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Direct point-based registration for precise non-rigid surface matching using Student's-t mixture model

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ABSTRACT

One of the main challenges in the non-rigid surface matching is to match complex surfaces with absence of salient landmarks (marker-less) and salient structures (structure-less). We propose an accurate non-rigid surface registration method, called DSMM, to match complex surfaces based on a dense point-to-point correspondence alignment. The key idea of our approach is to model the correspondences on surfaces by using Student's-t mixture model and represent local spatial structures via Dirichlet distribution and the directional springs. Firstly, we formulate the problem of alignment of two point sets as a probability density estimate, modeling one set as Student's-t mixture model centroids, and the other one as observation data. We subsequently incorporate spatial representations of vertices on the surfaces into the prior probability of the finite Student's-t mixture model by exploiting the Dirichlet distribution and Dirichlet law. We later explicitly add an additional structure regularization to get an approximate isometric and near-conformal transformation. Finally, we obtain closed-form solutions of registration parameters using Expectation Maximization (EM) framework, leading to a computationally efficient registration method. We compare DSMM with other state-of-the-art direct point-based non-rigid surface matching methods based on finite mixture models on artificial shapes with large deformation and real complex shapes from various segmented brain structures. DSMM demonstrates its statistical accuracy and robustness, outperforming the competing

1. Introduction

Surface matching is a key component in many computer vision applications, such as medical image registration, image analysis, computer graphics, and shape matching. Complex surfaces, such as large deformation, missing correspondences, and absence of salient landmarks or features (structures), lead to great challenges for precise and robust surface matching in the medical applications. The general idea of surface registration is to estimate a mapping T from IR^D to IR^D, which yields the best transformation between correspondences. However, searching for the dense correspondences encounters several challenges:

1. Absence of landmarks (marker-less): The main advantages of landmarks are that they can easily identify the correspondences between surfaces and reduce the search-space for possible correspondences. However, surface matching of interest tissues usually does not present salient regions, locations, or reliable landmarks.
2. Absence of structures (structure-less): Surfaces of interest tissues usually do not present a clear structure that can be used as reliable markers. Matching of surfaces without a clear structure is a more complex problem, as it is difficult to establish a straightforward map between structure-less surfaces.
3. Large deformation: The interest tissues usually undergo large and complex deformation due to respiratory motion, surgical intervention, or lesion. In this case, the spatial configurations of surfaces are significantly different, leading to a grand challenge for searching precise correspondences between surfaces with highly convoluted warp.

As a consequence of absence of salient landmarks, prominent structures (or features), large deformation, and missing correspondences, an ideal surface matching method should have an ability to handle these degenerations. Fig. 1 intuitively demonstrates a great challenge for surface registration methods to match the near-plane surfaces (marker-less and structure-less simultaneously).

Direct point-based surface matching methods consider the locations of vertices as available signatures for identifying the

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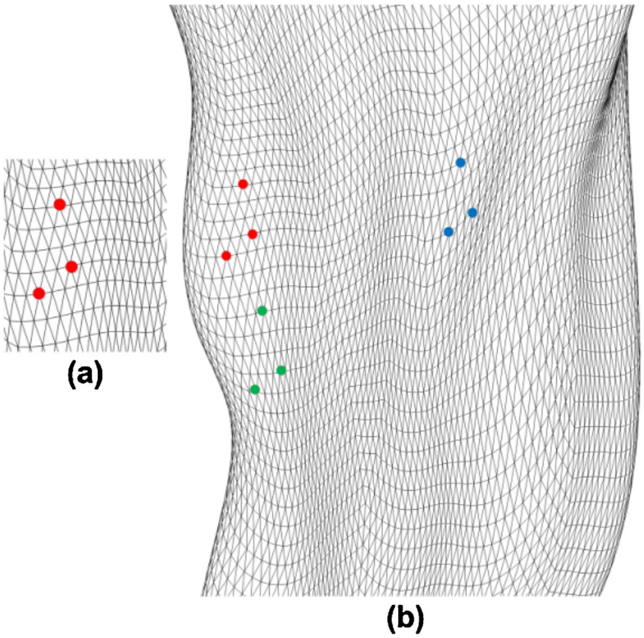

Fig. 1. Several point configurations on a near-plane surface region. (a) Points on a sub-mesh, (b) point sets with same configurations on a full mesh. Point configurations on the nearly plane surface (the full mesh shown in subfigure (b) have exactly same geodesic distances to each other. The red points on the sub-mesh should be aligned to the red ones on the full mesh. However, the red points on the sub-mesh could be possibly aligned to the blue ones or the green ones due to the matching methods only utilize the geodesic distance between the points on the near-plane surface. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

correspondences. A vertex on the template surface is mapped to the corresponding one by computing the geodesic distance in the feature space. The main advantage of the direct point-based registration approach is its fast implementation and adequate flexibility for incorporating various features to drive the warp. However, the deformation of direct point-based surface registration methods is driven by locations of vertices, completely ignoring spatial structures of the surface. The most popular direct point-based registration method is the well-known Iterative Closest Point (ICP) methods [1] and its variety [2,3] due to their low computation complexity. Instead of aligning a one-to-one correspondence based on a closest distance criterion, Robust Point Matching (RPM) [4] alternatively estimates soft-assignment of correspondences and transformation, leading to allow for fuzzy correspondences. Chui et al. [5] proposed TPS-RPM method, which used Thin-Plate-Spline (TPS) to re-parameterize the transformation. Tsin and Kanade [6] proposed a kernel-correlation-based point set registration method, considering the non-rigid point set registration as an alignment between two distributions. Myronenko et al. [7] later proposed Coherent Point Drift (CPD) algorithm, which enforced points drift coherently by regularizing the transformation following the Motion Coherence Theory (MCT) [8,9]. Jian and Vemuri [10] modeled both point sets using Gaussian mixture model (GMM) and introduced a general robust framework involving the minimization of the L_2 distance between two Gaussian mixtures.

Several other methods are introduced to match two surfaces by using graph spectrum to estimate the mapping on the spectrum coordinates. The graph spectrum is introduced as a subset of Laplacian eigenvalues and eigenvectors. Graph spectrum is a core to incorporate a transformation regularization due to the fact that the low frequency eigenvectors, corresponding to the small eigenvalues, represents low frequency harmonics [11]. Spectral methods have been used in many applications, such as segmentation [12], shape registration [13], hierarchical structures [14], data cluster [15], and anatomical structure studies for cortical folds [16–18]. Umeyama [19], Scottand and Longuet-Higgins [20] proposed spectral methods for the correspondence problems. Unfortunately, the spectral correspondence methods usually begin with a rigid eigenvector alignment to account for translating and scaling the spectral coordinates [21], which needs an additional robust non-rigid point set registration to precisely find correspondences on spectral coordinates.

In this paper, we focus on the surface matching model which is a key problem in non-rigid surface registration. We introduce a direct point-based non-rigid surface registration approach, which considers each vertex on the surface as characteristic signatures, modeling one vertex set as s finite mixture model centroids, and the other set as data set. Subsequently, we incorporate smoothness of the warp by using transformation regularization and structure regularization of the template surface, leading to an ability to handle complex surfaces and an approximate isometric and near-conformal matching.

The rest of this paper is organized as follows. We firstly propose our hybrid energy function containing similarity, transformation regularization, and structure regularization in Subsection 2.1. We also present the main idea of the Student's-t mixture model (SMM) and the local structure representation by using the Dirichlet distribution for matching surfaces and introduce the implementation details of our method in the rest subsections of Section 2. Section 3 contains some quantitative evaluations on various tissues in brain for neuroimaging application. Finally, we present a discussion and conclusion in Section 4.

2. Proposed method

2.1. General methodology

We assume that we have a target surface $S^1 = \{X, \Xi^X\}$ and a template surface $S^2 = \{Y, \Xi^Y\}$, where $X = (x_1, \ldots, x_N)^T$ and $Y = (y_1, \ldots, y_M)^T$ denote vertices on the given surfaces; Ξ^X and Ξ^Y denote the undirected edge sets. The general methodology of surface registration is to estimate a mapping $T: S^1 \to S^2$, which yields the best transformation between two surfaces. A perfect mapping should satisfy the following properties which are proposed in [22]:

(1) Similarity: $T(Y)$ should align the corresponding vertices on the template surface to point y_m ($y_m \in Y$) on the target surface;
(2) Transformation regularization: T should represent a plausible deformation of the surface;
(3) Structure regularization: $T(S)$ should be as structurally similar to S as possible, meaning that $T(S)$ should distort the surface S as little as possible.

The property (1) indicates that the transformation T should accurately align the corresponding points (vertices) between two surfaces. The property (2) incorporates some spatial regularization for surface registration, such as the smoothness of transformation, which can enforce the points drift coherently [7] and leads to a sound transformation. The property (3) states that the transformation should attempt to keep the structure similarity between the original surface and the transformed surface. In order to synchronously satisfy the introduced properties, we consequently introduce a hybrid energy function consisting of three terms

$$E(T) = E_{\mathrm{sim}}(T) + \frac{\lambda_1}{2} E_{\mathrm{trans}}(T) + \frac{\lambda_2}{2} E_{\mathrm{str}}(T) \quad (1)$$

E_{sim} measures the geodesic distance between corresponding points of the target surface and the template surface, and drives the warp of the template surface. The regularization $E_{\mathrm{trans}}(T)$ incorporates some spatial constraints to enforce the smoothness of the