Multimodality and Non-rigid Registration of MRI' Brain Image

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ABSTRACT

Registering different kinds of clinical images widely used in diagnostic and surgery planning. However, cause of tumor growth or effected by gravity, human tissue has plenty of non-rigid deformation with clinically. Non-rigid registration allows the mapping of straight lines to curves. Therefore, such local deformation makes registration more complicated. In this work, we mainly introduce intra-subject, inter-modality registration. This paper mainly studies the nonlinear registration method of 2D medical image registration. The general medical image registration algorithm requires manual intervention, and cost long registration time. In our work to reduce the registration time in rough registration step, the barycenter and the direction of main axis of the image is calculated, which reduces the calculation amount compared with the method of using mutual information.

Key Words : Non-rigid Registration, Inter-modality, Intra-subject, Registration

1. Introduction

The overly of multimodal image data helps us understand and analyze different regions of the medical image. There are a large number of different modalities images for the doctor analysis under the same coordinate system. Computer-aided diagnosis involves a variety of different medical imaging modalities, CT, MRI, and ultrasound [1].

We integrate the information of the human body into a coordinate system by register and fusion, so that can observe information change such as size, shape, position, and gray scale. It is used to study the whole process of the occurrence and development of the disease, and then to plan the treatment plan. The superposition of pre- operative images and intra-operative images is significant for such precise treatment like image-guided surgery or radiation therapy [2-4].

The fusion of the two images can greatly enhance the doctor's understanding of the patient's structure, improve the accuracy of the surgery, and improve the accuracy of the treatment. And as the basic step in fusion, researchers propose many methods in registration. Registration refers to a series of space transform between two images. Matchi ng two images so that corresponding coordinate points correspond to the same physical region of the scene. The difficulty of multimodal registration is that different human tissues exhibit huge grayscale differences cause of image acquisition, and the image contains many complementary information and common information[1].

Because tumor exhibits complex pathological feature, MRI scan image as standard pulmonary imaging can reveal the characteristic of abscesses, tuberculosis, cancer and tumor-like lesion. By observing the modules location in MRI images, the abnormal structure can be clearly judged and quantified in T2 images, and T1 images emphasize certain contrast characteristics of anatomical structures. Overlaying two kinds of images could assist doctors work efficiently in diagnosis. And in the field, most disclosed data are mainly marked in MRI images. For this experiment we use aligned T1 and T2slices from Kaggle dataset [2]. Section 2 shows registration model, and experiment result shows in section3, and last section will be conclusion.

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2. Registration Model

2.1 Methodology

Approaches of image registration can be classified into nonparametric and parametric method. Parameter method such as affine transformation is B-spline based FFD, etc.[5]. The variables can be constrained in few numbers by parameterizing the deformation, but the complexity of the deformation is also limited. The non-parametric method expresses the deformation of the image as a displacement field. Each pixel has a displacement that can represent a more complex deformation, but it requires more variables to solve. And it causes large computational consumption.

The traditional registration flow chart is shown in Fig. 1. At present, the methods for medical image registration mainly fall into two categories: voxel-based registration and feature-based registration. The mutual information method is a voxel-based registration method [6], which is mostly used for multimodal medical image registration. At this work, we use T1 to T2 weighted MRI brain image.

2.1.1 Prepossessing

For implement, the data acquiring from database are in DICOM format, which makes difficulty in processing. Therefore, the first step is converting DICOM MRI scan images into JPEG gray scale image.

2.1.2 Rough registration

At the first stage of registration, calculate the barycent er and the direction of main axis of the image to achieve rough registration. Overlapping the images under the unified coordinate system. The main axis direction is the largest eigenvalue of the covariance matrix which shows in equation (1). The result shows in Fig. 2(c).

$$C = \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix} \tag{1}$$

$$C_{11} = \Sigma_{x,y}(x-\bar{x})^2 * I(x,y)$$
$$C_{12} = \Sigma_{x,y}(x-\bar{x}) * (y-\bar{y}) * I(x,y)$$
$$C_{21} = \Sigma_{x,y}(x-\bar{x}) * (y-\bar{y}) * I(x,y)$$
$$C_{22} = \Sigma_{x,y}(y-\bar{\bar{y}})^2 * I(x,y)$$

And the fine registration will establish upon the rough registration so that can acquire initial condition. to decrease computational consumption as the result shows in section 3.

2.1.3 Fine registration

In this step we use a steepest gradient descent (SGD) optimizer and Mattes' mutual information (MMI) metric. Mutual information-based method has been accepted as an automated method in traditional image registration. The purpose of the rough registration is to obtain an approximate transformation for the two different positions of images 7, so that the two sets of transformed data are as close as possible in the coordinate space. Thereby, narrowing the difference between the two images provides a better initial position for further fine registration, and can converge more quickly[8-9].

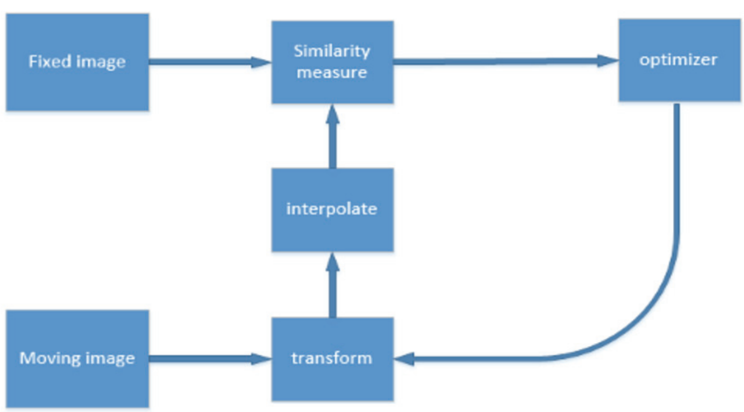

Fig. 1. Algorithm flow chart.

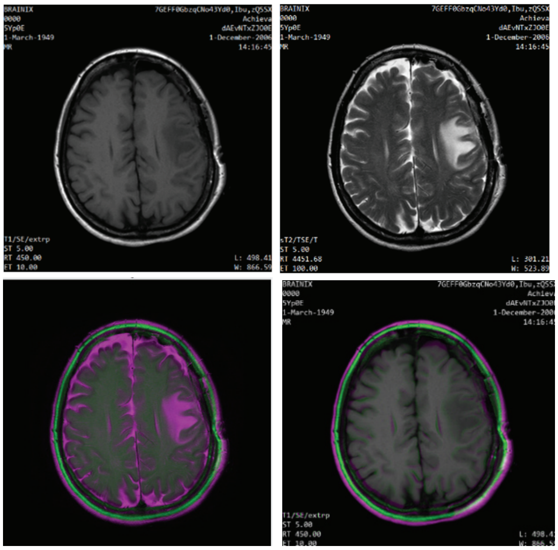

Fig. 2. (a) MRI T1, (b) MRI T2, (c)Rough registered, (d) Final registered.

3. Experiment Result

3.1 Experiment result

The Fig. 2 (a) and Fig. 2 (b) are source of MRI. The Fig. 2 (c) is visualized as difference between two images after rough registration. Fig. 2 (d) visualized the difference after registration finish.

Comparing our method with Classic Demon Registr ation123 which cost 38.67s, our method reaches 21.09 s in MRI registration.

4. Conclusion

This paper studies the nonlinear registration between T1 and T2 images of MRI, and the traditional mutual information registration is improved, which reduces the computational cost. In the future improvement process, the termination condition can be changed to achieve more accurate registration results.

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