A Novel Medical Image Registration Method Based on Mutual Information and Genetic Algorithm

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Abstract

Originating from information theory, mutual information, as a measure for image registration, has drawn much attention and has been shown to be successful. Mutual information should be maximal when the two different images are perfectly aligned. There exist many optimization schemes applied to mutual information matching problems, most of which are local and require a starting point. In this paper, we propose an improved genetic algorithm as a search engine to overcome this problem. To reduce the search data size, multi-resolution optimization strategy is adopted; meanwhile, adaptive sizes of the crossover and the mutation pools along with the changes of resolution are proposed to prevent the process from stalling at a local maximum, accordingly improve the capability with the local search of genetic algorithm. Experiments show our algorithm is a robust and efficient method which can yield accurate registration results.

1. Introduction

Given two image sets acquired from the same patient but at different times or with different devices, medical image registration problem can be stated in general as an optimization problem of finding the transformation function and the transformation parameters that optimize some similarity metric between the two images. It can be expressed as

$$a^* = \arg opt(S(F(x), R(T_a(x)))) \qquad (1)$$

where R and F are the images to be registered; T_a is the transformation, characterized by the transformation parameters a, that will be applied to the coordinate of each grid point x in F; S is an intensity-based similarity measure calculated over the region of overlap of the two images. Through the transformation, the corresponding points in the two image sets have the same anatomic locations. Image registration has been an important research topic because of its great value in a variety of applications. For medical image analysis, an image showing functional and metabolic activity—such as single photon emission computed tomography (SPECT), positron emission tomography (PET), and magnetic resonance spectroscopy (MRS)—is often registered to an image which shows anatomical structures, such as magnetic resonance image (MRI), computed tomography (CT), and ultrasound. These registered multimodality images lead to improved diagnosis, better surgical planning, more accurate radiation therapy and other countless benefits [1].

Since mutual information (MI) made its entrance into the field of medical image registration, it has been adopted by a large number of researchers for numerous applications [2]. Research into the measure currently takes up a substantial part of medical image registration research because MI-based registration is successful for a variety of image modalities. But a major difficulty in the registration problem using MI as the criterion is the existence of local maxima. It is possible that the obtained maximum may not be the global maximum of the search space and only part of the search space leads to the expecting maximum. This problem becomes even severe if the images are of low resolutions.

In this paper, a novel MI-based registration method is proposed. This method combines a simple yet powerful search strategy based on improved Genetic Algorithm (GA) with a wavelet-based multi-resolution manner. Adaptive sizes of the crossover pool and the mutation pool are adopted to prevent the process from stalling at a local maximum. Combination of the multi-resolution strategy and adaptive parameters of GA accelerates convergence of the iterative process.

2. MI-based image registration

2.1. Mutual information

The mutual information of two random variables A and B is defined by

$$I(A,B) = \sum_{a,b} P_{A,B}(a,b) \log \frac{P_{A,B}(a,b)}{P_A(a) \cdot P_B(b)} \quad (2)$$

where $P_A(a)$ and $P_B(b)$ are the marginal probability mass functions and $P_{A,B}(a,b)$ is the joint probability mass function. MI measures the degree of dependence of A and B by measuring the distance between the joint distribution $P_{A,B}(a,b)$ and the distribution associated with the case of completely independence $P_A(a) \cdot P_B(b)$, by means of the relative entropy. MI is related to entropies by

$$I(A,B) = H(A) + H(B) - H(A,B) \quad (3)$$

The size of the overlapping part of the images influences the mutual information measure. Studholme et al proposed a normalized measure of mutual information [3], which is less sensitive to changes in overlap:

$$NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)} \quad (4)$$

The strength of the MI similarity measure lies in the fact that it is a general method without the need of image preprocessing; it depends merely on the existence of a statistical relation, hence posing less stringent demands on the relation between the images' gray values. To employ MI as a similarity measure, we need to utilize the concept of the two-dimensional (2-D) histogram of an image pair, namely, the joint histogram. A joint histogram is created by plotting (*a*, *b*) point for every pair of corresponding voxels. The joint probability mass function in the calculation of MI of an image pair can then be obtained by normalizing the joint histogram of the image pair as

$$P_{A,B}(a,b) = \frac{h(a,b)}{\sum_{a,b} h(a,b)} \quad (5)$$

When transforming points from one image to another, interpolation is usually required to estimate the gray values of the resulting points. A serious problem with interpolation is that it can cause artifacts in the registration function, which resulting in a pattern of local extreme and hampering the optimization process. Pluim et.al [4][5] examined the mechanisms resulting in the interpolation artifacts in detail. Because of the existence of local maxima, 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.

GAs have been known to be robust for search and optimization problems. Image registration can take advantage of the robustness of GAs to improve the chances of finding the global optimum of the registration function. At the same time, optimization strategy proposed in this paper is performed in a multi-resolution manner to accelerate the convergence of the iterative process. Here we employ the wavelet decomposition approach to construct an image pyramid. To decrease the sensitivity of the method to local maxima in the registration function and improve the local search ability of GA, adaptive sizes of the crossover pool and the mutation pool along with the resolution changes are presented.

2.2. Multi-resolution image registration

Multi-resolution is often used in search space and search data reduction techniques. The coarse-to-fine strategy has been used to improve the efficiency of many image-processing tasks [6], including image registration [7][8][9]. Employing this coarse-to-fine scheme has at least two advantages. The first one is the acceleration of the optimization process [9] and the second one is the increase in the range of transformations within which a specified similarity measure is a monotonic function of misregistration [7]. Using coarse-to-fine representation, the registration begins the search for a good input reference transformation at the coarse resolution image, which is usually compressed or reduced to smaller size than the original image. The search is then refined further and further using each of the finer images and moving towards the full resolution images. The same procedure is repeated until the finest level is reached.

The construction of the image pyramid is the core of multi-resolution optimization approach. Many image pyramid construction algorithms are proposed, including Burt's Laplacian pyramid [6], wavelet-based pyramid [9], cubic spline pyramid [10] and the pyramid obtained by down sampling the image [11].

In this paper, we employ the wavelet decomposition approach to construct an image pyramid because wavelet-based multi-resolution preserves most of the important features of the original data even at a low resolution. It also eliminates weak higher resolution features while highlighting strong image features.

3. Improved genetic algorithm for medical image registration

3.1. Genetic algorithms: concept and definitions

GA was formally introduced by John Holland and his colleagues [12]. GAs are computational models of natural evolution in which stronger individuals are more likely to be the winners in a competitive environment. Iterations of GA correspond to generations of evolution. A set of potential solutions, called a chromosome. The initial population is evaluated. In this process, each individual receives a fitness value determined by a user-defined fitness function which is generally a function of the decoded bits contained in each candidate's chromosome. These candidates will be selected for the reproduction in the next generation based on their fitness values. The selected candidates are combined using the genetic recombination operation "crossover". The crossover operator exchanges portions of bit strings for the next generation. The "mutation" is then applied to perturb the bits of the chromosome as to guarantee that the problem space is never zero. The whole population is evaluated again in the next generation and the process continues until it reaches the termination criteria. In recent years, GAs have been intensively investigated and applied to many optimization problems [13].

GA can be used to avoid process getting trapped in local optima and to achieve computation efficiency. They have been applied to image registration problems recently [14][15]. Dasgupta and MeCregor proposed a structured GA (sGA) for automatic registration of digital images [16]. The sGA lies primarily in its redundant genetic material and a gene activation mechanism. But none of the above mentioned GA-based image registration works can't completely solve the premature convergence problem resulted by the presence of multiple local optima. Moreover, they are all time-consuming because the data sets are very large.

In our work, taking advantages of the influence of the GA's parameters on optimization performance and the ability of multi-resolution strategy to reduce the search space, we make the sizes of crossover and mutation pool be tuned with the resolution changes in order to prevent the algorithm from becoming trapped on local optima and to reduce computation. The following subsection describes our algorithm.

3.2. GA-Based image registration in multi-resolution manner

In GAs, mutation is used to maintain genetic diversity from one generation of a population of chromosomes to the next. Accordingly, it can avoid local extrema of the process by preventing the population of chromosomes from becoming too similar to each other and slow or even stop evolution.

Using MI as the criterion of the registration problem, the existence of local maxima is the major difficulty which becomes even severe when the image sizes at the coarsest level are very small. The reason that the process stalling at a local maximum is that a locally optimal parameter vector enters into the replication pool and the population diversity is low thereby. GA can avoid process getting trapped in local optima. To increase the mutation pool is a reasonable remedy to maintain the variability of the chromosome. So, we adjust the mutation pool with the resolution changes to solve the problem. Meanwhile, the size of crossover pool is decreased correspondingly in order to maintain the elite population. The wavelet-based decomposition method is applied to create multi-resolution image representation in order to accelerate the process and reduce the search space.

We describe our algorithm of multi-resolution image registration based on GA and MI as Table 1:

Given two images to be registered, choose one as the floating image F and the other one as the reference image R. *Max-level* is denoted as the number of levels F and R will be decomposed. Furthermore, we define *cur_level* to indicate the current level at which the two image pyramids are $F\_decomposed$ and $R\_decomposed$ are the images of R and F after wavelet decomposition, respectively. *transT* is defined the transformation obtained at current level. β is a adjuster.

The two original images are decomposed using wavelet decomposition to produce multi-resolution images. General 3-D wavelet based multi-resolution pyramid decomposition procedure to obtain the image at a coarser level is summarized in Figure 1[17].
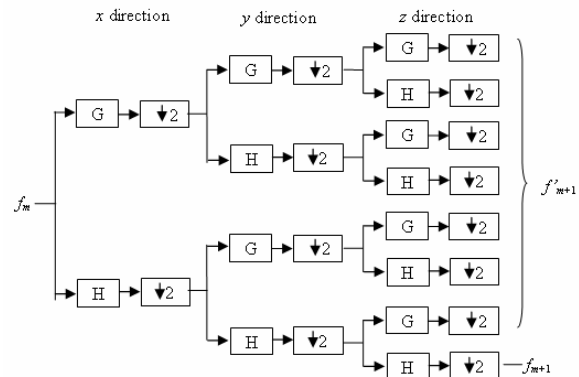

Figure 1. One level wavelet decomposition from resolution m to m+1

Table 1. The algorithm proposed in this paper

PROCEDURE: Image registration based on our method
Input: *F* and *R*
Output: *transT*[0]
BEGIN
/*Wavelet-based decomposition for *F* and *R*/
F_decomposed←wavelet_decomposed(*F*)
R_decomposed←wavelet_decomposed(*R*)
for *cur_level*←*Max_level*-1 to 0 do
/*Read the *R* and *F* at current level as input images*/
ReadImage (*F_decomposed* [*cur_level*]);
ReadImage(*R_decomposed* [*cur_level*]);
/*Compute the MI of the two input images at current level*/
mi←MICompute(*F_decomposed*[*cur_level*]),
R_decomposed[*cur_level*]);
/*Adjust the mutation pool and crossover pool according to cur_level */

mutation_operation← β /*cur_level*;

crossover_operation← β **cur_level*;

/*Use adaptive parameters of GA and the obtained transformation at previous level as the input parameters of the optimization procedure*/
transT[*cur_level*]←GA_Optimization(
mutation_operation,crossover_operation,
transT[*cur_level*+1]);
end
output *transT*[0];

END

As shown in Figure 1, the filtering is performed first by convolving the input image with H (low pass) and G (high pass) in the *x* direction. This is followed by down sampling each output along x direction. Then the two resulting images are further processed along the y direction followed by down sampling along the *y* direction. The same procedure is performed in the z direction. At the output, the source image at resolution level *m* is decomposed into eight subimages: an image at coarser resolution level *m*+1, the rest seven images contain detailed signal at resolution level *m*+1 in different direction. The filtering can be repeated by using the coarser resolution image as the input source image at the next level until the desired level is reached. We apply low pass filter H in *x*, *y* and *z* directions to obtain the whole pyramid.

The GA-based optimization initially searches from the level that contains smallest wavelet-compressed images toward the highest resolution wavelet-compressed images. For each level of multi-resolution, the best result found in the previous level is used as a center of the search.

In order to find a relationship between the resolution level m and the size of mutation and crossover pools, a

factor β is introduced. The size of mutation pool is increased by β. A larger number of new genes are introduced into the gene population. This process helps the algorithm to climb out from local maximum points and continue its search for the global optimum solution. At the same time, the size of the crossover pool is decreased by β along with the resolution level decreasing. The existence of local maxima is severe when images at coarser level, so the size of the mutation pool should be increased in order to maintain the population diversity and improve the capability with local search of GA. Determining the global search ability primarily, the size of the crossover pool should be decreased in order not to destroy the elite population pattern.

4. Experiment results

We consider the 3D brain image registration problem and apply our algorithms to this important application. Image volumes of CT, MR and PET modalities obtained from patients undergoing neurosurgery at Vanderbilt University as part of the project "Evaluation of Retrospective Image Registration"[18][19]. Five types of images, including CT, PET images and three types of MR images were used. MR images are MR_PD, MR_T1 and MR_T2 images. For the MR image volumes, two volume sets were available. They were volumes before and after image rectification, a technique used to correct MR images for static field inhomogeneity [20][21].

A practice data set provided by Vanderbilt University for which the gold standard was available to us, was used to perform our experiments. Figure 2 shows selected image slice of these three modalities. The size of each slice is [512×512] for CT images, [256×256] for MR images and [128×128] for PET images. The slice thickness for this data set is either 4mm (CT and non-rectified MR) or 8mm (PET).

Normalized mutual information defined in Eq (5) was employed as the similarity measure. In our experiments, number of generations, selection rules and mutation rules, we tested various setting of the GA parameters, such as population size, mutation and crossover probabilities, and others. Based on the convergence time and quality of the solutions, we then fixed the parameters. The value of β is select based on other parameters. We use nearest neighbor algorithm as the interpolation method.

For CT to MR registration task, both CT and MR image intensities are linearly binned into 256 gray levels. While for PET to MR registration task, we use 64 gray levels to represent each image volume because

of the relatively few samples available in PET images compared to CT images.
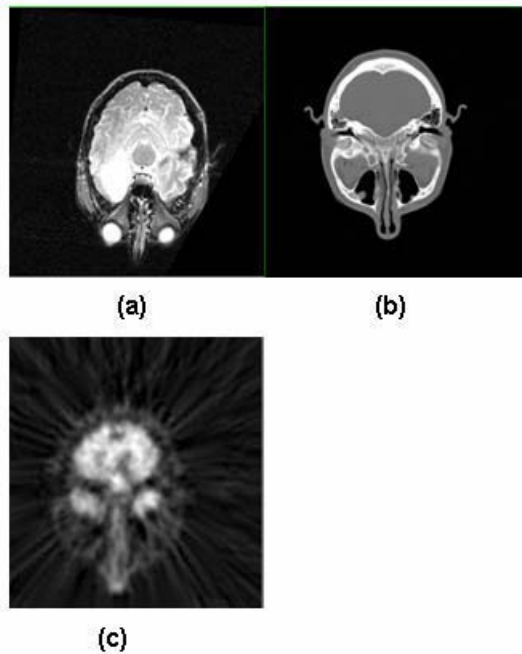

Figure 2. Images of different modalities used in the experiments. (a) The first slice of MR-PD image (b) The first slice of CT image (c) The first slice of PET image

Experiment results for CT to MR and PET to MR registrations are shown in Table 2 and Table 3, respectively. In each table, the first columns denote the maximal, minimal and mean errors compared with the gold standard.

We define the diagonal distance in a voxel to indicate the size of a voxel. For CT to MR registration, the size of a voxel is the diagonal distance in a MR image's voxel, shown at below:

$$\sqrt{1.25^2 + 1.25^2 + 4.0^2} \approx 4.373 \,(\text{mm})$$

And for PET to MR, the size of a voxel is the diagonal distance in a PET image's voxel, depicted as follows:

$$\sqrt{2.590723^2 + 2.590723^2 + 8.0^2} \approx 8.799 \,(\text{mm})$$

It is easily seen from the table 2 and table 3 that the registration errors are all less than the size of a voxel, so we conclude that applying our improved GA-based image registration in multi-resolution manner for two set of above images can obtain subvoxel registration accuracy. Figure 3 is the registration results of the CT to MR-PD.
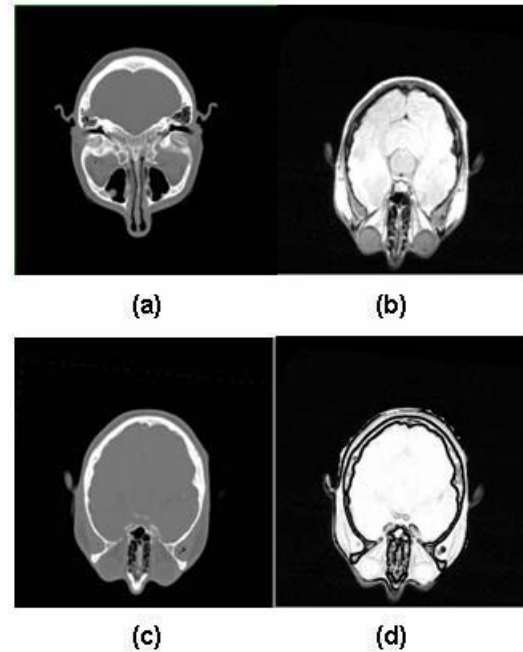

Figure 3. Results of matching CT and MR-PD images. (a) The first slice of CT image before Registration (b) The first slice of MR-PD image before Registration (c) The first slice of CT image after registration (d) The image which combines MR-PD with the boundary of the transformed CT image

As shown in Figure 3, the original distance between CT and MR-PD image is quite large in common world coordinate. After registration using the method proposed in this paper, they are aligned perfectly. For eyeballing test, we add the boundary of the transformed CT image to the MR-PD image, as shown in Figure 3(d). Perfect registration result is shown in the boundary.

Table 2. Registration errors for CT to MR

Error(mm)	CT_PD	CT_T1	CT_T2	CT_PDrf	CT_T1rf	CT_T2rf
maximum	2.8308	2.6826	2.8314	1.7890	1.7980	1.0320
minimum	0.0832	0.0523	0.9564	0.0756	0.0685	0.0876
mean	0.7652	0.6483	1.1087	0.5304	0.4632	0.7541

Table 3. Registration errors for PET to MR

Error(mm)	PET_PD	PET_T1	PET_T2	PET_PDrf	PET_T1rf	PET_T2rf
maximum	8.6869	7.1482	7.1680	6.2103	6.4620	6.0120
minimum	0.4068	0.2973	0.1985	0.1887	0.1864	0.2783
Mean	4.8652	3.1350	3.5327	3.2876	2.1039	3.0919

5. Conclusions and future works

In this paper, we have presented an efficient subvoxel MI-based image registration method combing an improved GA-based search technique with the multi-resolution wavelet image representation. To overcome the influence of the existence of local maxima using MI on the registration results, we adopted adaptive sizes of the crossover and mutation pool to improve the local search ability of GA. Experiments has showed our algorithm can yield good results.

The process using GA-based optimization is time-consuming, which has been alleviated in some sort by combing multi-resolution strategy. The challenges ahead lie in the field of how to accelerate the process substantially without accuracy loss.

Moreover, our experiment results have shown accuracy for the rigid transformation. Future research will consider using non-rigid transformation that takes into consideration distortion.

Acknowledgements

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