Multi Resolution Medical Image Registration Using Maximization of Mutual Information & Optimization By Genetic Algorithm

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Abstract–**Biomedical image registration or geometrical alignment of 2-D/2-D image data is increasingly important in diagnosis, treatment planning, computer-guided therapies and in biomedical research. In this paper we present affine registration of same modality images and different (MR & CT) modality images. Automatic registration is achieved by maximization of a similarity metric, which is Mutual Information (MI) or Relative Entropy, based on the concept of information theory. Registration based on MI usually requires an optimization technique to achieve correctly aligned images. There exist many optimization schemes, most of which are local and require a starting point. Unfortunately the functions of similarity metric used in the present problem are nonconvex and irregular and therefore global methods are often required. In this paper, we have implemented Genetic algorithm as an optimization technique to overcome these problems. Experimental results show our algorithm is a robust and efficient method.**

I. Introduction

MEDICAL imaging provides insights into the size, shape and spatial relationships among anatomical structures. In radiotherapy planning, dose calculation is based on the computed tomography (CT) data, while tumor outlining is often better performed in the corresponding magnetic resonance imaging (MRI). Additionally functional imaging is becoming increasingly important both clinically and in medical research. Positron emission tomography (PET) and single photon computed tomography (SPECT) imaging provide information on blood flow and metabolic processes. Very often areas of the body are imaged with different modalities. These images are used in a complimentary manner to gain additional insights into the phenomenon. For these different modalities to be useful, they must be appropriately combined or fused. Before images can be fused, they must be geometrically aligned. This alignment process is known as registration [1]. Registration is also used in treatment planning, brain mapping and image guided therapies (neurosurgery, orthopaedic surgery are very common).

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There are many approaches to biomedical image registration. The gold standard utilizes markers placed on the region of interest [2]. Other approaches include correlation of geometrical features [3]-[5]. Much work has recently focused on intensity based approaches, in which the intensity values (color or gray level) are used to compute similarity measures between the images.

In this paper we have proposed to use intensity based mutual information (MI) or relative entropy to describe the dispersive behavior of the 2-D histogram. If the images are geometrically aligned MI of the corresponding pixel pairs is maximal. Because no assumptions are made regarding the nature of the relation between the image intensities in both modalities, this criterion is very general and powerful and can be applied automatically without prior segmentation on a large variety of applications [6].

The main choices involve in image registration are interpolation technique, estimation of the probability distributions and the search strategy to optimization the similarity metric [7]-[8]. Unfortunately, the similarity metric is generally not a smooth function and contains many local optima [9]. Because of this, the choice of optimization routine has a large influence on the results of the registration method, particularly on the robustness of the method with respect to the initial transformation. In the current paper the search strategy for maximizing the similarity metric is multiresolution approaches for Genetic algorithm (GA). GA is based on the natural survival-of-the-fittest principle and selecting the best of the new generation by crossover and mutation operators [10]-[13]. The optimization scheme is initialized with a population of random solutions and searches for optima by updating the generations. In practice, registration success is mostly dependent on the initial orientation before any optimization technique is applied [14]. The rough idea of the initial orientation of the images to be registered can be achieved from the reduced resolution [15]-[16]. Thus we have proposed multiresolution registration method by maximizing mutual information.

II. Image Registration Process

The transformation applied to register the images can be categorized according to the degrees of freedom. Though rigid body transformation (including rotation and translations only) is generally performed in the previous works [1],[3],[6], elastic transformation is much more realistic (as most body tissues are deformable to some degree). In the registration problem, sometimes the images to be registered are called *floating image* **F**, which is transformed into the *reference image* **R**. In this paper we have restricted the transformation **T** to *affine transform* only, which is much more practical in biomedical imaging.

A. Affine Transform

The affine transformation preserves the parallelism of lines, but not their lengths or their angles. It extends the degrees of freedom of the rigid transformation with a scaling factor for each image dimension and additionally, a shearing in each dimension. Thus affine transform is much closer to the anatomic body deformation.

Let **T** denote the spatial transformation that maps features or coordinates from one image to another image. For 2-D affine registration the transformation matrix is:

$$x' = a*x + b*y + c \tag{1}$$

$$y' = d*x + e*y + f \tag{2}$$

or in matrix notation:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = T \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{3}$$

where **T** is a 2 × 3 matrix of coefficients:

$$T = \begin{bmatrix} abc \\ def \end{bmatrix} \tag{4}$$

B. Similarity Metric (Objective Function)

Mutual information (MI) is a basic concept from information theory, measuring the statistical dependence between two variables or the amount of information that one variable contains about the other. Let two variables, A and B, with marginal probability distribution, $p_A(a)$ and $p_B(b)$ and joint probability distribution $p_{AB}(a,b)$. MI, $I(A,B)$, measures the degree of dependence of A and B by measuring the distance between the joint distribution $p_{AB}(a,b)$ and the distribution associated to the case of complete independence $p_A(a) . p_B(b)$ i.e.,

$$I(A,B) = \sum_{a,b} p_{AB}(a,b) \log \frac{p_{AB}(a,b)}{p_A(a)\, p_B(b)} \tag{5}$$

MI is related to entropy by the equation

$$I(A,B) = H(A) + H(B) - H(A,B) \tag{6}$$

With $H(A)$ and $H(B)$ being the entropy of A and B, respectively, $H(A,B)$ their joint entropy.

$$H(A) = -\sum_{a} p_A(a) \log p_A(a) \tag{7}$$

$$H(A,B) = -\sum_{a,b} p_{AB}(a,b) \log p_{AB}(a,b) \tag{8}$$

The most straightforward way to estimate the joint probability distribution of intensities in two images is to compute a joint histogram of intensities. The feature space or joint histogram is a two-dimensional plot showing the combinations of gray values in each of the two images for all corresponding points. When the images are correctly registered, corresponding anatomical structures overlap and the joint histogram will show certain clusters for the gray values of those structures.

C. Optimization

The optimum of the similarity metric is assumed to the corresponding transformation that correctly registered the images. Since similarity metric is a non-convex function and contains many local optima, choice of search strategy to optimize it, is important in registration problem.

A method little used in image registration is Genetic algorithms (GAs), which are search algorithms based on the mechanics of natural selection and natural genetics**.** A possible solution is represented as a chromosome in a string structure with each element representing one parameter in the solution. A collection of possible chromosomes then forms a population, which produces another generation through a search process. The search process adopts "the fittest survives" rule after a structured yet randomized information exchange within the existing generation to yield a new generation. Basically GA uses three operators — selection (or reproduction), crossover and mutation to achieve the goal of evolution. Genetic algorithms are not just simple random walk; they efficiently exploit the information to speculate on new search points with expected improved performance. This method is allowed to make escapes from local optima and the chromosomes will approach the global optimum. To apply GA in our registration problem, we have encoded the transformation parameters by the binary numbers to form the chromosomes in a particular generation and optimized them to achieve the best possible result.

C. Multiresolution Approach

The fundamental theory of multiresolution imaging is to study the images at more than one resolution. A powerful but simple structure for representing the images at more than one resolution is the image pyramid. The base of the pyramid contains the highest resolution representation of the image; the apex contains a lowest-resolution approximation. With moving up the pyramid, both size and resolution of the images decrease. In the present problem, we have used two levels Haar transform to achieve multiresolution approach. From reduced size and resolution images, we have a rough idea of transformation parameters for which the similarity metric may become optimum in the higher resolution. These ideas are used to compute the initial population of GA optimization in the actual size and resolution images.

III. EXPERIMENTAL RESULTS

In this paper, the optimal transformation parameters of matrix **T** (described in Equ. 4) are to be searched by using genetic algorithms. The chromosomes of initial population are formed by concatenating six binary coded parameters of matrix **T**. The number of bits should be chosen as small as possible to minimize the time of convergence of Genetic Algorithm. In the present problem, the parameters are assigned ±7 units each. Therefore four bits are assigned for each parameter. We start with GA population 30 initially, and after 3rd generation, optimal solution is achieved.

In the present problem, we have registered the ventricular region of the brain images, since any deformities in this region cause serious nervous disorderness. The dataset contains CT and MR (both T1 & T2) brain images.

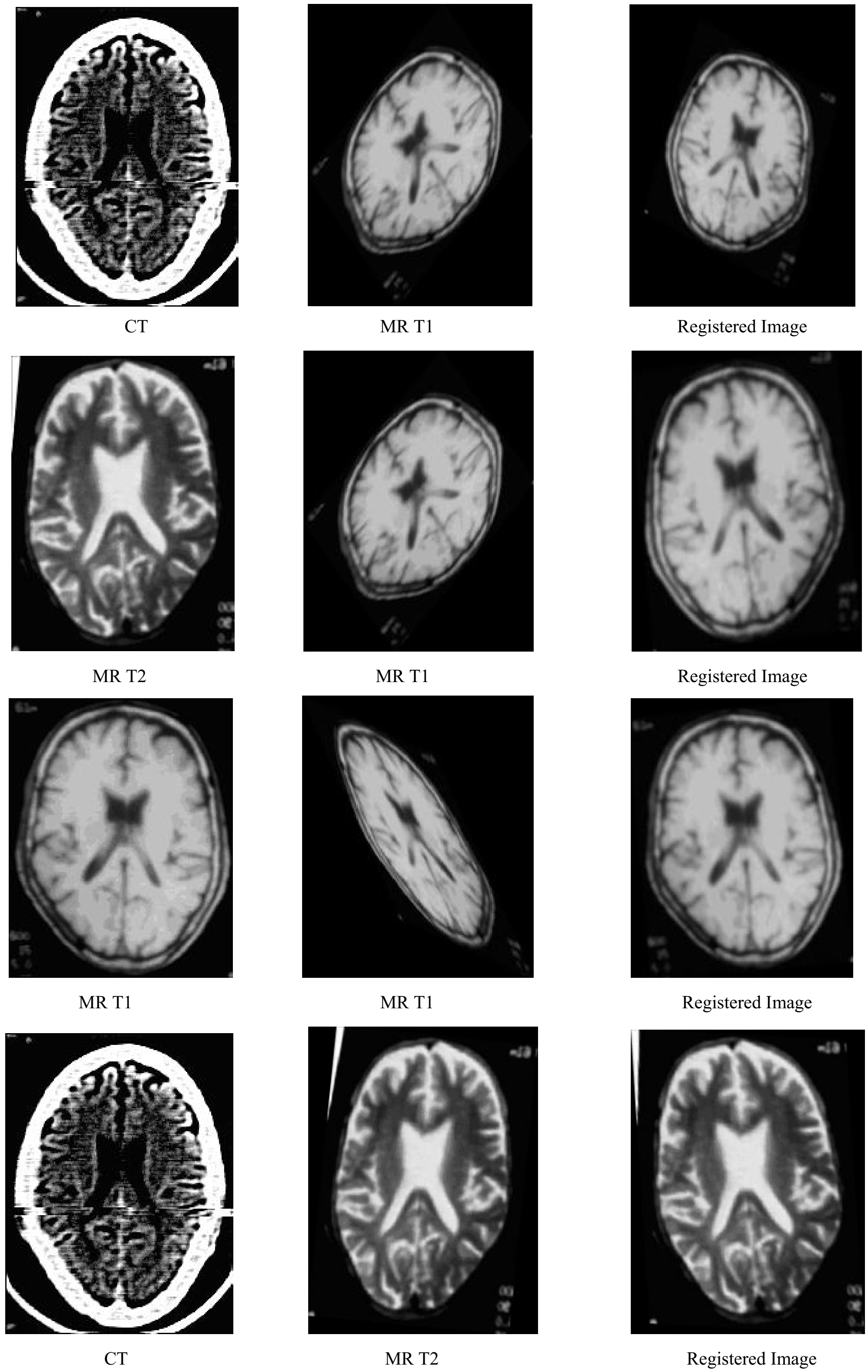

Fig. 1: Multimodality (CT & MR) and same modality image registration by Mutual Information maximization.

IV. DISCUSSION

MI measures statistical dependence of two or more random variables by comparing the joint probability distribution with that of the marginal distributions. Since no assumptions are made regarding the nature of this dependence, the MI criterion is highly data independent and allows for robust and completely automatic registration of multimodality images in various applications without any prior segmentation or other preprocessing steps.

Estimations of the image intensity distributions are obtained by computing the joint histogram from the entire overlapping part of both images. Other schemes can be used to estimate the image intensity distributions by using Parzen windowing [17] on a set of samples taken from the overlapping part of both images. Further experiments are needed to draw a conclusion on the superiority of these methods.

The proposed method discussed in this paper, implemented for affine registration of CT and MR (T1 & T2) images of the brain of the same patient. Since affine transform is much closer to the anatomic body deformation, it is clear that MI based affine registration may provide more practical approach to the other applications.

The optimization of MI based registration is achieved by using genetic search algorithms. We have noticed that for low resolution images the initial order in which the parameters are optimized strongly influences the optimization robustness in the actual resolution images. For low resolution images, the optimization technique often fails to converge to the global optimum, because of the lack of finer details.

Furthermore, the use of MI for multimodal image registration is not restricted to the image intensity only, other derived features such as gradient or edges can be used as well [18]. Selection of other appropriate and efficient optimization techniques is an area of further research. The process, GA-based optimization is time consuming and thus future challenges lie in the field of how to accelerate the optimization process substantially without accuracy loss.

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