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Deformation invariant attribute vector for deformable registration of longitudinal brain MR images

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ABSTRACT

This paper presents a novel approach to define deformation invariant attribute vector (DIAV) for each voxel in 3D brain image for the purpose of anatomic correspondence detection. The DIAV method is validated by using synthesized deformation in 3D brain MRI images. Both theoretic analysis and experimental studies demonstrate that the proposed DIAV is invariant to general nonlinear deformation. Moreover, our experimental results show that the DIAV is able to capture rich anatomic information around the voxels and exhibit strong discriminative ability. The DIAV has been integrated into a deformable registration algorithm for longitudinal brain MR images, and the results on both simulated and real brain images are provided to demonstrate the good performance of the proposed registration algorithm based on matching of DIAVs.

1. Introduction

Deformable registration of 3D brain images has been an important research area in the field of neuroimaging, and a variety of methods have been developed over the past two decades [1,3,4,6,7,9,10,12,14,26,28,34,35,41,42]. Based on registered brain images, one can perform group or individual analysis of neuroanatomic structures to assess differences in terms of age, gender, genetic background, and handedness, etc. [2,6,24,37], to define disease-specific signatures and detect individual cortical atrophy [36,39], to automatically label and visualize cortical structure [18], to map brain function [38,39,40], or to perform neurosurgical planning [15].

In general, 3D brain image registration methods fall into the following two broad categories: similarity-based methods and feature-based methods. In similarity-based methods, the registration is achieved by seeking to maximize the similarity between the template image and the reference image via a deformation model, which can be based on elastic, biomechanical, fluid, or parametric approach [12,26,42]. The general similarity measures for deformable image registration could be intensity [13], mutual information [16,23,32,41], or local frequency representation [45]. In feature-based methods, anatomical feature such as surface, landmark points, or ridge are first detected in two brain images [28,43], and then a spatial transformation is used to map correspondence features.

One central issue in deformable brain image registration algorithms is to develop morphological features for the detection of anatomic correspondences between the model image and the subject image. Recently, several methods for defining the attribute vector with rich geometric information have been proposed, such as moment-based method [28], wavelet-based method [43], and local spatial intensity histogram-based method [29]. In moment-based attribute vector method [28], MR brain images are first segmented into GM, WM, and CSF, and then the attribute vector of each voxel is extracted by computing the rotationally invariant moment feature in a spherical region for each tissue class. Since the moment-based attribute vector can be used to capture distinctive local anatomical information, it has been successfully applied to deformable volumetric MR brain image registration [28]. In the wavelet-based attribute vector method [43], the attribute vector is calculated from wavelet high-pass sub-images by applying the radial profiling method. The wavelet-based attribute vector then serves as the morphological signature for each voxel in deformable registration [43]. In the local spatial intensity histogram-based method [29], local spatial intensity histograms are first computed in a spherical region in each level of multi-resolution images and the attribute vector is then defined by calculating regular moment features. The local spatial intensity histogram is rotationally invariant and captures spatial information by integrating multi-resolution local histograms.

Although these above attribute vectors are translationally and rotationally invariant, the deformation between two longitudinal volumetric images is typically nonlinear. To address this problem,

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we propose a novel attribute vector that reflects the underlying anatomy and geometric information, while being deformation invariant. Deformation invariance means that the attribute vectors are the same, or very close, with the continuing homeomorphic deformation of 3D volumetric image. The deformation invariant attribute vector (DIAV) is very desirable in deformable registration of longitudinal brain images because: (1) the DIAV embodies rich geometric and intensity information of the voxel; (2) the similarity between DIAVs is a good indicator of anatomic correspondences, especially in longitudinal or time-series brain image data, as the corresponding anatomic landmarks will have similar morphological profiles; and (3) the DIAV represents the morphological signature of a specific voxel throughout the deformation procedure and thus reduces the ambiguity in anatomic correspondence detection.

Our work was particularly inspired by Ling and Jacob's method [20] for 2D image matching using geodesic intensity histogram (GIH), which is the intensity histogram of pixels extracted within a geodesic distance as deformation invariant local descriptor. We extended this work to the deformation invariant attribute vector in 3D brain images [19] and validated the method using synthesized deformations of 3D brain MR images. Our experimental studies show that the proposed DIAV achieves good deformation invariance. In addition, the DIAV embodies rich geometric and intensity information, and is quite distinctive to reduce the ambiguity in anatomic correspondence detection. Based on the matching of DIAV, a deformable registration algorithm has been developed for registration of longitudinal brain MR images. Experimental results on both simulated and real brain images are provided to demonstrate the performance of the proposed registration algorithm.

2. Method: deformation invariant attribute vector

2.1. Deformation invariant attribute for 2D images

This section briefly presents the basic idea of the method introduced by Ling and Jacobs for deformation invariant 2D image matching (please refer to [20] for more details). Motivated by the Beltrami framework [31], Ling and Jacobs treated a 2D intensity image as a surface embedded in 3D space, by assigning an aspect weight α to the intensity value as the third coordinate, and weighting the first two coordinates (x and y) by $1-\alpha$. As α increases, the image deformation has less influence on the geodesic distance, which is the distance of the shortest path between two points on the embedded surface. By taking the limit of α to 1, the geodesic distance becomes deformation invariant. In [20], the fast marching algorithm [27] is used to compute the geodesic distance on the embedded surface. The authors also did sampling in the geodesic distance support region (within certain geodesic level curves) to obtain deformation invariant neighborhood samples for interest points and then used a geodesic intensity histogram as deformation invariant local descriptors for 2D image matching by the χ^2 distance. This method is sound in theory and achieves promising matching results in practice.

2.2. Deformation invariant attribute for 3D images

In this subsection, we first extend the framework of deformation invariance in 2D space to 3D. Then, we design the deformation invariant attribute vector in 3D image using the geodesic intensity histogram.

2.2.1. 3D image embedded in 4D space

We treat a volumetric image as a 3D surface embedded in 4D space. Let $G(x,y,z)$ be a volumetric image defined as $G{:}R^3 \to [0,1]$. We consider the deformation as a homeomorphism between images [20], meaning that the mapping is one-to-one. Denote the embedding of an image $G(x,y,z)$ with aspect weight α as $\sigma(G;\alpha) = (x' = (1-\alpha)x, y' = (1-\alpha)y, z' = (1-\alpha)z, g' = \alpha G(x,y,z)$. Let γ be a regular curve on σ, and parameter $p \in [p_1,p_2]$ (p_1 and p_2 are the boundary points). Then we have:

$$\begin{aligned}\gamma &= (x'(p), y'(p), z'(p), g'(p)) \\ &= ((1-\alpha)x(p), (1-\alpha)y(p), (1-\alpha)z(p), \alpha G(x(p), y(p), z(p)))\end{aligned} \tag{1}$$

The length of curve γ is computed as

$$\begin{aligned}s &= \int_{p_1}^{p_2} |r'(p)| dp \\ &= \int_{p_1}^{p_2} \sqrt{{x'_p}^2 + {y'_p}^2 + {z'_p}^2 + {g'_p}^2}\, dp \\ &= \int_{p_2}^{p_1} \sqrt{(1-\alpha)^2 {x_p}^2 + (1-\alpha)^2 {y_p}^2 + (1-\alpha)^2 {z_p}^2 + \alpha^2 {G_p}^2}\, dp\end{aligned} \tag{2}$$

Take the limit of α to 1:

$$\lim_{\alpha \to 1} s = \int_{p_1}^{p_2} |G_p| dp \tag{3}$$

In the above formulas, the subscript p denotes partial derivative, e.g., $x_p = dx/dp$, $G_p = dG/dp$. From Eq. (2), it is apparent that when α is large (e.g., approaching 1), it is the intensity change (represented by G_p) that dominates the length (s) of the curve γ. When taking the limit of α to 1, it is obvious that the curve length only relies on the intensity of volumetric image G, which indicates that the curve length (s) achieves deformation invariance when $\alpha \to 1$.

2.2.2. Geodesic distance in 3D image

As shown above, the geodesic distance between two points, which is the shortest path between them on the embedded surface, is deformation invariant when α approaches 1. Given an interest point $p(x,y,z)$ in 3D image, the geodesic distance from it to the other points on the embedded surface $\sigma(I;\alpha)$ can be computed using the fast marching algorithm [27]. The fast marching method was developed to effectively solve the problem of front propagation, involving computing a new position of an initial curve when a force F is applied. A function T denotes the time when the curve reaches a position, and the Eikonal equation governs the curve propagation:

$$|\nabla T| F = 1 \tag{4}$$

where ∇T is the gradient of T. In our application, we use the extended fast marching method in 3D image in [8]. To compute the geodesic distance, the parameter T in the Eq. (4) is set as the geodesic distance, and the marching speed F is set to:

$$F = \frac{1}{\sqrt{(1-\alpha)^2 + \alpha^2 G_x^2 + \alpha^2 G_y^2 + \alpha^2 G_z^2}} \tag{5}$$

where the subscripts (x, y and z) denote partial derivatives. Fig. 1 shows a color-coded geodesic distance map from a selected voxel (marked with a red cross) to other voxels in a volumetric MR brain image. Here, the red color indicates small geodesic distance, while blue color indicates large geodesic distance. For convenient visual inspection, we only show selected 2D orthogonal slices. In the example, α is set to be 0.98. Evidently, the geodesic distance in 3D image can be used to capture the geometry of image intensities.

2.2.3. Deformation invariant attribute vector

As both the geodesic distance (when $\alpha \to 1$) and intensity are deformation invariant, we can use geodesic distance histogram to define deformation invariant attribute vector (DIAV). Given an interest voxel p, along with neighboring voxels in the geodesic