Deformable Registration for MRI Medical Image

Li Binglu[*], YoungSeop Kim[*†] and Yong-Hwan Lee[**]

[*†] Dept. Electronics and Electrical Engineering, Dankook University, Korea
[**]Dept. of Digital Contents, Wonkwang University

ABSTRACT

Due to the development of medical imaging technology, different imaging technologies provide a large amount of effective information. However, different imaging method caused the limitations of information integrity by using single type of image. Combining different image together so that doctor can obtain the information from medical image comprehensively. Image registration algorithm based on mutual information has become one of the hotspots in the field of image registration with its high registration accuracy and wide applicability. Because the information theory-based registration technology is not dependent on the gray value difference of the image, and it is very suitable for multimodal medical image registration. However, the method based on mutual information has a robustness problem. The essential reason is that the mutual information itself is not have enough information between the pixel pairs, so that the mutual information is unstable during the registration process. A large number of local extreme values are generated, which finally cause mismatch. In order to overcome the shortages of mutual information registration method, this paper proposes a registration method combined with image spatial structure information and mutual information.

Key Words : Non-Rigid Registration, Mutual Information, Spatial Structure

1. Introduction

Medical image registration now plays an important role in medical image processing, for providing more diagnostic information in one image to the physicians. Hence it can avoid subjective evaluation which will lead to wrong spatial corresponding.

It can be seen that clinical registration usually requires registration of multiple modes for the same patient. However, due to the different emphasis from different modes of imaging, gray scale express huge differences between images. And medical images are difficult to perform point feature extraction, so the general method is difficult to achieve registration [1].

Image registration methods are classified into grayscale-based and feature-based registration. The grayscale-based method generally does not need to perform complex pre-processing on the image but uses the statistical information of the image itself to measure the degree of similarity of the image, which is relatively simple to implement. In the development of several decades, many image registration methods based on gray information have been proposed, such as cross-correlation method, sequential similarity detection matching method, and interactive information method. The feature-based matching method firstly performs preprocessing on the registration image, that is, the process of image segmentation and feature extraction. Then, the extracted features are used to complete the matching between the two image features, which can establish matching relationship between the images.

Although the above two methods have their own advantages, and have achieved good results, but these two methods also hav e their own shortages. The registration method based on image g rayscale is relatively slow; feature-based method is complex, and incomplete feature extraction cause low matching rate. And it is sensitive to mismatching. This greatly limits the application of th e above two methods in practical engineering [2][3][4].

In this paper, we are introducing the two methods and comparing their advantages and disadvantages. And these two registration methods will be utilized to define a new metric function M to guide

[†]E-mail: wangcho@dankook.ac.kr

the transformation parameter optimization.

The algorithm firstly uses an effective operator to extract the edge contour from medical image. Then calculate the edge covariance. And combined with the traditional mutual information metric for a new measure function definition to guide the transformation parameter optimization. Finally, combined with the steepest gradient descent strategy to achieve image registration.

2. Registration model

2.1 Methodology

The image registration steps using the proposed method are as follows:

1) First calculate the mutual information MI(A, B) of the two images
2) Using the LoG operator to perform edge detection on images A and B [5]
3) Calculate the CI, which we will introduced in section 2.2.
4) Calculate the new metric we defined in 2.2 and use SGD as the optimization algorithm to find the best registration transformation parameters
5) According to the optimal registration transformation parameter, interpolated by the PV method.

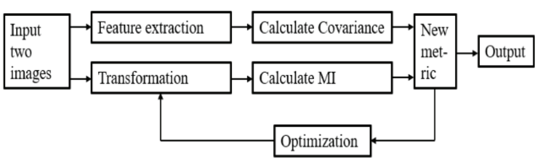

Fig.2.1 Algorithm flow chart.

2.2 Proposed metric

The image registration algorithm based on mutual information only uses the statistical information of the image gray scale, ignoring the relationship between the pixel position, and does not consider the information of the gray level change. On this basis, this paper improves the robustness of image registration. The distribution based on mutual information of this paper, and increases the position information to improve the robustness of the algorithm.

When the two images A, B are geometrically registered, it means that the pixel at the geometric edge $\boldsymbol{f_a}$ corresponds to the other edge image $\boldsymbol{f_b}$ is the most stable, and the calculation of their interaction variance should be minimal[6].

$$CI[f_a, f_b] = \left(\frac{\bar{\sigma}_{1.2}^2}{\bar{\sigma}_1^2}\right) + \left(\frac{\bar{\sigma}_{2,1}^2}{\bar{\sigma}_2^2}\right)$$

$H_a(n)$ and $H_b(n)$ represent the number of pixels with a gray value of n. Defining $E_{b,a}(n)$ and $\sigma_{b,a}^2(n)$:

$$E_{b,a}(n) = \frac{1}{H_a(n)} \sum_{f_a(x,y)=n} f_b(x, y)$$

$$\sigma_{b,a}^2(n) = \frac{1}{H_a(n)} \sum_{f_a(x,y)=n} \left(f_b(x, y) - E_{b,a}(n)\right)^2$$

After combing with mutual information I(A,B), we can get a new metric：

M（A,B）=I(A,B)/(1+CI(A,B))

3. Experiment result

3.1 Experiment result

In order to verify the non-rigid registration performance of the algorithm, we are using MR-T1 and MR-T2 medical images for the registration experiment.

Clinically, T1-weighted MRI images can be used to observe the anatomy of human tissues and organs. T2-weighted MRI images can be used to observe lesions. By registering T1-weighted and T2-weighted brain MRI images, doctors can obtain more brain tissue structures. In this experiment, a fully registered T1-weighted image and a T2-weighted image were used to verify the registration method. A T1-weighted MRI image is defined as a floating image, and a T2-weighted image is defined as a reference image [7][8].

Cause there is no golden standard to evaluate the result, Therefore, we use some indirect evaluation method to evaluate the registration effect. Here we set three experience to show the performance of our algorithm.

Experiment 1: Registration effect display

Fig.3.1 is a graph obtained by using the proposed similarity metric, and show the different by false color, Fig. 3.1(c) shows the result before registration and Fig.3.1(d) shows the result after registration：

Checkerboard is one of the most representative experimental diagrams of the nonparametric registration model. This experiments to verify the effectiveness of the improved registration model proposed in this section. And the Fig.3.1(g) shows the traditional mutual information method and Fig.3.2(h) shows the new metric registration results.

Experiment 2: Comparing the smoothness and convergence of two registration metric surfaces.

In the quantitative evaluation of the registration result, it is difficult to give a quantitative evaluation result by the general method. According to measure curve, the Peak Deviation (the deviation between the position where the global maximum occurs and the optimal position); Maximum value (the global maximum); And the root means square error (RMES) between the peaks are the characteristics of the comprehensive evaluation of the quantitative indicators. If the floating image is perfectly aligned with the reference image, then the matching curve will appear as a smooth, sharp, convex function with no local extrema [9-11].

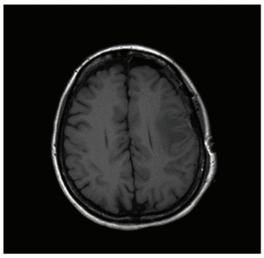

Fig. 3.1(a) MRI-T1.

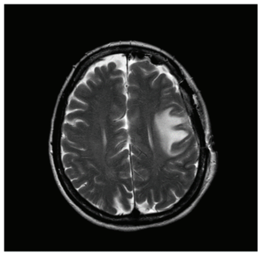

Fig. 3.1(b) MRI-T2.

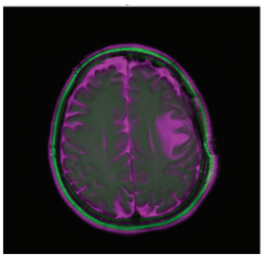

Fig. 3.1(c) Before.

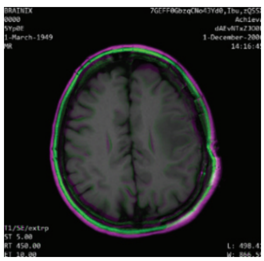

Fig. 3.1(d) After.

Fig. 3.2(e) MRI-T1.

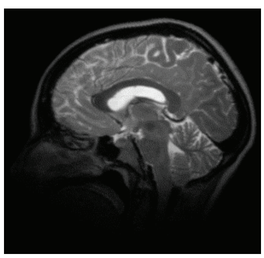

Fig. 3.2(f) MRI-T2.

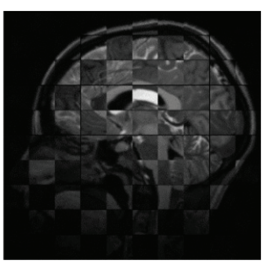

Fig. 3.2(g) MI.

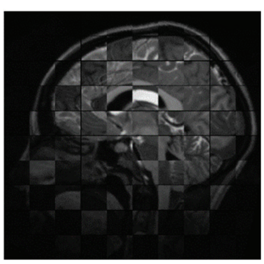

Fig. 3.2(h) New metric.

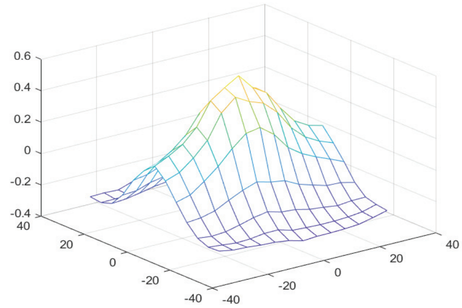

Fig. 3.1(i) MI matching curve.

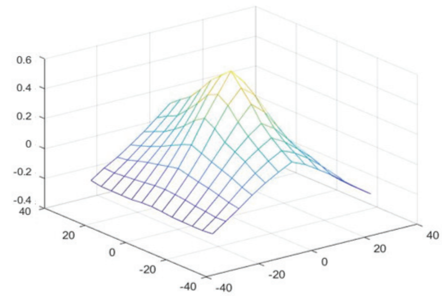

Fig. 3.1(j) New metric.

Experiment 3: Anti-noise experiment

In order to prove the universality of the proposed measure, Gaussian noise of 0.1, 0.2, and 0.3 is added to the floating image respectively. The registration measure in the experiment adopts the steepest gradient descent method as the optimization strategy, and the number of iterations is 100 times. Each registration measure was averaged 10 times. And the accuracy of the registration was evaluated using MSE. The error comparison results are shown in Fig. 3.1(k). It can be seen that in the case of no noise, the measurement registration error in this chapter is the smallest. When noise is introduced into the image, the errors of the two registration measures increase as the noise variance increases.

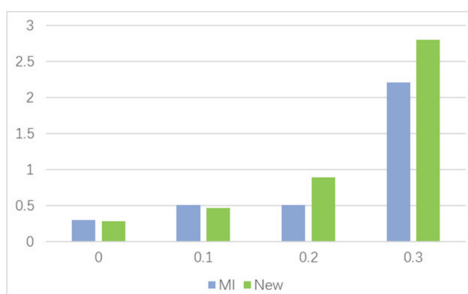

Fig. 3.1(k) Error comparison.

4. Conclusion

The goal of image registration research is to improve the accuracy, robustness, and speed of registration. The core issue is finding the registration standard and a well-functioning registration metric.

The image registration improvement algorithm proposed in this paper, based on the maximum mutual information method. It utilizes the method based on gray and feature comprehensively and performs edge detection operator on the image to obtain the edge image. Thus, defining a new measure function. The object function is then optimized using the steepest gradient descent method.

The experiment shows the improved method has high registration accuracy. Through the drawing of the measurement curve, the peak of the image is sharp, which facilitates to find the optimal registration.

The method proposed in this paper is a kind of registration method combining the feature and the gray level. It is necessary to perform edge detection on the image first. Therefore, the edge detection has impact on the final registration result. Due to the complexity of the measure function, there is some increase in the complexity and runtime of the algorithm, and further research is needed to reduce the time required for registration.

The mutual information-based registration method is essentially an optimization problem. In the future research, the optimization algorithm needs to be further studied, and the object function should be optimized to reduce mismatch and improve the operation speed.

Acknowledgement

This study was carried out as a fund of the project to support the development of information and communication broadcasting standard in 2019.

Reference

1. Jenkinson, Mark, and Stephen Smith. “A global optimization method for robust affine registration of brain images.” Medical image analysis 5.2 (2001): 143-156.
2. Maes, Frederik, et al. “Multimodality image registration by maximization of mutual information.” IEEE transactions on Medical Imaging 16.2 (1997): 187-198.
3. Mattes, David, et al. “Nonrigid multimodality image registration.” Medical Imaging 2001: Image Processing. Vol. 4322. International Society for Optics and Photonics, 2001.
4. Pluim, Josien PW, JB Antoine Maintz, and Max A. Viergever. “Mutual-information-based registration of medical images: a survey.” IEEE transactions on medical imaging 22.8 (2003): 986-1004.
5. Vercauteren, Tom, et al. “Non-parametric diffeomorphic image registration with the demons algorithm.” International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Berlin, Heidelberg, 2007.
6. Van den Elsen, Petra A., E-JD Pol, and Max A. Viergever. “Medical image matching-a review with classification.” IEEE Engineering in Medicine and Biology Magazine 12.1 (1993): 26-39.
7. Liu, Changchun, Ke Li, and Zhongguo Liu. “Medical image registration by maximization of combined mutual information and edge correlative deviation.” 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference. IEEE, 2006.
8. McAuliffe, Matthew J., et al. “Medical image processing, analysis and visualization in clinical research.” Proceedings 14th IEEE Symposium on Computer-Based Medical Systems. CBMS 2001. IEEE, 2001.
9. Nuyts, Johan. “The use of mutual information and joint entropy for anatomical priors in emission tomography.” 2007 IEEE Nuclear Science Symposium Conference Record. Vol. 6. IEEE, 2007.
10. Johnson, Kisha, et al. “Mutual information as a similarity measure for remote sensing image registration.” Geo-spatial Image and Data Exploitation II. Vol. 4383. International Society for Optics and Photonics, 2001.
11. Binglu, and Youngseop Kim. “Multimodality and Non-rigid Registration of MRI' Brain Image.” Journal of Semiconductor and Display (2019) : 102-104.

접수일: 2019년 6월 15일, 심사일: 2019년 6월 21일,
게재확정일: 2019년 6월 25일