Novel Elastic Registration For 2-D Medical And Gel Protein Images

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Abstract

A novel elastic image registration approach is proposed, which can register both 2D medical images and gel electrophoresis automatically and accurately. Firstly, the global affine registration method based on image intensity is used to initialise a starting estimation of the robust registration algorithm. Then, by using iterative landmark based algorithm, the affine registration results are registered to further improve the accuracy in the second step, in which, the novel automatic landmark localization method is introduced and the thin-plate spline is used to refine the registration precision. Experimental results are presented for the registration of the 2D Phantom images and gel electrophoresis.

Keywords: Image registration, medical imaging, elastic registration, affine transformation, thin-plate spline, gel electrophoresis

1 Introduction

Image registration is widely used in biomedical imaging, which includes methods developed for automated image labeling and pathology detection in individuals and groups. Registration algorithms can encode patterns of anatomic variability in large human populations, and can use this information to create disease-specific, population-based brain atlases. They may fuse information from multiple imaging devices to correlate different measures of brain structure and function. Also, registration algorithms can even measure dynamic patterns of structural change during brain development, tumor growth, or degenerative disease processes. For more information, please refer to works of Van 1993, Maintz 1998.

Image registration is equally important to biological systems, e.g. in proteomic research, two-dimensional gel electrophoresis is an important tool for investigating differential patterns of qualitative and quantitative protein expression. The paradigm of protein profiles matching methods is usually divided into three steps: pre-processing; spot detection and pattern matching.

These matching algorithms often have drawbacks of high computational expense and low precision. There has a growing amount of interest in applying medical image registration in gel image processing, refer to papers of Dunn 2001 and Veeser 2001.

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. Principally, elastic registration approaches can be distinguished into intensity-based and landmark-based methods (Rohr 2000).

Intensity-based approach is one of the principal medical image registration methods. These kinds of approaches directly exploit the image raw intensities, for example, Kim 1997, Viola 1995. The main advantage of these schemes is that an explicit segmentation of the images is not required.

The other principal approach to registration of medical data is based on landmarks. The different landmarks can be classified into points, curves (lines), surfaces and volumes, Maurer 1993. One main advantage of using landmarks is that the transformation often can be stated in analytic form, which leads to efficient computational schemes. However, extracting labeled and corresponding landmarks from the two images is a difficult and time-consuming.

In this paper, we divide our automatic registration approach into two steps. During the first step, based on image intensity, the two images are registered rigidly and an initial guess of the final registration is provided. However, because of tissues' complicated deformations, the rigid registration method cannot provide registration results with adequate accuracy. So, during the second step, using thin-plate spline method, we register the images iteratively to solve non-rigid matching. By minimizing the bending energy, the corresponding landmarks selected automatically are forced to good match. We test our algorithm with both simulated medical image and gel electrophoresis.

2 Registration Method

2.1 Step One: Intensity-based Affine Image Registration

A global affine registration is used to initialize the robust pixel-to-pixel matching algorithm. Because of the rigid structure of the brain skull and also the not very large distortions introduced by imaging sensors, the affine registration, even if not extremely accurate, is a good initial guess of the final registration result.

We use the rapid registration algorithm developed by Woods in 1993 and 1998 as first-step registration method, and we carry out this affine registration using Powell's optimization method (Powell 1964).

We assume that on the basis of such a global affine registration, the images are registered up to small local elastic deformation.

2.2 Step Two: Landmark-based Elastic Image Registration

2.2.1 Thin-plate Spline (TPS) Approach

The use of thin-plate spline interpolation for registration purpose in medical imaging was first proposed by Bookstein in 1989. The main reason for choosing the thin-plate splines in our algorithm is because it can produce a smoothly interpolated spatial mapping.

2.2.2 Automatic Landmark Points Localization and Elastic Registration Using Iterative Algorithm

Usually, landmark points are localized manually or semi-automatically and the procedure of extracting corresponding landmarks from the two images is difficult. In our approach, iterative algorithm is used to localize the landmarks automatically and to refine the registration. The thin-plate spline (TPS) is used as elastic registration method and also helps in landmark localization. The sum of squared differences (SSD) is used to measure the quality of the registration and serves as the stopping criterion of the iteration.

2.2.3 Convergence Criterion

One of simply convergence criteria is the sum of squared differences (SSD) between the images, which exhibits a minimum in the case of perfect registration. In our experiments, if the similarity reducing ratio of each iteration is less than 1 percent then the algorithm will stop.

$$E = \sum e^2 = \sum_{(x,y)} (I_T(x,y) - I_S(x,y))^2$$

$$Similarity\ \mathrm{Re}ducingRatio = SSD_i / SSD_{i-1}$$

2.2.4 Algorithm Description

The registration algorithm is described as follows:

STEP 1: Intensity-Based Rigid Registration: Registration Initialization

STEP 2: Landmark-Based Elastic Registration Using TPS: Iterative Automatic Registration

1. The Reference Image Computation

The difference image between the template (T) and the corrected study (CS) serves as the reference image in the following steps.

2. Region-of-Interest (ROI) Definition

The zero regions imply that these regions in T and CS have been registered perfectly and will be neglected in the following registration iterations. The non-zero regions of the reference image are defined as Region-of-Interest (ROI).

3. Reference Landmarks Definition

In the reference image, some ROI boundary points are selected as reference landmarks: $L_R = \{(x_i, y_i) \mid (x_i, y_i) \in ROI \wedge i = 1, \cdots m+n\}$.

4. Landmark Localization in Template (T)

(1). Points in T, which have the same coordinates as the reference landmarks are selected as landmarks of T: $L_T = \{(x_i, y_i) \mid (x_i, y_i) \in L_R\}$, supposed to have m points in the set;

(2). Other n landmarks are searched in their corresponding 8-adjacent regions respectively and the closest to the reference landmarks are selected as landmarks:

$$L_{TA} = \left\{ \begin{array}{c} (x_j, y_j) \mid (x_j, y_j) \in 8-adjacent-regionof(x_p, y_p) \\ \wedge \text{closest to}(x_p, y_p)((x_p, y_p) \in L_R \wedge (x_p, y_p) \notin \mathrm{L_T}) \end{array} \right\},$$

with n points.

Landmark points of template image are $L_{TP} = L_T \cup L_{TA}$.

5. Landmark Localization in Corrected Study (CS)

(1). Points in CS, which have the same coordinates as the reference landmarks are selected as landmarks of CS: $L_{CS} = \{(x_i, y_i) \mid (x_i, y_i) \in L_R \wedge (x_i, y_i) \notin L_T\}$, assumed to have m points;

(2). Other m landmarks are searched in their corresponding 8-adjacent regions respectively and the closest to the reference landmarks are selected as landmarks:

$$L_{CSA} = \left\{ \begin{array}{c} (x_j, y_j) \mid (x_j, y_j) \in 8-adjacent-region\ of\ (x_q, y_q) \in L_R \\ \wedge \text{closest to } (x_q, y_q)((x_q, y_q) \in L_R \wedge (x_q, y_q) \notin L_{CS}) \end{array} \right\},$$

with n points.

Landmark points of corrected study image are $L_{CSP} = L_{CS} \cup L_{CSA}$.

6. Elastic Registration Using TPS

7. If the stopping criterion (SSD) is not met, Goto 1.

3 EXPERIMENTS

3.1 Experimental Data Preparation

We use both 2-D simulated medical images and gel electrophoresis as experimental data. The experiments are carried out by the following procedures:

(1) Designate an image I_r as the template image;

(2) Create the study image I_s by

Firstly, elastically deforming I_r using polynomial warping:

$$x' = a(x,y) = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij} x^j y^i$$

$$y' = b(x,y) = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} q_{ij} x^j y^i \ .$$

We set polynomial coefficients as p=[0,0,0.93,0] and q=[0,0,1.08,0] in our experiments and the non-zero coefficients represent stretching factors along x and y respectively.

Secondly, rotating the image by $\theta = 5^\circ$;

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

(3) Register the images using our algorithm.

3.2 Experiments Using Simulated Medical Images

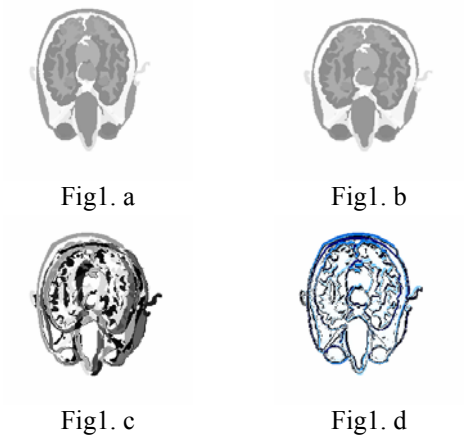

Fig1. a Fig1. b

Fig1. c Fig1. d

Figure 1: Intensity-based Affine Registration.

a and b are the template and study images respectively; c is the difference between the two images; d is the result of the first-step registration.

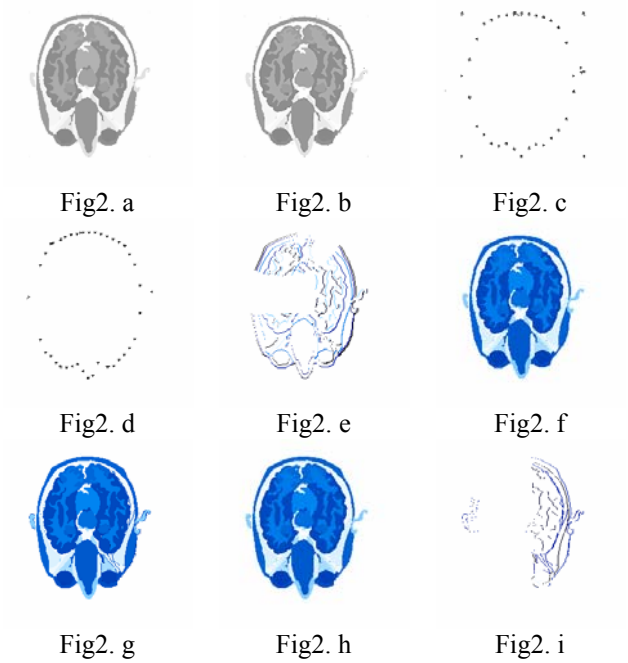

Fig2. a Fig2. b Fig2. c

Fig2. d Fig2. e Fig2. f

Fig2. g Fig2. h Fig2. i

Figure 2: Automatic Elastic Registration

a and g are the template images with landmark points (marked by black dots); b and h are the corrected study images with corresponding landmark points (marked by black dots); in c and d, the arrows show the displacements between the corresponding landmarks; e and i are the difference between the template and the corrected study images after registration iterations using TPS.

3.3 Experiments Using Gel Electrophoresis

The proposed registration algorithm is validated by using human cerebrospinal fluid (CSF) protein gel electrophoresis data.

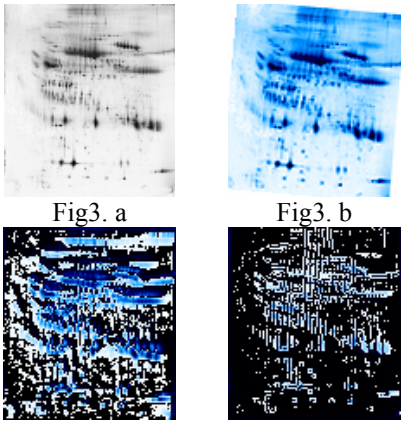

Fig3. a Fig3. b

Fig3. c Fig3. d

Figure 3: Intensity-based Affine Registration on Gel Electrophoresis

The first and the second column are the template and study images respectively; the third column is the difference between the two images; the fourth is the first-step registration result.

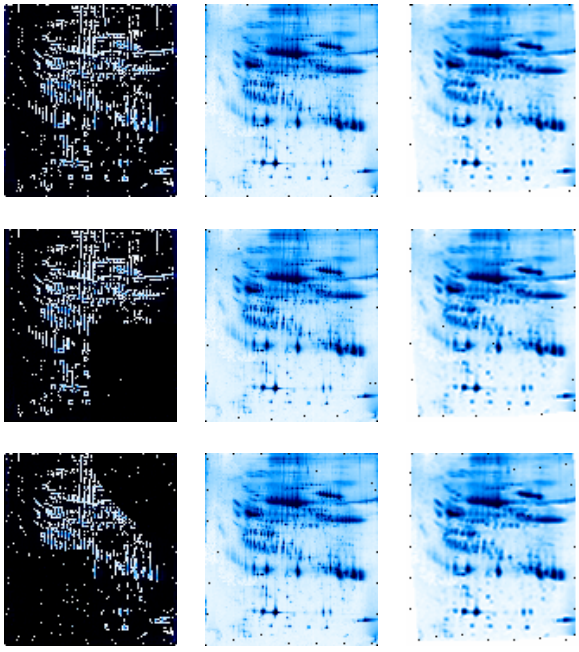

Figure 4: Gel Electrophoresis Registration with Automatic Landmark Localization.

The first column is ROI of the registration iterations; the second column is the template images with landmark

points (marked by black dots); the third column is the corrected study images with corresponding landmark points (the black dots).

4 Conclusions

We have described an elastic medical image registration algorithm where the images are firstly registered rigidly on the basis of images intensity and then through the second step, the elastic deformations are corrected iteratively based on landmark points that are localized automatically.

The algorithm has three attractive features. Firstly, by using both the raw intensity and landmark points as feature space, the registration approach can register the medical images with high performance. Secondly, it is a fully automatic registration algorithm. Thirdly, the algorithm provides a promising method for registering both medical images and gel electrophoresis and localizing landmarks automatically.

The algorithm has been validated by simulated data and two-dimensional gel electrophoresis. It has been demonstrated that the algorithm has high precision in coping with both rigid and elastic deformations and it is a potential resolution for clinical image registration and a promising tool for comparison and analysis of 2-D protein profiles.

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