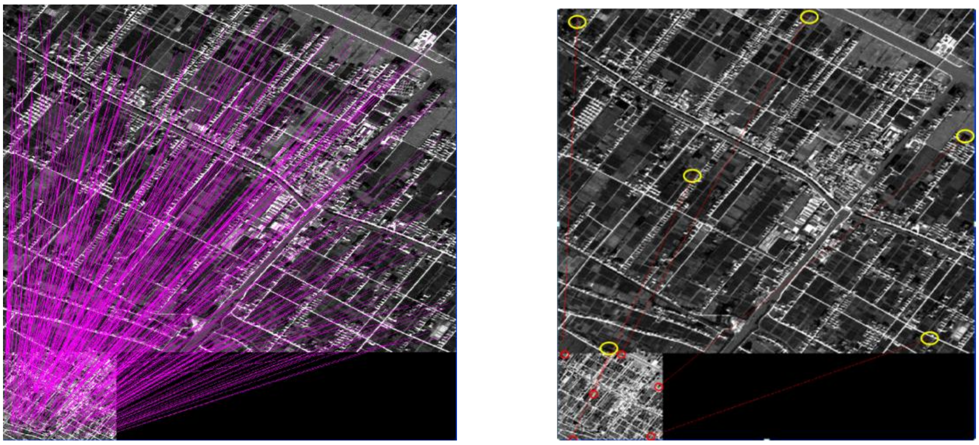

Fig. 1. (a) image matching result with the original SIFT; (b) image matching result with the optimized SIFT

6.2. Image registration with different time and sensor

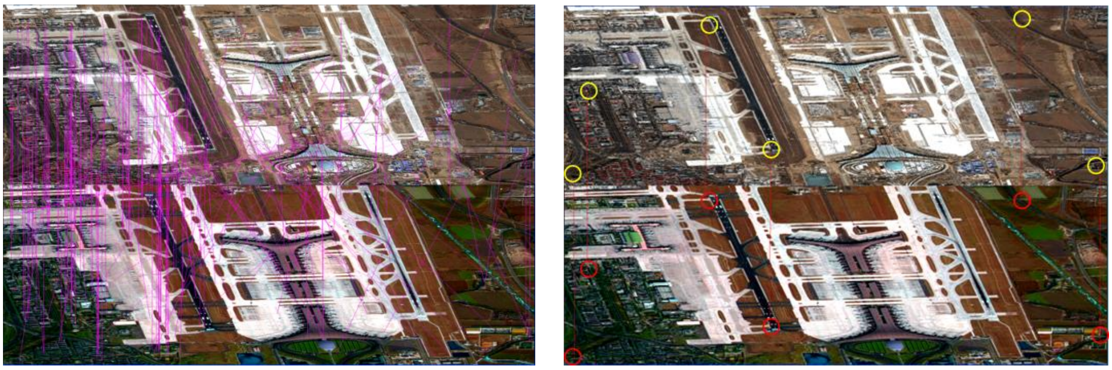

Fig. 2. (a) image matching result with the original SIFT; (b) image matching result with the optimized SIFT

Figure 3 shows the application of SIFT into the remote sensing images with different time and different sensor in the region of Beijing Capital Airport, the above is the colour image from the Quickbird satellite, and the below is the Spot5 fusion image with panchromatic and multispectral images. Both have the same resolution of 2.5m. But as the former is shot on October 13, 2007, and the latter is shot on March 10, 2009, there is a clear difference in surface features, so the success rate of matching becomes relatively lower. Figure.2 reflects the matching result when the NN/SCN is 0.5, a total of 206 matching points, of which 48 points are correct, which means the correct matching rate is 23.3%. Because of the big difference between the images and the existence of similar features, the accuracy of the registration becomes much lower. Figure 4 reflects the registration result with the method of the optimized SIFT algorithm with the same imagery (The corresponding selected matching points marked by a coloured circle). It can be found that even though there are great differences in the surface features in the two images, the optimized SIFT algorithm can still extract the matching points with the best space distribution. After the consistency test, all the matching points selected by this algorithm meet with the requirements of the visual judgments.

Finally, allow me to mention the speed of the algorithm, the experiment is carried out in the C++ programming language, in the Core i7 860@2.80GHZ processor, 2GB of memory, the running time of the optimized SIFT algorithm is almost the same as that of the original SIFT algorithm. And the finished time is closely linked to the image size and the number of matching points.

7. Conclusion

This paper presents an improved SIFT feature matching algorithm. First of all, with the application of SIFT algorithm, we can extract a large number of matching points, and then select the precise matching points with the method of maximum of minimum distance cluster. This optimized SIFT algorithm can effectively avoid the noise points, structural unrelated matching points, so this can largely improve the accuracy of image matching. Moreover, unlike the SIFT Feature Matching based on K-means clustering [6] which cannot determine the K value, this optimized SIFT algorithm can appoint the final number of the clusters. However, the accuracy of the matching for the next geometric correction by this optimized SIFT algorithm quantitatively needs further study.

8. Acknowledgements

This work was supported by the National High-Tech Research and Development Plan of China under Grant No. 2006AA12Z118, the National Natural Resources and Geo-spatial Basic Information Database under Grant No.JCXXK-HT2008-015 and the National Natural Science Foundation of China under Grant No. 60972142. Thanks are due to my colleague Jingtao Zhang for assistance with valuable suggestion with this method.

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