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Fast 3D Medical Image Registration Based on Geometric Feature Invariants

Juping Gu
1. School of Electrical Engineering,Nantong University,Nantong 226019,China; ;2. School of Automation,Nanjing University of Science and Technology,Nanjing 210094,China;

Tianyu Cheng
2. School of Automation,Nanjing University of Science and Technology,Nanjing 210094,China;

Jianping Wang
1. School of Electrical Engineering,Nantong University,Nantong 226019,China; ;

Hua Liang
1. School of Electrical Engineering,Nantong University,Nantong 226019,China; ;

See next page for additional authors

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Fast 3D Medical Image Registration Based on Geometric Feature Invariants

Gu Juping[1,2], *Cheng Tianyu*[2], *Wang Jianping*[1], *Hua Liang*[1], *Zhao Fengshen*[1], *Jiang Ling*[1]
(1. School of Electrical Engineering, Nantong University, Nantong 226019, China;
2. School of Automation, Nanjing University of Science and Technology, Nanjing 210094, China)

Abstract: Aiming at the of large amount of computational data and low registration efficiency in 3D cranial medical image registration, a fast registration method based on geometric feature space constraints is proposed. *The algorithm extracts three-dimensional contour point clusters, and proposes a feature construction method based on the optimal fitting ring of point clusters. The feature rings and the centroids of each layer are used as feature quantities, and the fast registration is completed by using Iterative Closest Point (ICP) method.* The experimental results show that the method has less computation amount, high satisfactory registration accuracy and much faster registration speed than the traditional ICP algorithm. It is an effective real-time three-dimensional registration method.

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基于几何特征不变量的快速 3D 医学图像配准

顾菊平[1,2]，程天宇[2]，王建平[1]，华亮[1]，赵凤申[1]，蒋凌[1]
（1. 南通大学电气工程学院，江苏 南通 226019；2. 南京理工大学自动化学院，江苏 南京 210094）

摘要：针对颅部三维医学图像配准计算量大、配准效率低等问题，提出了一种基于几何特征空间约束的快速配准方法。*提取三维轮廓点云，提出了一种基于点云集最优拟合环的特征构造方法，并以每个特征环和每个层的质心用作特征量，通过使用迭代最近点(Iterative Closest Point, ICP)方法完成快速配准*。实验结果表明，与传统的 ICP 算法相比，该方法计算量小，配准精度高，配准速度快。它是一种有效的实时三维配准方法。

关键词：3D 医学图像；快速配准；几何特征不变量；迭代最近点
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Introduction

Due to the different imaging principles of the device, medical images can be divided into anatomical images (CT, X-ray, etc.) and functional images (PET, FMRI, et al.). Anatomical images can provide bone morphology information, and functional images can provide soft tissue metabolic information such as blood vessels and muscles. The purpose of medical image registration is to perform spatial matching and data fusion on a variety of information medical images, and analyze the patient lesions comprehensively. Medical image registration is a key technology, and it plays an important role in

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medical fields such as disease surveillance, surgical navigation and disease diagnosis. The multimodal 3D cranial registration studied in this paper is an important branch in medical registration, which is important to both theory research and clinical applications.

Comparing with 2D registration, 3D medical image registration has a lot of improvement in computational complexity and spatial freedom. Its typical characteristics are large data volume and complicated calculation process. Typical registration methods in multimodal 3D medical image registration include feature point-based[1-2], voxel-based[3-4] and geometric feature-based[5-6]. The literature [7] proposed the mutual information (MI) method combined penalty splines and joint histograms, to solve the local extremum problem and optimize the registration accuracy. The accuracy of object matching is enhanced by mutual information algorithm with quantifying voxel information. And the algorithm has been recognized as an effective similarity measure in multi-modal medical image registration. Nowadays, the mutual information algorithm is used on the software platform of clinical registration melting which has been sold by some foreign companies. Although the registration accuracy of mutual information type algorithm is effective, its huge data volume and complicated calculation process make the algorithm execution consume a long time, which causes obstacles to the rapid analysis of clinical lesions. Therefore, ensuring the accuracy of registration and increasing the speed of registration greatly is the main research direction of medical image registration. In order to improve the registration speed，some scholars have applied Iterative Closest Point(ICP) in the field of medical image registration to improve the registration efficiency. As literature [8] introduced a lookup matrix in the point cloud matching step to improve overall performance of ICP, which enhanced algorithm convergence and robustness. In literature [9], the Gaussian probability model is integrated into the bounded registration problem. The Gaussian model is updated by transforming the distance and variance between the point sets, which improves the speed and accuracy of registration. However, the ICP algorithm still has problems which is easy to fall into local optimum and iterative time consumption. And the accuracy of ICP is generally inferior to the mutual information method. Although the registration speed has been significantly improved, the overall efficiency is still not ideal.

The algorithm based on pure geometric features can greatly reduce the computational complexity of 3D registration, and it is a registration method worthy of in-depth study. Continuing this idea, the literature [10] introduces geometric algebra into the geometric feature registration of medical images. The geometric position constraints of 3D cranial images are reconstructed and a new similarity measure for medical image registration is constructed. It can be seen that the geometric features of skull contour can be well reflected based on spatial geometric feature invariants, and the three-dimensional spatial location of tissues and organs can be located.

Based on the advantages of pure geometric features in medical image registration, a new spatial similarity measure of the optimal circle is proposed, which combines ICP algorithm so as to achieve fast three-dimensional image registration. The core of this algorithm is to construct relative geometric invariants by using cranial geometric features and reduce computational complexity. Experiments show that the registration speed of this method is very fast, and it

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could complete multi-modal three-dimensional medical image registration in a few seconds. It has high real-time performance, and the registration accuracy of the algorithm is also satisfactory.

This paper presents a multi-modal 3D medical image registration method based on relative geometric invariants. In the next section, we will introduce the preprocessing method of medical image. The third section is the construction method of the optimal ring feature invariant. The fourth section is the validation of the algorithm and the analysis of the experimental results. The last section is the summary of the algorithm and the conclusion of this paper.

1 Pretreatment Method

The fast registration algorithm in this paper is implemented by three main steps including preprocessing, the first ICP registration based on unit ring and the second ICP registration based on optimal ring. The preprocessing of three-dimensional medical image is fundamental to pure geometric feature registration, including three main steps: uniform spatial resolution, edge segmentation and outline extraction.

Due to the different imaging equipment, the resolution of multimodal images is different. The medical images in this paper were from the RIRE database of Vanderbilt University. For patient 001, the initial spatial resolution is shown in Tab. 1.

It can be seen that the spatial resolution must be unified before registration. According to the voxel ratio provided by the database, the unified spatial resolution is shown in Tab. 2.

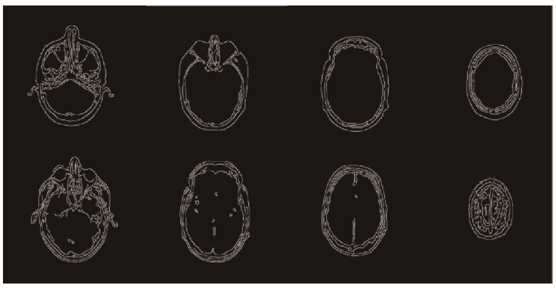
Tab. 1 Spatial resolution of the original data

Modal	Resolution			Element Spacing/mm		
	x	*y*	*z*	*x*	*y*	*z*
CT	512	512	29	0.6535	0.6535	4.0000
PD	256	256	26	1.2500	1.2500	4.0000

Tab. 2 Unified resolution

Modal	Resolution			Element Spacing/mm		
	x	*y*	*z*	*x*	*y*	*z*
CT	334	334	116	1.0	1.0	1.0
PD	320	320	104	1.0	1.0	1.0

Because of the imaging characteristics of CT and MR modes, edge segmentation is easy to achieve. In this paper, Canny operator is used for edge segmentation. Canny operator is an edge extraction algorithm based on structural information. It is widely used in various visual processing systems. Outer contour of three-dimensional skull is extracted by way of scanning in four directions successively after edge segmentation. The effect of edge segmentation and outline extraction by Canny operator is shown in Fig. 1 and Fig. 2. It can be seen that the geometric features of the three-dimensional image of the cranium are significant, and the registration method based on geometric features is worth further research and mining.



Patient-001
CT

Patient-001
mr_PD

Fig. 1 Edge segmentation

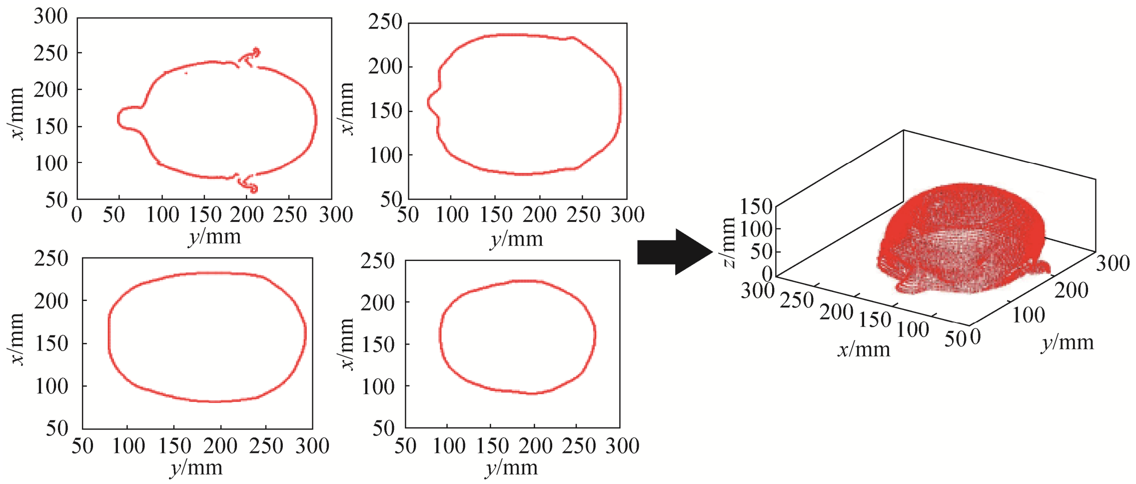


Fig. 2 Outer contour extraction of 3D Image

2 Construction of Relative Geometric Feature Invariants

We can regard the skull as a rigid body, and 3D image registration as a rigid body motion. The geometric features of three-dimensional skull are prominent, so the relative geometric feature invariants of each modal are constructed to achieve fast registration. Firstly, the contour point cloud after pretreatment is regarded as feature data set $FT\{p_i\}_{i=1}^{n}$, $RF\{q_i\}_{i=1}^{m}$. Then a unit ring with unknown center is constructed in each 2D slice layer along the Z-axis direction. Here, the maximum value of the sum of distances from the data set to the unit ring is set as a constraint condition. Then the 2-norm from the point set to the center of a circle can be expressed as:

$$D(o_j)=\sum_{i=1}^{n}\left\|d(p_{j,i})\right\|^2=\sum_{i=1}^{n}\left\|p_{j,i}-o_j\right\|^2=$$
$$\sum_{i=1}^{n}[(x_{j,i}-x_{j(o)})^2+(y_{j,i}-y_{j(o)})^2] \quad (1)$$

The center of the ring o_j corresponding to the minimum value of the above formula can be expressed as: $o_{\min}=\arg D(o_j)$. Obviously, this is a problem of finding the maximum value of a multivariate function. Here, the first-order partial derivative method is used to find the extremum. Then the center of the unit ring can be expressed as:

$$o_j=(\frac{1}{n}\sum_{i=1}^{n}x_{j,i},\frac{1}{n}\sum_{i=1}^{n}y_{j,i}) \quad (2)$$

The center of the optimal unit ring forms the feature point set f_1, whose spatial structure is shown in Fig. 3. It can be seen that the feature set f_1 has obvious geometric characteristics due to the constraints of facial contour, and then the ICP algorithm will be used for its first iteration registration.

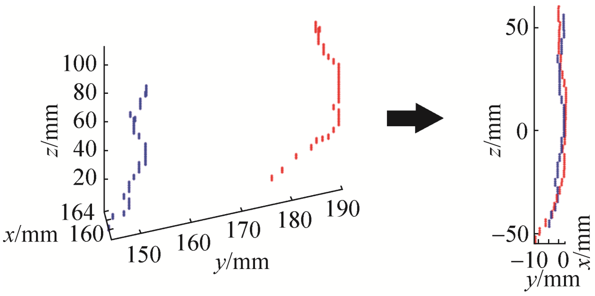


Fig. 3 Geometric structure of centroid point set

The Iterated Closest Points method uses the way of two point sets overlapping as much as possible to achieve registration. The ICP steps can be summarized as follows:

step 1: Find the corresponding points of the floating mode data set $FT\{p_i\}_{i=1}^{n}$ in the reference mode $RF\{q_i\}_{i=1}^{m}$.

step 2: The rigid body transformation H_k which minimizes the average distance of the corresponding points is obtained, and the translation parameter T_k and the rotation parameter R_k are also obtained.

step 3: A new floating mode data set $FT\{p_j^{<2>}\}_{j=1}^{n}$ is obtained by using the rotation and translation parameters of the previous step.

step 4: Calculate the loss function of two data sets:

$$E_k=\left\|H_k p^{<k>}-q\right\|^2 \tag{3}$$

If $\sigma = E_k < \varepsilon$, the registration is completed, otherwise go to step one and start the iterative calculation.

When the number of iterations is completed or $\sigma < \varepsilon$, the first iteration registration is achieved. But this only completes rough registration, the purpose of this step is to match facial orientation. On this basis, the best fit ring will be constructed to calculate the second relative geometric feature invariant.

Firstly, based on the new data set $FT\{p'_i\}_{i=1}^{n}$ and $RF\{q_i\}_{i=1}^{m}$, a circle with unknown radius is constructed in each 2D slice layer along the Z-axis direction, and these centers coincide with $\{C_j^1\}_{j=1}^{Z}$. When the sum of the distances from the data set to the ring is the minimum, the radius of the optimal fitting ring is determined. Then the 2-norm of the point set to the center of the circle can be expressed as:

$$D'(r_j)=\sum_{i=1}^{n}\left\|d'(p'_{j,i})\right\|^2=\sum_{i=1}^{n}\left\|sqrt\left\|p'_{j,i}-o_j\right\|^2-r_j\right\|^2 \tag{4}$$

Panning the dataset to the origin of o_j, the above formula can be updated to:

$$D'(r_j)=r_j^2-2\sum_{i=1}^{n}(x_i'^2+y_i^2)^{\frac{1}{2}}r_j+\sum_{i=1}^{n}(x_i'^2+y_i^2) \tag{5}$$

According to the quadratic maximum of one variable, we can get:

$$r_j=\frac{1}{n}\sum_{i=1}^{n}(x'^2_i+y'^2_i)^{\frac{1}{2}} \tag{6}$$

Since the face orientation has been registered, the maximum value of the Y-axis direction of the optimal fitting ring is chosen to form the feature point set f_2, as shown in Fig. 4.

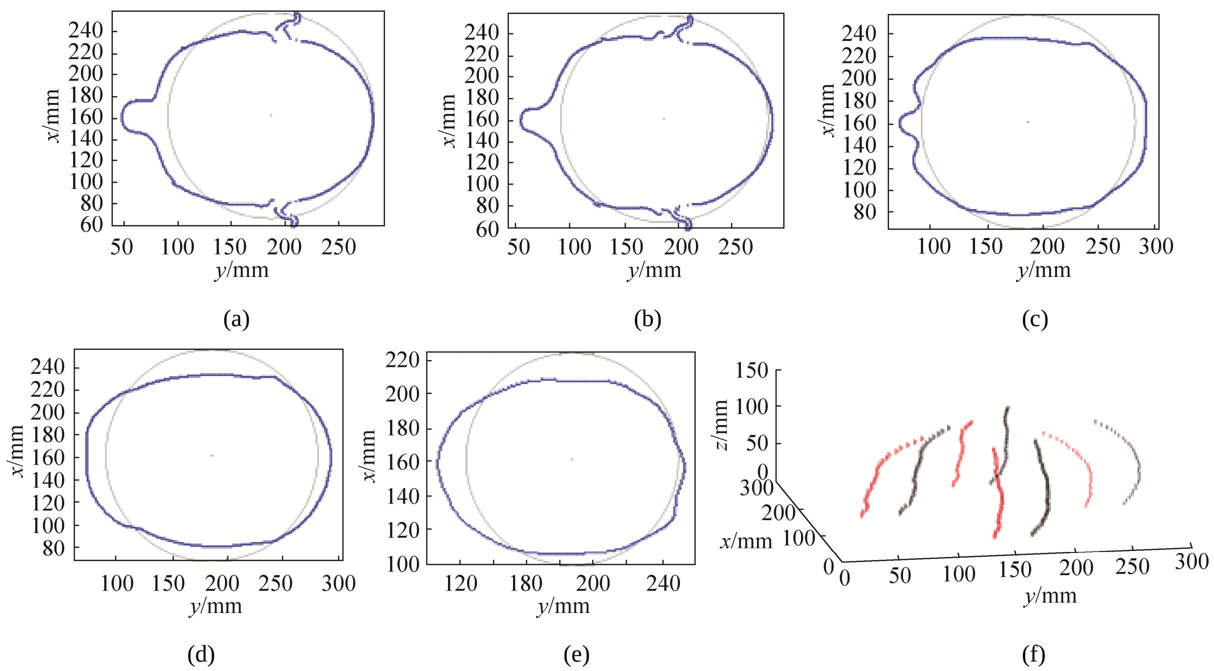


Fig. 4　Feature point set of optimal fitting ring

Among them, Fig. 4(f) is the maximum value of the optimal circle in four directions. Obviously, feature set f_2 can represent the geometric characteristics of skull contour better. So the feature point set f_2 is used for the second ICP registration, and all the registration operations are completed.

3 Experiments and Analysis

We download CT and MR_PD, MR_T1, MR_T2 brain data of patient 001 to patient 009 from the RIRE database, and completed registration of CT to MR_PD, CT to MR_T1 and CT to MR_T2 separately. A total of 27 registration experimentsare carried out based on the proposed algorithm. Before registration, we mark the four corners of the two modes separately for error comparison after registration. Take CT to MR_PD of patient 001 as an example. The effect of registration is shown in Fig. 5, and the fusion effect is shown in Fig. 6.

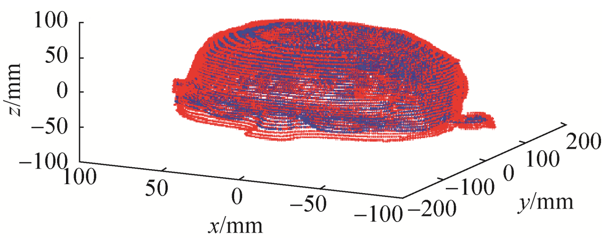
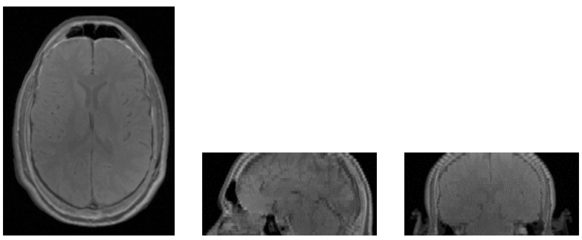


Fig. 5 Marked position after registration



(a) X-Y Direction (b) Y-Z Direction (c) X-Z Direction

Fig. 6 Fused Profile

Calculate the maximum error, minimum error and evaluation error of the registration by using the distance of the marked points as a measure. The results of the registration effect compared with the ICP algorithm based on all point cloud are shown in Tab. 3.

Tab. 3 Comparison of registration errors

Registration Method	Average Error/mm	Median Error/mm	Maximum Error/mm
Traditional ICP Method	2.67	3.79	5.31
Fast Registration Method	2.81	3.65	6.17

As can be seen from the table, the accuracy of registration based on geometric feature invariants in this paper is still satisfactory. Comparing with traditional ICP algorithm, this algorithm is not easy to fall into local optimum. Next, the registration speed is compared on the same computer. The processor is Intel(R) Core(TM) i7-6700HQ CPU@2.60GHz, RAM: 12.0 GB. The comparison results of registration speed are shown in Tab. 4.

Tab. 4 Registration speed comparison

Registration Method	Average time consuming /s
Traditional ICP Method	52.80
Fast Registration Method	5.61

Obviously, the registration speed of this method is very fast. The average registration time of the algorithm is less than 10 s, and the efficiency is much higher than that of the traditional ICP method. This is mainly because the relative geometric invariants constructed by this method can better present the cranial geometric characteristics. On the premise, the constructed feature invariants reduce the registration calculation greatly, which makes the registration speed extremely fast under the condition of better registration accuracy. Experimental simulations show that, except for the preprocessing time, the average time of the iterative optimization process is less than 2 s.

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4 Conclusion

In this paper, a fast registration algorithm of multi-modal 3D medical image based on relative geometric invariants is proposed. Constructing invariants based on cranial geometric space constraints is used for ICP iterative calculation, which greatly reduces the computational complexity and improves the registration speed significantly. Specifically, the method first completes preprocessing to extract the cranial contour data set, and then completes the first ICP registration based on the optimal unit loop, and finally completes the second ICP registration based on the optimal fitting ring. The experiment is carried out with the image from RIRE database. The results show that the method has high registration accuracy and fast registration speed. It is an effective registration method with immediacy, which provide the possibility for the clinical real-time registration of multi-modal 3D medical images.

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