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Automatic deformable surface registration for medical applications by radial basis function-based robust point-matching

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ABSTRACT

Deformable surface mesh registration is a useful technique for various medical applications, such as intra-operative treatment guidance and intra- or inter-patient study. In this paper, we propose an automatic deformable mesh registration technique. The proposed method iteratively deforms a source mesh to a target mesh without manual feature extraction. Each iteration of the registration consists of two steps, automatic correspondence finding using robust point-matching (RPM) and local deformation using a radial basis function (RBF). The proposed RBF-based RPM algorithm solves the interlocking problems of correspondence and deformation using a deterministic annealing framework with fuzzy correspondence and RBF interpolation. Simulation tests showed promising results, with the average deviations decreasing by factors of 21.2 and 11.9, respectively. In the human model test, the average deviation decreased from 1.72 ± 1.88 mm to 0.57 ± 0.66 mm. We demonstrate the effectiveness of the proposed method by presenting some medical applications.

1. Introduction

1.1. Background

Image registration has been an essential technique in medical applications including multi-modality image registration for diagnosis or planning, statistical analysis for population study, in-room surgery/treatment guidance, and intra- or inter-patient study [1,2]. With the extensive use of multi-modal imaging and new treatment techniques, the requirement for a robust registration algorithm for comparing or fusing images representing the same structures obtained under different conditions or modalities is ever increasing. Medical image registration has long been classified as rigid or affine; however, deformable transformation is now available as an alternative method for improving registration accuracy. Deformable (or non-rigid) registration is comparatively more complicated and involves modeling the local distortion in addition to translation, rotation, and scaling. According to the type of data, deformable registration is categorized into volumetric or surface. Volumetric registration uses the voxel information of volume images. Many approaches have been actively investigated, including mutual information (MI) [3], free-form deformation (FFD) based on B-spline [4,5], and Demon deformable registration [6,7]. Deformable surface registration (DSR) registers two surface meshes consisting of point and triangular elements. Non-rigid point registration is a well-known method in this category for registering two point sets [8,9]. Many DSR approaches have been proposed robust high-speed automatic DSR has been difficult to achieve. Typically, the user must define the corresponding point sets manually; this is a tedious and time-consuming task, because it requires exploring and defining the fiducial points in 3D repeatedly. Automatic methods have been unstable or slow, with runtimes of tens of minutes for thousands of input points.

To overcome these difficulties, we propose a robust and fast technique for automatic DSR. The proposed method automatically determines the corresponding points and local transformations in a deterministic annealing framework. Every registration iteration consists of two steps, automatic correspondence finding and local deformation. Unlike previous methods, we use radial basis function (RBF) interpolation [10] for local deformation, which yields fast and stable solutions. We evaluate the accuracy and performance of the proposed method using synthetic simulation tests. The sample applications presented in this paper demonstrate the robustness and versatility of the proposed method, which enable its use in other medical fields such as patient setup for surgery or

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radiotherapy (RT) using 3D optical scanning, modification of radiotherapy planning, and patient-specific modeling.

1.2. Related work

Various algorithms exist for non-rigid point set registration. In this section, we present an overview of the non-rigid registration methods and identify our motivation. Li et al. presented a template-based deformable registration by large-scale and fine-scale process [11]; however, their method requires a template model focusing only on single-view systems. Bonarrigo et al. proposed a non-rigid registration of partially overlapping surfaces from a deforming model by nonlinear physics-inspired deformation, with a computation time of 10 min for 9600 points [12]. Recently, Myronenko and Song proposed a probabilistic method, Coherent Point Drift (CPD), for both rigid and non-rigid point set registration [13]. They demonstrated promising results. However, naive CPD is rather slow, and it is not obvious that their fast implementation of non-rigid CPD outperforms the other methods. CPD originated from a registration method using Gaussian mixture models [14].

Robust point-matching (RPM) accepts two point sets as input and iteratively calculates the correspondence between the sets and transformation that registers them. Rather than assigning a one-to-one mapping for every pair of points, the correspondence is obtained in RPM using soft assignment in fuzzy logic [15]. Chui and Rangarajan developed thin-plate spline-based RPM (TPS-RPM) for non-rigid mapping, which yielded better results than rigid deformation did [16]. Li et al. investigated an automatic non-rigid registration for whole body CT mice images [8]. Their method used skeletons for correspondence through RPM, and an intensity-based algorithm refined the transformation with spatial adaptation of the transformation's stiffness and RBF interpolation. However, the method involves volumetric registration, and they reported an average running time of 171 min for mice skeleton studies. Wang and Fei [9] proposed non-rigid B-spline-based point-matching (BPM), which combines B-spline-based local deformation with an RPM framework. They argued that compared to TPS-RPM, BPM could decrease the degrees-of-freedom from thousands of parameters to a small number of B-spline coefficients. However, despite demonstrating acceptable results, BPM remains computationally slow, with a reported average computing time of 45 min for input surfaces with 4500 points. Other approaches to B-spline-based free-form deformation for volumetric registration include using Xie and Farin's hierarchical B-Splines [17], and more can be found in [4]. For robust and efficient surface deformation, RBF interpolation [10] can also be used. Its scale-independent characterization is well suited for reconstructing surfaces from non-uniformly sampled data. This analogy is perfectly applicable to our problem of local deformation from corresponding points of two input surfaces. We thus propose an RBF-based RPM to utilize these advantages to their fullest for yielding an efficient automatic DSR algorithm.

2. Methods

2.1. Deformable registration framework

Given two point sets of a source surface $\boldsymbol{S}$:{s_i, i=1, 2, …, n_s} and a target surface $\boldsymbol{T}$:{t_j, j=1, 2, …, n_t}, the deformable registration problem is to determine an optimal spatial transformation $\boldsymbol{f}$ that deforms $\boldsymbol{S}$ to fit $\boldsymbol{T}$. In general, s_i and t_j represent the spatial coordinates of the surface points in 3D, and $\boldsymbol{f}(s_i)$ is the coordinates of $\boldsymbol{S}$ that result from the deformable registration while preserving the topology. First, rigid transformation for global transformation $\boldsymbol{f}_{global}$ is calculated to provide suitable initial conditions for the local transformation $\boldsymbol{f}_{local}$. To obtain $\boldsymbol{f}_{global}$, we use point-to-plane iterative closest points (ICP) [18,19], a widely used rigid transformation method. If the initial postures of $\boldsymbol{S}$ and $\boldsymbol{T}$ are considerably different, three pairs of corresponding points are required by the user input before applying ICP. ICP solves the optimization problem that minimizes the following error function.

$$E = \sum \left[(Rs_i + q - s_i')\cdot n_i \right]^2 \quad (1)$$

where s_i, s_i', R, q, and n_i are the source points, s_i's projected points onto $\boldsymbol{T}$ with the direction of n_i, rotation matrix, translation vector, and s_i's normal vector, respectively.

After $\boldsymbol{f}_{global}$ roughly aligns $\boldsymbol{S}$ to $\boldsymbol{T}$, a local transformation $\boldsymbol{f}_{local}$ is computed to change the local shape to minimize the deviations between $\boldsymbol{f}_{global}(\boldsymbol{S})$ and $\boldsymbol{T}$. For robust and fast computation of $\boldsymbol{f}_{local}$, we propose an RBF-based RPM, with each iteration consisting of two steps: automatic correspondence finding and RBF deformation. The framework solves the interlocking optimization problems of the correspondence and the local transformation under the deterministic annealing scheme. Fig. 1 shows the deformable registration framework algorithm. In the deterministic annealing procedure, the algorithm searches for correspondences with a wide range in the beginning stages, while covering only the local range at the end. The parameter κ specifies the deterministic annealing temperature, which we determined to be reduced linearly by $\kappa_{n+1} = 0.90\kappa_n$. The temperature parameter κ weights the fuzziness regarding the distance in the cost function. We set the initial value of κ as $\kappa_0 = 0.5$, as suggested by Chui and Rangarajan [16], although κ_0 values did not significantly affect the results in the experiments. When the deformation results converge at a specified level (if the deviation change is below a threshold between successive iterations), we terminate the annealing procedure.

```
Prepare the source and target surface point sets
Compute the global transformation f_global by iterative closest points
Initialize the temperature parameter κ_0=0.5
Repeat iterations until the convergence below a threshold difference
   Update the correspondence matrix M
   Compute the local deformation f_local by RBF and the correspondence
   Decrease κ_{n+1}=0.9·κ_n
```

Fig. 1. Pseudocode of RBF-based robust point-matching algorithm.

2.2. Automatic correspondence finding

Automatic correspondence finding has been a popular topic in character recognition and pattern matching [15]. A key RPM characteristic is that the correspondence is obtained by soft-assignment, rather than one-to-one mapping [8,9,15]. A point s_i of $\boldsymbol{S}$ relates to the points of $\boldsymbol{T}$ with a fuzzy ratio m_{ij},

$$m_{ij} = \frac{1}{\kappa} e^{-\frac{\|t_j - f(s_i)\|^2}{2\kappa}} \quad (2)$$

for i=1, 2, …, n_s, and j=1, 2,…, n_t. The correspondence of $\boldsymbol{S}$ and $\boldsymbol{T}$ is obtained using a fuzzy matrix $\boldsymbol{M}$={m_{ij}}. $\boldsymbol{M}$ is more fuzzy at the beginning with larger κ, and the fuzziness decreases with smaller κ at the end of the deterministic annealing process. To reject the outliners, we define a point as a outlier if the point's distance to any point in the other surface is larger than $3\sqrt{\kappa}$ in the extra row and column (i=n_s+1, j=n_t+1) of $\boldsymbol{M}$ [9,15]. The target point $\bar{t}_i$ on $\boldsymbol{T}$ corresponding to a source point s_i on $\boldsymbol{S}$ is computed as follows.

$$\bar{t}_i = \sum_{j=1}^{n_t} m_{ij} t_j \bigg/ \sum_{j=1}^{n_t} m_{ij} \quad (3)$$