Elastic Medical Image Registration Based on Image Intensity

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Abstract

A two-step elastic medical image registration approach is proposed, which is based on the image intensity. In the first step, the global affine medical image registration is used to establish one-to-one mapping between the two images to be registered. After this first step, the images are registered up to small local elastic deformation. Then the mapped images are used as inputs in the second step, during which, the study image is modeled as elastic sheet by being divided into several subimages. Moving the individual subimage in the reference image, the local displacement vectors are found and the global elastic transformation is achieved by assimilating all of the local transformation into a continuous transformation. This algorithm has been tested on both simulated and tomographic images.

Keywords: image registration, medical imaging, elastic registration, affine transformation

1 Introduction

Medical imaging modalities can be divided into two major categories: anatomical and functional modalities. Anatomical modalities, depicting primarily morphology, include X-ray, CT, MRI, US etc. Functional modalities, depicting primarily information on the metabolism of the underlying anatomy, include SPECT, PET, which together make up the nuclear medicine imaging modalities. Since information gained from two images acquired in the clinical track of events is usually of a complementary nature, proper integration of useful data obtained from the separate images is often desired. The process of registration is a fundamental task in image processing which seeks to match two data sets, which may differ in such things as time of acquisition, image properties, or viewpoint [1][2][13]. Registration of both intra-subject and inter-subject images has been the subject of extensive study in medical imaging literatures. It is important for several reasons. Firstly, images obtained from different modalities can be superposed only after accurate registration. Visualization and quantitative analysis can be improved by such superposition. Secondly, atlas images accurately registered to patient data can be used for automatic identification of brain anatomy and for lesion location. Thirdly, image registration can assist in monitoring treatment by, for example, allowing accurate comparison of brain tumor size and location during treatment over time. Finally, it is hypothesized that proper statistical study of the morphology of both normal and diseased brains can be conducted only with good registration across diverse population.

Registration is the determination of a one-to-one transformation between two image spaces which maps each point of an image onto corresponding points of another image. Generally, the transformations can be divided into rigid and non-rigid transformations. The rigid methods can be used to cope with rotation and translation differences between the registered images. Specific problems arise due to differences in patient posture for different studies, possible differences in organ shape and volume (e.g., stomach and bladder content), so elastic or non-rigid methods are required to cope with local differences between the images. The elastic transformations are based on models from elasticity theory and describe local deformations. The central idea behind elastic registration is to consider images as continuous bodies and to model the geometric differences between images such that they have been caused by elastic deformation [9]. Principally, registration approaches can be distinguished into landmark-based and intensity-based schemes. Landmark-based schemes first extract landmarks (e.g., points, curves, surfaces) from images and then compute a transformation based on these features. With intensity-based schemes, the image intensities are directly exploited to compute the transformation.

The approach we propose in this paper has two main advantages over existing registration methods: firstly, it can cope with rigid deformation and local elastic deformation as well; secondly, on the basis of image intensities, the approach requires no human intervention.

2 Registration Method

Intensity-based approaches for elastic registration of medical images directly exploit the image intensities. The main advantage of these schemes is that an explicit segmentation of the images is not required. However, for global elastic transformation, the number of parameters to be optimized is generally too large to be feasible in practice. In this paper, we present the two-step registration approach based on raw image intensities.

2.1 First Step: Global Affine Registration

A global affine registration is used to initialize the robust voxel-to-voxel matching algorithm. The affine registration, even if not extremely accurate, is a good initial guess of the final registration.

2.1.1 Method

We use the rapid algorithm developed by Woods[4],[5] which calculates the ratio of one image to another at each voxel in the brain and then aligns the two images such that the variance of this ratio across all voxels is minimized. We register the two images using affine transformation which have nine degrees of freedom (three rotations, three translation and three scaling degrees of freedom) instead of rigid transformation which only has six degrees of freedom.

2.1.2 Optimization

This affine registration step is carried out using Powell's optimization method [6]. We assume that on the basis of such a global affine registration, the images are registered up to small local elastic deformation.

2.2 Second Step: Elastic Registration

In this step, the matched images are used as inputs and the study image is modeled as elastic sheet by being divided into equal size windows which number is less than the number of voxels. A local transformation is found in each individual window and the global elastic transformation is achieved by assimilating all of the local transformation into continuous transformation.

2.2.1 Method

The elastic registration is performed by the following procedures:

a. Finding the best position for individual study subimage

The study image is modeled as elastic sheet by being divided into some number (less than the number of voxels) of square windows. Optimizing the local similarity with the subimage of the reference image by moving the individual window on the reference image within a searching rang iteratively

b. The determination of local displacement field

Displacement vectors for each voxel in the individual subimage are determined by the position differences between the original and the new subimage voxels. Let V_i^t be the voxel position of subimage (window) *i* at iteration *t*. We use the transformation (in this paper, we limit it to translation) T^t to transform V_i^t into V_i^{t+1}.

$$V_i^{t+1} = T^t(V_i^t) \qquad (1)$$

The local displacement field in the window *i* is:

$$D_i = \{V_i^{t+1} - V_i^t\} = \{T^t(V_i^t) - V_i^t\} \qquad (2)$$

c. Global Elastic Transformation

The local displacement fields found are translated into global elastic transformation by cubic interpolation. The elastic registration is achieved by applying the global elastic transformation to the study image.

2.2.2 Criterion

Any automatic registration method requires an objective criterion whose role is to measure the similarity of the study image with respect to reference image. Suppose that I_{swi} (x,y,z) and I_{Rwi} (x,y,z) are the *ith* sumimages of study image and its corresponding same size neighbourhood in the reference image respectively. Taking a warping function *g*, we can get a warped version of the subimage of the study image.

$$I_{wswi}(x,y,z) = I_{swi}(g(x,y,z)) \qquad (3)$$

We want to find such a warping function *g* so that the warped subimages of study image are as close as possible to the corresponding subimages of the reference image, in the sense of sum squared distance (SSD):

$$E = \sum e^2 = \sum_{(x,y,z)\in I} \left(I_{wswi}(x,y,z) - I_{Rwi}(x,y,z)\right)^2 \qquad (4)$$

3 Experimental Results

In this section, some experimental results achieved by our two-step elastic approach will be presented. We carry out experiments using 2-D images

3.1 Registration of phantom images

The experiments are carried out by the following procedures:

(1) Designate a phantom image I_r as the reference image;

(2) Create the study image I_s by

a. Firstly, elastically deforming I_r using polynomial warping;

b. Secondly, rotating the image by θ=5;

c. Finally, translating the image by (dx,dy)=(5,5)

(3) Register the images using our algorithm.

Fig. 1a

Fig.1b

Fig.1c

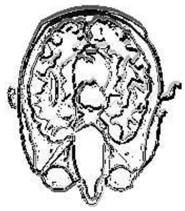

Fig.1d

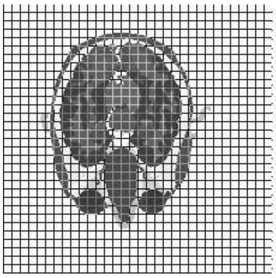

Fig.1e

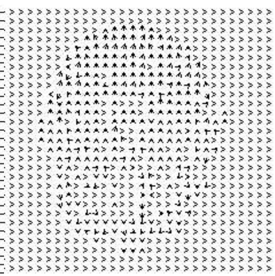

Fig.1f

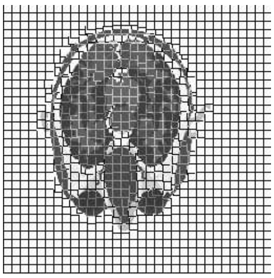

Fig.1g

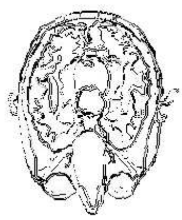

Fig.1h

Figure 1. Experiment of elastic registration of phantom images

Fig.1a and Fig.1b are the reference and study images respectively; Fig.1c is the difference between the two images; Fig.1d is the result of the first-step registration; Fig.1e is the study image after the affine transformation; Fig.1f is global displacement field; Fig.1g is the result of second-step registration with the registration deformation grid overlaid; Fig.1h is the difference between the two images after elastic registration

3.2 Experiments using MR image and artificial deformed MR image

In this series of experiments we adapt the experimental procedure slightly in the sense that I_r is now a MR image. The rest of the procedure as described in the previous experiment remains unaltered. We register the two images using windows of 4*4 pixels.

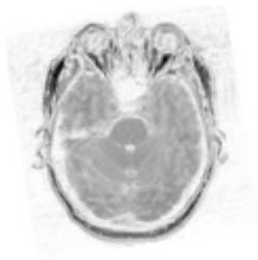

Fig.2a

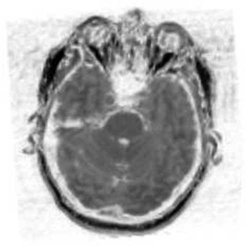

Fig.2b

Fig.2c

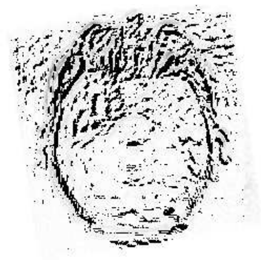

Fig.2d

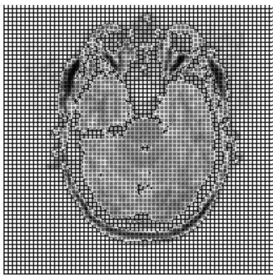

Fig.2e

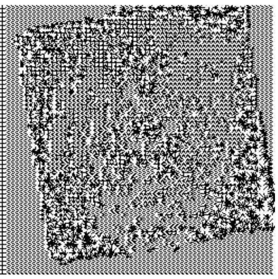

Fig.2f

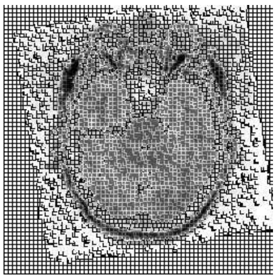

Fig.2g

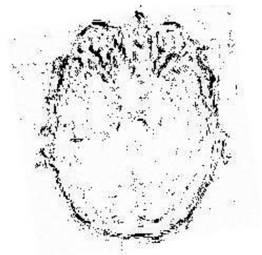

Fig.2h

Figure 2. Experiment of elastic registration of MR images

Fig.2a and Fig.2b are the reference and study images respectively; Fig.2c is the difference between the two images; Fig.2d is the result of the first-step registration; Fig.2e is the study image after the affine transformation; Fig.2f is global displacement field; Fig.2g is the result of second-step registration with the registration deformation grid overlaid; Fig.2h is the difference between the two images after elastic registration

4 Summary and Further work

We have described an elastic medical image registration algorithm where the images are firstly registered using global affine transformation and then through the second step, the local elastic deformations are matched.

We have implemented the algorithm and we have presented several experiment results involving synthetic images and medical images as well. The experimental results show that our algorithm has good performance in coping both rigid and local elastic deformations.

An attractive feature of this registration approach is that it can register the medical images with high performance. The other attractive feature is that it is an automatic algorithm, using the raw intensity as feature space, the algorithm need no human intervention and can perform registration automatically.

Further research will address the development of a more efficient elastic registration model which can register the more deformable organs images of liver, stomach and bladder.

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6 References

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