http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (8): 1571-1578, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.1571.1578

Hausdorff Distance Image Registration based on Features of Harris and SIFT

Liu Jicheng, Wu Linlin and Sun Huilin
Northeast Petroleum University, OilandGas field control and Dynamic Monitor Labortary, China

Abstract: Harris detection and SIFT(Scale-invariant feature transform) are frequently used to image registration, but they have the disadvantages of not adapting the variety of scale and low efficiency, respectively. Hausdorff distance method based on the feature of Harris and SIFT is discussed here. Corners of the reference and the registered image are extracted and fused by using Harris corner detection and SIFT feature retrieval to expend the search scope of corner. Then the similarity matching principle is adopted to get rid of the error corners and the improved Hausdorff distance algorithm is used to realize image registration. The experimental results demonstrate that the computation time declines about 45% compared with traditional Hausdorff distance algorithm. The method has stronger anti-noise ability and rotary robustness, which improves the efficiency and accuracy of registration.

Key words: Image registration, corner detection, SIFT features, Hausdorff distance, principle of consistency

INTRODUCTION

Image registration decides the transform parameters between images according to some similarity measurement, the two or several images of the same scene, which are gained from different sensors, visual angles and time, are transformed to the same coordinate system and realized best fit in pixel layer. Recently, image registration based on features becomes research focuses and the method consists of feature extraction, feature matching, transform model estimation and image transformation, where the feature extraction is the key problem. Many scholars come up with lots of feature extraction methods. Harris corner extraction algorithm (Harris and Stephens, 1988) uses the first derivative of the image, the operator characteristics extracted is reasonable and stable, but the algorithm is sensitive to scale. SUSAN algorithm (Smallest Univalue Segment Assimilating Nucleus) can directly compute the gray value of image without gradient operator to ensure the efficiency of the algorithm and locate accurately, it can also detect the junction point of the plurality of regions (Petez and Dennis, 1997). SIFT algorithm detects extremum points in scale space and determines its position and scale, which can define the extreme points accurately. By defining the gradient of the neighborhood as the main direction, the image coordinates are rotated to main direction to describe characteristics. SIFT algorithm has good scale robustness (Lowe, 2004; Mikolajczyk and Schmid, 2005; Brown and Lowe, 2003).

The efficiency, accuracy and complexity of registration are the important problems in image registration. The feature points need to be matched after obtaining them, in which the cost function or a distance function is usually used. The common feature matching method is to search the correspondence of the characteristics to calculate the similarity and obtains the change between the registration images. But it is very complex to calculate the corresponding characteristic. The registration results can't satisfy requirement if the mendacious, wrong or incomplete features are obtained. The advantages of Harris, SIFT and Hausdorff distance are combined in this paper to realize an effective image registration.

MATERIALS AND METHODS

Generally, the feature point matching algorithms include the Hausdorff distance method, relaxation labeling method, deterministic annealing algorithm and Iterative Closest Point algorithm (ICP). Hausdorff distance has obvious advantages compared with other distance measurements, for it only need to calculate the maximum distance between two point sets rather than match the distance one by one. Hausdorff distance has strong robustness against such situations as huge feature points set, pseudo-feature points and noise pollution, also it requires lesser computational complexity.

Hausdorff distance which measures the similarity degree of two point sets (Hrkac *et al*., 2007) is defined as follows:

$$H(A,B) = \max(h(A, B), h(B, A)) \quad (1)$$

Corresponding Author: Liu Jicheng, Northeast Petroleum University, OilandGas field control and Dynamic Monitor Lab., China

$$h(A, B) = \max (a, A) \min (b, B)(a-b) \quad (2)$$

$$h(B, A) = \max (b, B) \min (a, A)(b-a) \quad (3)$$

where A and B are two point sets, a and b are points in A and B, respectively, (•) is the distance norm between A and B such as L2 or Euclidean distance. According to this definition, the Hausdorff distance is obtained by computing all points' distance in the collection and reducing the number of points can decrease the computational complexity and improve the computational efficiency. The traditional Hausdorff distance uses the point sets retrieved during image edge detection procedure, although these point sets can represent the information of image, the number of edge point sets is more than feature point sets in most cases.

According to the above mentioned definition of Hausdorff distance, the more nearer of the Hausdorff distance means the more similarity of two sets. The feature point based image registration is actually to calculate the distance of points respectively. So, image registration can be regarded as to evaluate the similarity of feature points. The matching of feature points is transformed into the calculation of the Hausdorff distance of two feature point sets. To achieve image registration, the feature point sets should be retrieved first, then the Hausdorff distance between these sets can be exploited to realize image registration.

The Harris corner detection algorithm can retrieve the drastic vary points of luminance and these points can be used as feature points. These points contain important feature information of images, at the same time the number is less. The Harris algorithm is invariant to gray translation transformation, but is not invariant to image rotation and scale transform. But the SIFT feature retrieval algorithm is invariant to image rotation and scale transform and is unique, so it can overcome some deficiencies of Harris algorithm (Zhao and Lin, 2011). The steps of SIFT algorithm are as follows and the procedure is shown in Fig. 1.

- Detect the extreme points in scale space
- Accurate positioning the extreme points
- Specify direction for every key point
- Generate descriptors of key points

During the SIFT feature extraction, the k-d tree is created respectively on the intermediate s layer which holds feature points and another k-d trees is also generated on the reference image and matching image for each layer. Then, based on these two k-d tree, the nearest neighbor point is searched out and if the founded nearest neighbor point is identical, this point is considered as the matching point.

The image corner collection obtained by Harris corner detection is set up as A, the SIFT feature corner point collection obtained by SIFT feature extraction is set up as B, the feature point collection erased the repeated points in A and B is set up as C and the matching image's feature collection D is obtained by using the above process. By utilizing the gradient directional distribution characteristic of the key point's neighbor pixels, each key point is specified directional parameter as follows:

$$\begin{aligned} m(x,y) &= \sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2} \\ \theta(x,y) &= \tan^{-1}\left(\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)}\right) \end{aligned} \quad (4)$$

where, m (x, y) and θ (x, y) are the gradient module and direction. The scale of L is the same as that of each key point. Keep the rotation invariant by set up the coordinate rotation as the key point's direction. By using the Gaussian circular window to weight the gradient module value. Figure 2 describes the generation for the eigenvectors of a key point by using neighbourhood gradient. The 8*8 window is adopted with the key points as center. As shown in Fig. 2a, the black center point is the position of present key point, each little grid represents one pixel in key point neighbor's scale space, the arrow means the gradient direction of this pixel, the length of arrow represents the gradient module value and the circular represents the range for Gaussian weighted operation (the nearer to key point, the more contribution to gradient directional information). Then, the gradient directional histogram is computed on each 4*4 patch, draw the accumulation value for each gradient direction, then a seed point can be generated,. For the 8*8 window, there are four seed points, through which the SIFT eigenvector of the key point can be computed. Figure 2b shows the 2*2 patch consisted of four seed points and each seed point contains eight direction vectors information. The idea of neighborhood joint directional information enhances the ability of anti-noise algorithm, at the same time contain positioning error characteristics match also provides better fault tolerance, Finally, generate SIFT feature vector.

In the set of registration point obtained from the registered images, a point in one image only corresponds to a unique point in another image because the obtained point set is just the original matching points, there maybe include error corner points. According to the uniform constraint condition, the further matching operation should be applied to the corner collection. And the steps are as follows:

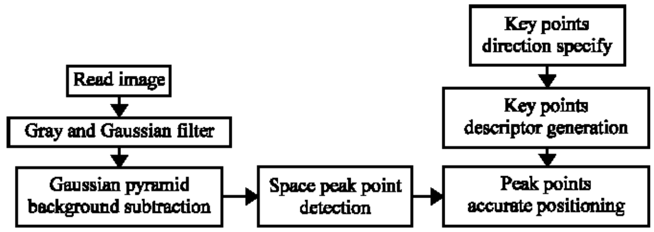

Fig. 1: SIFT algorithm procedure

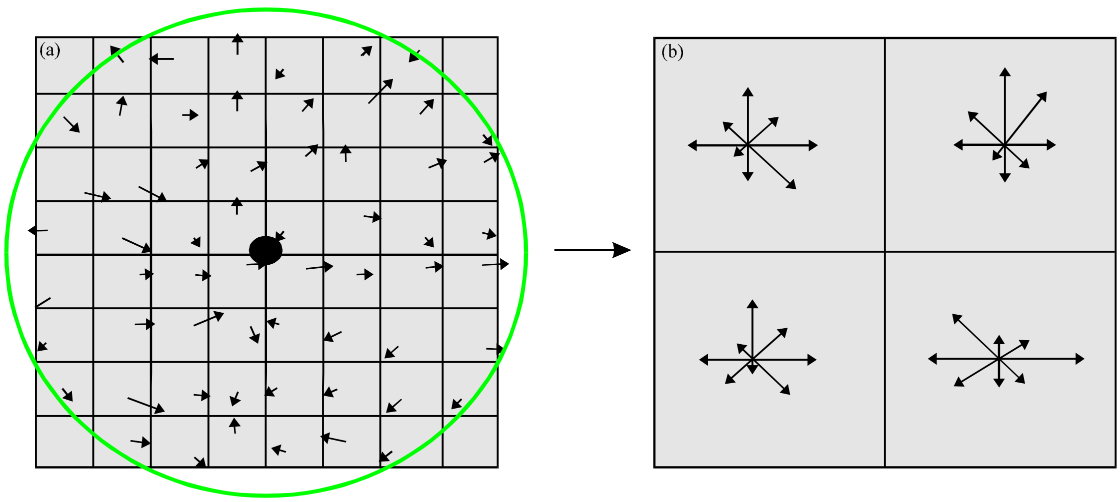

Fig. 2(a-b): Eigenvectors generated by the neighbourhood gradient of key points, (a) Neighbourhood gradient value and direction of the key point and (b) the SIFT eigenvector of the key point computed by four seed points

- Select a point C_i from the set C, find the nearest point D_1 and the second nearer point D_2 to C_i in set D in the meaning of Euclidean distance, using the ratio of the nearest distance S_1 and the second nearer distance S_2 to compare with the matching threshold, if the ratio is smaller than the threshold, the point C_i is matching to the nearest Euclidean distance point in set D. If the ratio is bigger, deleting this point
- Specify the point D_1 which is nearest to the set C_i as the reference point and calculate the matching feature point C_i in set C according to Step1
- Determine whether C_i and C_1 is coincident, if not, abandon it
- Ergodic points in set C, get the set C' and D'

To obtain the one-way Hausdorff distance h(A, B), the nearest distance between set A and B should be calculated first, then the maximal value is selected. Suppose that the Hausdorff distance has been calculated as S', if another h(A, B) is bigger than S', then the one-way distance need not to be calculated. As h(A, B) = max (h(A, B), h(B,A)), if h(A, B) is bigger than S', it means that h(A, B) is definitely bigger than S', the Hausdorff distance in this point cannot satisfy the condition. Conversely, if h (A, B), h (B, A) are smaller than S', it means that, in this position, the Hausdorff distance is less than S', according to Hausdorff distance, this location is more similar than the location derived S', Hausdorff distance will be assigned to S' and in turn the cycle continues, after traversing, the S' is the minimum value of the Hausdorff distance. It means that the biggest similarity of the image in this position, this position is the best matching position. This processing procedure reduces the unnecessary distance calculation in the traditional Hausdorff distance computation method and dramatically reduces the computation time. At the same time, the efficiency and accuracy of this algorithm is also improved. The algorithm processing procedure is shown in Fig. 3.

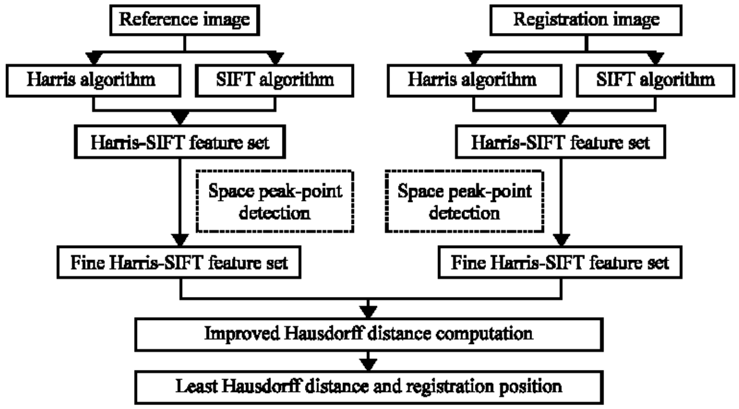

Fig. 3: Registration algorithm procedure

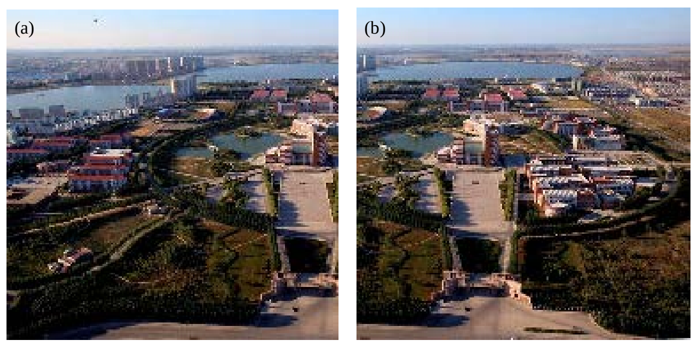

Fig. 4(a-b): (a) Reference image and (b) Registered image

EXPERIMENTAL RESULTS AND ANALYSIS

The pictures in Fig. 4 are selected as the experiment images for image registration. These two images are the pictures for one place with different gather position. The Fig. 4a is the reference image, whereas Fig. 4b is the to-be-registered image. The corner points result obtained by using the Harris corner detection algorithm and the SIFT feature extraction algorithm is shown in Fig. 5a and b, respectively. There are lots of wrong corner points and there are 341 and 404 corner points, respectively in these two images. The Fig. 6 shows a set of the feature points obtained by the bidirectional consistency. Through using this theory, most of the wrong feature points can be eliminated and the more accurate feature points can be conserved. There are 187 corner points in the left image of Fig. 6 and 197 corner points in the right image. Figure 7 is the composed image obtained by using of improved Hausdorff distance algorithm. From the image point of view, the position of the two images overlap has no deviation, it means that a seamless image registration can be achieved. Figure 8 is a classic harris the obtained corner points, which can be seen to contain too many error message the number of corner points, is not conducive to the calculation of the distance. Figure 9 is the registration results based on conventional Hausdorff distance and LTS-Hausdorff distance.

From the image registration results, the registration results of Fig. 7 and 9a and b are substantially the same. The operation time of different algorithms are 1752.541, 1484.898 and 949.2645 sec corresponding to Hausdorff distance algorithm, Lts-Hausdorff diatance algorithm and the proposed algorithm respectively, It can be seen that the time of proposed algorithm, which uses a point-generation line, narrowing the scope of the set of points such that the rapid increase in the computational efficiency of the Hausdorff distance, required has about 45.83% savings compared to the traditional Hausdorff distance, means that the proposed algorithm greatly reduces the computational complexity.

The robustness to scale and rotation operation of proposed algorithm is also evaluated. The image used to examine the robustness of the proposed image is shown

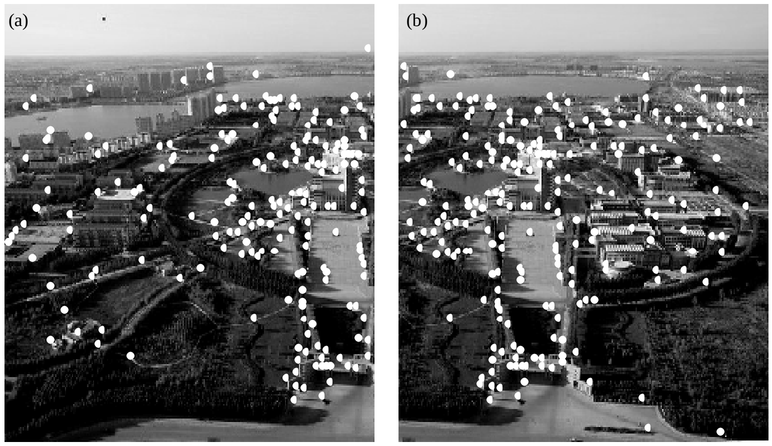

Fig. 5(a-b): (a) Corners of Fig. 4a, Obtained by Harris feature algorithm and (b) Corners of Fig. 4b obtained by SIFT feature algorithm

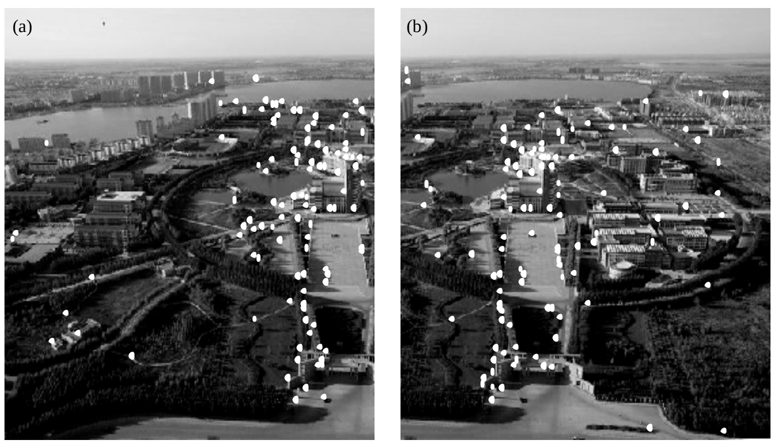

Fig. 6(a-b): (a) Feature points collection obtained by bidirectional consistency of Fig. 4a and (b) Feature points collection obtained by bidirectional consistency of Fig. 4b

Fig. 7: Composed image using improved Hausdorff distance registration algorithm

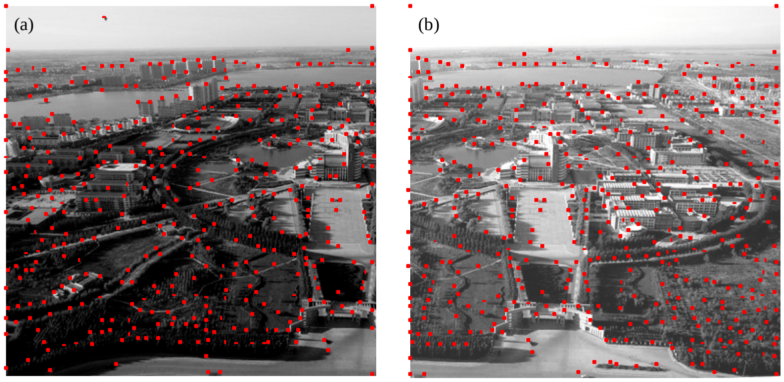

Fig. 8(a-b): (a) The corners of Fig. 4a using classic Harris detection algorithm and (b) The corners of Fig. 4b using classic Harris detection algorithm

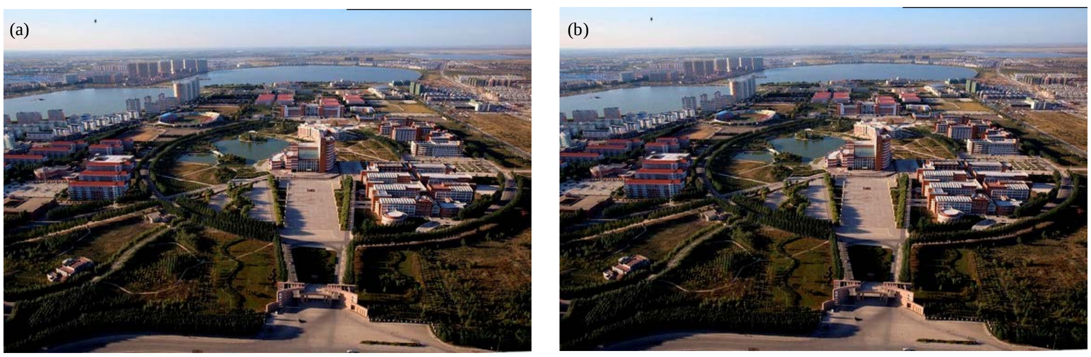

Fig. 9(a-b): (a) Composed image based on conventional Hausdorff distance and (b) Composed image based on LTS-Hausdorff distance

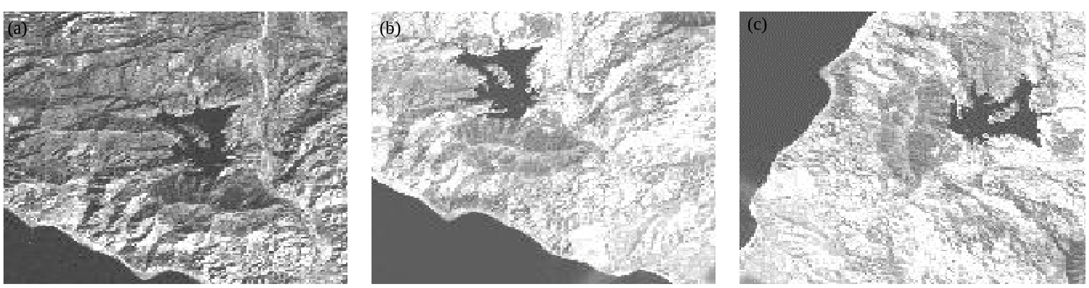

Fig. 10(a-c): Original images for robustness evaluation, (a) Original image, (b) Scaled image and (c) Rotated image

in Fig. 10. The Fig. 10a is the original image of the experiment and Fig. 10b is the scaled image. Figure 10c is the rotated image and the rotational angle of the second figure is 90 degrees, the scaled proportion is 1.02. The Fig. 10a is regarded as the reference image and the Fig. 10c as the to-be-registered image. Figure 11 is the initial feature points of Fig.10a and c. The Harris and SFIT feature points obtained by using bidirectional consistency criterion are shown in Fig. 12. The consistency operation significantly reduces the feature point numbers and leads to easier Hausdorff distance calculation. Fig. 13a illustrates the smallest Hausdorff distance points between Fig.10a and c and tagged by red lines. Through these tags the registration positions can be figured out more clearly. Figure 13 is the registration results, the overlapped area is showed directly.

Table 1 is the registration error computed by the proposed algorithm and Hausdorff distance method, respectively at the same rotation angle and scale proportion. With the scale and rotation angle become

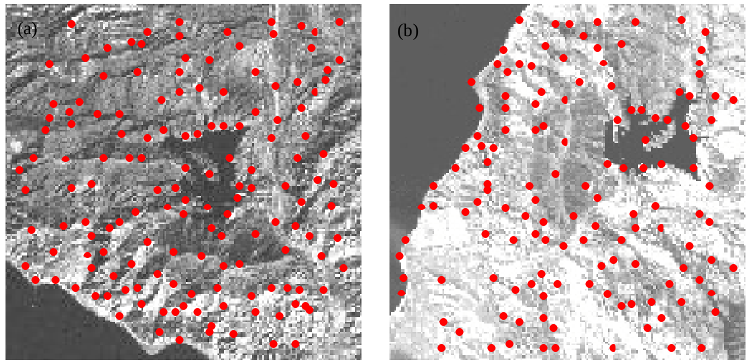

Fig. 11(a-b): (a) Initial feature points of Fig.10a and (b)Initial feature points of Fig.10c

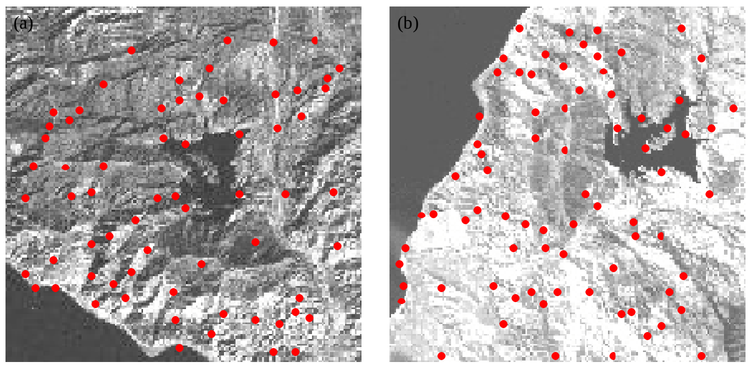

Fig. 12(a-b): (a) Feature points obtained by bidirectional consistency of Fig.10a and (b) Feature points obtained by bidirectional consistency of Fig.10c

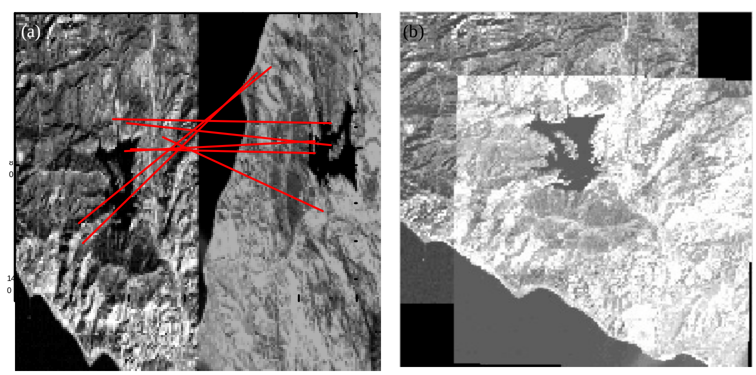

Fig. 13(a-b): (a) The least Hausdorff distance points from Harris-SIFT feature point set of Fig. 10a and c, in which red lines can mark the registration location more clearly and (b) Registration result of Fig. 10a and c

Table 1: Marison of rotation angle and scale proportion between the proposed algorithm and practical value

Methods	Actual scale	Measured scale	Scale error (%)	Actual rotation angle	Measured rotation angle	Rotation angle error (%)
Proposed algorithm	0.98	0.981941	0.19806	0.50	0.501061	0.21220
	1.00	0.997921	0.20790	1.0	1.002733	0.27330
	1.02	1.025114	0.50137	2.0	2.009137	0.45685
Hausdorff distance algorithm	0.98	0.982203	0.224796	0.50	0.504100	0.82000
	1.00	1.004015	0.40150	1.0	1.007499	0.74990
	1.02	1.030649	1.04401	2.0	2.037834	1.89200

bigger, the registration error increases whenever the proposed algorithm or the Hausdorff distance method are adopted. But the improved algorithm shows more advantage obviously. When the scale proportion is 1.02 and the rotation angle is 2 degree, the scale error is 0.50137% and the rotation angle error is 0.4569% by using the proposed algorithm, while the scale error and rotation angle error obtained by Hausdorff distance method are 1.04401 and 1.892%, respectively. Therefore, the proposed improved algorithm has strong robustness to scale and rotation transform.

CONCLUSION

In this study, the improved Hausdorff distance for Harris and SIFT feature is used to transfer lines to points, decrease right corner points number while increase right corner points and the accuracy of image feature points is improved further. During the calculation of Hausdorff distance, the computational complexity is decreased through excluding the error points and the blind points. The robustness of the proposed algorithm is also evaluated by applying the experiment of scaled and rotated images and the effectiveness of proposed algorithm is analyzed and justified.

ACKNOWLEDGMENTS

The study is supported by the Program for New Century Excellent Talents in University of Heilongjiang Province (NO.1154NCET001) and New Century Excellent Talents of Ministry of Education of the P.R.C (NO.NCET-09-127).

REFERENCES

Brown, M. and D.G. Lowe, 2003. Recognising panoramas. Proceedings of the 9th IEEE International Conference on Computer Vision, Volume 2, October 13-16, 2003, Nice, France, pp: 1218-1225.

Harris, C. and M. Stephens, 1988. A combined corner and edge detector. Proceedings of the 4th Alvey Vision Conference, September 2, 1988, Manchester, UK., pp: 147-151.

Hrkac, T., Z. Kalafatic and J. Krapac, 2007. Infrared-visual image registration based on corners and hausdorff distance. Proceedings of the 15th Scandinavian Conference on Image Analysis, June 10-14, 2007, Aalborg, Denmark, pp: 383-392.

Lowe, D.G., 2004. Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vision, 60: 91-110.

Mikolajczyk, K.I. and C. Schmid, 2005. A performance evaluation of local descriptors. IEEE Trans. Pattern Anal. Mach. Intell., 27: 1615-1630.

Petez, M.M. and T.J. Dennis, 1997. An adaptive implementation of the SUSAN method for image edge and feature detection. Proceedings of the International Conference on Image Processing, Volume 2, October 26-29, 1997, Santa Barbara, CA., USA., pp: 394-397.

Zhao, M. and C.Q. Lin, 2011. Registration of infrared and visible images based on improved SIFT feature. Opto-Electron. Eng., 38: 130-136.