Medical Image Registration Using B-Spline Transform

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***Abstract* — Hierarchical B-spline has been widely used for shape modeling in many fields. Registration result is achieved by minimizing a cost function which represents the cost associated with the image similarity. In this paper we present an application of this concept in the form of free-form deformation with a newly proposed metric. This new metric combines the mean square metric and the distance of both pixels which come from the fixed image and moving image respectively. With this new metric, better performance can be obtained. Also, one new metric based on the mutual information and NCC (Normalized Cross Correlation) is proposed to increase registration precision.Two experiments results both show higher image similarity and better metric value.**

Keywords - Free form deformation, hierarchical B-splines , image registration

I. Introduction

Image registration is a procedure of finding a spatial deformation to match two images. It has received considerable attention in the areas of medical image analysis and computer vision. Furthermore, the concept of image registration has been gaining acceptance both in research and practice as an important way to process the image in many disciplines. For example, in the hospital domain, it can be used to match different medical images taken from different patients or from the same patient at the different time.

Existing image registration techniques are classified into two broad categories: manual registration and automated registration. Manual registration techniques have been widely used in the practical applications. The current automated registration techniques can be more explicitly classified into two broad categories: area-based and feature-based techniques. The measure of similarity usually includes the normalized cross correlation, the correlation coefficient and the sequential-similarity[1][5].

Generally, the major process of the image registration consists of the following steps :

1）Select one suitable similarity measure to evaluate image registration effects according to the specific registration data, for instance, in the multimodal medical image registration similarity measures not completely based on gray value such as mutual information measure should be chosen , and when in the modality medical image registration similarity measures based on gray value such as mean squares metric could be chosen.

2) Select one suitable transformation according to the complexity of image transformation .When the deformation is relatively simple such as linear deformation, simple transformation model should also be chosen. when the image deformation is complicated, non-linear deformation model should be chosen. There are so many non-linear transformation models to be chosen in which spline transformation model is of significantly importance. Spline transformation is gaining more and more attention in the registration transformation for its good performance in the local region deformation and registration.

3）Select one suitable interpolation method according to the accuracy requirement in registration results. When demand for registration accuracy is high and efficiency demand is relatively low the linear interpolation method could be chosen. Otherwise nonlinear interpolation method should be preferred.

4）Select one suitable optimization method to optimize the similarity chosen in the step 1) and initialize the related parameters such as initial searching step length in the chosen optimization method.

In this paper, an image registration method is proposed, in the form of free-form deformation with a newly proposed metric. The proposed metric combines the mean square metric and the distance between two pixels, which come from the fixed image and moving image respectively.

This paper is organized as follows: Section II gives a brief introduction to the B-spline Transform and the Free deformation (FFD). Section III discusses the proposed image registration algorithm, and the metric for image registration performance assessment. Section IV evaluates the proposed method with an example. Results analysis is described in the Section V. The concluding remarks are given in the Section VI.

II. Related Work

A. Affine Transform Model

The global transformation model describes the overall image motion. The simplest transformation model is the linear transform in which six parameters are used to describe the size of image rotation and scale[2]. Affine transformation and projection transformation are both representative of linear transformations, the mathematical expressions of affine transformation can be written as :

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$$T_{affine} = \begin{pmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \\ \theta_{31} & \theta_{32} & \theta_{333} \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} \theta_{14} \\ \theta_{24} \\ \theta_{34} \end{pmatrix} \qquad (1)$$

B. B-Spline Transform Model

In general, the affine transformation only captures the global image motion .As a result of this, more useful transformation models are required in the registration process, those transformation models are used to simulate the local image deformations. The local features of medical images change with different patients and ages. Therefore, simulating the local deformation is relatively difficult. FFD model based on B-spline is a good local deformation model, which is a powerful tool for 3D deformable object modeling[3]. The basic idea of FFD deformation model is to control points distributing on the surface of FFD deformable object.To define a FFD based on the spline, the domain of the image volume can be defined as[4] [6][7]:

$$\Omega = \{(x, y, z) \mid 0 \le x \le X, 0 \le y \le Y, 0 \le z \le Z\}$$

Let Ψ denote a $n_x \times n_y \times n_z$ mesh of control points $\Psi_{i,j,k}$ with uniform spacing δ . Then, the FFD can be written as the 3-D tensor product of the familiar 1-D cubic B-spline：

$$T_{nongrid}(x, y, z) = \sum_{l=0}^{3}\sum_{m=0}^{3}\sum_{n=0}^{3} B_l(u)B_m(v)B_n(w)\Psi_{i+l,j+m,k+n} \quad (2)$$

Where $i = \lfloor x / n_x \rfloor - 1$, $j = \lfloor y / n_y \rfloor - 1$, $u = x/n_x - \lfloor x/n_x \rfloor$, $v = y/n_y - \lfloor y/n_y \rfloor$, $w = z/n_z - \lfloor z/n_z \rfloor$

And where represents the Lth basis function of the B-spline model:

$B_0(u) = (1-u)^3/6$, $B_1(u) = (3u^3 - 6u^2 + 4)/6$, $B_2(u) = (-3u^3 + 3u^2 + 3u + 1)/6$, $B_3(u) = u^3/6$.

Since the B-spline is controlled locally, it is computationally efficient when facing with a large number of control points. There is a very good mathematic property in the basis function of the cubic B-Spline, that is, changing control point only causes changes of the region around the local neighborhood of that control point. The control point perforoms as parameters of the B-spline model. When during the global rigid deformation[8], a relatively large spacing of control points would be preferred, while a small spacing of control points is more suitable in local non-rigid deformations.

There are so many kinds of transformations used in the non-rigid registration, such as transformation based on smooth regional variation which is mainly described by a small number of parameters[9][11], besides ,the transformation based on the displacement fields is also of significant importance in the registration . The mostly used transformation in image registration is the spline transformation which have been used for around fifteen years. Each control point in a thin-plate spline transformation model will cause a global influence on the whole image, which means that when the position of one point is perturbed, all other points around in the transformed image will also change accordingly. This property is obviously one disadvantage which will limit the capability to do relatively complex or localized transformation deformations. By contrast, the transformation model based on the B-spline is only defined in the limited region of each control point, as a result of this, the change of one control point will only affect the neighborhood region of that point[10] .This non-rigid registration technique based on the B-spline becomes more and more popular since its superiority in the transparency[8], general applicability and computational efficiency.

Spline-based image registration techniques have been studied in the image processing and other related fields such as computer graphics for so many years. Image processing techniques based on the spline-based displacement fields have recently been used in the computer graphics, in this technique the morphing operation can be done with the manually specified field correspondences. Spline technique is also used in the elastic deformation registrations. In the image registration smoothness of the registration result is so important, with the B-spline transformation, high smoothness can be obtained, however, the preservation of topology is not guaranteed. Rueckert[2] imposed some hard constraints to produce well deformation fields and the preservation of the topology can also be ensured through the use of soft constraints. Many extensions based on the FFDs have also been proposed earlier. While FFDs are usually uniform, some non-uniform approaches have also been proposed.

C. Similarity Metrics in Image Registration

There are many metrics used in the image registration. How to choose the best metric mainly depends on the specific situation in which we perform the image registration .There are some frequently used metrics, which are listed as follows[12]:

Mean Squares Difference Metric:

Sum of squared differences between intensity values. It requires two objects to have intensity values in the same range. The mathematic definition of this metric can be written as follows:

$$MSD = \frac{\sum_{i=0}^{N}(A_i - B_i)^2}{N} \qquad (3)$$

N is the number of points used in the whole registration process, A_i and B_i are the correspondent point in the registration process.

Normalized Cross Correlation:

Correlation between intensity values divided by the square rooted autocorrelation of target and reference objects. This metric allows to register objects whose intensity values are related with a linear transformation. The mathematic definition of this metric can be written as follows:

$$C(A,B)=\frac{\sum_{i,j}[a_{i,j}-mean(A)]\times[b_{i,j}-mean(B)]}{\sqrt{\sum_{i,j}[a_{i,j}-mean(A)]^2}\sqrt{\sum_{i,j}[b_{i,j}-mean(B)]^2}} \quad (4)$$

Mutual Information:

Mutual information is based on the information theory[13][14] concept. Mutual information between two pictures measures how much information can be known from one if only the other one is already known. That is, once the better registration has been performed, the larger mutual information value should be obtained . The mathematic definition of this metric can be written as follows:

$$I(A,B)=H(B)-H(B\mid A)=H(A)+H(B)-H(A,B) \quad (5)$$

in which :

$$H(A)=-\sum_a p_A(a)\log p_A(a)$$

$$H(B)=-\sum_b p_B(b)\log p_B(b)$$

$$H(A,B)=-\sum_{a,b} p_{A,B}(a,b)\log p_{A,B}(a,b)$$

III. Metric Combined with Distance and MSD

Based on the Mean Squares Metric, a new metric is proposed, considering that only the squares of the differences between the value of correspondent point may not be appropriate. Besides, It can be believed that when the better performance has been performed , the less distance between the correspondent point in the registration process can be achieved. When the performance of the registration reaches the best, the distance between the correspondent point should be zero though this is just a ideal situation. This paper proposes a new factor as a new component of the newly proposed metric---distance between the correspondent point which shows how far one point is away from another point before and after transformation. This new metric is named as the D-Metric.(Distance) in this paper. And this metric is expressed in the form of the mathematical as follows:

$$\text{N - Metric} = \text{Mean Squares Metric} + c\times Distance \quad (6)$$

or $N-Metric=\sum_{l=0}^{N}(A_i-B_i)^2+c\times \text{Distance}$

$$\text{Distance}=\sqrt{(x_1-x_2)^2+(y_1-y_2)^2} \quad (7)$$

$(x_1,y_1),(x_2,y_2)$ are locations of the correspondent points from two images to be matched. Where c is the factor which balances the ratio between two factors: Mean Squares Metric and distance .The value 0.5 is employed here as the first step to find the best value which is used to reach the best registration metric value . A_i and B_i are gray values of the correspondent points respectively.

In order to obtain better performance , the multilevel model is adopted to process this registration .That is, the registration process gradually begins with the coarse level to finer level with N-Metric. The multilevel model is a good way to decrease the computation consumption since that the algorithm always get better performance before it continues with the next level registration. By considering the efficiency , the level number is set as three in this paper. The level number can be set as large as possible if the efficiency is out of the consideration and then the better performance will be achieved .

The detailed definition of the newly proposed metric has been stated above, in the next, this metric will be employed in the registration process and the experiment result will reveal the advantage of the newly proposed metric. The non-rigid registration algorithm which is used in the experiment can be summarized in Figure.1 .

Calculate the optimal affine transform.
Initialize the control points Ψ .
Repeat
Calculate the $N-Metric$ to the non-rigid transformation parameters Ψ :

$$\nabla c=\frac{\partial N(\Theta,\Psi^l)}{\partial \psi^l}$$

While $|\nabla c|>\varepsilon$ do

Recalculate the control points $\Psi=\Psi+\mu\frac{\nabla c}{\|\nabla c\|}$

Recalculate the gradient vector ∇c
Increase the control point resolution by calculating new control points Ψ^{L+1} from Ψ^L
Increase the image resolution
Until finest level of resolution is reached.

Figure 1. Non-rigid registration algorithm

IV. Metric Combined with MI and NCC

Through normalized cross-correlation metric ,the similarity of local region of two corresponding points can be obtained. The similarity of The correspondent points P and Q can be defined as follows, and are the size of the local region around the correspondent points.

$$R(P,Q)=\frac{\sum_{i=-n/2}^{n/2}\sum_{j=-m/2}^{m/2}([\mathrm{I}(x+i,y+j)-\bar{I}])([\mathrm{T}(x'+i,y'+j)-\bar{T}])}{\sqrt{(\sum_{i=-n/2}^{n/2}\sum_{j=-m/2}^{m/2}[\mathrm{I}(x+i,y+j)-\bar{I}])^2}\sqrt{\sum_{i=-n/2}^{n/2}\sum_{j=-m/2}^{m/2}[\mathrm{T}(x'+i,y'+j)-\bar{T}])^2}} \quad (8)$$

In which:

$\bar{I}=\frac{1}{mn}\sum_{i=-n/2}^{n/2}\sum_{j=m/2}^{m/2}[\mathrm{I}(x+i,y+j)]$ is the average gray value of the fixed image.

$\overline{T} = \frac{1}{mn} \sum_{i=-n/2}^{n/2} \sum_{j=-m/2}^{m/2} [\mathrm{T}(\mathrm{x}' + \mathrm{i}, \mathrm{y}' + j)]$ is the average gray value of the moving image.

The computation of this metric is aimed at the similarity of the local region of the correspondent points. With higher similarity metric ,the absolute value of this metric is closer to 1. In order to make this metric adapt to the multi-model registration, the computation of this metric will employ the gradient image of the original image respectively. The specific definition of this metric in multi-model registration is as follows:

in which:

$$R(P, \mathrm{Q}) = \frac{|R(P_x, \mathrm{Q}_x)| + |R(P_y, \mathrm{Q}_y)|}{2} \tag{9}$$

P_x and P_y are the gradient image of image P along x and y axis respectively, Q_x and Q_y are the gradient image of image Q along x and y axis respectively.

As to the computation of the gradient image ,the gradient value of image f in the point (x, y) can be mathematically defined as:

$$\nabla f(x, y) = \frac{\partial f(x, y)}{\partial x} i + \frac{\partial f(x, y)}{\partial y} j \tag{10}$$

In order to simplify the computation,the computation of the Partial derivative can be replaced with the differential:

$$\frac{\partial f(x, y)}{\partial x} = f(x+1, y) - f(x, y) \tag{11}$$

$$\frac{\partial f(x, y)}{\partial y} = f(x, y+1) - f(x, y) \tag{12}$$

Finally ,the mathematical definition of the metric combined with MI and NCC is given as:

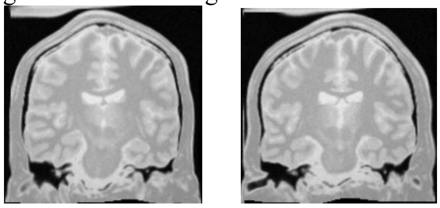
$$S(A, B) = \sum_{(P,Q) \in A \cap B} (|R(P, \mathrm{Q})| \times I(\mathrm{P}, \mathrm{Q})) \tag{13}$$

$I(\mathrm{P}, \mathrm{Q})$ is the mutual information of the local region around the correspondent point P and Q which comes from the fixed image A and moving image B respectively.

V. EXPERIMENTS AND RESULTS

A Experiment Based on N-Metric

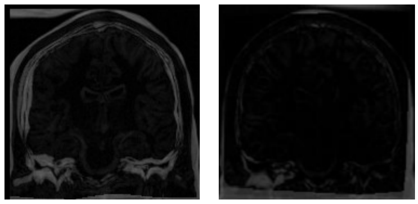
By adopting the ITK(insight toolkit) and VC++ , two experiments are evaluated in this paper to confirm the better effect of the newly proposed metric N-Metric, by comparing with the Mean Square Metric. The data of the first experiment from the Huaxi Medical College.The second group data is downloaded from the official site of the ITK . ITK is an open-source software system to support the Visible Human Project[15]. ITK employs leading-edge segmentation and registration algorithms in two, three, and more dimensions. The ITK registration frame is adopted here to realize the experiment and evaluate the applicability of the newly proposed metric . The empirical value c in the N-Metric is set as 0.5 and the resolution level is set as 3 .The input images are shown in Figure 2



Fixed Image Moving Image

Figure. 2. Input images

The difference image is employed here to compare the effect of two experiments. The difference image with the N-Metric before and after the registration are shown in Figure 3. And the moving image after registration is shown in Figure 4. The comparison of metric values with the mean square difference and N-Metric are shown in the Table I. Experiment 2 and results are shown in Figure 5.The change of distance of respondent point in the process of registration is shown in table II.



Before Registration After Registration

Figure. 3. The difference image with the N-Metric before and after registration.

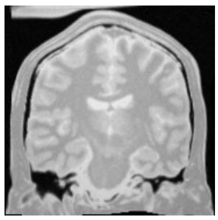


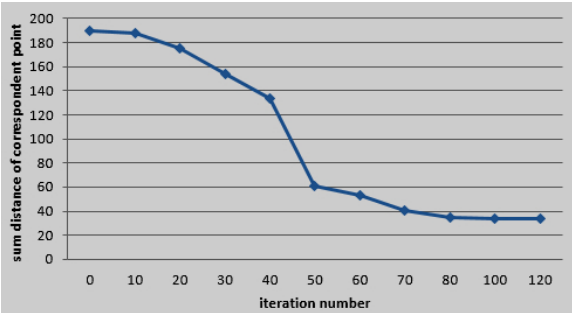
Figure. 4. Moving image after registration

Figure. 5. Results of experiment 2

TABLE I: Metric values with the mean square difference and N-Metric

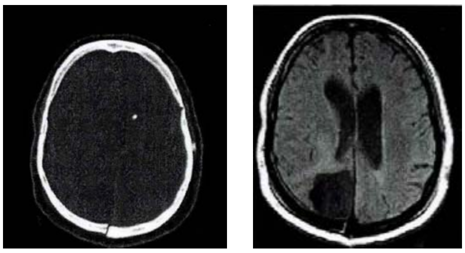
Metric/Experiment	Experiment 1	Experiment 2
Mean Square Metric	192.3	178.3
N-Metric	189.4	177.5

TABLE II: change of sum distance of correspondent point



B Experiment Based on the Metric Combined with MI and NCC

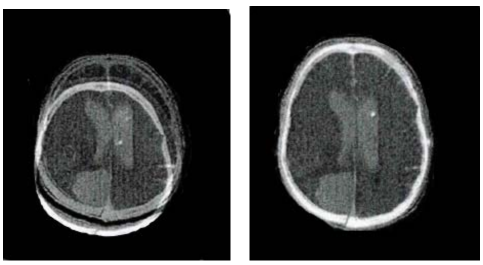
The input images are shown in Figure 6, the size of the local region around the correspondent point is set to be 3×3,with B-Spline transformation as the transformed model.



Fixed Image Moving Image

Figure 6 Input images

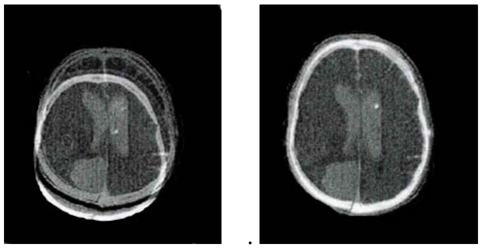
The difference image with MI before and after the registration are shown in Figure 7.



Before Registration After Registration

Figure 7 The difference image with the this Metric before and after registration

The difference image with the Metric combined with MI and NCC before and after the registration are shown in Figure 8.



Before Registration After Registration

Figure 8 The difference image with the this Metric before and after registration

The comparison of the MI value , normalized MI value and the joint entropy value of the registration results based on the new metric and MI metric respectively is given in table III.

TABLE III: Metric values with the mean square difference and N-Metric

comparison	Before registration	MI registration	Registration based on MI and NCC
MI	2. 2	2. 34	2. 45
Normalized MI	1. 45	1. 457	1. 468
Joint entropy	9. 68	9. 46	9. 43

VI. Results Analysis

The newly proposed metric N-Metric consists of two parts which are both nonnegative. During the process of the registration, the aim is always to minimize the metric value ,and this paper reveals that by combining with N-Metric, the metric value becomes smaller than the general mean square metric, that means in the case of N-metric , the better performance will be achieved. Therefore it can be confirmed that with the newly proposed metric N-Metric to register the image, the performance can be improved. The experienced parameter depends on the specific case. More then one experiment should be finished to search and set the best parameter which is suitable to the specific image.

With the metric combined with MI and NCC in the registration and the comparison experiments, better registration performance could be obtained. Table III obviously shows that the registration results based on the new metric combined with MI and NCC is better than one only based on MI metric.

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VII .CONCLUSION AND FUTURE WORK

This paper proposes two new metrics, one is N-Metric which combines the gray value difference with the distance of correspondent point before and after transformation., the other is the metric which combines MI and NCC. By comparing the results of experiments , it is confirmed that the newly proposed metric has the ability to achieve the better performance when matching the same image data. Through optimizing the hierarchical model with the metric value[16], much better performance can be obtained. In future , since the performance of the N-Metric based image registration , which is simply considered to be decided only by the image value and Euclid distance before and after registration process, is arbitrary, some other factors such as smoothness should also be considered into the registration process . Besides, other forms of distances based on the Euclid distance which may achieve better results also can be proposed. Moreover, the mean squares of value differences which forms the N-Metric is more suitable to the same model image ,as a result, the mutual information theory can be taken into account when dealing with multi-model images. Given that the image segmentation sometimes can help simplify the registration process , research on segmentation is underway at the same time[17] , with the registration results ,better image fusing results can be better obtained[18] .

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