Satellite Cloud Image Registration by Combining Curvature Shape Representation with Particle Swarm Optimization

Xiang Zhang
College of Mathematics, Physics and Information Engineering, Zhejiang Normal University, Jinhua, China
E-mail: zxmoran@163.com

Chang-jiang Zhang[1,2*]
1. College of Mathematics, Physics and Information Engineering, Zhejiang Normal University
Jinhua, China
2[*].State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, Beijing, China
E-mail: zcj74922@zjnu.cn

Abstract—**A new feature point extraction algorithm which is used to match the satellite cloud image feature point is proposed. The new algorithm is proposed by combining corner detection with curvature scale space. The new algorithm can accurately extract the satellite cloud image corner points in different positions and directions. In order to accurately match the corner points of two source images, an overall restricted condition, which combines angle difference, gray level difference, relative distance and normalized correlation coefficient of the two matched corner points, is used to improve the matching accuracy. Finally, particle swarm optimization algorithm is used to obtain the optimal registration parameters. The optimal registration parameters are used to accurately match the two source images. The experimental results show that the proposed algorithm can accurately match the satellite cloud images and better than traditional image registration methods.**

Index Terms—**satellite cloud image, registration, corner point matching, particle swarm optimization**

I. INTRODUCTION

Image registration is to bring two different images into alignment so that pixel positions correspond to equivalent points in the space of the object imaged [1]. Image registration is widely used in medical imaging, video dynamic, image monitoring, pattern recognition, satellite remote sensing images, and industrial testing areas, as a key technology in multi-sensor image fusion areas. At present, the method of image registration includes the fully automatic image registration and the semi-automatic image registration. The automatic image registration, which is mainly based on pixel grayscale, includes the mean difference of gray-scale, the mutual information [2], the invariant moments, the interrelated frequency [3] and the wavelet transform [4]. These methods of image registration based on pixel grayscale are sensitive to the gray-scale transformation, the rotation of the target, deformation and occlusion. The semi-automatic image registration method based on the control points of the images is better to maintain the displaced features, deformation features and rotation invariant features. Because of the better adaptability, Feature points have less dependence of the small gray changes. It reduces computation in the whole matching process. The sensitive of the changes of the feature point location helps to improve the matching accuracy.

Multi-channel satellite cloud image registration is important in typhoon prediction because the registration accuracy directly affect the quality of the multi-channel satellite cloud image fusion. A good fusion satellite cloud image will result in a accurate location for typhoon center. In this paper, the method of satellite cloud image registration is based on the image feature points. Firstly, the feature corner points of the two matching image are extracted by CSS corner detection methods [5]. Secondly, In order to accurately match the corner points of two images, an overall restricted condition, which combines angle difference, gray level difference, relative distance and normalized correlation coefficient of the two matched corner points, is used to improve the matching accuracy. Finally, particle swarm algorithm is used to obtain the optimal registration parameters. The method of image registration in this paper saves a great deal of time in the whole registration process. As the particle swarm algorithm is applied to optimize the registration parameters, it also improves the matching accuracy. The Flowchart of the registration method in this paper is showed as follows:

II. CSS CORNER-DETECTION METHOD

The CSS technique is suitable for recovering invariant geometric features (curvature zero crossing points and/or extrema) of a planar curve at multiple scales. To compute it, the curve L is first parameterized by the arc length parameter u:
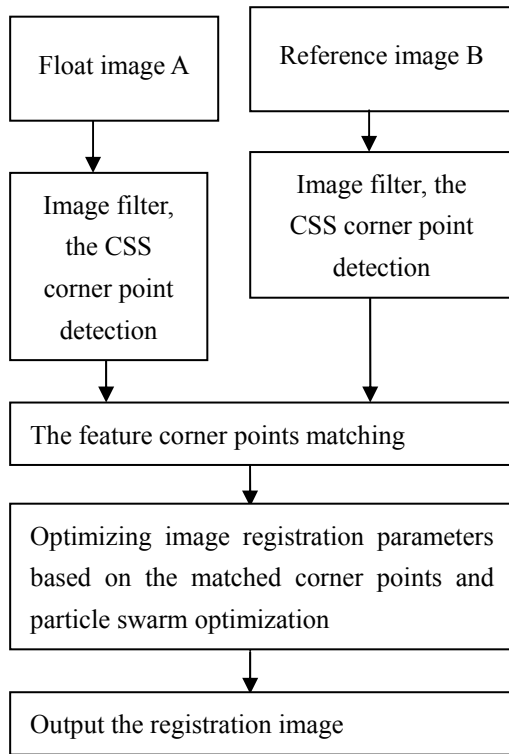
$$L(\mu) = (x(\mu), y(\mu)) \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

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┌──────────────────┐   ┌──────────────────┐
│  Float image A   │   │ Reference image B │
└──────────────────┘   └──────────────────┘
         │                      │
         ▼                      ▼
┌──────────────────┐   ┌──────────────────┐
│  Image filter,   │   │  Image filter, the│
│   the CSS        │   │  CSS corner point │
│  corner point    │   │    detection      │
│   detection      │   │                   │
└──────────────────┘   └──────────────────┘
         │                      │
         ▼                      ▼
┌────────────────────────────────────────┐
│     The feature corner points matching  │
└────────────────────────────────────────┘
                    │
                    ▼
┌────────────────────────────────────────┐
│ Optimizing image registration parameters│
│ based on the matched corner points and   │
│ particle swarm optimization              │
└────────────────────────────────────────┘
                    │
                    ▼
┌────────────────────────────────────────┐
│       Output the registration image     │
└────────────────────────────────────────┘
```

Figure 1. Flowchart of image registration

An evolved version L_σ of L can then be computed. L_σ is defined by:

$$L(\mu,\sigma) = (x(\mu,\sigma), y(\mu,\sigma)) \ldots\ldots\ldots (2)$$

Where

$$x(\mu,\sigma) = x(\mu) \otimes g(\mu,\sigma),$$

$$y(\mu,\sigma) = y(\mu) \otimes g(\mu,\sigma);$$

where $\otimes$ is the convolution operator and $g(\mu,\sigma)$ denotes a Gaussian of width σ. Note that s is also referred to as the scale parameter. The process of generating evolved versions of G as s increases from zero to infinity (∞) is referred to as the evolution of L. This technique is suitable for removing noise from and smoothing a planar curve as well as gradual simplification of its shape. In order to find curvature zero-crossings or extrema from evolved versions of the input curve.

$$X(\mu,\sigma) = \frac{X'(\mu,\sigma)Y''(\mu,\sigma) - X''(\mu,\sigma)Y'(\mu,\sigma)}{(X'(\mu,\sigma)^2 - Y'(\mu,\sigma)^2)^{3/2}} \ldots(3)$$

Where:

$$X'(\mu,\sigma) = X(\mu) \otimes g'(\mu,\sigma)$$

$$X''(\mu,\sigma) = X(\mu) \otimes g''(\mu,\sigma)$$

$$Y'(\mu,\sigma) = Y(\mu) \otimes g'(\mu,\sigma)$$

$$Y''(\mu,\sigma) = Y(\mu) \otimes g''(\mu,\sigma)$$

Corner point is defined as the curvature of the absolute value of the local maximum point of the digital curve due to the impact of noise will exist in many low-scale local maximum points. As the scale increases, the noise is real

smooth left corner of the local maximum point [6]. CSS corner detection method is used to find these local maximum points as the candidate corner points. The process of CSS image corner detection is as follows:

• Utilize the Canny edge detector to extract edges from the original image.
• Extract the edge contours from the edge image:
  —Fill the gaps in the edge contours.
  —Find the T-junctions and mark them as T-corners.
• Compute the maximum of the curvature to determine the corner candidates by comparing the maxima of curvature to the threshold t and the neighboring minima.
• Track the corners to the lowest scale to improve localization.
• Compare the T-corners to the corners found using the curvature procedure and remove corners which are very close [7].

Through the above processing, we get the feature corner points of the float image and reference image. Now, we extract the feature corner points of two satellite images as an example .Fig. 2 and Fig. 3 are cut from an infrared 1-channel satellite image and a visible-channel image, which are transmitted by China FY-2 satellite at 6:00 on September 23, 2008 (Beijing Time). Fig. 4 and Fig. 5 show the extracted feature corner points of the two images. The method can provide us the true and reliable feature corner point information for image registration [8].
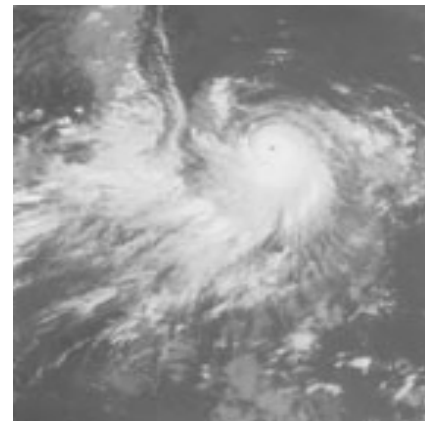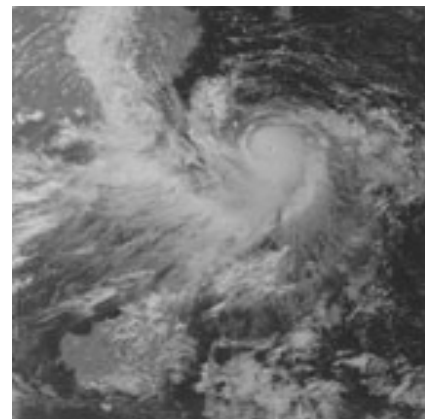

Figure 2.   Float image
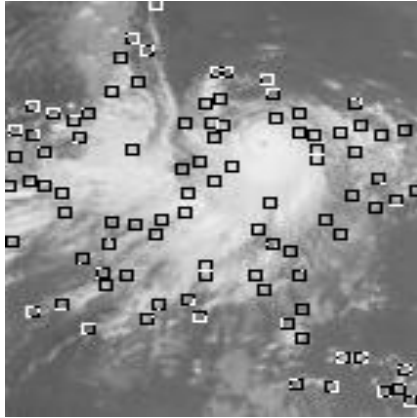

Figure 3. Reference image
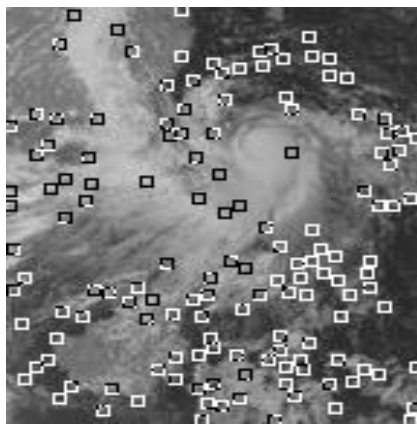
Figure 4.   Corner points of the float image

Figure 5. Corner points of the reference image

III.   THE IMAGE CORNER POINTS MATCHING

According to the interrelated information of the reference corner points and the float corner points, we design four parameters to correlate to each other's corner points. They are angle difference, gray level difference, relative distance and normalized correlation coefficient. The input reference image is I, the float image is F. (x, y) is the pixel coordinates.

Where, angle difference of corner point reflects the angle information of every corner point of the image. It can be defined as follows:

$$\theta_I(x,y) = a\tan 2(I(x+1,y) - I(x-1,y),$$
$$I(x,y+1) - I(x,y-1)); \quad .....(4)$$

$$\theta_F(x,y) = a\tan 2(F(x+1,y) - F(x-1,y),$$
$$F(x,y+1) - F(x,y-1)); \quad .....(5)$$

$$\theta(x,y) = \theta_I(x,y) - \theta_F(x,y). \quad ....(6)$$

$\theta_I(x,y)$ and $\theta_F(x,y)$ show angle information of the reference image and the float image at (x, y). $\theta(x,y)$ is angle difference of the two image at (x, y).

Gray level difference reflects the feature corners' gray difference between the reference image and the float image. It can be defined as follows:

$$M(x,y) = I(x,y) - F(x,y) \quad ....(7)$$

Where $I(x,y)$ is the gray value of reference image at (x, y), $F(x,y)$ is the gray value of the float image. $M(x,y)$ is the gray difference of the two image at (x, y).

The relative distance between the corner points means the relative distance at the Corresponding feature corner points of reference image and the float image. If (x_I, y_I) is coordinate of the Corner point of image I, and (x_F, y_F) is coordinate of the Corner point of image F，D（x，y）is the relative distance between the corner points. So the formula is

$$D(x,y) = \sqrt{(x_I - x_F)^2 + (y_I - y_F)^2} \quad ...(8)$$

The normalized correlation coefficient between the corner points reflects their correlation[9]. When the coefficient C is greater than a certain threshold, this illustrates that the two corner points correlate each other. C is defined as:

$$S = \sum_{i=-k}^{k}\sum_{j=-l}^{l}[I(u+i,v+j) - \overline{I(u,v)}]$$
$$\times[F(m+i,n+j) - \overline{F(m,n)}];$$

$$K = \sqrt{\sum_{i=-k}^{k}\sum_{j=-l}^{l}[(I(u+i,v+j) - \overline{I(u,v)}]^2}$$
$$\times\sqrt{\sum_{i=-k}^{k}\sum_{j=-l}^{l}[(F(m+i,n+j) - \overline{F(m,n)}]^2};$$

$$C = \frac{S}{K} \quad ....(9)$$

In which, (u,v) and (m,n) are the corner points' coordinates of the images to be matched. K and I are the length and width of the rectangular window, which center on the corner point (u, v) of the reference image. In this paper, we suppose that k=I=3, $\overline{I(u,v)}$ and $\overline{F(m,n)}$ express the average gray value of the reference image and the float image in the window. They can be defined as follows:

$$\overline{I(u,v)} = \frac{\sum_{i=-k}^{k}\sum_{j=-l}^{l}I(u+i,v+j)}{(2k+1)\times(2l+1)} \quad ....(10)$$

$$\overline{F(m,n)} = \frac{\sum_{i=-k}^{k}\sum_{j=-l}^{l}F(m+i,n+j)}{(2k+1)\times(2l+1)} \quad ....(11)$$

After we get the angle difference, gray level difference, the relative distance and the normalized correlation coefficient, we consider (9) as a constraint condition to construct a new function $K(x,y)$, which matches the corner points of the reference image and the float image. Where:

$$K(x,y) = \theta(x,y) + M(x,y) + D(x,y). \quad ....(12)$$

By setting a threshold ξ =1.70, when

$K(x, y) \leq \varepsilon$, (x_I, y_I) and (x_F, y_F) are defined as a pair of matched corner points. In this condition one corner point in the reference image perhaps matches more than one corner point in the float image, so one corner point of the float image is. In these matched corner points, we consider the smallest K(x, y) as the final matched corner point pairs. Due to the last work, we can get several pairs of the accurate matched corner point suites (p_i, q_j), where,

p_i is the matched corner point of the reference image, and q_j is the matched corner point of the float image[10].

IV. THE REGISTRATION BETWEEN FLOAT IMAGE AND REFERENCE IMAGE

After we have got the matched corner point suites (p_i, q_j), an affine transformation function is used to make the two images match [11].

$$(X, Y) = s \cdot (x, y) \cdot \begin{vmatrix} \cos\partial & \sin\partial \\ -\sin\partial & \cos\partial \end{vmatrix} + \begin{vmatrix} t_x \\ t_y \end{vmatrix} \dots\dots(13)$$

Where, (x, y) is the coordinate of the float image, and (X, Y) is the coordinate of the reference image. s is the scaling parameter between the reference image and the float image. ∂ is the rotation parameter. t_x is the sliding distance along x direction between the coordinates, and t_y is the sliding distance along y direction between the coordinates [11].

In order to match the two images, we have to know the s, ∂, t_x and t_y. Firstly, we build a new equation groups, which takes s, ∂, t_x and t_y as unknown parameters. It can be described as follows:

$$\begin{cases} p_{i1} = s \cdot q_{j1} \cdot \begin{vmatrix} \cos\partial & \sin\partial \\ -\sin\partial & \cos\partial \end{vmatrix} + \begin{vmatrix} t_x \\ t_y \end{vmatrix} \\ p_{i2} = s \cdot q_{j2} \cdot \begin{vmatrix} \cos\partial & \sin\partial \\ -\sin\partial & \cos\partial \end{vmatrix} + \begin{vmatrix} t_x \\ t_y \end{vmatrix} \end{cases} \dots (14)$$

In order to get the more accurate parameters, particle swarm algorithm (PSO) [12] is used to solve the equation groups. They are very useful for image registration. The basic steps of PSO are as follows:

- Initializing a group of particles with the size of N, and setting the initial position and velocity;
- Calculating the fitness value of each particles;
- Comparing the fitness value of each particles with its fitness value at the best position, if the result is better, we will make it as the current position;
- Comparing the fitness value of each particles with the fitness value at the best position in the whole process; if the result is better, we will make it as the best position in the whole process;

- Updating the current position and the velocity of the all particles;
- Determining the conditions for the termination of the algorithm. Output the final results;

Algorithm termination conditions are as follows: the running time of algorithm to reach the maximum; the total number of individuals to achieve maximum fitness value; algebraic evolution reaches its maximum; after several generations, the individual fitness value is not improved obviously.

Generally speaking, PSO, which is applied in image registration, mainly optimizes the registration parameters. While we get the more accurate parameters, the better image registration we will get. PSO is an important part for the whole registration processes. Specific steps of the optimization parameters are as follows:

Step1. Set the number of iterations, the maxi- -mum initialization velocity, the number of the particles and the learning factor.

Step2. Initialize the position and velocity of the particles, set the initialization position of the particles as the initialization ultimate value.

Step3. Setting the fitness function by the affine transformation function, and calculating the fitness;

Step4.According to the termination conditions, the procedure will not stop until the best value is produced;

Step5. After output the optimal parameters, making the two images matched;

According to the PSO process, we can get the optimums, which are s, ∂, t_x and t_y. In order to facilitate equations optimization, a new function $\phi(s, \partial, t_x, t_y)$ is defined as follows:

$$\phi(s, \partial, t_x, t_y) = (p_{i1} - (s \cdot q_{j1} \cdot \begin{vmatrix} \cos\partial & \sin\partial \\ -\sin\partial & \cos\partial \end{vmatrix} + \begin{vmatrix} t_x \\ t_y \end{vmatrix}))^2$$

$$+ (p_{i2} - (s \cdot q_{j2} \cdot \begin{vmatrix} \cos\partial & \sin\partial \\ -\sin\partial & \cos\partial \end{vmatrix} + \begin{vmatrix} t_x \\ t_y \end{vmatrix}))^2 \dots\dots(15)$$

PSO is used to optimize this function in order to get the global optimum fitness value. When it comes ture, parameters s, ∂, t_x and t_y are the final results, which are applied for image registration.

V. EXPERIMENTAL RESULTS

In the experiment, the float image and the reference image are cut from an infrared 1-channel satellite image and a visible-channel image, which are transmitted by China FY-2 satellite at 6:00 on September 23, 2008(Beijing Time). The sizes of the two images are both 174×163. Fig. 2 is the float image, and Fig. 3 is the reference image. Fig. 4 is the float image with the extracted corner points. Fig. 5 is the reference image with the extracted corner points.

From Fig. 4 and Fig. 5, we can find that not all of the corner points of the float image can get the appropriate matching point in the reference image. Those unmatched corner points are called unreal corner points, which will

be excluded by the following work. The coordinates of the corner points of the float image, which have been applied in the affine transformation function, are listed in table.1. The very matched corner points of the reference image are listed in the table.1, too. The value of the affine transformation parameters, which are optimized by GA, are as follow: $\partial = 0.0211$; s=0.9711;

$t_x = 1.0661$; $t_y = 1.1257$; The parameters of the PSO optimization are set as follows: the number of the particles is 200, the number of iterations is 1000, the learning factor is 2, the initialization velocity is 0.01; The very matched corner points include 30 pairs, in which there are 8 pairs of matched points are listed in Table I.

TABLE I.
SOME COORDINATES OF THE CORNER POINTS TYPE SIZES FOR CAMERA-READY PAPERS

Float image	Affine transformation	Reference image
（3, 100）	（3.02, 100.33）	（3, 101）
（97, 134）	（95.91,135.05）	（96,135）
（89, 120）	（88.15,121.10）	（88,121）
（129,57）	（128.45, 59.16）	（128,59）
（63, 80）	（62.85, 81.20）	（63,81）
（134,83）	（133.12,84.97）	（133,85）
（20, 80）	（20.27, 80.72）	（20,81）
（101, 114）	（100.10, 115.29）	（100,115）

In order to further verify the performance of our proposed algorithm, four other images are used to make registration. The results are as follows: Fig. 6 is the float image with the corners points matched. Fig. 7 is the reference image with the corners points matched.

Fig. 8 and Figure 9 are cut from an infrared 3-channel satellite image and a visible-channel image, which are transmitted by China FY-2 satellite at 6:00 on September 22, 2008 (Beijing Time). Fig. 8 is the float image, Fig. 9 is the reference image.

Fig. 10 is the float image with the extracted corner points. Fig. 11 is the reference image with the extracted corner points. Fig. 12 and Fig. 13 are cut from an infrared 1-channel satellite image and a visible-channel image, which are transmitted by China FY-2 satellite at 8:00 on September 23, 2008 (Beijing Time). Fig. 12 is the float image, Fig.13 is the reference image. Fig. 14 is the float image with the extracted corner points. Fig. 15 is the reference image with the extracted corner points.
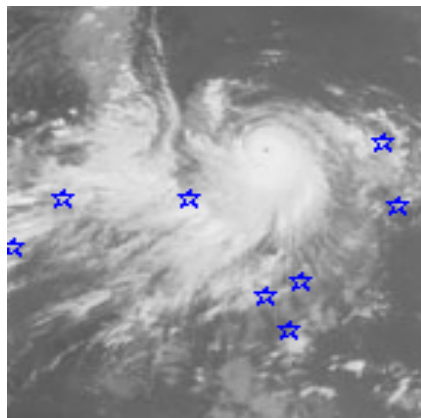

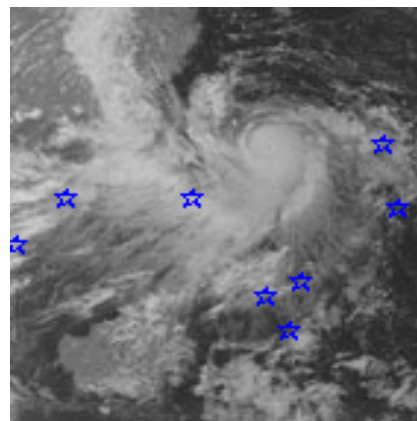Figure 6.　Feature corner points of the float image
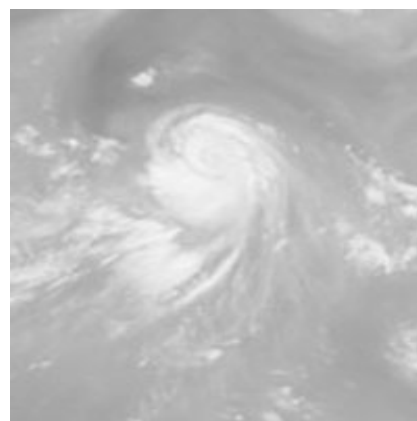

Figure 7 Feature corner points of the reference image

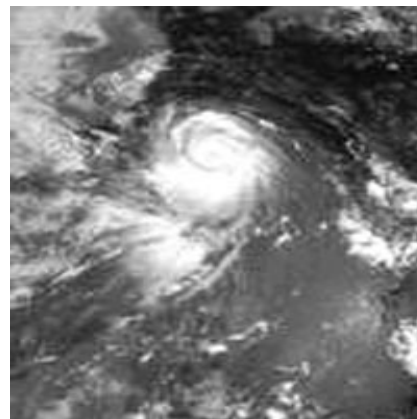
Figure 8. Float image

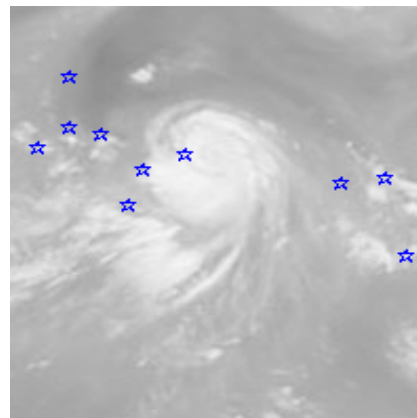Figure 9. Reference image
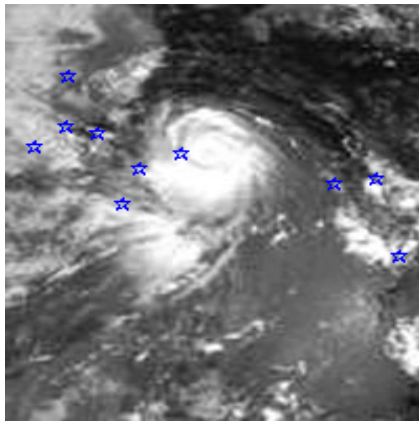

Figure 10. Feature corner points of the float image

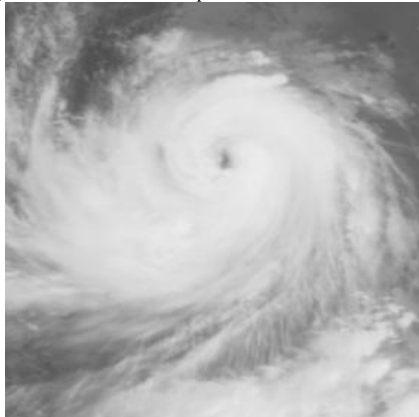Figure 11. Feature corner points of the reference image
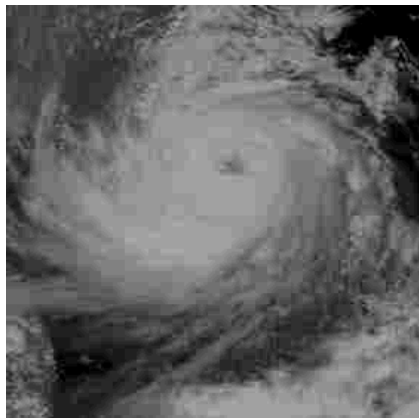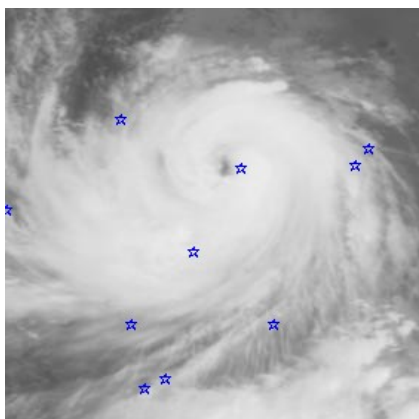

Figure 12.   Float image

Figure 13. Reference image

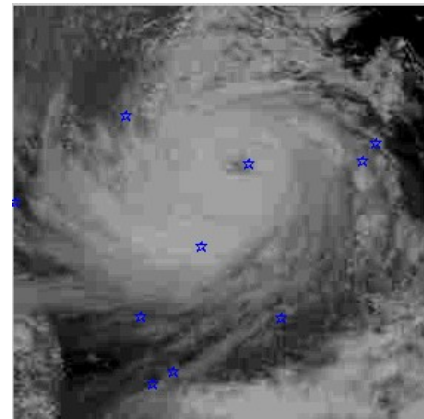Figure 14.   Feature corner points of the float image

Figure. 15 Feature corner points of the reference image

Compared with the classic image registration based on mutual information, the image registration algorithm in this article saves much time and improves the registration accuracy. The error accuracy of the image registration is calculated by the following function:

$$Erro = \sqrt{(X-a)^2 + (Y-b)^2} \ \ldots\ldots\ldots(16)$$

Where: *(X, Y)* is the coordinate of the final matched corner points of the reference image. *(a, b)* is the coordinate, which is calculated in function (13) by inputting the coordinate of the very matched corner points of the float image. The average error of the coordinates of ten matched corner points, which is calculated in every matched image, is called registration error. Fig. 16 shows the error curve, which is calculated by twenty pairs of images.
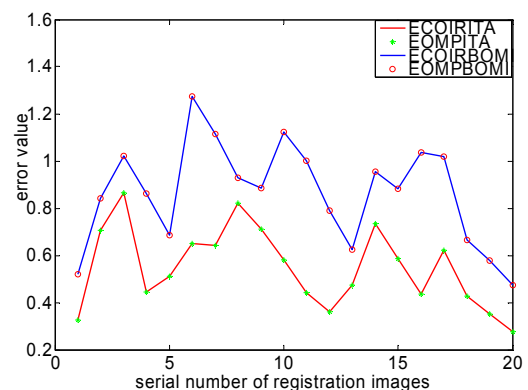

Figure 16. Error curve of registration images

In this graph, ECOIRITA is the abbreviation for Error Curve Of Image Registration In This Article, EOMPITA is the abbreviation for Error Of Matched Points In This Article, ECOIRBOMI is the abbreviation for Error Curve Of Image Registration Based On Mutual Information, EOMPBOMI is the abbreviation for Error Of Matched Points Based On Mutual Information.

VI.   CONCLUSION

The high accuracy of image registration, which is realized in this article, is much valuable for image fusion, and some other related fields. Because of the high

accuracy and the very computing of the CSS corner point extraction algorithm, we can get many corner points from each images. Through multiple constraints, the corner points of float image are used to match the corner points of reference image. Then, several pairs of corner points are applied in an affine transformation function, which can help completing the whole work of image registration. In the very process, PSO is used to optimize the affine transformation parameters, which are much more useful for image registration. However, if the position deviation between the reference image and the float image is very far, the final accuracy of image registration will decrease. This should be improved by the following work.

REFERENCES

[1] Ying Yang,Xin Gao. Remote sensing image registration via active contour model [J]. AEU International Journal of Electronics and Communications. 2009, 63(4):227-234.

[2] UlaşBağcı,JayaramK.Udupa,LiBai.Viergever. The role of intensity standardization in medical image registration[J]. Pattern Recognition Letters. 2009, 31(4): 315-323.

[3] Anton Bardera , Miquel Feixas , Imma Boada , Mateu Sbert. Image registratiom by compression[J]. 2010, 180 (7):1121-1133

[4] Gang HongYun Zhang. Wavelet-based image registration technique for high-resolution remote sensing images[J]. Computers & Geosciences. 2008, 34 (12):1708-1720.

[5] Mohammad Awrangjeb, Guojun Lu. An Improved Curvature Scale-Space Corner Detector and a Robust Corner Matching Approach for Transformed Image Identification [J]. IEEE Transactions on Image Processing, 2008, 17(12): 2425-2441

[6] Dinggang Shen. Fast image registration by hierarchical soft correspondence detection[J]. Pattern Recognition. 2009, 42(5): 954-961.

[7] lkaabi, eravi. Iterative Corner Extraction and Matching for Mosaic Construction[C]. Proceedings of the Second Canadian Conference on Computer and Robot ViSion, Canadian, 2009:48-56

[8] Farzin Mokhtarian,iku Suomela. Robust Image Corner Detection Through Curvature Scale Space[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1998, 20(12): 1376- 1381

[9] Belongie S,Malik J,Puzicha J.Shape Matching and Object Recognition Using Shape Contexts[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002,24(4):509-522

[10] Etienne Vincent, Robert Laganière. Detecting and matching feature points[J]. Journal of Visual Communication and Image Representation. 2005, 16(1): 38-54

[11] Paul Dare , Ian Dowman. An improved model for automatic feature-based registration of SAR and SPOT images [J]. ISPRS Journal of Photogrammetry and Remote Sensing. 2001, 51(1): 13-28

[12] Yuanbin Mo, Hetong Liu, Qin Wang. Conjugate direction particle swarm optimization solving systems of nonlinear equations[J]. Computers & Mathematics with Applications. 2009, 57(12): 1877-1882

Xiang Zhang is currently a M.S. candidate of College of Mathematics, Physics and Information Engineering, Zhejiang Normal University, china. He received his B.S. degree in 2008. His current research interests include Image processing and multi-media signal processing.

Changjiang Zhang received the Ph.D. degrees in control theory and control engineering from Beijing Institute of Technology, China, in 2004. He joined the Department of Electronic Information and Engineering, Zhejiang Normal University, China, in 2004. He is currently a Professor of Signal and Information Processing at the Zhejiang Normal University, where he is the head of the Image and Graphic Processing group. He is currently a member of Satellite Remote Sensing and Enviroment Disaster Group, Zhejiang Normal University, China. He is currently a member of China Society of Image Graphics and Chinese Meteorological Society. His current research interests include image processing, remote sensing, wavelet transform, multi-scale geometry analysis, machine learning and their applications.