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Automatic Sulcal Curve Extraction on the Human Cortical Surface

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Abstract

The recognition of sulcal regions on the cortical surface is an important task to shape analysis and landmark detection. However, it is challenging especially in a complex, rough human cortex. In this paper, we focus on the extraction of sulcal curves from the human cortical surface. The previous sulcal extraction methods are time-consuming in practice and often have a difficulty to delineate curves correctly along the sulcal regions in the presence of significant noise. Our pipeline is summarized in two main steps: 1) We extract candidate sulcal points spread over the sulcal regions. We further reduce the size of the candidate points by applying a line simplification method. 2) Since the candidate points are potentially located away from the exact valley regions, we propose a novel approach to connect candidate sulcal points so as to obtain a set of complete curves (line segments). We have shown in experiment that our method achieves high computational efficiency, improved robustness to noise, and high reliability in a test-retest situation as compared to a well-known existing method.

1. Introduction

In neuroimaging studies, sulcal fundic regions of the human cortical surface are key regions for monitoring brain growth, analyzing group variability, and discovering disease patterns. A prerequisite to sulcal analysis is the consistent parcellation of sulcal regions. A common way to achieve that is volumetric coregistration of a regional parcellation template, yet it often yields inaccurate boundaries due to the folded nature of the cortical surface. Another possibility is to delineate curves along sulcal curves. Although sulcal curves can be defined in various ways depending on applications, it is reasonable to assume that sulcal curves are traced along the deepest fundic regions. However, a critical challenge for sulcal curve delineation is the existence of noise on the cortical surface introduced from by image acquisition and the surface reconstruction.

Curvature-based sulcal extraction methods have been reported in.¹⁻⁴ Curvatures have the nice property to capture local, geometric characteristics at a given point. However, these methods are especially sensitive to noise. To alleviate that, a smoothing kernel is commonly employed, which needs to be chosen carefully as otherwise large portions of the surface are smoothed out. Moreover, sulcal curves do not always pass through points with the maximum curvature as discussed in.⁵

Shi et al.⁶ applied the Hamilton-Jacobi equation on the cortical surface to extract sulcal curves by solving the Eikonal equation (a special form of the Hamilton-Jacobi equation). Seong et al.⁷ further proposed a more general solver that computes anisotropic geodesics. In their method, the cortical surface is first segmented into seed regions by thresholding a sulcal depth map, and anisotropic skeletons are then computed by solving the Hamilton-Jacobi equation. This method requires careful parameter tuning to determine candidate points that belong to potential sulcal curves. Since initial segmentation is based on a sulcal depth map, depending on the initial seed regions, sulcal curves are unlikely to capture sulcal fissures in which one single curve is insufficient to represent such wide regions.

Sulcal depth information has been employed for sulcal curve extraction. Kao et al.⁸ used the sulcal depth measures to select candidate sulcal points and connected/refined them to have a set of curve segments. Le Troter et al.⁵ utilized a geodesic density map using sulcal depth to extract sulcal curves. In this method, sulcal basins are segmented from the cortical surface to compute the shortest geodesic paths between all possible two points of the basins. To determine sulcal points, they compute a density map of the paths that measure how often each vertex belongs to all possible paths. This is based on the assumption that the shortest paths are highly likely to have an intersection with sulcal curves. However, this method is sensitive to initial computation of the sulcal depth map as well as parcellation of the sulcal basins prior to the processing.

In this paper, we propose a novel sulcal curve extraction on the cortical surface using the line simplification method⁹ that approximates a polyline with a small number of the original points. The line simplification method is considerably less sensitive to local variation as it focuses on computing a global line pattern. Ideally, the sulcal points will remain after simplification. The whole procedure is briefly summarized as follows. First, we select candidate points by thresholding a principal curvature map. Since the line simplification is defined for 1D curves, we cut the surface to produce contours at all surface points, with respect to the direction of maximal negative curvature. We then check which points are preserved after simplification. Finally, we connect a selection of these candidate points to obtain complete sulcal curves.

2. Methods

Given a triangulated mesh with a set of vertices V , our goal is to find $U \subseteq V$ that consists of sulcal points located at the deepest sulcal region so as to represent sulcal curves. We first select a set of candidate points by simple, relatively generous thresholding of the maximal negative principal curvature. To employ the line simplification method, we then find a plane that maximizes curvature at each point $\mathbf{v} \in V$ and compute the intersection between the plane and the surface. A point is added to U if it is preserved after line simplification. Finally, we compute the sulcal curves from the detected points. The proposed method consists of three main parts: surface slicing, sulcal point detection, and sulcal curve delineation. A schematic overview of the proposed method is illustrated in 1.

2.1 Slicing and Contour Extraction

The line simplification method has been originally designed for 1D polylines. To extend the idea to a surface, we need to extract most meaningful lines from the surface at every vertex/point. Here, we propose the use of a planar intersection along a given direction. At a given point $\mathbf{v}$, we denote $\alpha(s)$ as the parametrized curve along the tangential direction $\mathbf{T}$. Then, the curvature with respect to $\mathbf{T}$ is given by

$$k(\mathbf{T}) = \left\| \frac{d\mathbf{T}}{ds} \right\|. \quad (1)$$

Since our interest is to check if $\mathbf{v}$ is potentially a sulcal point, its curvature k needs to have maximal negative value in 2D space. A maximal negative curvature is defined here along the direction associated with the first principal curvature k_1 , assuming $k_1 < k_2$ where k_2 is the second principal curvature. Thus, we use the direction of k_2 as the normal of the plane for each vertex $\mathbf{v} \in V$. Let $\mathbf{T}_{k_2}$ be the second principal direction associated with k_2 at $\mathbf{v}$, respectively. Thus, the plane equation is given by

$$\mathbf{T}_{k_2} \cdot (\mathbf{x} - \mathbf{v}) = 0. \quad (2)$$

We assume that there are neither holes on the surface nor self-intersections. Therefore a cut between the plane and the surface yields closed loops that are not self-intersecting. For the intersection test, we need to check for every edges on the surface if it holds Eq. 2. We further expedite edge culling by using a hierarchy of axis-aligned bounding boxes (AABB). Finally, we sort these intersections in counter-clockwise order with respect to the plane normal to obtain closed loops. Figure 3 illustrates an example of contour extraction for schematic case and the actual cortical surface.

2.2 Sulcal Point Detection

Once a contour is obtained along the principal direction at $\mathbf{v}$, we apply the line simplification method to select the least number of points that represent the contour, and check if $\mathbf{v}$ remains after simplification. Here is a brief summary of the line simplification method. For a given polyline, the two endpoints $\mathbf{p}_0$ and $\mathbf{p}_1$ are connected as a horizontal line. Then, the point $\hat{\mathbf{p}}$ along the polyline with the maximum distance from the line is selected:

$$\hat{\mathbf{p}} = \arg \max_{\mathbf{p}} \|(\mathbf{p}_1 - \mathbf{p}_0) \times \mathbf{p}\| \cdot \|\mathbf{p}_1 - \mathbf{p}_0\|^{-1}. \quad (3)$$

The initial curve is split into two segments at the selected point $\hat{\mathbf{p}}$ and the two endpoints. The method is then recursively applied to the two curve segments until the maximum distance is below a given threshold.

In our problem setting, we first find the two endpoints having maximal distance among all possible pairs of points on the contour to split it into the two longest possible curves as stated in.⁹ We then apply the line simplification method to one of the two curves that contains the testing point $\mathbf{v}$. The method yields a set of candidate points, and the number of

the points varies according to the threshold value. If $\mathbf{v}$ is reported as a local maximum by the line simplification method, we collect $\mathbf{v}$ into U as a sulcal point. Figure 3 shows an example of candidate points chosen by the line simplification method. Since potential sulcal points lie along valley regions, they have negative principal curvatures. Thus, we reduce the number of tests by choosing a generous thresholding of curvatures. In our experiment, we empirically set this threshold to -0.01. We note that such thresholding is mainly for computational time reduction.

2.3 Curve Delineation

In order to connect the candidate points into complete curves, we first estimate potential endpoints of (yet unknown) sulcal curves. For all points $\mathbf{u} \in U$, we collect sulcal candidate points within a sphere $S(\mathbf{u})$ of radius of r , called inner points, defined by the indicator function:

$$I(\mathbf{v}, \mathbf{u}) = \begin{cases} 1 & \text{if } \|\mathbf{v} - \mathbf{u}\| \leq r, \\ 0 & \text{otherwise,} \end{cases} \quad (4)$$

where $\mathbf{v} \in U$. Note that r is chosen under the assumption that the sulcal regions are separated from each other by least r mm of Euclidean distance. We set r to 4.0 mm in this experiment, which is based on the average width of the sulcal regions in the MNI-305 template.¹⁰ Then we determine those candidate points to be endpoints for which every inner point in $S(\mathbf{u})$ is located within an octant centered at $\mathbf{u}$. This is easily achieved by testing the sign of the inner products of all points within $S(\mathbf{u})$, i.e. no lines connecting inner points to the center point have a separating angle above 90 degrees. Let $E \subseteq U$ be the set of the endpoints determined by this way. Once E is computed, for each sulcal point $\mathbf{u} \in U$, we find candidate neighboring vertices $\mathbf{s}$ that hold $I(\mathbf{s}, \mathbf{u}) = 1$. Now, we connect sulcal points in U , starting from an endpoint in E . To find the neighbor sulcal point at $\mathbf{u}$, we compute the weighted, shortest distance from $\mathbf{u}$ to $\mathbf{s}$. The distance weighting is based on the assumption that the tangential direction of the sulcal curve changes smoothly along the curve. Thus, the weighted distance is given by the following form:

$$D(\mathbf{s}, \mathbf{u}) = \|(\mathbf{s} - \mathbf{u}) \times \mathbf{T}_{\mathbf{u}}\|, \quad (5)$$

where $\mathbf{T}_{\mathbf{u}}$ is the tangent vector at $\mathbf{u}$. Therefore, the neighboring sulcal point $\hat{\mathbf{s}}$ at $\mathbf{u}$ is obtained by

$$\hat{\mathbf{s}} = \arg \min_{\mathbf{s}} D(\mathbf{s}, \mathbf{u}). \quad (6)$$

However, $\mathbf{T}_{\mathbf{u}}$ is unknown since we have no prior knowledge of the sulcal curve. We instead estimate $\mathbf{T}_{\mathbf{u}}$ using the local principal direction. A sulcal curve is finally determined when $S(\mathbf{u}) = \emptyset$. The curve estimation is finished if every element in E has been connected. Figure 4 shows the estimated curves from sulcal points.

3. Results

All experiments were performed on a PC equipped with an Intel Core (TM) i5-3570K 3.4 GHz CPU with 12.00 GB memory, and only a single core was used. It took 1-2 m to obtain a full set of complete curves on the surface on average. Quantitative verification on clinical data is extremely difficult as there is no ground truth for such sulcal curve data.

Qualitatively we successfully compared our results to standards in the field such as BrainVisa. In the following sections, we mainly focus on the reliability and reproducibility of our method versus other methods.

3.1 Noise Sensitivity

We created synthetic surfaces by vertex wise perturbation of an existing brain surface model. Perturbations were simulated via local Gaussian displacements of the vertices. We selected the left hemisphere of the MNI-305 average healthy control template surface, also employed in,¹⁰ as the original brain surface model for our noise experiments. Figure 5 shows the detected sulcal curves with different levels of perturbation. Visually, there is no significant difference from the original surface. For quantitative evaluation of the robustness to noise, for each sulcal point on the original surface, we measured the distance to the corresponding, closest point on the perturbed surface. In this experiment, we observed that for each level of noise, the average distance was 0.505 ± 0.616 , 0.776 ± 0.629 , and 0.982 ± 0.702 mm, respectively, which indicates that the average distances are reasonable given the original MR image resolution (1.0 mm).

3.2 Reproducibility

We used the Kirby reproducibility dataset on 21 healthy volunteers with no history of neurological disease as described in. Scan-rescan imaging sessions were acquired at the F.M. Kirby Research Center (Baltimore, MD, USA), and T₁-weighted scans were acquired using MP-RAGE sequence. We used the BrainVISA pipeline to generate surfaces from the dataset with sulcal ribbon extraction. We also projected the extracted sulcal ribbons onto the sulcal fundi to have sulcal curves for comparison. Figure 6 shows an example of the sulcal curves extracted by using our method. We computed closest distances at sulcal points between two corresponding surfaces and averaged those along each sulcus. Since closest distance computation is asymmetric, we measured distances from both corresponding surfaces and then selected the maximum of the two sulcal average distances. Figure 7 illustrates the maximum average distances of the corresponding surfaces. It is important to note that the sulcal extraction in the BrainVISA pipeline generates only the set of the major curves as its output. On the other hand, our method extracted also minor curves, which is a significant disadvantage as one would expect higher reproducibility errors in those smaller curves. Despite that disadvantage, our results show that the proposed method has less average distance than BrainVISA. We achieved 2.01 ± 0.33 mm (average $\pm$ standard deviation across all 21 cases) with our method, while BrainVISA showed an average distance of 2.89 ± 0.73 mm (paired t-test: $p \leq 0.0001$).

4. Discussions and Conclusions

We presented a novel sulcal curve extraction employing a well-established line simplification method. We have shown in the experiment that our method captures sulcal curves robustly in the presence of noise, as well as shows high computational efficiency. When compared with BrainVISA, a standard neuroimaging tool, our method shows significantly improved reproducibility. The proposed method has several advantages: First, the parameter tuning is quite simple as there is a small set of parameters (sulcal fundus threshold and sulcal sphere radius) and the results are robust to reasonable changes in the parameters. Second, no preprocessing is required on the surface. Moreover, the sulcal point detection can be straightforwardly expedited by using multiple cores (e.g., GPU processors), as every slice is independent of each other. In future work, we will focus on robust sulcal curve labeling by incorporating anatomical prior knowledge.

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Figure 1. Schematic overview of the proposed method. For each candidate sulcal point, a single contour is extracted. The line simplification is then employed to filter non-sulcal candidates.

Figure 2.

Contour extraction. Left: Schematic situation with dotted curves indicating several cutting planes. The first (maximal negative curvature) and second principal directions are colored by *red* and *green*, respectively. The cutting plane is orthogonal to the second principal direction. Middle: Example contour on actual cortical surface. Right: Successful candidate point on example contour.

Figure 3.

Negative curvature points (*red*) and detected sulcal points (*blue* and *green*, where sulcal endpoints are colored in green). The vertices with negative curvatures (*red*) are selected for candidate sulcal points. Since the candidate vertices are spread over a large portion of the sulcal fundic regions, they are further filtered out by the proposed method, which eventually selects sulcal points (*blue*).

Figure 4.

The estimated curves with endpoints in the lateral (*left*) and medial (*right*) views. The sulcal curves are reconstructed from the detected sulcal points. Each curve is labeled with a distinct color. End points are highlighted via larger dots. Sulcal regions with branches are represented as several curves with junction points.

Figure 5.

Robustness to noise. Sulcal points are detected on the surface perturbed by a random noise.

$\Delta_{\max}$ indicates the maximum displacement of the vertex. The detected sulcal points (*blue*) and the estimated curves (*red*) are stable across levels of noise. The quantitative evaluation also shows that the average distance to the corresponding points is less than 1.0 mm.

Figure 6.

Sulcal curve extraction from the different scans for the same subject. Two sets of curves are labeled with respective colors (*red* and *blue*). The two sets are well aligned in the same space (*third column*).

Figure 7.

The maximum average distances of the extracted sulcal curves on the 21 subjects in the Kirby reproducibility dataset. The proposed method achieves consistent results over those obtained in the BrainVISA pipeline.