Two-step image registration by artificial immune system and chamfer matching

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Image registration is the precondition and foundation in the fusion of multi-source image data. A two-step approach based on artificial immune system and chamfer matching to register images from different types of sensors is presented. In the first step, it extracts the large edges and takes chamfer distance between the input image and the reference image as similarity measure and uses artificial immune network algorithm to speed up the searching of the initial transformation parameters. In the second step, an area-based method is utilized to refine the initial transformation and enhance the registration accuracy. Experimental results show that the proposed approach is a promising method for registration of multi-sensor images.

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With the rapid development of remote sensing technology and the current diversity of new sensors, plenty of multi-source remote sensing data in the same area are usually got. However, image registration is the precondition and foundation in the fuse of multi-source image data. Many algorithms of image registration have been developed, as categorized in Ref. [1]. According to the nature of features used, image registration can be generally grouped into two categories: area-based methods and feature-based methods. Area-based methods use the whole image contents to estimate the transformation parameters. They are divided into three types: correlation-like methods, Fourier methods, and mutual information methods[1]. Area-based methods can provide high registration accuracy up to a fraction of a pixel[2,3]. But the computing cost of such methods is high. In contrast to area-based methods, feature-based methods utilize extracted features to estimate the registration parameters. The most widely used features include points[4,5], lines or curves[2,6,7], and regions[1,8]. The primary merits of feature-based methods are their abilities to handle large misalignments with relatively short execution times, but registration accuracy of such methods depends on the quality of features extracted.

In this paper, a rough-to-fine image registration based on artificial immune system (AIS) and chamfer matching is developed. This method consists of two steps. The first step is a robust feature-based method that does not need to establish a correspondence among the features of images. It extracts the large edges using the method that based on wavelet and Canny edge detector, and takes chamfer distance as similarity measure and uses artificial immune network algorithm to speed up the searching of the initial transformation parameters. In the second step, an area-based method is utilized to refine the initial transformation and enhance the registration accuracy.

Image registration is the process of estimating an optimal transformation between two images, a reference image and an input image. Chamfer matching is used to get the initial transformation parameters. It finds the best fit of edge images from the reference image and the input image by minimizing a generalized distance between them. We take the method based on wavelet transform and Canny edge detector to extract the large edges. This approach can preserve the large-resolution edges and ignore the sharp textures. So it can effectively reduce the noise influence and produce proper edges for the following applications.

The matching measure between two edge images can be calculated as follows[7].

1) Use distance transformation operation to convert the reference edge image to an approximate distance image.

2) Extract the edge pixels in the input edge image and convert them to a list of coordinate pairs, with each pair being the row and column numbers of an edge pixel.

3) Calculate the root mean square (RMS) average, called the "edge distance", as the matching measure:

$$d = \frac{1}{3}\sqrt{\frac{1}{n}\sum_{i=1}^{n} v_i^2}, \tag{1}$$

where n is the number of edge points in the input edge image and v_i is the distance value of the distance image at the position that the ith edge point in the input edge image corresponds to. The average is divided by three to compensate the unit distance tree in the distance transformation operation.

To reduce noise influence and obtain more efficient image matching results, we do not take all of the edge points in the input edge image into account, but only concern the points with the distance value less than a threshold t when calculating RMS. The threshold t is defined as

$$t = q\text{th}v_i, \quad i = 1, 2, \cdots, n. \tag{2}$$

In the above definition, $q\text{th}v_i$ denotes the qth quantile value of v_i over the set v, for some values of q between zero and one. For example, the 1st quantile value is the maximum and the $\frac{1}{2}$th quantile value is the median.

Each transformation of the input edge image corresponds to an edge distance. The transformation with the minimal edge distance is defined as the transformation with the best fit. The edge distance function to be minimized is usually nonconvex and has many local minima, apart from the global one. Traditional optimization methods are easy to fail being trapped in one of the local minima, so an optimization algorithm based on AIS, opt-aiNET[9], is used to find the best transformation. Opt-aiNET developed by taking inspiration from some evolutionary properties of the human immune system has a powerful global exploration capability.

Opt-aiNET is basically a mutation-based evolutionary search procedure within a population with dynamic size allocation. Each individual of the population corresponds to a cell in the immune system that is encoded as a real-valued vector in an Euclidean shape-space, and the affinity between two cells is represented by their Euclidean distance. The initial population can be selected heuristically or randomly. Each cell generates a certain number of clones (offspring cells) by the clonal expansion; each clone is subjected to a mutation rate inversely proportional to the fitness of the parent cell. The mutation is

$$c' = c + aN(0,1), \quad a = (1/\beta)\exp(-f^*), \tag{3}$$

where a is the amount of mutation, c' is a mutated cell c, $N(0,1)$ is a Gaussian distribution with variance 1, β is a parameter that controls the decay of inverse exponential function, and f^* is the fitness of a cell normalized in the interval [0,1].

The fitness of the maturated clones is evaluated and only the best point from each clone is allowed to proceed in the optimization process, while the others are excluded. The above cycle is repeated until the average fitness is stable. The cells in the network interact with each other, and if two cells are closer than a user-defined threshold, the one with lower fitness is eliminated to avoid redundancy, while a number of randomly generated (fresh) cells are introduced into the present population. The termination criterion is determined by the size of memory population or a user-defined maximum number of iterations.

When using opt-aiNET to solve the edge distance function, the antibody is the transformation parameters, and the fitness is minus "edge distance". There are numerous types of spatial transformations, we only consider the "rotation-scale-translation" (RST) transformation on the first step. The stopping condition is determined by the maximum fitness of cells and a user-defined maximum number of iterations. Figure 1 shows the flow diagram of chamfer matching based on opt-aiNET.

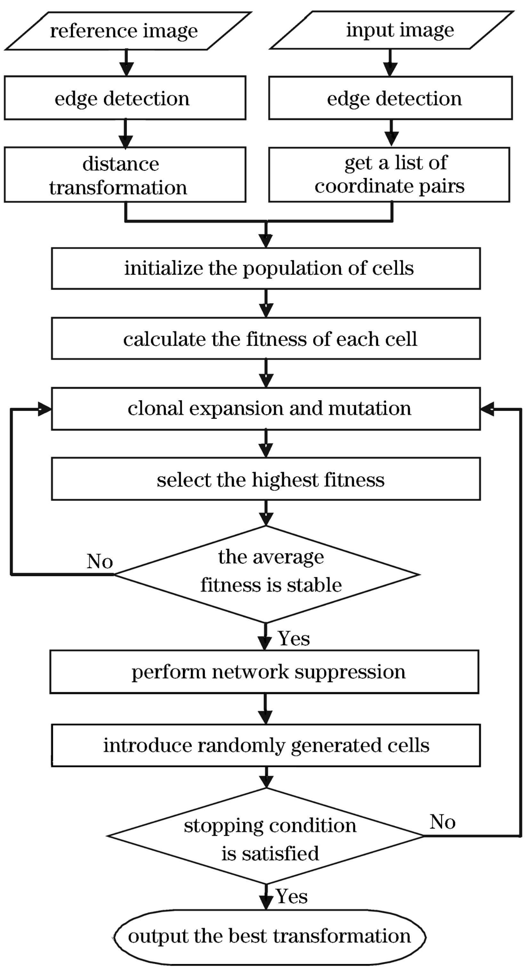

Fig. 1. Flow diagram of chamfer matching based on opt-aiNET.

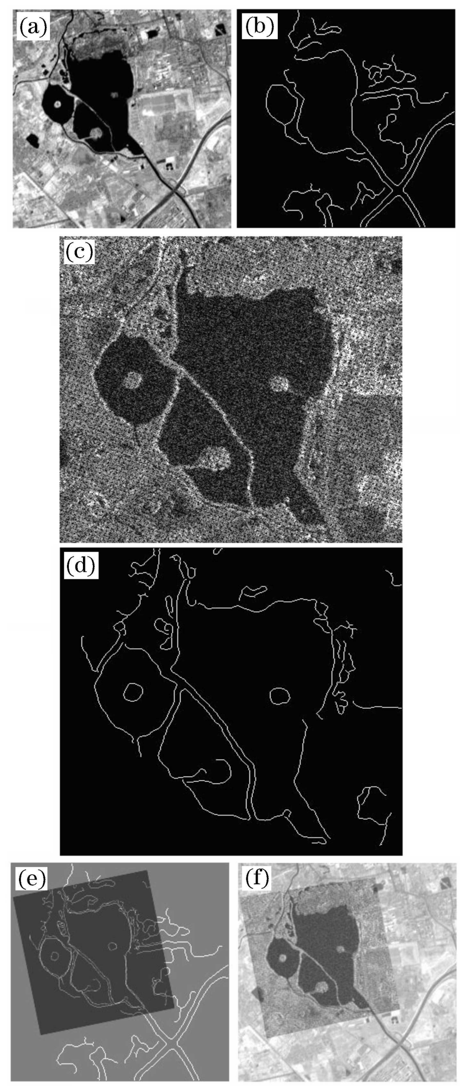

Fig. 2. (a) Reference image and (b) its edge image; (c) test image and (d) its edge image; (e) mosaic of (b) and (d); (f) mosaic of (a) and (c).

The transformation obtained from the first step above may not meet the requirement of high registration accuracy. We use an area-based method given in Ref. [10] to refine the transformation parameters to further increase the registration accuracy. Being different from those traditional area-correlation methods that directly use image intensities, this method transforms the images into Laplacian-energy images, which is performed by high-pass filtering the image with a Laplacian filter and then squaring it. It uses Newton's method to find the transformation parameters which maximizes the sum of all normalized-correlation-based local similarity values. It does not rely on sparse image features and does not eliminate the detailed variations within local image regions, and can be applied for multi-sensor image registration.

In order to test the proposed approach based on AIS and chamfer matching, computational experiments are conducted on two multi-sensor images (thematic mapper (TM) and synthetic aperture radar (SAR)), and the results are shown in Fig. 2. In the experiment, the input image and the reference image have been decomposed into three scale gradient images in edge extraction. The quantile value is 0.7, the parameter β is [2,2,0.1,0.01], the net size is 40, the clone number is 30, and the iteration number is up to 60. The registration result is shown in Fig. 2(f) and the final parameters are $t_x = 84.9949$, $t_y = 37.512$, $\theta = 0.0001$, $k = 0.4000$, $d = 0.1531$. Note the significant difference in scale between the two images (due to significantly different internal sensor parameters). It shows that the proposed method can correctly register the two images with much misalignment.

In conclusion, a two-step image registration approach based on AIS and chamfer matching is presented. We achieve both efficiency and accuracy by combining these two methods. Experimental results have demonstrated that our method can be applied to register multi-sensor images.

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