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Spatial Information Based Medical Image Registration Using Mutual Information

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***Abstract*—Image registration is a problem that arises in many image processing applications whenever information from two or more scenes has to be aligned. A new approach to the problem of multimodality medical image registration is proposed, using a basic concept from spatial information, mutual information, and relative entropy, as a new matching criterion. Firstly, the feature characteristics like location, edge strength and orientation are taken into account to compute a joint probability distribution of corresponding edge points in two images. Then the mutual information based on this function is minimized to find the best alignment parameters. Finally, the translation parameters are calculated by using Powell algorithm. The experiment results showed that the method have achieved a good performance.**

***Index Terms*—medical image, image registration, Spatial information, Feature characteristics, Mutual information**

I. INTRODUCTION

Image registration is a valuable technique for medical diagnosis and treatment. In image registration the use of an adequate measure of alignment is a crucial issue. Current techniques are classified in two broad categories: area based and feature based. All methods include some similarity measure. Mutual information (MI) is currently a popular registration method to sca1e the similarities between two image sets and for convenience of calculation and analysis [1]． It was first proposed as a registration measure in medical image registration in 1995． independently by Viola and Wells [2]and by Collignon [3]． Now MI has been accepted by many researchers as one of the most accurate and robust retrospective registration methods. However, mutual information is not a panacea method. Despite the general promising results, mutual information-based matching can result in misregistration when the images are of low resolution or the images contain little information or there is only a small region of overlap [5]. The mutual information registration function can be ill-defined, containing local maxima. A possible solution to reduce the failure of MI registration can be by using the spatial information and optimization algorithm． At present, many researchers have proposed some hybrid mutual information algorithms to enhance the performance of image registration, such as Pluim et al [1] combined mutual information with gradient method, Yao Yucui et al [6,7,8] employed mutual information with morphological gradient approach to improve the registration accuracy and robustness.

In this paper, a new approach to the problem of multimodality medical image registration is proposed, using a basic concept from spatial information, mutual information, and relative entropy, as a new matching criterion. In addition, this paper focus on the registration approach of multimodality image and a modified particle swarm optimization algorithm is proposed to restrain local maxima of mutual information function and improve the registration accuracy.

This paper is structured as follows: In Section 2, we present the mathematical model of spatial information detection approach. Section 3 describes the coarse registration based on the principal axes algorithm. The feature point set extraction approach and energy function of mutual information based the spatial information is presented in Section 4. Then in Section 5, the feasibility of our approach is illustrated where we show registration results for medical 2D examples. Finally, this paper is closed in section 6 with a brief conclusion.

II. CONTOUR FEATURE DETECTION

Contour feature is a significant part of information extracted from an image which provides more detailed understanding of the image. Common features include corresponding points, edges, contours or surfaces. In order to get a more accurate contour of the medical images, it's necessary to eliminate the interference of image noise and get the actual size of the tilt image as much as possible. According to those edge detection operators, such as Sobel, Log, Candy and other conventional edge detection operator, usually get a low positioning accuracy and a poor performance of anti-noise for medical image. Mathematical morphology is a new image processing method based on geometry algebraic and topology, which is proposed by French scholar G. Matherom and J. Seera [8]. It set the object-oriented for research, and the objects can be contacted through the structural elements. Expansion and corrosion is the basic operations of the morphology, and the opening and closing operators can be further expanded by the expansion and corrosion operators.

The morphology gradient is a nonlinear difference operator determinate by the difference value of maximum

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and minimum structural elements in definition domain, used to achieve the edge detection of the image or signals. Let $f(x, y)$ be original image and $g(x, y)$ be structural element, then the formula of morphology gradient operator is:

$$Grad(f) = (f \oplus g) - (f \Theta g) \tag{1}$$

Where $\oplus$ denotes the expansion operator, Θ denotes the corrosion operator. From (1), we can see that the operator make the input image gray-scale step to become even more dramatic. According to the principle of generalized morphological filter, as far as possible to improve the integrity and richness of edge feature detail and obtain the smoothness edge curves, the improved morphology gradient operator is designed based on the expansion, erosion, opening and closing four operators for image anti-noise characteristics. The improved morphology gradient operator is described as

$$IGrad(f) = (f \circ g) \oplus g - (f \bullet g) \Theta g \tag{2}$$

We call $IGrad(f)$ as the improved morphology gradient operator. In order to extract the direction information of the edge pixels and easy to construct vector group at the same time, we select two cross and cross-shaped 3×3 structural elements, and make them symmetrical and complement each other. Because the random noise may be smaller than the width of the structural elements of the width, which are mixed with the processed images, therefore, it's very difficult to obtain the best filtering effect by using the separate structural element, so they can be used as the linear combination form due to complementary characteristic of the two structural elements. The optimum weighted coefficients can be determined by the least mean square adaptive method, and the improved morphology gradient filter operator can be written as:

$$FGrad(f) = c_1 IGrad1(f) + c_2 IGrad2(f) \tag{3}$$

Where c_1, c_2 are the weighted coefficients, the $IGrad1$ and $IGrad2$ are the improved morphology gradients with the two structural elements.

The main purpose that the improved morphological gradient operator is introduced and applied to quickly identify the probable location of the edge and edge points, while the image is rapidly de-noised in the image processing. After the medical image is processed by the proposed new operator, it can be achieved an available gradient image with the direction information. Then the data set of the edge point vector group $\{E_1, E_2, \cdots, E_n\}$ can be stored as the data list, where $E_i = < e_i, \theta_i >$, e_i is the edge point i in the two-dimensional plane coordinates, and θ_i is the edge gradient direction. In addition, the improved morphological gradient filter can overcome the shortcoming of tend to produce the image edge blur which is often caused by the linear filtering method in image smoothing, and it's easy-to-parallel computing to better meet the real-time image processing requirements. In the experiment, the selected structural elements are[0 10;1 1 1;0 1 0] and [1 0 1;0 -1 0;1 0 1].

III. Principal Axes Algorithm Based Coarse Registration

A Principal Axes Algorithm

Suppose that image F is of $M \times N$ pixels with its upper left pixel being $(1,1)$, and $f(x, y)$ is the gray value at point (x, y). Since some moments of an image region are invariant to geometric transformation such as translation, rotation, and scale change, they are widely applied to object classification and identification. If $f(x, y)$ is a 2-D discrete function, then the moment of order $(p+q)$ is defined as

$$M_{p,q} = \sum_{x=1}^{M} \sum_{1}^{N} x^p y^q f(x, y) \tag{4}$$

Then the central moment is expressed as

$$M'_{p,q} = \sum_{x=1}^{M} \sum_{1}^{N} (x - \overline{x})^p (y - \overline{y})^q f(x, y) \tag{5}$$

Where $\overline{x} = M_{1,0} / M_{0,0}, \overline{y} = M_{0,1} / M_{0,0}$ the $(\overline{x}, \overline{y})$ is called centroid coordinates of the object. The moment of the object having rotated by θ, or computed with reference to axes X' and Y', is invariant to rotation transformation. The rotation angle θ is as follows:

$$\tan 2\theta = 2M'_{1,1} / (M'_{2,0} - M'_{0,2}) \tag{6}$$

Application of the above formula to calculate the difference of two images about the centroid coordinates and principal axis angle separately, and then initial registration parameters ($\Delta x, \Delta y, \Delta\theta$)can be obtained and used as the initial registration parameters for coarse registration.

B Model estimation

As in [9], we assume that the type of transformation is rigid and not deformable; the model that describes the geometric transformation has the following expression:

$$P_d = RP_s + T \tag{7}$$

Where, $P_s(x, y, z)$ is a source point; $P_d(x', y', z')$ is transformed corresponding point;R=[R_{11} R_{12} R_{13};R_{21} R_{22} R_{23};R_{31} R_{32} R_{33}] is a rotation matrix; $T = [T_x, T_y, T_z]^T$ is a translation vector.

Assumed that the α, β, γ are the angles of the transformed image rotated by x,y,z axes separately, then R can be rewritten as: $R = R_\gamma R_\beta R_\alpha$.

C Coarse registration method

The principal axes algorithm can be described as follows:

Firstly, calculate the centroid, and eigenvectors of the source and target images via an eigenvalue decomposition of the covariance matrices.

Secondly, align the centers of mass via a translation.

Finally, for each image determine the angle $\Delta\theta$, the maximal eigenvector forms with the horizontal axis, and rotate the test image about its center by the difference in angles. The images are now aligned.

IV. THE HYBRID MUTUAL INFORMATION ALGORITHM

An important characteristic of an image is the high degree of correlation among the neighboring pixels. In other words, these neighboring pixels possess similar feature values, and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering.

Recently, a new clustering algorithm called K-harmonic means(KHM) has been introduced by Zhang et al.[10,11] in 2000, which is arose from an optimization criterion based on the harmonic mean. This algorithm shows promised in finding good clustering solutions quickly, and outperforms k-means and Gaussian expectation-maximization in many tests. The KHM algorithm also has a novel feature that gives more influence to data points that are not well-modeled by the clustering solution.

In this paper, the KHM algorithm is used to extract the feature point sets of the medical images based the edge point vector group $\{E_1, E_2, \cdots, E_n\}$, and we select the number of clustering centre K=150 that means the feature point sets has 150 points. The more detail bout KHM algorithm, reference to[10,11].

Mutual Information is an error metric (or similarity metric) used in image registration based on ideas from information theory [1]. The strategy is this: minimize the information content of the difference image. The mutual information between two unlabeled point-sets is a function of the chosen spatial mapping (for example, rigid, similarity, affine). The energy function of the feature points matching will be presented based on mutual information following.

Denote the feature point-sets of pre-registration medical images by $X = \{X_i, i = 1, 2, ..., N_1\}$ and $Y = \{Y_i, i = 1, 2, ..., N_2\}$ respectively. The point sets are assumed to be in $\Re^2$ or $\Re^3$. Then, a suitable choice for the distance measure between X and Y is:

$$D(T) = \sum_{i=1}^{N} \| X - TY \|^q . \qquad (8)$$

In (8), following the KHM clustering algorithm, we choose $q = 3.5$, T is the rigid spatial mapping linking the two point-sets in this paper. With the spatial mapping T, the mutual information between the point-sets is a function of the joint probability P:

$$MI(P) = M(X,Y) = \sum_{i=1}^{N_1}\sum_{j=1}^{N_2} P_{ij} \log \frac{P_{i,j}}{\sum_{k=1}^{N_1} P_{kj} \sum_{l=1}^{N_2} P_{il}}, \quad (9)$$

where the joint probability

$P_{ij} = P\{I = i, i \in (1,2,...,N_1), J = j, j \in (1,2,...,N_2)\}$

the above joint probability characterizes the likelihood of obtaining a pair of features (i, j), i form X and j form Y. Intuitively, the likelihood should be large if i and j are homologies and small if they are not. The solution for the joint probability is :

$$P_{ij}(T) = \exp(-\alpha D_{ij}(T) - \lambda) . \qquad (10)$$

In (10), α and λ are two Lagrange parameters, the constraints on the expected value of the point matching distance measure and the probability sum respectively. The more detailed discussion about α and λ, reference to see [14].

$$\begin{aligned} E_{MI}(P,T,\lambda,\alpha) &= \alpha(\sum_{ij} P_{ij} D_{ij}(T) - d) + \\ &\lambda(\sum_{ij} P_{ij} - 1) + \sum_{ij} P_{ij} \log P_{ij} - \kappa MI(P) \end{aligned} . \quad (11)$$

In (11) The noise level is,

$$d = \sum_{ij} D(T) \frac{\exp(-\alpha D(T))}{\sum_{ij} \exp(-\alpha D(T))} .$$

$\kappa > 0$ is a new parameter which acts as a weight on the mutual information vis-a-vis the entropy and the distance measure. If $\kappa = 1$, the separate entropy term and the joint entropy in the mutual information perfectly match one another. In this paper, we choose $\kappa \in [0.3,1]$ in the optimization processing. Our approaches to minimizing the energy function in (12):

$$\partial^* = \arg \min E_{MI}(P,T,\lambda,\alpha) . \qquad (12)$$

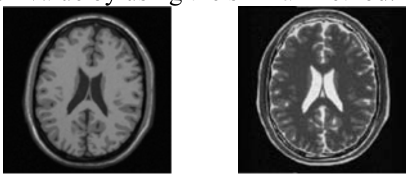
The best registration would be achieved if the objective function (metric function) reaches the global minimum. However, the function generally contains a set of local minimums. To solve multiple local minimum problems, a Powell algorithm is developed to solve the registration problem in this paper.

V. THE SIMULATION AND EXPERIMENT

We implement registration of brain image to confirm performance of proposed algorithm in last section. The algorithms are implemented by using Matlab 7.1 on a Pentium IV, 2.8 GHz, 1GB RAM computer, and image file is from database (www.bic.mni.mcgill.ca/brainweb). In the following experiment, the parameters in translate procedure is initialized as search space in x direction is x∈[-20, 20] and y direction is y∈[-20, 20], the search space in rotation is θ∈[-15° ,15°].

A Experiment I.

In Fig. 1, the image (a) and image (b) are illustrated. The size of each image is 512×512 pixels under DICOM format and the whole images have good quality and don't require a pre-treatment. In our experiment, image Fig.1(b) as source image and image Fig. 1(a) serve as target image. The two images are alignments by using MI and the presented hybrid MI (PHMI) method in this paper separately. And our experiment results are shown in Tab.1 and Tab. 2. The Tab. 1 shows the comparison of experiment result for image registration transform parameters (Δx, Δy, Δ θ), and the Tab. 2 shows the results of the spatial transform parameters and mutual information value by using the similar method.



(a) Target image (b) Source image

Figure 1. Brain images for registration

TABLE 1. COMPARISON OF REGISTRATION PARAMETERS

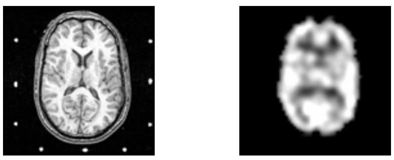
		Δx (pixel)	Δy (pixel)	Δθ (°)
Standard Value of Transformed		12	10	-10
Average Searching Value	MI	12.86	9.42	-10.38
	PHMI	12.16	10.02	-10.17

TABLE 2. THE SPATIAL TRANSFORM PARAMETERS AND MUTUAL INFORMATION

Algorithm	**MI**	**PHMI**
Solving times	100	100
Average Value	167.64	130.09
Standard deviation	7.567	3.12
Mutual information	2.157	2.541
Average times (s)	386.2	315.6

B Experiment II.

In this experiment, the two brain images (Shown in Fig. 2.) of the same patient are registered to test the performance of the presented new method in separately 100 times. The size of each image is 256×256 pixels, and the MR images is set as source image. The registration results are shown in table 3. After this simulation, we can see that the PHMI algorithm in accuracy and speed with the more obvious advantages than the other two algorithms.



(a) MR image (b) SPECT image

Figure 2. the two registration images

TABLE.3 THE COMPARISON REGISTRATION RESULTS

Algorithm	MR-SPECT	
	Time(s)	Success rate
MI	2168	72%
PHMI	1275	98%

VI. CONCLUSIONS

In the paper, we have presented an innovative PHMI method for the automatic registration of medical image, and it has achieved a good performance. This registration is actually a problem of searching optimum parameters in multi-dimension space. The existence of local maxima in object function brings much trouble in optimizing process. In this paper, we use Powell to extend the searching ability, the method can guarantees registration convergence to the global optimum. Though combining spatial information and mutual information as criterion for multimodality medical image registration still remains problems unsolved, the experiments results prove that the proposed method has robustness and effectiveness.

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