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# Medical image registration based on gray distribution correlation

Xiaohua Shu[1,2]*, Zhenkang Shen[2], Xiaowei Long[1]

[1]Dept. of Electrical Engineering, Hunan University of Technology, Zhuzhou, (CHINA)

[2]ATR Lab. National University of Defense Technology, Changsha, (CHINA)

E-mail : sxhdata@126.com

## ABSTRACT

To improve the precision and time consuming of medical image registration, an image registration technique based on the registration measurement is developed and proposed. In this method, a new matching measurement based on gray distribution correlation of the images is proposed, this parameter quantifies aligning degree of two medical images. Comparing with other similarity measurement, such as normal mutual information, the calculation cost spent in this registration method is low. Experiment results show that this method is valid and fast. and enhance robustness of image registration.

## KEYWORDS

Medical image; Image registration; Registration measurement; Multi-resolution; Joint distribution.

## INTRODUCTION

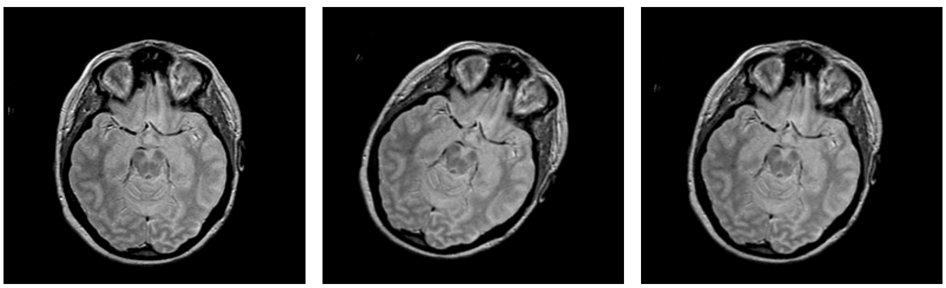
Medical images processing is widely used in different aspects nowadays. For example, in illness diagnosis, illness check-up and track, observing change of ill tissue, images registration is generally used. Exact registration may facilitate images analyses and processing. There are some aligning measurements so far, such as correlation function [1], mutual information [2-3], square error[4], etc. However, calculation of these parameters needs a lot of time in image registration. In this work, By analyzing the gray joint probability of two correlative images, a new matching measurement is proposed. This parameter quantifies aligning degree of two images. Basing on the analysis, a new registration method is presented.

## IMAGE ALIGNING MEASUREMENT--DEVIATING MEASUREMENT

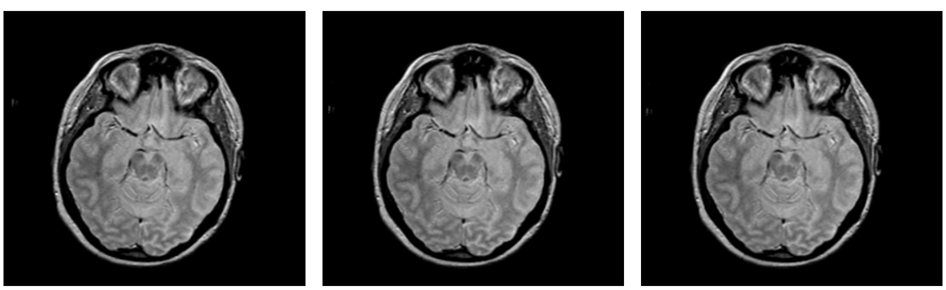
Given two images A and B, A is the image to be registered, B is the reference image. Since the two images belong to mono-modality images, their gray property is similar; consequently, the aligning degree of the two images must associate with their gray joint distribution.

### Similarity measurement

In order to analyze the relation between the aligning degree of two images and their gray joint distribution, an image is translated and rotated with various parameters. The original image and the transformed images are showed in the figure 1 respectively, the image 1# is the original MR image of human brain, and the image 2#~6# is the rotated samples of the image 1#, and so on.



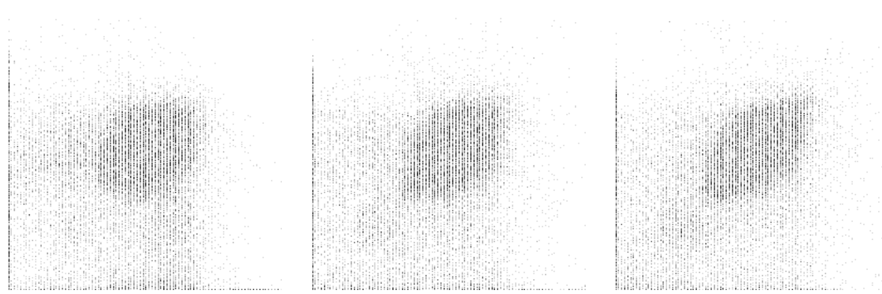
**a) original image (image 1#)** **(b) 25° sample (image 2#)** **(d) 10° sample (image 3#)**



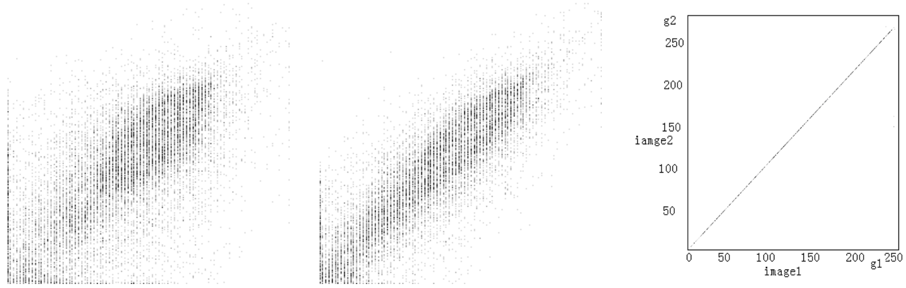
**(d) 5° sample (image 4#)** **(e) 3° sample (image 5#)** **(f) 1° sample (image 6#)**

**Figure 1 : MR image of human brain and its rotated samples**

The gray joint distribution of the MR image of human brain and its rotated samples is showed in figure 2.



**(a) 25°sample** **(b) 10°sample** **(c) 5° sample**




**(d) 3° sample** **(e) 1° sample** **(f) 0° sample**

**Figure 2 : Gray joint distribution of the original image with its rotated samples**

There are two random variables x and y, their distribution function are represented as P(x) and P(y),and their joint distribution function is represented as P(x,y). If the two random variables are independent, there would be:

$$P(x,y) = P(x)P(y) \tag{1}$$

If the two random variables are strongly correlated, the difference between P(x,y) and P(x)P(y) would be become larger. the greater the difference, the stronger the correlation between the two random variables. Therefore the difference between P(x,y) and P(x)P(y) can express the The degree of correlation of the two random variables x and y. This idea can be applied to describe the image registration degree, and the image similarity measure can be constructed. $P_A$(i)denotes the gray distribution function of the image A, $P_B$(j)denotes the gray distribution function of the image B, $P_{AB}$(i,j)denotes the joint distribution function of the image A and B. The similarity measure SM(A,B) can be defined as:

$$SM(A,B) = \sum_{i,j} \left| P_{AB}(i,j) - P_A(i)P_B(j) \right| \tag{2}$$

SM(A,B) reflects the alignment degree of the image A and B. When the two images are completely unrelated, $P_A$（i） and $P_B$（j） are independent of each other, i.e.

$$P_{AB}(i,j) = P_A(i)P_B(j) \tag{3}$$

At SM(A,B)=0, the degree of alignment of the two images is the smallest. When the alignment degree increases, the correlation of $P_A$ (i) and $P_B$ (j) increases, and the difference between $P_{AB}$（i, j） and $P_A$ (i)$P_B$ (j) increases, SM(A,B) also increases. When the correlation of the two images becomes the most, the SM(A,B) would reach the maximum value, and the alignment degree of the image A and B reaches the maximum value. Therefore, SM(A,B) can be used to express the alignment degree of the images. The measurement formula (2) satisfies the following properties:

(1) Symmetry: SM(A,B)= SM(B, A);

(2) Non negative: SM(A,B) $\geq$0;

(3) If two images A and B are registered completely, SM would reach the maximum. When the SM(A,B) reaches the maximum, the registration of the two images would be completed.

**Images registration-- Similarity measurement maximization**

The goal of images registration is searching a space geometry transform (T), so that the SM between the image $A' = T\{A\}$ and reference image B should be maximized, i.e. maximizing $SM[T(A), B]$. For 2D images, the space transform function T is a 2D coordinate geometry transform, expressing as:

$$(x', y') = T_\xi(x, y) \tag{4}$$

$\xi$ denotes the parameter set of geometry transform (T), for rigid transform, needing 3 parameters: rotation parameter $\Delta\theta$ and translation parameters $\Delta x$ , $\Delta y$ . Thus, the image registration procedure becomes the search of optimal parameter set $\xi^*$, i.e.

$$\xi^* = \arg\max_{\xi} SM[T_\xi\{A\}, B] \tag{5}$$

## REGISTRATION PARAMETERS OPTIMIZATION

The images registration based on maximizing SM is a process of searching optimal parameters. Different optimal strategies produce different effects, and directly affect the speed and precision of registration. In the work, Powell optimal algorithm would be choosed, and the iterative search is executed in each dimension [5]. Accordingly, the SM continually increases untill reaches the maximum.

## MULTI-RESOLUTION DECOMPOSITION

To accelerate registration, a strategy of image pyramid decomposition is employed. Firstly, image registration is performed at the coarsest scale, due to the less amount of data, the number of iterations is largely reduced and the parameter converges fast, at the same time, the algorithm robustness enhances, and the registration parameters are approximate. With the increase of the number of iterations, registration is performed on a finer scale with the parameter of the previous scale as initial parameters. This process is iterated until the finest scale is reached. The computational cost performed at the finest level would almost occupy the majority of computational cost of the whole optimization. Consequently, in order to reduce the amount of refinement necessary to reach convergence, the initial parameter for this last level is very important. A coarse-to-fine strategy is successful because the optimization takes advantage of good starting conditions.

Figure 3 is a 3-level decomposition of MR image using Gaussian template [6-7].

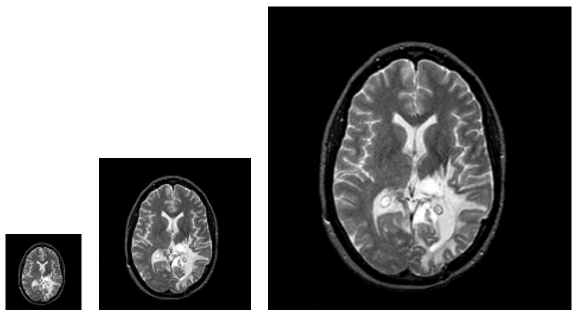


**Figure 3 : 3-level decomposition using Gaussian template**

## EXPERIMENTAL RESULTS

To analyze the performance of the method, the comparative experiment is performed. Another aligning measurement, such as normal mutual information (NMI) [8-10],is often used. The result of the comparative experiments is shown in table 1. In the table, $\delta x$, $\delta y$, $\delta\theta$ denote the horizontal mean error (unit: pixel), vertical mean error(unit: pixel) and rotation mean error(unit: degree) of registration parameter .

**TABLE 1 Registration precision comparison for NMI and SM**

| | NMI | SM |
|---|---|---|
| horizontal mean error $\delta x$ | 0.91 | 0.31 |
| vertical mean error $\delta y$ | 0.67 | 0.56 |
| rotation mean error $\delta\theta$ | 0.71 | 0.51 |

The comparison of registration time cost for NMI and SM is shown in table 2. In the table 2, $\delta\theta$ denotes rotation angle (unit: degree), time unit: second.

**TABLE 2 Registration time cost comparison for NMI and SM**

| | NMI (s) | SM (s) |
|---|---|---|
| $\delta\theta=25^\circ$ | 3.51 | 1.32 |
| $\delta\theta=10^\circ$ | 2.96 | 1.13 |
| $\delta\theta=5^\circ$ | 2.75 | 1.05 |
| $\delta\theta=3^\circ$ | 2.54 | 0.99 |
| $\delta\theta=2^\circ$ | 2.13 | 0.92 |
| $\delta\theta=1^\circ$ | 1.52 | 0.71 |

From the table 1 and table 2, it is shown that the method based on SM excels that based on NMI. Since this registration method based on SM needn't calculation of logarithm and fractional values, so the calculating cost is low. Therefore, this algorithm is valid and fast.

## CONCLUSION

In this work, by analyzing the gray joint distribution function of two correlative images, a new matching measurement is proposed. This parameter quantifies aligning degree of two images. Therefore, a new approach of images registration is presented. In this approach, the images registration becomes the maximizing of the similarity measurement of the two images. In order to accelerate the registration, a multi-resolution strategy is developed, in which a coarse-to-fine strategy is adopted. Comparing with the other similarity measurement,such as NMI, this registration approach needn't calculation of logarithm and fractional values, so the calculation cost is low, and the experiments show that this method is fast and more accurate.

## ACKNOWLEDGMENT

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