International Journal of Control and Automation
Vol. 9, No. 6 (2016), pp.51-58
http//dx.doi.org/10.14257/ijca.2016.9.6.04

An Improved SIFT Algorithm for Image Registration Based Realization of the Vision Figure

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Abstract

The purpose of this paper is to eliminate the mismatch points of image registration. Analyzing the SIFT algorithm and finding mismatch source, according to the source to develop solutions to eliminate the error matching points. And compared with the traditional SIFT registration results. In this paper, firstly do initial matching with SIFT algorithm, then use the feature of key points in spatial domain to eliminate the error matching, Finally, using RANSAC algorithm to do the final debugging. Experimental results show that the improved SIFT algorithm can better eliminate mismatch points.

***Keywords**: Image Registration;Sift Algorithm;Several-for-one Matching;Ransac Algorithm*

1. Introduction

Image registration is the process of two or more images were matched or overlayed that acquire at different time, different sensors or under different conditions. It has been widely used in remote sensing data analysis, image processing, computer vision and other fields.

As research continues, image registration algorithm needs more stable, accurate, faster. Among them, DavidLowe presents a new local feature descriptors. That is SIFT(Scale Invariant Feature Transform)[1,2]. The algorithm can remain light, rotation, noise, zoom unchanged and has good robustness[3].SIFT is the most efficient algorithm between feature detection and matching algorithm. It can be extract stable feature points in the image and can generate feature descriptor of greater independence, thereby getting the matching result of greater accuracy. Owing to obtain high accuracy matching points is the key to the task like subsequent registration, recognition and retrieval. So to improve the accuracy rate of matching is particularly important. In this paper, we based on conventional SIFT algorithm, combined with the feature of key points in spatial domain[4], added bidirectional matching[5]and RANSAC algorithm[6] to eliminate false matching points.

2. Sift Algorithm

2.1. SIFT Review

Scale-invariant feature transform is a computer vision algorithm to detect and describe localized image features. It seeks the extreme points in the space scale. And extract its position, scale, rotation invariant. Its range of applications include object recognition, robotics map perception and navigation, image stitching, 3D modeling, gesture recognition, motion tracking and image alignment. Local image features description and detection can help identify objects, SIFT feature is based on a number of points of interest on the local appearance of the object regardless of the size of the image and rotate. The

ISSN: 2005-4297 IJCA

perspective of tolerance For light, noise, slightly change is quite high. Based on these characteristics, They are highly significant and relatively easy to capture. In a large number of female characteristics in the database, it is easy to recognize objects and little mistake. Characterization using SIFT obscured for some object detection rate is quite high, SIFT object features even need only three more than enough to calculate the position and orientation. SIFT feature large amount of information, for fast and accurate matching in vast databases.

Features SIFT algorithm :

- SIFT features are local features of the image, its rotation, scaling scaling, brightness variation to keep invariance perspective of change, affine transformation, noise is also to maintain a certain degree of stability
- Unique is good, informative, suitable for rapid mass characteristics in the database, an exact match;
- Large amounts of property, even though a handful of objects may also produce a large number of SIFT feature vectors
- High speed, optimized SIFT matching algorithm can even achieve real-time requirements
- Scalability, and features can easily be combined with other forms of vectors

SIFT algorithm can solve the problem:

Target state Environment in the scene And imaging characteristics of imaging equipment and other factors affecting image registration and Performance of target recognition and tracking. The SIFT algorithm can be solved to some extent.

- Rotation, scaling, translation (RST) of the target
- Image affine / projection transformation (viewpoint viewpoint)
- Illumination effect (illumination)
- Target occlusion (occlusion)
- Debris scene (clutter)
- Noise

The essence of SIFT algorithm is to find the key points (feature points) in different scale space and calculate the key points. To sift the search is the key point to some very prominent, will not light, affine transform, noise and other factors change, such as angle, edge points, dark zone highlights and bright scotoma *etc*.

2.2. Scale Space Extreme Detection

The SIFT algorithm first converts the image at different scales of Gauss blur and down-sampling, obtain Gaussian pyramid. Then let each group of adjacent upper and lower image in Gaussian pyramid subtraction.,obtain the Difference of Gaussian scale-space(DOG space).

Scale space of an image $L(x, y, \sigma)$ is defined as a change scale of the original image $I(x, y, \sigma)$ with the Gaussian function $G(x, y, \sigma)$ convolution：

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y, \sigma) \tag{1}$$

Among them, $G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)} / 2\sigma^2$, (x, y) is image pixels, σ is space scale factor, the size of σ determines the smoothness of the image. Large-scale corresponding the overview of image features.Small-scale corresponding minutiae characteristics of image.

The generation of space extreme points, requires each sampling point to be compared with all of its proximal points, to see whether it is greater than the adjacent points of its image and scale domain or small.Intermediate detection point and the same scale 8 adjacent points compare with the upper and lower adjacent scales corresponding 9 x 2 in total 26 points, to ensure that in the scale space and the 2D image space can detect extreme points.While the precise positioning of the extremum point is to accurately determine the location and scale of key points by fitting three-dimensional quadratic function, at the same time, remove the key point of low contrast and unstable edge response points(the DOG operator will cause strong edge response), in order to enhance the matching stability, improve noise immunity.

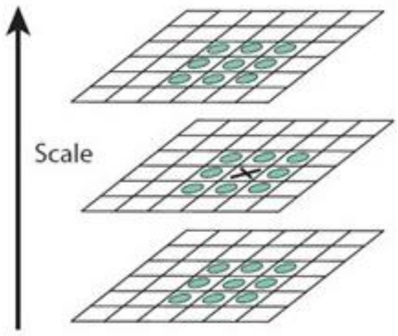

Figure 1. DOG Space Threshold Detector

2.3. Determine the Direction of the Key Points

In order to make the operator possess rotation invariance, we need to use the key point of the gradient direction distribution characteristics of the neighborhood pixels for each key point distribute direction parameters. For critical points detected in the DOG, its amplitude and direction is calculated as follows(L is the dimension of each key point):

$$m(x,y)=\sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2} \tag{2}$$

$$\theta(x,y)=\tan^{-1}(L(x,y+1)-L(x,y-1))/(L(x+1,y)-L(x-1,y))$$

Among them, L is the dimension of each key point. Thus, the key point detected containing location, size and orientation is SIFT feature points of image.

2.4. Key Description Operator

In order to make the key point does not vary with various changes of light,angle *etc*.That need to establish a set of vectors for each critical point as a feature descriptor. This descriptor includes not only the key point, should also contribute to its key points surrounding pixels, and the descriptor should have a high uniqueness, in order to increase the probability of correctly matching feature points.

To ensure rotational invariance, after obtaining the main direction of the key points, in the center of key points select 16×16 windows, and image coordinate axis to follow the main rotation direction of the critical points.And in the 16×16 pixel window, calculate the gradient direction and amplitude for each pixel,goto gaussian-weighted. Finally, the window is divided into 4×4 small one, calculate eight directions of histograms of oriented gradients on each small window, and draw each gradient direction accumulated value, this can form a seed point.

One of the key points is made up of 4×4 total 16 seed points, each seed points has eight direction vector information, such a feature point can be formed 128-dimensional SIFT feature vectors. This joint neighborhood directional information is an effective way to enhance the anti-noise performance of SIFT algorithm, and also has good fault tolerance for positioning error matching.

3. Improved Sift Algorithm

3.1. Traditional SIFT Algorithm

When traditional SIFT algorithm for two images extracted respective feature points matching, firstly calculate each feature point of the first image nearest neighbor match in second image, that is the minimum Euclidean distance of key points between the descriptor vector. By previously described, the key point SIFT descriptor is 128-dimensional feature vector. Lowe's SIFT algorithm uses conventional nearest neighbor and next nearest neighbor distance ratio to execute matching feature points, the experience value of ratio is 0.8. Because of the high-dimensional feature space, a similar distance may has a number of errors match.

The traditional SIFT methods also do not consider duplicate matching, several-for-one matching and other false match, matching accuracy has greatly optimized space.While calculating the direction of SIFT key points, the same key point may has a main direction, one or more secondary direction. In SIFT algorithm we can be classified them into different feature points. All or part of the feature points that might occur correct pointt, but they are actually the same point, this will generate repeat matching phenomenon. Exhaustive search for matches among SIFT feature may also have one-to-many, several-for-one match. In addition to duplicate matching, and many-to-one-matching, inevitably may also have other mismatch. Those need to be eliminated one by one; otherwise the subsequent image registration accuracy will have great impact.

3.2. Improved Traditional SITF Algorithm

We base on the initial matching points obtained after near neighbors and secondary ratio registration, and then eliminate errors one by one.

Among them, for repetitive match and several-for-one match, extract all of them by comparing with the index value of the pixel and coordinates of the corresponding point pairs, to guarantee the uniqueness and one-to-one correspondence. The mismatch in other areas, we based on geometry relationship, excluding the coordinate difference of corresponding point from apparent greater or less than adjacent points coordinate difference. Owing to the adjacent point, its corresponding matching point in the geometric position could also be adjacent. If the difference between a matching point with the coordinates of the adjacent match points difference is very obvious, it is likely to be false matches. The above steps of matching points process can only be guaranteed the key point B in image 2(Two images that to be matched are image 1 and image 2) is a matching point of point A in image 1.Conversely the key point B of image 2 is not necessarily the matching point to A in image 1, so there will still be false matching points. Thus, we introduce the idea of bilateral matching. After above processing steps, the rest matching points are basically correct. Finally, for the rest matching points, we use RANSAC algorithm improve matching accuracy. The reason why the use of RANSAC is because after the completion of image registration can use matching feature points to set solving transformation matrix between image mosaic, here is the eight parameter projective transformation model as a mosaic image transformation model, transformation relations are as follows

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{3}$$

From the above relational expression, for each pair of matching points, we can set up two equations. Therefore, in theory, only four pairs of matching points are required to determine the transformation matrix of the eight parameters. But because of the existence of the inevitable mismatch in the matching point.The accuracy of the transformation matrix is lower..But RANSAC algorithm can be used to include all of the feature points that contain a large number of points. To find an accurate internal point by multiple sampling. And estimate the image of a single stress matrix. Therefore, the RANSAC algorithm is used to solve the transformation matrix.

3.3 Image Fusion

After these steps that we've got the transformation matrix H between images, we can determine the overlap between the images and the formation of a mosaic map. However, direct splicing can make the image in the middle of a clear gap and the effect of the visual effect, and therefore need to get the mosaic map fusion.

In order to obtain better visual effect, First of all, the image is adjusted to adjust the brightness of the mosaic image so that the brightness of the two pieces to be mosaic image, Then the overlapping regions are fused by the weighted average method, So as to achieve the purpose of seamless splicing.

The principle of weighted average fusion method is as follows

$$f(x,y)=\begin{cases} f_1(xy) & (x,y)\in f_1 \\ d_1 f_1(x,y)+d_2 f_2(x,y) & (x,y)\in f_1 f_2 \\ f_2(x,y) & (x,y)\in f_2 \end{cases} \tag{4}$$

That belongs to image part 1 of gray value is entirely from the image 1 belongs to the image of gray value is entirely from the image 2, belongs to the overlapping regions of the gray value from in the corresponding position in image 1 and image in the value weighted averag

The algorithm flow chart is shown in figure 2.

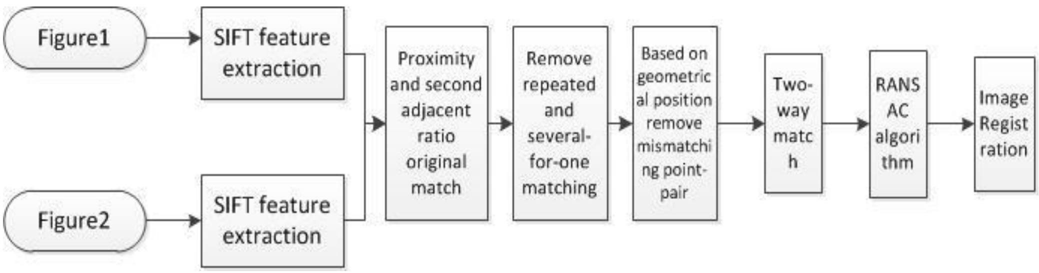

Figure 2. The Algorithm Flow Chart

4. Experimental Results

Experiments select the vision and object to verify that the method is feasible , using matlab platform, image sizes are $384\times479, 384\times497$, ratio is 0.8.

Based on experimental results, the feature points of figure3 is 1318 and 1522, affine matrix H is

$$H=\begin{bmatrix} 1.0414 & -0.0003 & 240.3741 \\ 0.0002 & 0.9655 & -1.0098 \\ 0.0000 & -0.0000 & 1.0000 \end{bmatrix} \tag{5}$$

Table 1. The Match Points after Each Step of Figure3

Table Head	**The match points after each step**						
	Proximity and second adjacent ratio mathing		***Remove repeat and several-for-one matching***		***Geometrical position remove matching***		***Two-way matching***
Matching points	***Forward***	***Reverse***	***Forward***	***Reverse***	***Forw ard***	***Rever se***	292
	396	406	325	329	312	309	

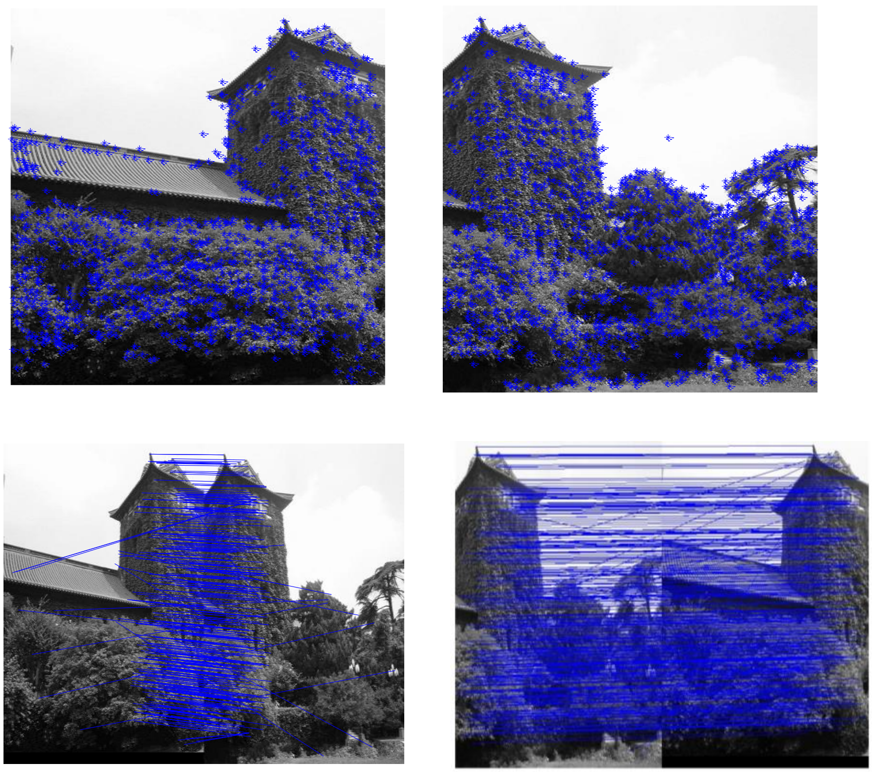

Figure 3. Proximity and Second Adjacent Ratio Mathing

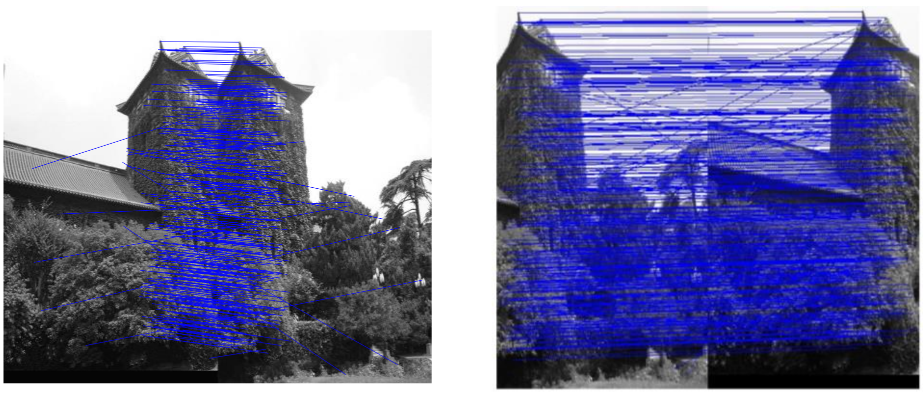

Figure 4. Remove Repeat and Several-for-one Matching

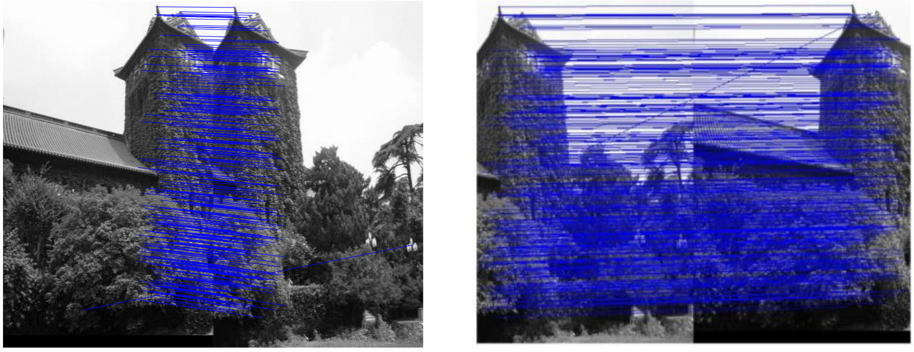

Figure 5. Geometrical Position Remove Matching

Figure 6. Two-Way Matching and Final Registration

5. Conclusions

This article we analyze the deficiencies on the SIFT algorithm, and improve matching accuracy from the feature points. First, remove the duplicate matching and several-for-one matching. Second, use regional geometric location to remove obvious mismatch. Next, using two-way matching algorithm to remove possible unconspicuous mismatch. Finally, further processing using RANSAC algorithm. In the verification experiment, we have compared with the traditional SIFT algorithm. Test results show that this improved algorithm has been greatly improved in the registration accuracy than the traditional SIFT algorithm.

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