A GLOBAL OPTIMAL REGISTRATION METHOD FOR SATELLITE REMOTE SENSING IMAGES

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Commission III, WG III/6

KEY WORDS: Image Registration, Remote Sensing, Multi-temporal, Multi-sensor, Change Detection, Global, Simplex Method, Genetic Algorithm**.**

ABSTRACT:

One of the main obstacles in image registration is the precise estimation of a mapping function that determines geometric transformation between two image coordinate systems. For conventional image registration methods, their registration results are not the global optimal, and accuracy is low because only a few local control points are used for the estimation. In this paper, we develop a global optimal method in order to get a registration approach with high accuracy. In our method, an energy function that is directly related to the parameters of the mapping function is defined in the whole image. Thus, estimation of the global optimal mapping function can be solved through energy optimization. In defining the energy function, we choose a strength measure that is based on contour edge points. It is demonstrated that the strength measure is insensitive to image radiometric distortion. Therefore, our method is applicable for various kinds of images, even for different sensors images. In order to solve the energy optimization, we design a pipelining hybrid framework that combines genetic algorithms (GAs) and a simplex method (SM). The GAs are applied firstly to look for a few initial guesses from some sub-images, and then the SM is employed to get the optima of the energy function near these initial guesses. It is found that the pipelining hybrid framework is not trapped in a local optimum, and converges fast. Hence, one of the advantages of our algorithm is that it successfully avoids advanced feature extraction and feature matching in the image registration. Its characteristics are of automatic and robust. Experimental results have shown that our method can provide better accuracy than the manual registration.

1. INTRODUCTION

Image registration is a process of matching two images so that corresponding coordinate points in the two images correspond to the same geographic area. Image registration between two remote sensing images is a very important image pre-process step for data fusion and change detection [1], and its accuracy has a key impact on their post-process [2].

Existing image registration techniques are generally divided into three broad categories: manual registration, semiautomatic registration, and automatic registration. Generally they all follow three steps to register two images: firstly, a number of control points are chosen or extracted from the two images, and then these points are used to determine a mapping function. Finally the mapping function is utilized to resample the second image so as to bring it into alignment with the first image. Therefore, the precision of image registration is controlled by accuracy and veracity of the control points.

In the manual registration, a large number of control points that are uniformly distributed in the whole image must be selected manually. It is a very tedious and repetitive task especially when the image size is very large. Therefore, it is necessary to introduce automated techniques so that little or no operator supervision is required.

There are mainly two classes of automated registration: the area-based and feature-based methods. In the area-based methods [3], a small window of points in the first image is statistically compared with the same sized window in the second image. The centres of the matched windows are the control points. Feature-based methods usually consist of two steps: firstly, the common structural features [4] are extracted from the two images respectively, and then the matched features are utilized to acquire control points.

Almost all image registration techniques implement such a strategy in which a few local control points are exploited so as to determine the global mapping function. But accuracy and veracity of the control points are limited in real cases. Even though the control points are manually matched correctly, their measure accuracy is still on a pixel-level. Consequently, results from these techniques are not the global optimal, and the accuracy is not too high because a few points are not precise enough to introduce the global parameters. Therefore, it is necessary to estimate the mapping function in the global range. So far, few studies have been conducted on the global optimal solution though it is so important for precise image registration. Therefore, in this paper, our aim is to propose a global optimal image registration method in order to achieve a better performance of the image registration.

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2. A GLOBAL OPTIMAL IMAGE REGISTRATION

Suppose I_1 and I_2 are two images to be registered and they are acquired from the same geographical area on different dates or with different sensors. Here, I_1 is defined as a reference image, and I_2 to match the reference image is defined as a sensed image. The goal of the image registration is to rectify the sensed image I_2 into the coordinate system of the reference image I_1 and to make corresponding coordinate points in the two images correspond to the same geographical location. We assume that a geometrical transformation between the two image coordinate systems can be expressed by a unity polynomial mapping function, i.e.:

$$\begin{cases} x_1 = F_{x_R}(x_2, y_2) = \sum_{k=0}^{R}\sum_{m=0}^{k} a_{\frac{k(k+1)}{2}+m}\, x_2^{k-m} y_2^{m} \\ y_1 = F_{y_R}(x_2, y_2) = \sum_{k=0}^{R}\sum_{m=0}^{k} b_{\frac{k(k+1)}{2}+m}\, x_2^{k-m} y_2^{m} \end{cases} \qquad (1)$$

Where $R \in \{1,2\}$ represents a order of the polynomial, $C_R = \left\{ a_i, b_i, \left(0 \le i \le \frac{(R+1)(R+2)}{2} \right) \right\}$ is a set of the polynomial coefficients. Apparently there are six and twelve unknown parameters in the set C_1 and C_2 respectively. Thus, the central issue of the image registration is now to acquire the optimal coefficients $C_{R_{best}}$.

In the existing methods, control points are used to approximate coefficients C_R by the least-squares method. However, their fitting results are not the global optimal because only several limited local control points are employed to estimate coefficients C_R. Therefore, a new method must be developed to compute the optimal coefficients $C_{R_{best}}$.

The global optimal coefficients $C_{R_{best}}$ are the coefficients determining a geometric transformation through which the sensed image I_2 is completely matched with the reference image I_1. If measures for evaluating the match between two images are regarded as an energy function, the optimal coefficients $C_{R_{best}}$ can be estimated through the energy function optimization, i.e.

$$C_{R_{best}} = \arg\max\left(Energy(C_R)\right) \qquad (2)$$

In the following, we firstly discuss how to define the energy function, and then address the detail of the optimization.

2.1 Definition of the energy function

For two images taken at difference dates with the same sensor, there may be radiometric distortion due to variations in solar illumination, atmosphere scattering and atmosphere absorption, but structural features in the two images are basically consistent. These structural features include straight lines, closed curves, contours, regions, and so on. Even for two images acquired from difference sensors, structural features might have changed in the local range, but many salient structural features seldom change, such as roads and flat areas. Structural features are usually grouped by many edge points, so if there are no changes in the structural features, it is reasonable to assume there are no changes in the distribution of edge points. In other words, an edge point is likely to exist in the reference image I_1 at the location where there is an edge point in the sensed image I_2, and vice versa. Usually, all edge points are the local maximal of magnitude, thus their average edge strength is also the maximum. Therefore, an average edge strength of points in the reference image I_1 that are converted from edge points in the sensed image I_2 by using geometric transformation determined by the global optimal coefficients $C_{R_{best}}$ should be the maximum. According to this assumption, we can define the average edge strength as the energy function.

Let $E_2 = \{(x_{2_i}, y_{2_i})(1 \le i \le N)\}$ the edge points extracted from the sensed image I_2, where N is the number of edge points, and let image M_1 represent the edge strength (or magnitude) map of the reference image I_1. The energy function is defined as:

$$Energy(C_R) = \frac{1}{N}\sum_{i=1}^{N} M_1\left(F_{x_R}(x_{2_i}, y_{2_i}), F_{y_R}(x_{2_i}, y_{2_i})\right) \qquad (3)$$

where $F_{x_R}(x_{2_i}, y_{2_i})$ and $F_{y_R}(x_2, y_2)$ are computed in equation (1), $M_1(x, y)$ represents the edge strength of point (x, y) and needs bilinear interpolation because $F_{x_R}(x_{2_i}, y_{2_i})$ and $F_{y_R}(x_2, y_2)$ are real.

2.2 The energy function optimization

The energy function $Energy(C_R)$ in equation (3) is a non-linear high dimensional function, and has many local optima. Determinative local search methods are easily entrapped in a local optimum. By contrast, random global search algorithms are less likely to be trapped in local optima, but their computational costs are much higher. Therefore, not any one method solves this problem very well and the tradeoff is to combine them [5]. In this paper, we combine a random search algorithm and a determinative search method into a hybrid approach. In calculation, the approach is composed of the following two steps: firstly, we look for many sets of initial guesses of coefficients C_R in the global range by using a random search algorithm, and then we acquire the optimal coefficients $C_{R_{best}}$ near these initial guesses by a determinative search method.

Considering that it is not easy to gain the gradient of the energy function $Energy(C_R)$, we choose a SM [6] as the determinative search approach and GAs [7] as the random search algorithm. The whole optimization procedure is implemented in three stages: in the first stage, use the manual method to determine the initial guesses and the range of each parameter in coefficients C_R. In the second stage, for each parameter, acquire initial guesses closer to the optima with GAs. In the last stage, exploit a SM to search the best coefficients $C_{R_{best}}$. The detail of each method is given in the following.

2.2.1 Search the Optima by A SM

SM is a local search technique that uses the evaluation of the current data set to determine the promising search direction. It is an iterative procedure that runs as follows:

1) Initialization: construct a simplex with $n+1$ points in the n dimension search space (for function $Energy(C_1)$, n is equal to 6, and for function $Energy(C_2)$, n is equal to 12) and determine initial guesses for $n+1$ points X_i $(1 \le i \le n+1)$. We will estimate the initial guesses in the following 2.2.2.

2) Form new simplexes by replacing the worst point in the simplex with a new point generated by reflecting, expanding or contracting:

i) Initializing: at first, for each point in the simplex, compute its energy value according to equation (3). Secondly, find the minimum f_W, the second minimum f_N and the maximum f_B among these energy values and their respective points X_W, X_N and X_B. Thirdly, compute a centroid $\overline{X}$ of the remaining N points except the point X_W as follows:

$$\overline{X} = \frac{1}{n}\left(X_1 + X_2 + \cdots + X_{W-1} + X_{W+1} + \cdots + X_{n+1}\right) \quad (4).$$

ii) Reflecting: generate a new point X_R by reflecting X_W over the centroid $\overline{X}$:

$$X_R = \overline{X} + \left(\overline{X} - X_W\right) \quad (5).$$

Then compute the energy value f_R at the point X_R.

iii) Expanding: for $f_R > f_B$, a new point X_E further along the reflection direction is generated using the equation:

$$X_E = \overline{X} + \gamma\left(\overline{X} - X_W\right) \quad (6),$$

where $\gamma > 1$ is called as the expansion coefficients. Then compute the energy value f_E at the point X_E.

iv) Contracting: for $f_W < f_R < f_N$, a new point X_C close to the centroid $\overline{X}$ on the opposite side of X_W is generated by:

$$X_C = \overline{X} + \beta\left(\overline{X} - X_W\right) \quad (7),$$

where $\beta\,(0 < \beta < 1)$ is called as the contraction coefficient; for $f_R \le f_W$, a new point X_C close to the centroid $\overline{X}$ on the same side of X_W is generated using the contraction coefficient β

$$X_C = \overline{X} - \beta\left(\overline{X} - X_W\right) \quad (8).$$

Then compute the energy value f_C at the point X_C.

v) Replacing: for $f_E > f_R$, X_W is replaced by X_E; for $f_R \ge f_N$, X_W is replaced by X_R; for $f_C > f_W$, X_W is replaced by X_C; otherwise X_W is replaced by X_N.

3) Stop when

$$\left\{\frac{1}{n+1}\sum_{i=1}^{n+1}\left[Energy(X_i) - Energy\left(\overline{X}\right)\right]^2\right\}^{1/2} < \varepsilon \quad (9).$$

Where the ε is a predetermined threshold. The X_B is the global optimal coefficients $C_{R_{best}}$.

2.2.2 Determine the C_R initial guesses by GAs

GAs can be used to determine the initial guesses for the SM. Before discussing these, we will first consider how to apply GAs to optimize the energy function $Energy(C_R)$.

GAs [7] are global search and optimization techniques modeled from natural genetics, exploring search space by incorporating a set of candidate solutions in parallel. A GA maintains a population of candidate solutions where each solution is usually coded as a binary string called a chromosome. A chromosome encodes a parameter set (i.e., a candidate solution) for a set of variables being optimized. A set of chromosomes forms a population, which is evaluated and ranked by a fitness evaluation function. The initial population is usually generated at random. The evolution from one generation to the next involves three steps. First, the current population is first evaluated using the fitness evaluation function, then ranked based on its fitness values. Second, GA's stochastically select "parents" from the current population with a bias that better chromosomes are more likely to be selected. This is accomplished using a selection probability that is determined by the fitness value or the ranking of a chromosome. Third, the GA reproduces "children" from the selected "parents" using two genetic operations: crossover and mutation. This cycle of evaluation, selection, and reproduction terminates when an acceptable solution is found, when a convergence criterion is met, or when a predetermined limit on the number of iterations is reached.

In fact, only three components of GAs, such as decoding, and fitness evaluation of each chromosome, are related to a real optimization problem. In the following, we will first discuss the three components to the energy optimization, and then give out a detailed procedure for energy optimization.

1) The Encoding Scheme: In this paper, a binary string is adopted to represent a chromosome, and 8 bits is used to encode every parameter of coefficients C_R. Thus, the lengths of each chromosome for C_1 and C_2 are equal to 48 and 96 respectively.

2) The Decoding Scheme: every parameter of coefficients C_R is decoded as:

$$V = V_i + (C_v - 128) \times \frac{V_r}{256} \quad (10).$$

Where V is a parameter value to be acquired, V_i is the initial guess of the parameter; V_r is the range of the parameter, and C_v is decoded on 8 bits which corresponds to the parameter in the chromosome and is located in the range of between 0 and 255. In 2.2.3, we will address methods for computing each parameter's initial guess and its range.

3) The Fitness evaluation function: a chromosome is decoded to acquire a set of parameter values of coefficients C_R, and then these parameters are put into equation (1) and equation (3) in order to gain an energy value. The energy value is regarded as the fitness of the chromosome.

4) The Procedure for GAs:

i) Initialization: the initial population is generated at random. The population size is equal to $n \times 10$, where n is the number of dimension of coefficients C_R.

ii) At each generation

Compute each chromosome's fitness and find the best chromosome C_{best} with the maximal fitness.

Reproduce the next population. The selection probability is determined by the ranking of a chromosome.

Mutation operates on each chromosome, and the mutation probability is about 0.07.

One-point crossover operates on two chromosomes, and the crossover probability is 0.3.

iii) Stop when a predefined limit $MAXGAP$ on the number of iterations is reached. Decode the best chromosome C_{best} and get the optimal coefficients $C_{R_{best}}$.

2.2.3 Determine C_R initial guesses and their ranges

GAs need each parameter's initial guess and its range in the C_R. Through equation (1), we know that the second order coefficients in the C_2 must be located at the small range close to zero, thus, we may assume that these parameters will be smaller than a threshold T_s. Therefore these parameters' initial guesses are equal to 0, and their ranges are $2T_s$.

Now, we discuss how to appoint the other parameters' initial guesses and their ranges. In the C_1, there are six parameters, i.e., $a_0, a_1, a_2, b_0, b_1, b_2$. These parameters can represent a general affine transformation. When considering there is no need of high accuracy in the estimation of each parameter's initial guesses, we assume that the geometric transformation between two images is composed of the Cartesian operations of scaling (s), translation $(\Delta x, \Delta y)$, and rotation (θ), that is,

$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = s \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_2 \\ y_2 \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \quad (11).$$

Comparing equation (1) with equation (11), we have the relationship between parameters $a_0, a_1, a_2, b_0, b_1, b_2$ and parameters $s, \theta, \Delta x, \Delta y$. Therefore, each parameter's initial guess in the C_1 can acquired as follows: firstly two pairs of control points are manually selected, and then utilized to compute parameters $s, \theta, \Delta x, \Delta y$. The range of each parameter may be manually chosen to be large enough to cover the optimal values.

3. EXPERIMENTAL RESULTS

In this section, we give the experimental results divided into three parts. First, in order to evaluate the accuracy of the registration, we test our approach by using a pairs of synthetic images. Second, we apply our approach to register multi-temporal images. Lastly, we show some results of the image registration for a different sensor. Meanwhile, in order to test our approach, we compare the registration results of our approach with those of manual methods. In existing methods, the root mean square error (RMSE) between the match points provides a measure of registration. But RMSE is not suitable for evaluating our approach because we do not extract any match points. Here, we define a measure that is similar to but more precise than RMSE:

$$RMSE = \left(\sum_{y=0}^{H-1} \sum_{x=0}^{W-1} D(x,y)^2 \Big/ (W \times H) \right)^{\frac{1}{2}} \quad (12).$$

Where W, H are width and height of the sensed image respectively, and the distant $D(x,y)$ between the transformed point and the true point is defined as:

$$D(x,y) = \left(F_{x_R}(x,y) - G_x(x,y)\right)^2 + \left(F_{y_R}(x,y) - G_y(x,y)\right)^2 \quad (13).$$

Where $F_{x_R}(x,y)$ and $F_{y_R}(x,y)$ are computed by equation (1), and $(G_x(x,y), G_y(x,y))$ is the true coordinate of point (x,y) in the reference image, we define the maximum distant $D(x,y)$ as another measure for evaluating the accuracy of the registration,

$$\max D = \max_{0 \le x < W, 0 \le y < H} D(x,y) \quad (14).$$

To compute $D(x,y)$ in equation (13), we must know $(G_x(x,y), G_y(x,y))$ of the point (x,y) in advance. It is feasible for synthetic images pairs, but very difficult for real images pairs. In our experiment, we have found a rule between $RMSE$ and energy value: the $RMSE$ drops as the energy value increases. Therefore, the energy value can be regarded as another measure for evaluating the accuracy of registration, replacing $RMSE$. The rule will be found in the following part A. In order to evaluate registration differences between our approach and manual methods, we replace $\left(G_x(x,y), G_y(x,y)\right)$ in equation (13) with the transformed coordinate by using manual methods to compute the measures $RMSE$ and $\max D$ in equation (12) and (14). All experimental results from our approach and manual methods are shown in Table I.

In our experiment, the size of the experimental images is 512×512 and the predefined thresholds are the same in all examples. In C_R, the range of the translation coefficients is 20, and the range of the first and the second order coefficients is 0.2. The number of the iteration times in GAs is 15，and ε in inequation (9) is 0.5.

3.1 Evaluating the accuracy of registration

To evaluate the accuracy of our algorithm, we use PhotoShop software to clockwise rotate an image by 90 degrees. It is shown in Fig.1 (a)–(b). Thus, we can know their optimal transformation parameters in advance. Two pairs of control points ((159,63), (451,163)) and ((423,468), (43,423)) are manually selected from the two images to compute initial guesses.

(a) (b)

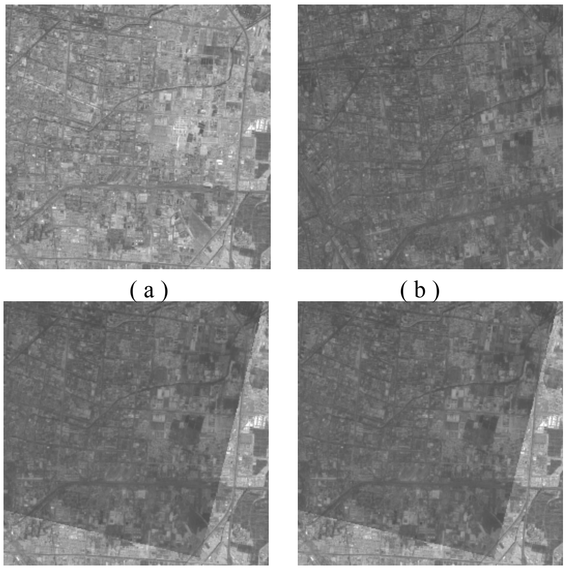
Fig.1. (a) initial image, (b) transformed image by clockwise rotating 90 degree of (a).

For the manual registration method, 20 pairs of control points are manually selected to register the two images.

From Table I we find that even though the initial guesses given are far from the optimal values; for example, $RMSE$ is more than 3 pixels. Our approach can still yield a good result that is very close to the optimum; its accuracy is much higher than that of the manual method.

3.2 Multi-temporal Image Registration

Fig.2 (a)–(b) shows a pair of SOPT images acquired on different dates. 17 pairs of control points are manually selected to register two images, and its result is shown in Fig.2 (c). The result of our approach is shown in Fig.2 (d). Because this pair of images was taken from the same sensor but on different dates, an operator can easily select control points with reasonably high accuracy. From table I, the transformation parameters obtained by the manual method are very close to those by our approach, and the $RMSE$ between them is less than one pixel. However,

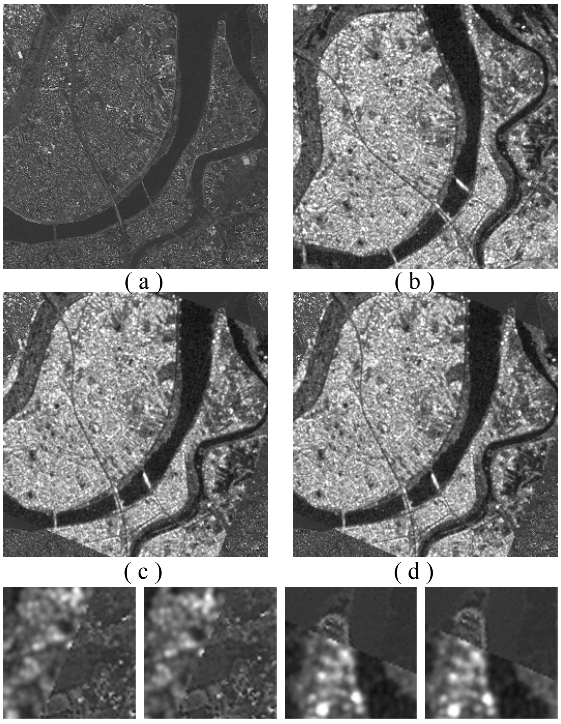


(a) (b)

(c) (d)

Fig. 2.（a）the reference image (b) the sensed image; (c) registration by manual; (d) registration by our method.

the registration results by our approach are better than those by the manual method because the energy value obtained by our approach is higher than those by the manual method.



(a) (b)

(c) (d)

(e) (f) (g) (h)

Fig. 3. (a) SPOT image; (b) SAR image; (c) registration by manual; (d) registration by our method; (e) and (g) are two sub images cut from the image shown in (c); (f) and (h) are two sub images cut from the image shown in (d).

3.3 Multi-sensor Image Registration

Fig.3 (a)–(b) shows a pair of SPOT and SAR images. 20 pairs of control points are manually selected to register the two images, and its result is shown in Fig.3 (c). The result by our approach is shown in Fig.3 (d). It is found that it is very difficult for us to select control points in this pair of images probably due to their large differences in radiometric. From Table I, we also know that differences of the transformation parameters from the two methods are large. The $RSME$ between them is more than 3 pixels and the $\max D$ between them is even more than 7 pixels. In order to test the two methods, we compare two pairs of 64×64 sub1images which are cut at the adjoins of two registered images. The two pairs of sub-images are shown in Fig.3 (e)–(h) scaled 4 times to be clear. From the first pair of images in Fig.3 (e)–(f), we find that there should be a road crossing through the center of images from the left-bottom corner to the right-top corner, but there is a distinct jump in the image Fig.3 (e) which is cut from the image registered by manual methods. In the second pair of images in Fig.3 (g)–(h), there is a place connecting land with a river. Although it is not very precise to compare the results from the two methods owing to changing water level of the river, we find that the link manner in Fig.3 (h) by our approach is more reasonable than in Fig.3 (g) by manual methods. Therefore, our approach is better than the manual methods.

Table I

Comparison Of The Global Optimal Registration Results With The Manual Registration Results Or With Truth

Test Data	Methods	a_0	a_1	a_2	b_0	b_1	b_2	*Energy*	*RMSE*	$\max D$
Synthetic Images	Optimal	0.00000	0.00000	1.00000	511.0000	-1.00000	0.00000	51.78687	0.00000	0.00000
	Initial	0.77563	-0.01030	0.99921	515.3251	-0.99921	-0.01030	34.13717	3.53358	6.51956
	Manual	-2.15291	3.01e-05	1.00452	512.8174	-0.99897	-0.00406	36.89599	1.70201	3.17100
	Our method	0.00099	6.18e-06	0.99998	511.0105	-1.00001	-7.39e-06	51.04321	0.00834	0.01258
Multi-Temporal Images	Initial	8.04031	0.96688	-0.23845	-120.3902	0.23845	0.96688	23.95547	0.81365	1.69900
	Manual	6.66587	0.97010	-0.24062	-119.9549	0.23776	0.96976	25.63776		
	Our method	5.95431	0.97262	-0.24227	-121.1075	0.24040	0.97059	26.64661		
Multi-Sensor Images	Initial	115.9111	0.92227	-0.39794	-86.73397	0.39794	0.92227	49.43873	3.82170	7.31851
	Manual	112.591	0.92473	-0.39309	-83.58278	0.37902	0.92597	49.54566		
	Our method	111.605	0.91877	-0.39289	-86.18712	0.39607	0.92361	49.98123		

4. CONCLUSIONS

In this paper, we propose a global optimal image registration method. In our method, we develop a new strategy in which a global mapping function is estimated by a few local control points, but acquires the mapping function in the whole image range. Therefore, the registration accuracy of our method is much higher than that of conventional methods. In our method, at first, we define an energy function that is directly related to parameters of the mapping function, and thus an estimation of the mapping function is translated into an energy optimization. On defining the energy function, we do not use similarity measures that are sensitive to radiometric distortion, but exploit the average edge strength that can describe structural features and shapes of scene. Therefore, our approach is not only applicable for registering images acquired from different sensors, but also for images acquired on different dates in which there may be big radiometric differences between the images because of variations in solar illumination, atmosphere scattering, and atmosphere absorption. Second, we present a hybrid scheme combining a SM and GAs sequentially to optimize the energy function: firstly, a statistical method is used to acquire a set of rough initial guesses for each parameter in the whole images, and then GAs are exploited to search further precise guesses of parameters from many sub-images. Finally a SM is employed to gain the global optimal parameters. One advantage of the hybrid scheme is that it is not easily entrapped in local optima, and converges fast.

In our method, we avoid exploiting advanced feature extraction and feature matching techniques. Thus, our approach successfully avoids the two inherent difficulties faced by existing methods. Therefore, our algorithm is robust and automatic.

The experimental results from our method have been compared with the ones by manual registration methods, and it is demonstrated that our method is very efficient and effective. Meanwhile, the energy function derived in this paper can be also regarded as an assessment criterion for the image registration.

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6. ACKNOWLEDGMENT

The work is supported by the Post Doctoral Fund of China.