Morphometric Analysis of 3D Surfaces: Application to Hippocampal Shape in Mild Cognitive Impairment

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Abstract

A computational framework is presented for morphometric analysis of 3D surfaces that aims to localize regionally specific shape changes between groups of 3D objects. This framework integrates a set of powerful surface modeling and processing techniques, including the spherical harmonics (SPHARM) description for surface modeling, a quaternion-based method for 3D shape registration, heat kernel smoothing for increasing surface signal-to-noise ratio, and random fields theory for statistical inference on the surface. The effectiveness of this framework is demonstrated in a computational neuroscience application for identifying hippocampal shape changes in Mild Cognitive Impairment (MCI).

Keywords: Shape analysis, surface modeling, heat kernel smoothing, Gaussian random fields.

1. Introduction

Statistical morphometric analysis is an important and challenging problem in computer vision and medical image analysis. In the brain imaging domain, the goal is to identify morphometric abnormalities in structures of interest that are associated with a particular condition to aid diagnosis and treatment. We present a computational technique for morphometric analysis of 3D surfaces to localize regionally specific shape changes between groups of 3D objects, and demonstrate the technique in a computational neuroscience application: identifying hippocampal shape changes in Mild Cognitive Impairment (MCI).

MCI [7] is characterized by memory complaints and impairment in the absence of dementia and confers a high risk for Alzheimer's disease (AD). Identifying hippocampal morphological abnormalities, in circuits required for learning and memory, may be critical for early diagnosis and treatment of MCI and AD. Volumetric analysis can identify hippocampal atrophy in MCI [7], but does not localize the structural changes. Shape analysis has the potential to provide important information above and beyond simple volume measurements and may localize regionally specific structural changes in the absence of volume differences. This study performs hippocampal shape analysis aiming at a global and local quantitative representation of shape changes in MCI.

Two issues are involved in this type of analyses: (1) how to describe a 3D shape; and (2) how to perform statistical analysis based on the shape description. The spherical harmonics (SPHARM) technique [1] is a parametric surface description using spherical harmonics as basis functions. It is suitable for surface comparison [8] and can deal with arbitrarily shaped but simply connected objects. We employ the SPHARM description to model a 3D shape and then derive a dual landmark representation. Multiple correlated statistical tests can then be performed directly on each surface landmark but require a correction scheme. One scheme proposed by Styner and Gerig [10] is to decompose 3D surfaces into planar images and then use the SnPM package [6] to analyze them.

To avoid using surface flattening that distorts the inherent surface geometry, we employ Chung's approach [2, 3, 4] to perform statistical inference directly on a surface manifold. Thus, our framework is an integration of the following powerful techniques: the SPHARM description for surface modeling, a quaternion-based method for 3D shape registration, heat kernel smoothing for increasing surface signal-to-noise ratio, and random fields theory for statistical inference on the surface.

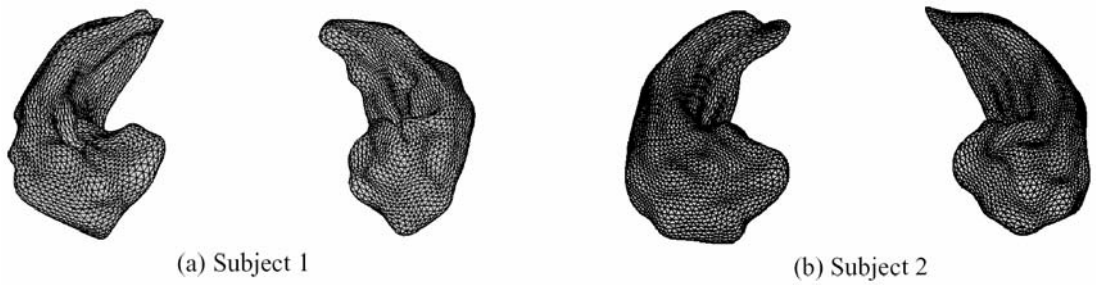

Fig. 1: Landmark representation for hippocampal shapes: mesh vertices are landmarks. These surfaces are reconstructed using the SPHARM description and aligned using a quaternion-based registration algorithm.

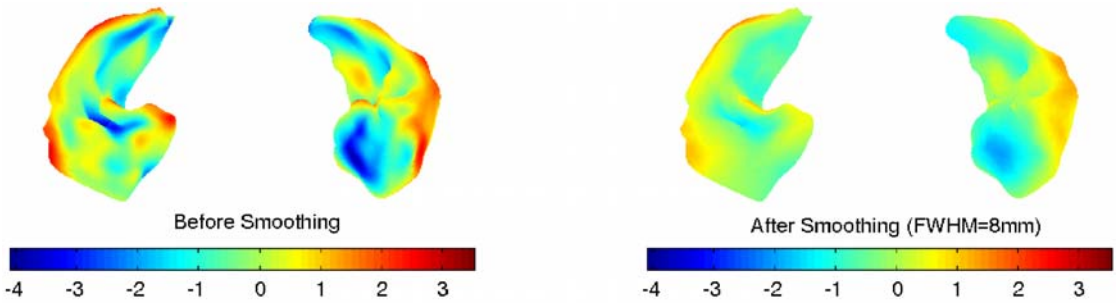

Fig. 2: Heat kernel smoothing: (left) the initial signal is mapped on to the surface; (right) the signal is smoothed using a heat kernel of FWHM = 8mm. Our scaling scheme forces the mean shape to have a total volume of 6780 mm^3.

2. Methods

This section describes our data set as well as surface modeling and statistical analysis approaches.

2.1. Hippocampal Data

Participants are 40 adults with amnestic MCI (age 72.5 ± 3.3), 40 adults with cognitive complaints (CC) but no impairment (72.6 ± 2.6), and 42 normal controls (CN) (70.8 ± 2.6). MRI scan data were acquired on a 1.5 Tesla GE scanner as a T1-weighted SPGR coronal series. The hippocampi were segmented using the BRAINS software [5]. A 3D binary image of isotropic voxels is reconstructed from each set of 2D hippocampal segmentation results.

2.2. Surface Modeling

The SPHARM description [1] is used for modeling all the hippocampal surfaces. The first step is to create a continuous and uniform mapping from the object surface to the surface of a unit sphere. This step is formulated as a constrained optimization problem with the goals of topology and area preservation and distortion minimization. The result is a bijective mapping between each point v on the surface and a pair of spherical coordinates θ and ϕ:

$$v(\theta,\phi) = (x(\theta,\phi), y(\theta,\phi), z(\theta,\phi))^T .$$

Now the object surface can be expanded into a complete set of spherical harmonic basis functions $Y_l^m(\theta,\phi)$, where $Y_l^m(\theta,\phi)$ denotes the spherical harmonic of degree l and order m. The expansion takes the form:

$$v(\theta,\phi) = \sum_{l=0}^{\infty} \sum_{m=-l}^{l} c_l^m Y_l^m(\theta,\phi),$$

where $c_l^m = (c_{lx}^m, c_{ly}^m, c_{lz}^m)^T$. The coefficients C_l^m up to a user-desired degree can be estimated by solving a set of linear equations in a least squares fashion. The object surface can then be reconstructed using these coefficients, and using more coefficients leads to a more detailed reconstruction.

The left and right hippocampi are treated as a single shape configuration, and so the spatial relation between them can be preserved. To create a shape descriptor for such a multiple-object configuration, we employ an approach proposed in [9] to remove the effects of scaling, rotation, and translation. First, the parameter space of each hippocampal surface is aligned according to the first order ellipsoid for establishing the correspondence across subjects. Next, after normalizing for the total volume, landmarks are created by a uniform sampling of two surfaces for each configuration. Finally, a quaternion-based algorithm is used to align these landmarks through the least square rotation and translation: subjects are first

aligned to a certain control and then aligned to the mean shape iteratively until the mean converged. Now each hippocampal pair is described by a set of normalized landmarks and these landmark sets are comparable across subjects (See Fig. 1 for example).

2.3. Statistical Analysis

For each landmark, the local shape change is defined as the distance between an individual and the mean along the normal direction of the mean surface. In order to increase the signal-to-noise ratio (SNR), Gaussian kernel smoothing is desirable in many statistical analyses. Since the geometry of a hippocampal surface is non-Euclidean, we cannot directly apply Gaussian kernel smoothing. Instead, we employ heat kernel smoothing, which generalizes Gaussian kernel smoothing to arbitrary Riemannian manifolds [2, 3]. The heat kernel smoothing is implemented by constructing the kernel of a heat equation on manifolds that is isotropic in the local conformal coordinates. By smoothing the data on the hippocampal surface, the SNR will increase and it will be easier to localize the shape changes. Fig. 2 shows sample heat kernel smoothing result.

To perform statistical inference directly on the surface, surface signals are modeled as Gaussian random fields. This theoretical model assumption has been checked using both Lilliefors test and quantile-quantile plots for our data. Detecting the region of statistical significant shape changes can be done via thresholding the maximum of the t random field defined on the hippocampal surface. The p value of the local maxima of the t field will give a conservative threshold. See [2, 3] for more details on how to create a corrected p value map using a t value map and other related information.

3. Results

To show the effectiveness of the proposed framework, we conduct an experiment for null data. The null data are created by randomly dividing all 122 subjects into two equal size groups. Clearly, our statistical analysis should not detect any morphological changes between these two groups. In fact, in the resulting t value map, all the t values are well below the cutoff value 3.26, see Fig. 3. We have also performed an experiment on a synthetic data set with a known group difference. The experimental results show that our framework can correctly localized this group difference.

We perform group analyses for CN versus CC, CC versus MCI, and CN versus MCI, using FWHM = 8mm for heat kernel smoothing. Fig. 4 shows the resulting t-maps of these analyses. Positive/negative t-values indicate that outward/inward directions change the mean to shapes of the first class. Statistically significant regions of shape changes only appear between CN and MCI. The CC group shows a more intermediate pattern.

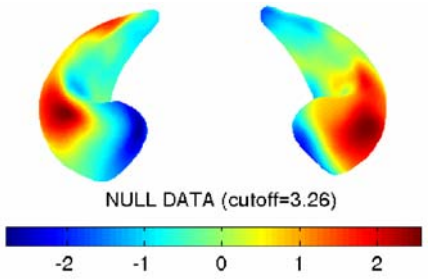

Fig. 3: t-map of the shape change for null data. The null data are created by randomly dividing all 122 subjects into two equal size groups. Clearly, our statistical analysis should not detect any morphological changes between these two groups. In fact, all the t values are well below the cutoff value 3.26.

In order to identify regions of statistically significant structural changes between CN and MCI, we threshold the t-map at the corrected p value of 0.05 (t value of 3.31) and create a visualization shown in Fig. 5. Three different views are displayed and significant regions are shown in red and blue colors. Red/blue colors indicate that outward/inward directions change the mean to CN. The structural changes in MCI are primarily located in the anterior right hippocampus and posterior left hippocampus.

From these experiments, we observe that shape analysis has the potential to inform early detection and is likely to be useful for longitudinal monitoring of response to therapeutic agents.

Data sets in the brain imaging domain are often relatively small due to the difficulty and expense of data collection. Thus, the computational cost of our framework is usually not a problem here, since all the steps except surface parameterization are very efficient for small sample set learning and surface parameterization is still feasible in our case; see [8] for more details about related time complexity analysis.

4. Conclusions

A computational framework is presented for morphometric analysis of 3D surfaces. This framework combines SPHARM surface modeling, quaternion-based registration, heat kernel smoothing, and random fields theory together for localizing regionally specific shape changes between groups of 3D objects. Its effectiveness is demonstrated in a

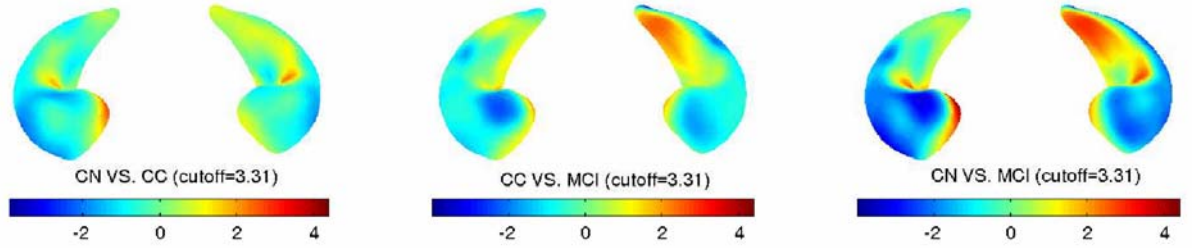

Fig. 4: *t*-maps of group analyses for CN versus CC (left), CC versus MCI (middle), and CN versus MCI (right), where FWHM = 8mm is used for heat kernel smoothing. Positive/negative *t*-values indicate that outward/inward directions change the mean to shapes of the first class. Regions of statistically significant shape changes only appear between CN and MCI.

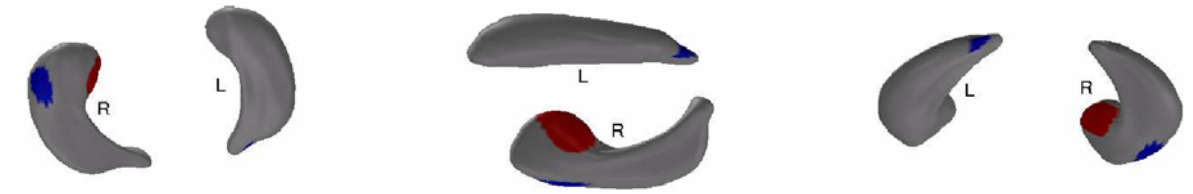

Fig. 5: Regions of statistically significant structural changes between CN and MCI. These regions are created by thresholding the *t*-map using the cutoff value 3.31, which corresponds to a corrected *p* value of 0.05 (*i.e.,* at 95% confidence level). Three different views are displayed. Red/blue colors indicate that outward/inward directions change the mean to CN. The structural changes in MCI are primarily located in the anterior right hippocampus and posterior left hippocampus.

computational neuroscience application for identifying hippocampal shape changes in MCI. This is a general framework and can be applied to other biomedical imaging problems where surface analysis of some type of structure is relevant.

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5. References

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