

A hybrid approach based on MEP and CSP for contour registration

Zhao Xiuyang^{a,b,*}, Zhang Caiming^b, Wang Yanan^a, Yang Bo^a

^a School of Information Science and Engineering, University of Jinan, No. 106 Jiwei Road, Jinan 250022, Shandong, PR China

^b School of Computer Science and Technology, Shandong University, Jinan 250101, Shandong, PR China

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ABSTRACT

Image registration is a fundamental task in 3D reconstruction from an image sequence. Although has been studied for decades, it is still rare to find a general, robust and automatic image registration method, and most existing image registration methods are designed for particular application. In this paper, image registration is boil down to a formula discovery problem to match feature points, we develop a new feature-based algorithm for contour registration automatically based on a hybrid approach combining Multi Expression Programming (MEP) with Clonal Selection Principle (CSP). Firstly, the image contours are extracted by fast global minimization of the active contour model, the feature point pairs which are used to establish training set of the hybrid approach are obtained using invariable moments. Secondly, the registration equations are acquired automatically by the proposed hybrid approach and the contours are then registered based on the equations. Experiments show that the proposed approach can be successfully applied to register the image pairs in which the contour information is well preserved.

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1. Introduction

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors [1]. Manual registration techniques commonly have been used in clinical application. In these methods, image registration relies on manual selection of feature points. In order to get reasonably good registration results, a large number of feature points must be selected across the whole image [3]. When the number of image pairs to be registered is large, human intervention becomes impractical, necessitating the use of automated image registration techniques [22].

The current automated registration techniques can be classified into two broad categories: area-based [5] and feature-based techniques [6–11]. In the area-based algorithms, a small windows of points in the sensed image is compared statistically with windows of the same size in the reference image [4]. A majority of the area-based methods have the limitation of registering only images with small misalignment [2].

Feature-based matching techniques use the image features to describe matching entities. The basic issues of feature-based matching techniques that needs to be addressed when developing a registration algorithm is what type of feature should be extracted from the images being registered, to be used in the search for the

geometric transformation that best aligns them [24]. In general, as described in Ref. [23], these features include edges, contours, surfaces, other salient features such as corners, line intersections, and points of high curvature, statistical features such as moment invariants or centroids, and higher level structural and syntactic descriptions.

In this study, the feature-based image registration is boil down to a formula discovering problem, the moment invariants technique is employed to extract the feature points of the image contours and a hybrid approach is used to develop the registering formulae.

The rest of the paper is organized as follows. Section 2 presents the related work. In Section 3, we extracted cement particle contours using the fast global minimization of the active contour model. Section 4 briefly describes the process of extracting point pairs. Formula discovering of registration model based on the hybrid approach is presented in Section 5. Several numerical experiments are performed in Section 6. Section 7 concludes the paper.

2. Related work

As described in Ref. [2], there are three critical procedures generally involved in the feature-based techniques: feature extraction, feature correspondence and transformation parameters estimation. Some recent methods of feature extraction include feature points extraction method based on the nonsubsampling contourlet transform [24], gradient-based salient point feature descriptor [25] and scale invariant feature transform (SIFT) combined with a shape descriptor method [26]. Feature correspondence is a crucial step

* Corresponding author at: School of Information Science and Engineering, University of Jinan, No. 106 Jiwei Road, Jinan 250022, Shandong, PR China.

E-mail address: zhaoxy@ujn.edu.cn (X. Zhao).

in image registration. Zavorin [27] compared the performances of several wavelet pyramids in the framework of multi-resolution sub-pixel image registration. Yu [28] used a combined technique including wavelet pyramid approach as well as a robust cross matching and an improved TIN construction strategy to match the multi-source remote-sensing images. Falco [29] used differential evolution to automatically register a set of 2D satellite images. Transformation parameters estimation is performed based on the detected features which have finished feature correspondence. The most recent methods of transformation parameters estimation include nonlinear least squares estimation [30] and TPS-RPM algorithm [31].

By analyzing the characteristics of image registration, we can find that the most challenging problem is how to acquire the transformation parameters, and image registration can be boiled down to a formula discovering problem.

Formula discovery is obtaining the formula between independent variable and dependent variable using a large number of test data. As described in Ref. [20], formula discovery is defined as follows: given a set of observation data $D = \{(x_i, y_i) | x_i \in R^n, y_i \in R, i = 1, 2, \dots, n\}$, discovery formula: $f: R^n \rightarrow R$ which satisfies the condition: $\sum |f(x_i) - y_i| \approx 0$. The common mathematical methods resolving formula discovery are curve-fitting method, regression analysis method, approximation theory and Genetic Programming (GP). GP has certain advantages compared with other methods. It provides a power and flexibility that potentially allows for the formula evolution, in addition to has the obvious benefit of automation [16].

GP is the iterative application of Darwinian principles of adaptation by natural selection and survival of the fittest to populations of computer programs [12]. In GP, individuals are represented with variable length hierarchical structures in the form of trees. The nodes of the tree consist of a terminal, a function and an operator. Since the level and the node of the tree structure can be variable, GP is very suitable for expressing complicated formula structure [13]. There are a lot of literature concerning on formula discovery based on GP. Keane used GP to find an approximation formula of specific functions [14]. Bickel derived three analytic approximation formulae for function describing performance of various selection schemes in GP [15]. Matthew proposed the automated discovery of numerical approximation formulae via GP [16]. Yeh [32] adopted Genetic Operation Tree (GOT) to automatically induce accurate and self-organized formulas to predict compressive strength of concrete.

Multi Expression Programming (MEP) is a new GP-based technique and a relatively new technique of evolutionary programming which is developed by Oltean [17]. MEP uses fixed length linear strings of chromosomes to represent programs in the form of expression trees that eliminates many disadvantages of the classical genetic programming. Although GP is very capable of discovering formula in many stories, it often discovers formulae with huge length which increase time complexity and restrict its wide use. This paper proposes a new feature-based approach to automatically register the cement particle contours based on a hybrid approach combining MEP with CSP.

3. Contour extraction

Contour extraction is an important step in the feature-based image registration system. Many techniques are available to extract contours. Snake is a classical contour extraction method, but traditional snake method has some disadvantages, such as it is easy to fall into local minimum and is sensitive to initial curve. Bresson improved the snake method by determining a global minimum of the active contour model [18].

The main idea of the fast global minimization of the active contour model is that it integrated the GAC (geodesic/geometric active contour) model and the ACWE (active contour without edges) model using a weighted function.

The energy function of GAC model is:

$$\min_C \left\{ E_{GAC}(C) = \int_0^{L(C)} g(|\nabla I_0(C(s))|) ds \right\} \quad (1)$$

where ds is the Euclidean element of length and $L(C)$ is the length of the curve C defined by $L(C) = \int_0^{L(C)} ds$. The function g is an edge indicator function. I_0 is the original image.

The energy function of ACWE model:

$$\min_{\Omega_C, c_1, c_2} \left\{ E_{ACWE}(\Omega_C, c_1, c_2, \lambda) = Per(\Omega_C) + \lambda \int_{\Omega_C} (c_1 - f(x))^2 dx + \lambda \int_{\Omega/\Omega_C} (c_2 - f(x))^2 dx \right\} \quad (2)$$

where f is a given image, Ω_C is a closed subset of the image domain Ω , $Per(\Omega_C)$ is the perimeter of the set Ω_C , c_1 and c_2 are the mean values inside and outside Ω_C respectively, λ is an arbitrary positive parameter.

Bresson introduced a weighting TV norm and integrated the GAC model and the ACWE model using the TV norm [18].

$$E_2(u, c_1, c_2, \lambda) := TV_g(u) + \lambda \int_{\Omega} r_1(x, c_1, c_2) \phi dx \quad (3)$$

where $r_1(x, c_1, c_2) = (c_1 - f(x))^2 - (c_2 - f(x))^2$

We can obtain the contours by minimizing Eq. (3).

4. Feature point pairs obtaining

In this paper, the feature point pairs are used to establish training set of the hybrid approach combining MEP with CSP, so reasonable and exact feature point pairs are critical to the final registration result.

Moment technique is utilized to represent the distribution of stochastic quantity in the statistics and it is also used to represent space distribution of substance in mechanics. If we consider the binary image or the gray scale image as two-dimensional density distribution function, moment can be used to represent the feature of one image.

Based on the first order moment, we calculate the centroid of every single contour as the feature points in the reference and the floating images respectively. The contour ellipse is a constant intensity elliptical disk with the same mass and second order moments as the original contour. In order to obtain sufficient feature points pairs, the semimajor axis and semiminor axis of contour ellipse are calculated. Each contour can obtain the other four feature points by finding the extreme points of semimajor axis and semiminor axis. The most resemble contours in two serial sections are picked out using hu's uniqueness theorem as described in our previous paper [33]. The corresponding five feature points of the most resemble contours are regarded as point pairs. By this method, we can obtain enough feature points to establish training set of the hybrid approach combining MEP with CSP.

The moment of a binary images $g(x, y)$ is given by

$$m_{pq} = \sum_x \sum_y x^p y^q g(x, y) p, \quad q = 0, 1, 2, \dots \quad (4)$$

where p and q define the order of moment.

The centroid of the object can be given using object moments:

$$\bar{x} = \frac{m_{10}}{m_{00}}, \quad \bar{y} = \frac{m_{01}}{m_{00}} \quad (5)$$

The semi-major axis and semi-minor axis of contour ellipse can be calculated as follows [19]:

- Semi-major axis:

$$a = \left(\frac{\mu_{20} + \mu_{02} + [(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2]^{1/2}}{\mu_{00}/2} \right)^{1/2} \quad (6)$$

- Semi-minor axis:

$$b = \left(\frac{\mu_{20} + \mu_{02} - [(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2]^{1/2}}{\mu_{00}/2} \right)^{1/2} \quad (7)$$

where μ are the central moments:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q g(x, y) \quad (8)$$

In every single contour, the coordinate values of five feature points are (\bar{x}, \bar{y}) , $(\bar{x} + a, \bar{y})$, $(\bar{x} - a, \bar{y})$, $(\bar{x}, \bar{y} + b)$ and $(\bar{x}, \bar{y} - b)$ respectively.

5. Formula discovery based on the hybrid approach

5.1. MEP technique

MEP is a genetic programming variant that uses a linear representation of chromosomes. MEP can automatically establish relational model between the given input variables and output variables. The unique feature of MEP is the ability of storing multiple solutions of a problem in a single chromosome which enhance the ability of complex formula excavating. Another advantage of MEP is that the representation of MEP is very easy and it does not need to transform into tree structure in the calculation process which makes it efficiently in genetic operators [17]. The MEP representation, evolutionary scheme and the fitness assignment process are briefly described in the subsections.

5.1.1. MEP representation and initialization

The MEP algorithm starts with a randomly selected population of individuals. The number of MEP genes per chromosome is constant. Each gene encodes a terminal or a function symbol. A gene that encodes a function includes pointers toward the function arguments. There are some restrictions for generating a valid MEP individual [17]:

1. First gene of the chromosome must contain a terminal which is randomly selected from the set of terminals.
2. All other genes are determined by randomly selecting a terminal from the set of terminals or a function from the set of functions. For all genes which encodes function, pointers have to be generated to address function arguments. All these pointers must indicate toward genes which have a lower index than the current gene.
3. The first symbol in a chromosome must be a terminal symbol.

In our method, the terminal set T is $\{x, y\}$ and the function set F is $\{+, -, *, /, ^, \sin, \cos\}$.

5.1.2. Fitness assignment

In this paper, the fitness function is based on the absolute error. The fitness of each sub-expression X_i may be computed using the formula:

$$f(X_i) = \frac{\sum_{j=1}^N (M - |C_{i,j} - T_j|)}{N} \quad (9)$$

where M is a constant which control the maximum fitness value. $C_{i,j}$ is the obtained result by the expression X_i for the fitness case j , T_j is the targeted result for the fitness case j . N is the number of the cases.

We compute the fitness of each sub-expression encoded in the MEP chromosome and the fitness of the entire individual is given by the fitness of the best expression encoded in that chromosome.

5.1.3. Genetic operators

Genetic operators used within MEP are crossover and mutation. Application of these operators preserves the chromosome structure. All offspring represent syntactically correct expressions [34].

Crossover. By crossover, two parents are selected and recombined. In our paper, we use the one-point recombination operator. One crossover point is randomly chosen and the parent chromosomes exchange the sequences at the right side of the crossover point.

Mutation. Each symbol in the chromosome may be the target of the mutation operator. There are some requirements in MEP mutation operator [35]: (1) if the current gene encodes a terminal symbol, it may be changed into another terminal symbol or into a function symbol. In the later case, the positions indicating the function arguments are randomly generated but must have a lower index than the current gene. (2) If the current gene encodes a function, the gene may be mutated into a terminal symbol or into another function. (3) If the current gene is the first gene, it must mutate into another terminal symbol.

5.2. Improvement of MEP using CSP

5.2.1. Overview of clonal selection principle

The immune system is responsible for responding and eliminating foreign molecules known as antigens. Antibodies are produced by the B cells of the immune system to recognize and eliminate the non-self antigen. The ability of the antibodies to recognize and respond to an antigen is known as its affinity [36]. Each B cell is specific to a given antigen. When the antibody receptors of a B cell recognize an antigen, that B cell is selected to proliferate and produce antibodies by cloning. This process is called clonal selection principle [40]. The new cloned cells are then subject to a process called affinity maturation. Within affinity maturation, the cell undergoes a high rate of mutation called hypermutation [36]. Hypermutation affects the genes that encode for the antibody molecule. Due to competition for binding antigen, the better B cells with higher affinity antibodies will be stimulated by the antigen and will grow at the expense of B cells expressing poorer or lower affinity antibodies [37]. In this way, the weakest (the less stimulated) cells are eliminated from the population.

Based on the clonal selection principle, the clonal selection algorithm [38] is developed. In the algorithm various immune system aspects are taken into account such as: maintenance of the memory cells, selection and cloning of the most stimulated cells, death of non-stimulated cells and maintenance of diversity [39].

5.2.2. The hybrid approach based on MEP and CSP

GEP retained the benefit of GA and GP. However, MEP also has the disadvantage of premature convergence just like GA. CSP can enhance the diversity of population, and has faster convergence

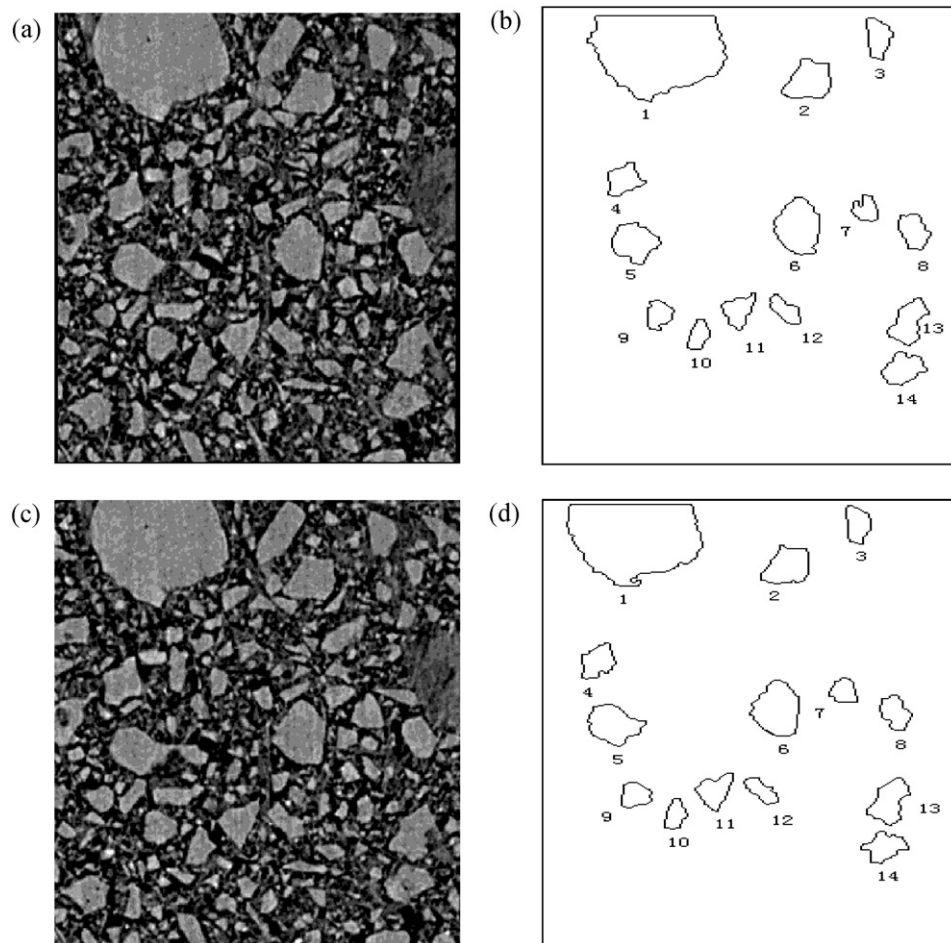


Fig. 1. The images and the corresponding contours: (a) the reference image; (b) the image contours of (a); (c) the floating image; (d) the image contours of (b).

speed. All the above advantages motivated our applying CSA into MEP to get better evolutionary algorithm for image registration.

According to CSA, only the n best individuals of population will be cloned and modified. In order to maintain the population diversity, some randomly generated individuals are selected to join the population, and some individuals with low fitness are deleted from the population. All the advantages of operators applied guarantee

that the algorithm can enhance the population diversity and find the global optimal solution quickly.

The set of formula can be obtained by limited combination of terminal set T and function set F which is defined in Section 5.1.1. The process of formula discovery based on the hybrid approach is to search a suitable formula in the solution space. The algorithm can be described as follows:

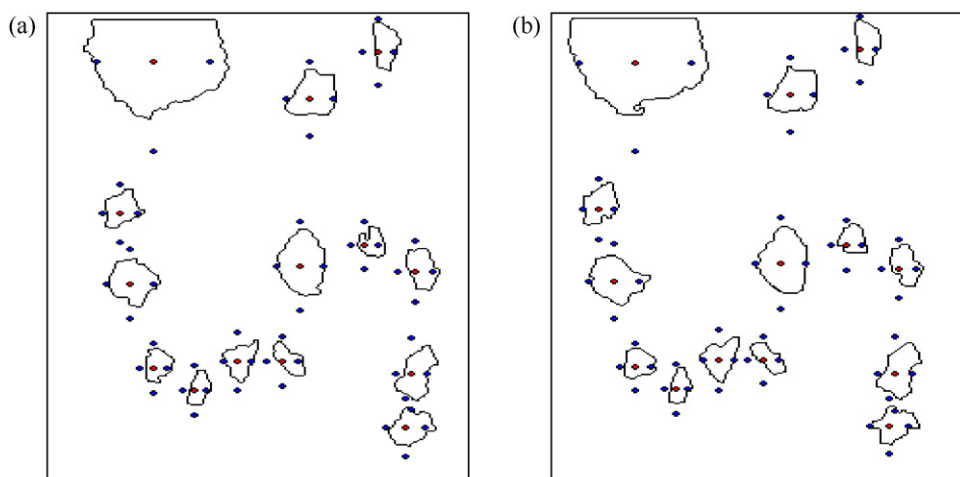
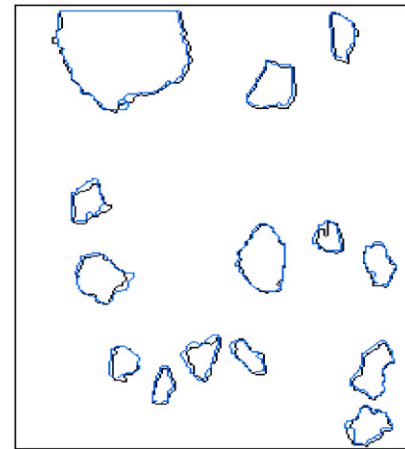


Fig. 2. The feature points: (a) the feature points of Fig. 1(b); (b) the feature points of Fig. 1(d).

Table 1

The coordinates of the feature points.

Feature points	Reference image		Floating image	
	x	y	x	y
1	178	81	188	78
2	68	108	80	105
3	181	119	191	117
4	90	129	59	121
5	47	124	102	126
⋮	⋮	⋮	⋮	⋮
69	171	26	182	30
70	155	26	166	30

**Fig. 3.** The registered images.

- (1) Generate a set (P) of candidate solutions randomly, composed of the subset of memory cells (M) and the remaining (P_r) population ($P = P_r + M$) [38].
- (2) Calculate the fitness value for every MEP individual according to Eq. (9). The fitness of a MEP individual is equal to the fitness of the best solution generated by one of the evolutionary algorithms encoded in that MEP chromosome.
- (3) Determine (Select) the n best individuals of population (P_n), based on an affinity measure, here is the fitness value; sort the individuals in descending order according to the affinity value.
- (4) Reproduce (Clone) these n best individuals of the population, giving rise to a temporary population of clones (C). The clone size is determined by Eq. (10) [41]:

$$N_c = \sum_{i=1}^N \text{round} \left(\frac{\beta N}{i} \right)$$

- (5) where N_c is the size of antibody population after clone. β is the clone coefficient, which is used to control clone size, i is the position of the antibody.

- (6) Submit the population of clones to a hypermutation scheme, where the hypermutation is proportional to the affinity of the antibody with the antigen. A matured antibody population is generated (C^*). The mutation method employed is uniform mutation. If the current gene encodes a terminal symbol it may be changed into another terminal symbol or into a function symbol, and if the current gene encodes a function the gene may be mutated into a terminal symbol or into another function [35].
- (7) Re-select the improved individuals from C^* to compose the memory set M . Certain proportion individuals are replaced by other improved members of C^* [38].
- (8) Generate a set of candidate solutions randomly, select the d best individuals, replace the same number of individuals in population C^* . The lower affinity cells have higher probabilities of being replaced.

Table 2

The main parameters in MEP.

Function set	Terminal set	Length of chromosome	Iteration number	Population size	Crossover probability	Mutation probability	β	n
+, −, *, /, ^, cos, sin	x, y	30	10,000	200	0.30	0.25	0.4	10

Table 3

The average registration accuracy of the 20 runs.

Contour number	Dn1	Dn2	Error in X direction	Error in Y direction	Total error
1	238	242	1.041629	0.430682	1.002204
2	93	95	1.773165	1.154675	1.215184
3	78	73	1.793395	1.566127	0.669544
4	74	82	1.442635	1.084335	1.012931
5	91	96	0.708695	0.427852	0.378942
6	108	110	0.591694	0.120349	0.514902
7	65	58	3.043567	0.701283	2.979477
8	73	73	1.156561	0.442539	1.005675
9	63	56	3.024336	0.526680	2.999587
10	58	60	1.118924	0.447981	0.890379
11	76	77	0.704344	0.456126	0.338674
12	59	60	0.793325	0.630041	0.307412
13	92	94	0.744375	0.387450	0.471489
14	77	85	0.601429	0.564872	0.660016

Table 4

Comparison of the proposed method with the other three methods.

	RPFGMI method	GEP	Classical MEP	Proposed algorithm
Total error in X direction	0.529029	0.448510	0.206396	0.184327
Total error in Y direction	0.451889	0.764631	0.605080	0.582964
Total error	0.796422	0.68796	0.648543	0.604379

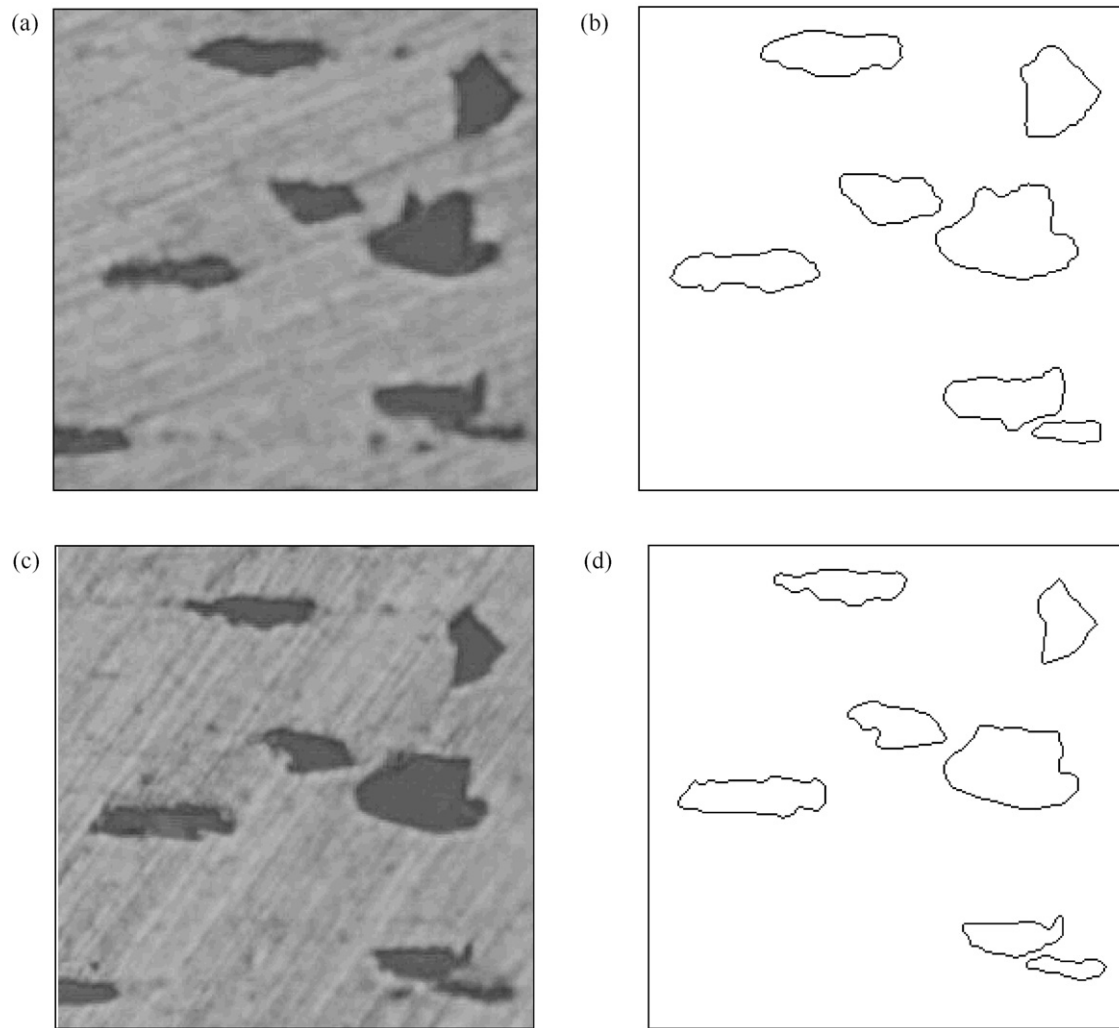


Fig. 4. The successive parallel sections and contours of SiC/Al composite: (a) the reference image; (b) the contour image of (a); (c) the floating image; (d) the contour image of (b).

- (9) The generation counter is increased $G=G+1$, and the new repertoire is submitted to step 2 for evaluation. The process continues iteratively until a quit criteria is met.

5.3. Contour registration based on the hybrid approach

The algorithm of contour registration based on the hybrid approach is given as follows:

Step 1. Extract contours of the serial images using the fast global minimization of active contour model.

Step 2. Obtain feature point sets A and B by calculating the first moment and the second moment of each contour in the two successive images. A is the feature point set of the floating image and B is the feature point set of the reference image.

Step 3. Select homologous feature points in A and B to form feature point pairs.

Step 4. The model formulae $f_x(x, y)$ and $f_y(x, y)$ are established automatically using the hybrid approach discussed in Section 5.2.

Step 5. Register the two image using the formulae $f_x(x, y)$ and $f_y(x, y)$.

6. Experimental results

In this section, we provide the experimental results for automated image registration. In the experiments, two successive images of the cement particle obtained by ID19 High-resolution Diffraction Topography Beam line in ESRF are the input. The reference image is shown in Fig. 1(a). The floating image is shown in Fig. 1(c).

6.1. Contour extraction and feature point pairs obtaining

The fast global minimization of the active contour model is used to extract contours. These extracted contours are shown in Fig. 1(b) and (d), which are corresponding to Fig. 1(a) and (c), respectively.

Based on the extracted contours in the two images, we calculate the centroid of every single contour, the semimajor axis and semiminor axis of the corresponding contour ellipses. 70 point pairs are detected in this way. Feature point pairs are shown in Fig. 2(a) and (b) where the centroids are marked in red color and the feature points extracted by contour ellipse are marked in blue color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.) The coordinates of the feature points are shown in Table 1.

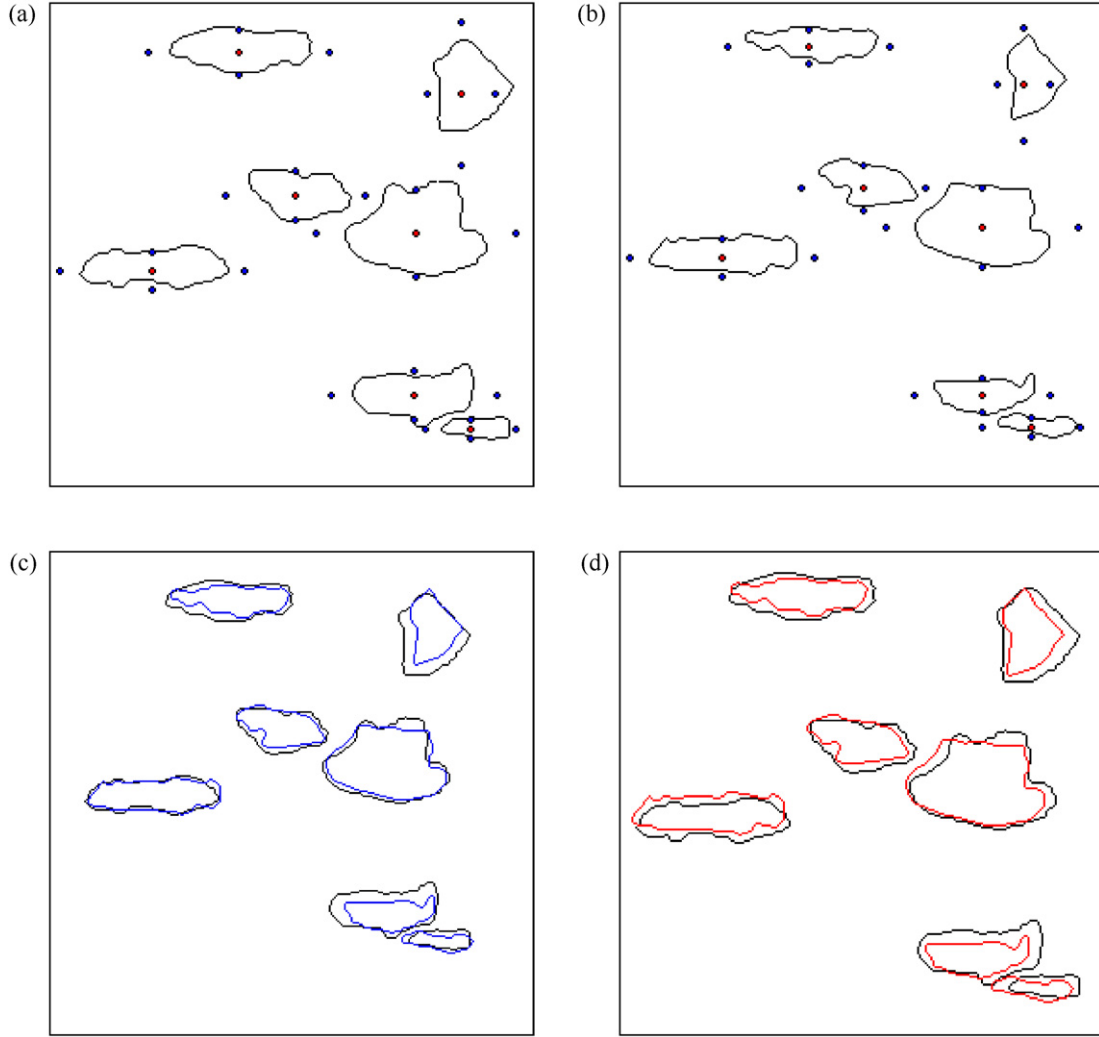


Fig. 5. The registration results: (a) the feature points of reference contours; (b) the feature points of floating contours; (c) the registration result of the proposed method; (d) the registration result of RPFGLM method.

6.2. Contour registration based on the hybrid approach

Given a number of feature point pairs from two images, the formulae of registration model can be established using the hybrid approach. In Table 2, we enumerate the main parameters in the hybrid approach.

The registration formula $f_x(x, y)$ can be acquired by the hybrid approach described in Section 5.2 whose inputs are x and y coordinate values of the reference image and x coordinate values of the floating image. The registration formula $f_y(x, y)$ also can be acquired by the hybrid approach whose inputs are x and y coordinate values of the reference image and y coordinate values of the floating image.

In order to estimate the registration accuracy, we need to define the matching error. In the traditional method, the distance of the point pairs is defined to estimate the accuracy of the image registration. However, the simple distance of point pairs is just the arithmetic mean of the distance of point pairs. It cannot estimate the matching error accurately. Illuminated by Ref. [21], we choose the weighted mean to estimate the registration accuracy.

Matching error is defined as follows:

$$\text{match error} = \sum_{ij} p_{ij} * d_{ij} \quad (10)$$

where d_{ij} is the distance of point pairs and p_{ij} is the joint probability distribution of the point pairs.

$$d_{ij} = \sqrt{\frac{\sum_{i=1}^m \sum_{j=1}^n (x_i - x_j)^2 + (y_i - y_j)^2}{m * n}} \quad (11)$$

where (x_i, y_i) is the point coordinates of reference image, (x_j, y_j) is the point coordinates of the floating image, m is the number of points in the reference image, and n is the number of points in the floating image.

$$p_{ij} = \frac{(p_{ij}/(p_i * p_j)) \exp(-\alpha * d_{ij}^2)}{\sum_{ij} (p_{ij}/(p_i * p_j)) \exp(-\alpha * d_{ij}^2)} \quad (12)$$

where $p_i = \sum_j p_{ij}$ and $p_j = \sum_i p_{ij}$ are the marginal probability.

We performed 20 runs of the proposed algorithm. 20 groups of formulae are acquired and the corresponding registration accuracy are calculated by Eq. (10). Eqs. (13) and (14) are the best group according to the registration accuracy.

$$f_x(x, y) = \sin\left(\frac{7.377213}{y}\right) + 0.992427 * x + 6.126674 \\ + \cos(x + 6.162249) * \cos x \quad (13)$$

$$f_y(x, y) = \frac{9.1171}{A} + (\sin B + A)^{0.998742} + \cos((y * (1 - B) + B) * (\sin B + A)) \quad (14)$$

where $A = 2.072512 + y$, $B = 1.504868 * y$

The floating image is transformed according to Eqs. (13) and (14), the result is shown in Fig. 3, where the contours from Fig. 1(b) are drawn in black and the contours from Fig. 1(d) are drawn in blue. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

The average registration accuracy of the 20 runs is shown in Table 3, where Dn1 and Dn2 are the point numbers of the corresponding contours in the reference and floating images respectively. We also estimated the integrated error of all the contours. The average of total error in x direction is 0.782094, in y direction is 0.543581 and the total error is 0.456245.

6.3. Comparison with previous methods

The performance of our approach is compared with the feature registration method using mutual information, which we call RPFMI proposed by Rangarajan in Ref. [21] that found optimal transform parameters by maximization of entropy and mutual information. In the meanwhile, we have discovered the registration formulae using the GEP and classical MEP for comparison. All the methods are applied to register the successive parallel sections of SiC/Al composite which are shown in Fig. 4(a) and (c). Fig. 4(b) is the contour image of Fig. 4(a), and Fig. 4(d) is the contour image of Fig. 4(c). Fig. 5(a) is the feature points of Fig. 4(b), and Fig. 5(b) is the feature points of Fig. 4(d). In all the following examples, we performed 20 runs of each algorithm. The graphs shown in each case are generated using the average performance of each algorithm. We show registration result in Fig. 5(c) of proposed method. For comparison, Fig. 5(d) shows the registration result from RPFMI method where the registration image is shown in red (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

The result of the comparison is shown in Table 4. The result shows that the proposed algorithm has better performance over the other three methods.

7. Conclusions

This paper proposed a novel image registration method based on a hybrid approach. In this work, we explored the critical elements for an automated contour registration system using composite serial sections. These elements included contour extraction, feature point pairs obtaining, formula discovery of registration model and contour registration. Attention has been paid to the feature point pairs obtaining and the formula discovery of registration model. In contour extraction, the fast global minimization of the active contour model is used. After the contour extraction, we adopt the first moment to calculate the centroid of the single contour in the reference and floating images and use the first moment and the second moment to calculate the semimajor axis and semiminor axis of contour ellipse, so for each contour we can obtain five feature points. The point pairs are acquired by finding the homonymy feature points. Formula discovery of registration model is then performed automatically by the proposed hybrid approach. We also present the registration results of the other three methods. The experiment results show that the proposed algorithm can achieve a more accurate registration.

In summary, we have derived a novel MEP and CSP based hybrid approach for feature-based registration. The technique of contour registration developed in this work is potentially powerful in terms of its registration accuracy and its automation. Experiments show

that this method can be successfully applied to registering the image pairs whose contour information is well preserved.

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References

- [1] B. Zitova, J. Flusser, Image registration method: a survey, *Image Vision Computing* 21 (11) (2003) 977–1000.
- [2] X. Dai, S. Khorram, A feature-based image registration algorithm using improved chain-code representation combined with invariant moments, *IEEE Transaction on Geoscience and Remote Sensing* 37 (5) (1999) 2351–2362.
- [3] L.M. Fonseca, B.S. Manjunath, Registration techniques for multisensor remotely sensed imagery, *Photogrammetric Engineering and Remote Sensing* 562 (1996) 1049–1056.
- [4] H. Li, B.S. Manjunath, S.K. Mitra, A contour based approach to multisensor image registration, *IEEE Transactions on Image Processing* 4 (1995) 320–334.
- [5] L.G. Brown, A survey of image registration techniques, *ACM Computing Surveys* 24 (4) (1992) 325–376.
- [6] G.O. Mason, K.W. Wong, Image alignment by line triples, *Photogrammetric Engineering and Remote Sensing* 58 (1992) 1329–1334.
- [7] J.S. Greenfield, An operator-based matching system, *Photogrammetric Engineering and Remote Sensing* 57 (1991) 1049–1055.
- [8] A. Goshtasby, G.C. Stockman, A region-based approach with subpixel accuracy, *IEEE Transactions on Geoscience and Remote Sensing* 24 (1986) 390–399.
- [9] A.D. Ventura, A. Rampini, R. Schettini, Image registration by recognition of corresponding structures, *IEEE Transactions on Geoscience and Remote Sensing* 28 (1990) 305–314.
- [10] J. Ton, A.K. Jain, Registering Landsat images by point matching, *IEEE Transactions on Geoscience and Remote Sensing* 27 (1989) 642–651.
- [11] R.M. Haralick, L.G. Shapiro, *Computer and Robot Vision*, Addison-Wesley, MA, 1993.
- [12] J.R. Koza, *Genetic Programming: On the Programming of Computers by Means of Natural Selection*, MIT Press, Cambridge, MA, 1992.
- [13] M. Hu, W. Sun, MHC regulation based immune formula discovering algorithm, in: *Proceedings of the 2007 IEEE International Conference on Granular Computing*, Washington, DC, USA, 2007, pp. 605–610.
- [14] M.A. Keane, J.R. Koza, J.P. Rice, Finding an impulse response function using genetic programming, in: *Proceedings of the 1993 American Control Conference American Automatic Control Council*, Ecanston, IL, 1993, pp. 2345–2350.
- [15] T. Bickle, *Theory of evolutionary algorithms and application to system synthesis*, PhD Thesis, Swiss Federal Institute of Technology, Zurich, 1996.
- [16] M. Streeter, L.A. Becker, Automated discovery of numerical approximation formulae via genetic programming, *Genetic Programming and Evolvable Machines* 4 (3) (2003) 255–286.
- [17] M. Oltean, C. Grosan, Evolving evolutionary algorithms using multi-expression, in: *Proceedings of the 7th European Conference on Artificial Life*, Dortmund, Germany, 2003, pp. 651–658.
- [18] X. Bresson, S. Esedoglu, Fast global minimization of the active contour/snake model, *Journal of Mathematical Imaging and Vision* 28 (2) (2007) 151–167.
- [19] R.J. Prokop, A.P. Reeves, A survey of moment-based techniques for unoccluded object representation and recognition, *CVGIP: Graphical Models and Image Processing* 54 (5) (1992) 438–460.
- [20] L. Todorovski, S. Dzeroski, Declarative bias in equation discovery, in: *Proceedings of the Fourteenth International Conference on Machine Learning*, San Francisco, CA, USA, 1997, pp. 376–384.
- [21] A. Rangarajan, H. Chui, J.S. Duncan, Rigid point feature registration using mutual information, *Medical Image Analysis* 3 (4) (1999) 1–17.
- [22] C.A. Shah, Y.W. Sheng, L.C. Smith, Automated image registration based on pseudo-invariant metrics of dynamic land-surface features, *IEEE Transactions on Geoscience and Remote Sensing* 46 (11) (2008) 3908–3916.
- [23] G. Hong, Y. Zhang, Combination of feature-based and area-based image registration technique for high resolution remote sensing image, in: *IEEE International Geoscience and Remote Sensing Symposium*, New York, 2007, pp. 377–380.
- [24] C. Serief, M. Barkat, Y. Bentoutou, M. Benslama, Robust feature points extraction for image registration based on the nonsubsampled contourlet transform, *AEU-International Journal of Electronics and Communications* 63 (2) (2009) 148–152.
- [25] J. Ros, C. Laurent, Description of local singularities for image registration, in: *Proceedings of the 18th International Conference on Pattern Recognition*, Hong Kong, China, 2006, pp. 61–64.

- [26] A. Kelman, M. Sofka, C.V. Stewart, Key point descriptors for matching across multiple image modalities and nonlinear intensity variations, in: *Proceedings of the IEEE Conference on Computer Vision Pattern Recognition*, Minneapolis, USA, 2007, pp. 1–7.
- [27] I. Zavorin, L. Moigne, Use of multiresolution wavelet feature pyramids for automatic registration of multisensor imagery, *IEEE Transaction on Image Processing* 14 (6) (2005) 770–782.
- [28] L. Yu, D. Zhang, E.J. Holden, A fast and fully automatic registration approach based on point features for multi-source remote-sensing images, *Computers & Geosciences* 34 (7) (2008) 838–848.
- [29] I.D. Falco, A.D. Cioppa, D. Maisto, Differential evolution as a viable tool for satellite image registration, *Applied Soft Computing* 8 (4) (2008) 1453–1462.
- [30] R. Bansal, L.H. Staib, A.F. Laine, D. Xu, J. Liu, B.S. Peterson, Calculation of the confidence intervals for transformation parameters in the registration of medical images, *Medical Image Analysis* 13 (2) (2009) 215–233.
- [31] H. Chui, A. Rangarajan, A new point matching algorithm for non-rigid registration, *Computer Vision and Image Understanding* 89 (2–3) (2003) 114–141.
- [32] I.C. Yeh, L.C. Lien, Knowledge discovery of concrete material using genetic operation trees, *Expert Systems with Applications* 36 (3) (2009) 5807–5812.
- [33] X.Y. Zhao, Y.S. Yin, B. Yang, Feature points based registration for composite serial sections, *Journal of Chemical Industry and Engineering* 58 (4) (2007) 1064–1068 (in Chinese).
- [34] M. Oltean, Solving even-parity problems with multi expression programming, in: *The 5th International Workshop on Frontiers in Evolutionary Algorithm*, North Carolina, 2003, pp. 315–318.
- [35] M. Oltean, Evolving winning strategies for Nim-like games, in: *World Computer Congress*, Toulouse, France, 2004, pp. 353–364.
- [36] S. Das, B. Natarajan, D. Stevens, P. Koduru, Multi-objective and constrained optimization for DS-CDMA code design based on the clonal selection principle, *Applied Soft Computing* 8 (1) (2008) 788–797.
- [37] M. Gong, L. Jiao, L. Zhang, Baldwinian learning in clonal selection algorithm for optimization, *Information Sciences* 180 (8) (2008) 1218–1236.
- [38] L.N. de Castro, F.J.V. Zuben, The clonal selection algorithm with engineering applications, in: *Proceedings of GECCO, Workshop on Artificial Immune Systems and their Applications*, 2000, pp. 36–37.
- [39] S.N. Omkar, R. Khandelwal, S. Yathindra, G.N. Naik, S. Gopalakrishnan, Artificial immune system for multi-objective design optimization of composite structures, *Engineering Applications of Artificial Intelligence* 21 (8) (2008) 1416–1429.
- [40] L.N. de Castro, J. Timmis, *Artificial Immune Systems: A New Computational Intelligence Approach*, Springer, London, 2002.
- [41] L.N. De Castro, F.J. Von Zuben, Learning and optimization using the clonal selection principle, *IEEE Transactions on Evolutionary Computation* 6 (3) (2002) 239–251.