Automatic sulcal line extraction on cortical surfaces using geodesic path density maps

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We present here a method that is designed to automatically extract sulcal lines on the mesh of any cortical surface. The method is based on the definition of a new function, the Geodesic Path Density Map (GPDM), within each sulcal basin (i.e. regions with a negative mean curvature). GPDM indicates at each vertex the likelihood that a shortest path between any two points of the basins boundary goes through that vertex. If the distance used to compute shortest path is anisotropic and constrained by a geometric information such as the depth, the GPDM indicates the likelihood that a vertex belongs to the sulcal line in the basin. An automatic GPDM adaptive thresholding procedure is proposed and sulcal lines are then defined. The process has been validated on a set of 25 subjects by comparing results to the manual segmentation from an expert and showed an average error below 2 mm. It is also compared to our previous reference method in the context of inter-subject cortical surface registration and shows an significant improvement in performance.

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Introduction

Various convenient representations of sulci have been proposed (Clouchoux et al., 2010; Le Goualher et al., 1999; Mangin et al., 1995; Tao et al., 2002), motivated by the close relationship between cortical folding, genetics and regional functional organization (Rakic, 2004), development (Régis et al., 2005), or to some extent cyto-architectoncy (Fischl et al., 2008). Those representations have been used to perform morphometrics (Mangin et al., 2004), localization (Clouchoux et al., 2010), inter-subject registration (Auzias et al., 2011a; Cachier et al., 2001; Collins et al., 1998; Hellier and Barillot, 2003), or to study the genetics of cortical gyrikenesis (Kippenhan et al., 2005). In the context of surface-based analysis, the fundus of sulci, represented by lines on the cortical surface, are now of clear interest. For instance, they can be used as landmarks for inter-subject cortical surface registration (Auzias et al., 2011b; Clouchoux et al., 2010; Joshi et al., 2007; Van Essen, 2005), or to characterize local sulcal variability (Fillard et al., 2007). Moreover, deep sulcal landmarks have been shown to define less variable patterns than the superficial folding information (Im et al., 2010; Lohmann et al., 2008; Régis et al., 2005), due to an earlier appearance and a stronger predetermination during folding process at the antenatal stage. Since manual delineation of sulcal lines on a cortical surface is a time consuming and operator dependant task that requires a dedicated software, it is critical especially when dealing with large cohorts of subjects to provide an automatic method to extract these lines.

Lines that are used to represent folds are named by different terms in the literature and are not always designating the same anatomical feature. Sulcal fundi are anatomically defined and are located in the depth of sulci, although no formal definition is available. Sulcal curves and sulcal lines are mathematical objects that are used to represent sulcal fundi or other related features. For instance they can be extracted from the outer grey-matter surface and represent the line at which the two banks of a fold meet (Tu et al., 2007). In this case the line is a mathematical feature that does not completely relate to a real anatomical feature. In what follows we use the term ‘sulcal line’ to designate the line that explicitly tries to represents sulcal fundi. Although they have an intuitive definition (one could think of them as the line that lies in the depth of a sulcus, where the curvature is maximum), sulcal lines are actually quite difficult to formally define in a way that fits the geometry of every sulcus and is consistent across individuals. Some attempts have been made to propose semi-automatic or automatic methods for their extraction. Two categories of methods are presented in the literature. The first category explicitly models sulcal fundi as single lines, either as geodesic paths (Khanjea et al., 1998; Shattuck et al., 2009) or active contours (Clouchoux et al., 2010; Vaillant and Davatzikos, 1997), and fits such lines in an optimal manner onto the cortical surface. The second category attempts to derive a suitable representation from the geometry of the surface, under the form of skeletons (Kao et al., 2007; Seong et al., 2010; Shi et al., 2008), and usually ends up providing a set of points on the surface indicating where sulcal fundi are located. In (Shi et al., 2008), an isotropic skeleton-based approach is presented, that extracts the Hamilton–Jacobi skeleton of previously segmented sulcal regions. This results in a thin set of points, homotopic to the sulcal regions. Nevertheless this set has to be pruned in order to select the level of complexity that is required and the process is sensitive to noise, which is a general drawback of skeletons. Alternatively, in (Kao et al., 2007) the skeleton is simplified by choosing the...
longest non-branching path between all endpoints. Another limitation comes from the fact that an isotropic distance function is used, hence producing a skeleton that lies at a medial distance from the sulcal region boundaries. The method then implicitly relies on a notion of symmetry of the sulcal region around the sulcal line without taking into account geometrical or depth information. Such information can be integrated in the process via an anisotropic geodesic distance function, as shown in (Seong et al., 2010). The result is a network of sulcal lines on which a pruning still needs to be performed. This same problem applies to (Li et al., 2010), a curvature-based method that preselects points based on geometrical criteria and must be followed by a pruning process and a broken line connection process.

On the contrary, methods that explicitly look for lines at the fundus of sulci do not need further processing and provide well-structured, sometime parameterized, set of points. This representation is particularly interesting in the context of inter-subject matching when sulcal lines are used as landmarks to explicitly match across subjects. Some papers have proposed to use active contours (Clouchoux et al., 2010; Vaillant and Davatzikos, 1997), a convenient way to enforce a specific representation and achieve a good level of regularity. On the other hand, active contours require an optimization procedure that can be time consuming if performed on a large number of sulci. Geodesic paths are an equally good way to guarantee a good structure when associated to a distance that takes into account geometrical characteristics that fit the definition of sulcal lines. In (Shattuck et al., 2009) it is proposed to define a sulcal line as the shortest path between two selected points, the length of the path depending on a function of local geometry such as curvature or convexity. The selection of end points being performed manually, it is proposed in (Joshi et al., 2007) to reduce this manual effort by selecting a subset of all sulcal curves that is optimal in a landmark-based cortical surface registration context. Our work takes place in the same context and we propose to fully automate the extraction of a chosen set of sulcal curves and corresponding end points. These curves are also defined as shortest paths according to a geometry-or anatomy-dependent metric, and they are primarily meant to be used as landmarks for inter-subject cortical surface matching (Auzias et al., 2011b; Clouchoux et al., 2010). This framework requires the lines to be accurately located on the surface, in a manner that is robust to noise and robust to the variability that can be observed particularly at the extremities of the sulcal lines, as described in (Durrleman et al., 2009; Fillard et al., 2007). For this specific reason it is critical to extract sulcal lines that stay in the depth of the sulcus and do not include the lower depth more variable extremities, while keeping as much length as possible. The only work that explicitly tackles the detection of the two end points has been presented in (Tu et al., 2007). The method extracts sulcal lines on the outer grey-matter surface and involves a supervised learning phase. Instead, we propose a geometry-based method and we introduce in this paper the concept of Geodesic Path Density Map, a measure that indicates within each sulcal basin how likely it is at each location that a geodesic path between points of the boundary go through that location. In the next section we present our method with a number of preprocessing steps, the definition of Geodesic Path Density Maps, and their automatic thresholding to automatically determine the end points of each sulcal line. Then we present experiments and discuss the results, compared with those of the previous method we used in the same context (Clouchoux et al., 2010).

Methods

We present here our method. It is based on the definition of geodesic paths on the inner cortical surface mesh as proposed by (Shattuck et al., 2009). We briefly present the data preprocessing and mesh extraction process, and then we recall the definition of geometry-constrained geodesic path on the cortical mesh. We then define and build a geodesic path density map within each sulcal basin. Finally, those maps are thresholded in an adaptive manner in order to find a specific geodesic path in each basin.

Methods

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Fig. 1. Preprocessing pipeline with a) T1 MRI, b) cortical mesh, c) cortical sulci, d) labeled cortical sulci.
Data preprocessing and mesh extraction

For building cortical meshes from T1 MR images we use the anatomical segmentation pipeline in the BrainVisa software (Cointepas et al., 2010). This fully automatic pipeline results in a triangular mesh of the inner cortical surface of each hemisphere (Fig. 1b), together with a fully automated labeling of all cortical sulci (Perrot et al., 2011; Rivièreme et al., 2002) (Figs. 1-(c,d)). The mesh is represented by a set of vertices \( V = \{v_1, v_2, ..., v_n\} \) connected by edges \( E = \{e_1, e_2, ..., e_m\} \). Cortical sulci are represented by a set of voxels within the fold. The principles behind our method do not require specifically BrainVisa meshes and would work with meshes produced by other packages such as FreeSurfer (Dale et al., 1999) or BrainVoyager (Goebel et al., 2006). Nevertheless we use the automatic labeling provided by BrainVisa as shown further to identify sulcal basins and select specific sulcal lines.

Sulcal basins

Sulcal basins are often defined as regions with a negative mean curvature. Using this criterion, the entire cortical surface is segmented in regions defined around folds and that contain one or several sulcal lines (e.g. like in Fig. 2-a). In order to run our method we need to over-segment these basins using the automatic sulci labeling provided by BrainVisa. The goal is twofold: being able to select specific sulcal lines (e.g. like in regions de
c
f
erature. Using this criterion, the entire cortical surface is segmented in

\[ B \subset V \]

...where \( \alpha_k \) is a cost function associated to vertex \( v_k \):

\[ \alpha_k = \frac{1}{(1 + \exp(\lambda \cdot c_k))^{\gamma}}. \]

and \( c_k \) is the external function (e.g. curvature) at \( v_k \). The two parameters \( \lambda \) and \( \gamma \) control the influence of \( c_k \) versus the overall length of the path. More precisely, \( \lambda \) controls the slope of the sigmoid, i.e. the label of the closest 3D sulcus. Because there can be an ambiguity with very close nearby sulci, a filtering step is added: for each node, the label is chosen as the one of the closest sulcus that is in a 45° solid angle around the normal to the surface at this node (i.e. the sulcus is towards the outside of the cortical surface, Figs. 2-(b,c)). This results in a set of labeled sulcal basins \( B_{lab} \subset B \) as shown in Fig. 2-d.

Geodesics paths

In (Shattuck et al., 2009), a sulcal line is defined as the shortest path between two well-chosen points, with a metric constrained by a function of external measurement such as curvature or convexity of the surface. This method is implemented in a semi-automated context such that the user has to choose two end points, and the sulcal line is automatically found as the geodesic between them. Even though there is an operator-dependent residual variability due to the choice of the two end points, the idea is that robustness is guaranteed on most of the length of the sulcal line since the path will try to optimize the cost function. We briefly summarize here the idea of the method. For a more extensive description, the reader should refer to (Shattuck et al., 2009). If one considers the connected weighted graph \( G = (V, E, W) \) with \( W = (w_1, ..., w_c) \) the set of weights on the edges, it is possible to find the path between any two vertices that minimizes the sum of weights along its edges using Dijkstra’s algorithm (Dijkstra, 1959; Surazhsky et al., 2005). The weight \( w_i \) associated with the edge \( e_i = (v_k, v_l) \) is defined as:

\[ w_i = (\alpha_k - \alpha_l) ||v_k - v_l||, \]

where \( \alpha_k \) is a cost function associated to vertex \( v_k \):

\[ \alpha_k = \frac{1}{(1 + \exp(\lambda \cdot c_k))^{\gamma}}. \]

and \( c_k \) is the external function (e.g. curvature) at \( v_k \). The two parameters \( \lambda \) and \( \gamma \) control the influence of \( c_k \) versus the overall length of the path. More precisely, \( \lambda \) controls the slope of the sigmoid, i.e. the

Fig. 2. Basin with negative mean curvature (a), with the surrounding sulcal voxels (b) used for labeling each vertex (c), resulting in three different sulcal basins (d).
rate of change between nodes that weigh a lot and nodes which do not, and $\gamma$ determines the influence of the external function in the weighting function. $\gamma$ can be positive to force paths to follow negative curvatures (e.g. sulcal lines), or negative to force paths to follow positive curvatures (e.g. gyral crowns). In (Shattuck et al., 2009) the authors chose a local measure of convexity at each vertex. For our particular purpose we advocate the benefit of using a normalized geodesic depth map. Indeed, inside large U-shaped folds the expected

![Fig. 3](image1.png)  
(top) Mean curvature and (bottom) normalized depth information with the corresponding geodesic path between two points. The colormap shows low negative curvature (resp. high positive depth in red and null curvature (resp. null depth) in blue. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

![Fig. 4](image2.png)  
A sulcal basin with a) a few geodesic paths between pairs of points on the boundary; b) the resulting geodesic path density map; c) the thresholded GPDM; d) the final sulcal line.
sulcal line is not always at maximum curvature or convexity, but it is at maximum depth (see Fig. 3). When a small branch is located along the side of a main fold, some maximum of curvature can be found within this branch whereas the use of geodesic depth reduces the problem. The geodesic depth is defined as the geodesic distance between each vertex of a sulcal basin and the closest vertex that belongs to the crown of a gyrus (Cachia et al., 2003). As proposed in this reference, gyrus crowns are defined using the convex hull of the grey/white interface. An equivalent geodesic depth computation method can be found in (Rettmann et al., 2002).

After computing the geodesic depth, we normalize it such that it varies between 0 and 1 within each sulcal basin of $B_{lab}$. This way, all sulcal basins are processed in the same way, independently of their maximum depth. An example of a geodesic path between two points in a sulcal basin, superimposed with the normalized geodesic depth is shown in Fig. 3.

**Geodesic path density maps and automatic sulcal line extraction**

In this section, we present the main contributions of this paper, that are 1) the definition of a new function within each sulcal basin, the geodesic path density map (GPDM) that indicates at each vertex the likelihood that this vertex belongs to the sulcal line, and 2) the associated thresholding strategy which results in a sulcal line.

If one takes two random points on the boundary of a sulcal basin, it is likely that the geodesic path between those points will go via the deepest part of the basin, simply because the geodesic path algorithm has been designed for that purpose. This is illustrated on Fig. 4-a), where a lot of the shortest paths between pairs have a common part where the sulcus is the deepest. Based on this idea, we propose to consider all pair of points on the boundary of a given sulcal basin. For each pair, the geodesic path between the two points is computed and a counter is incremented at each vertex that belongs to this path. This results in a value at each vertex that indicates the number of paths that go through that particular vertex, hence indicating the likelihood of the vertex to belong to the deepest part of the sulcus. After normalization such that values vary between 0 and 1 within the sulcal basin, one gets the geodesic path density map as shown in Fig. 4-b). A pseudocode implementation of the GPDM construction is presented in algorithm 1. Obviously the complexity of this algorithm is not optimal, and the computation of all geodesic paths from one boundary point to all the other boundary point can be largely optimized.

**Algorithm 1.** construction of the GPDM function for a sulcal basin $S$

```plaintext
for $x \in S$
    $GPDM(x) \leftarrow 0$
end for

for $u \in S_b$ do
    for $v \in S_b \setminus u$ do
        $P = \text{geodesicpath}(u,v)$
        for $x \in P$ do
            $GPDM(x) \leftarrow GPDM(x) + 1$
        end for
    end for
end for

for $x \in S$ do
    $GPDM(x) \leftarrow GPDM(x) \div \max_{y \in S} GPDM(y)$
end for
```

In order to select the part of the sulcal basin that corresponds to the sulcal line, as illustrated in Fig. 4-c), one needs to first threshold the GPDM. This threshold depends on the depth and geometry of the sulcal basin; therefore we propose to define an adaptive thresholding strategy. Let us consider the histogram $H(t)$ of the GPDM values in a sulcal basin, with $t \in [0;1]$, and a binning of 0.02, as illustrated on Fig. 5. This histogram typically shows at least two modes: the first mode corresponds to the walls of the sulcal basin, through which few geodesic paths go, and the following modes correspond to the sulcal line and possibly subparts of it, depending on the geometry of the basin.

For each threshold value $t \in [0;1]$, we define $N_e(t)$ the number of extremities of the thresholded GPDM. An extremity is defined as a vertex of the mesh that has less than two neighbors in the set.

Therefore we propose the following adaptive threshold selection, illustrated on Fig. 5:

- Smooth the histogram $H(t)$ with a Gaussian smoothing of variance $\sigma^2 = 2$ for robustness to noise.

![Fig. 5. GPDM histogram (grey) with $N_e$ (green), the smoothed histogram (black) and its local minima (orange), and the selected threshold (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)](image-url)
* Find first local minimum \( t_m \) of \( H(t) \) such that \( N_N(t_m) \) is the minimum value of \( N_N(t) \).
* Decrease \( t \) incrementally with a step \( dt \) equal to the histogram binning, and stop at the first value \( T \) such that \( N_N(T) = N_N(t_m) \) and \( N_N(T - dt) \neq N_N(t_m) \).

Once the GPDM thresholded at value \( T \), the sulcal line is defined as the longest geodesic path within the resulting set (e.g. in Fig. 4-d, it is the geodesic path between the two points that are the furthest apart in the red set shown in Fig. 4-c), which ensures that the sulcal line is indeed a line with no thickness.

**Experiments**

Experiments were performed on a set of 25 subjects. For each subject, T1 MRIs (1 x 1 x 1 mm resolution) were processed using the BrainVisa segmentation pipeline (Cointepas et al., 2010). This resulted in fine meshes (~150,000 vertices) of the inner cortical surface for each subject, as well as a voxel-based ribbon-like representation of all sulci (Mangin et al., 1995). Based on this representation, the sulci were then manually identified on each subject’s left hemisphere: central sulcus (CS), superior frontal sulcus (SFS), superior temporal sulcus (STS) and the anterior calloso-marginal anterior fissure (CMF) (see Fig. 6). These specific sulci were chosen because they represent major landmarks in the inter-subject cortical surface matching (Auzias et al., 2011b; Clouchoux et al., 2010), and because they show a variety of configurations: the CS is a robust sulcus, connected in the large majority of cases, with a higher variability at its ventral extremities, sometimes showing a fork; the SFS shows a higher variability, with several sulcal basins, and a connection with the superior precentral sulcus, both sulci sharing a common sulcal basin; the STS has a variable number of sulcal basins, and a connection with the superior temporal sulcus, both sulci showing a fork; the SFS shows a higher variability, with several sulcal basins, and because they show a variety of

For each subject’s left hemisphere and the 4 chosen sulci, our automatic sulcal line extraction process was performed, as well as the snake-based extraction method presented in (Clouchoux et al., 2010). The latter was our reference method in the context of inter-subject cortical surface mapping. An expert also manually drew all 100 sulcal lines in a vertex-by-vertex fashion. Manual drawing was performed with the only instruction that the resulting sulcal lines were to be used for inter-subject registration. Based on this, the expert drew one line per sulcal basin. Although no strict procedure was enforced to choose the sulcal line end points and their detection was performed on a per sulcus basis, a few implicit rules can be stated: end points were chosen just before the abrupt change of depth that can sometimes be observed at the extremities of the sulcal basins; when a sulcal basins ends with a ‘fork’, the sulcal line stops before the fork; in doubt, sulcal lines stop at a point equidistant to all neighboring boundary points. The result of this manual extraction was then used as a reference to assess performances of automatic extraction methods. For our GPDM method, the two only parameters of the method were empirically set at \( \gamma = 2 \) and \( \lambda = 15 \). Note that the process is robust to parameter variations and that for \( \lambda > 15 \) results are identical. In order to quantitatively evaluate the performances of the two automatic methods, we measured the distances between the extracted sulcal lines and their manual reference using Haussdorf-distance based measures, as proposed in (Tu et al., 2007). Let us define two measures of distances between an extracted sulcal line \( S \) and its reference \( G \):

\[
H_{av}(S, G) = \frac{1}{|S|} \sum_{s \in S} \min_{g \in G} d(s, g),
\]

\[
H_{wor}(S, G) = \max_{s \in S} \min_{g \in G} d(s, g),
\]

where \( d(s, g) \) is the geodesic distance between vertices \( s \) and \( g \) in millimeters. \( H_{av} \) measures the average of the distance between points on \( S \) to their closest point on \( G \), while \( H_{wor} \) measures the worst case fit from curve \( S \) to curve \( G \). In order to symmetrize measurements we define:

\[
HS_{av}(S, G) = \frac{(H_{av}(S, G) + H_{av}(G, S))}{2},
\]

\[
HS_{wor}(S, G) = \frac{(H_{wor}(S, G) + H_{wor}(G, S))}{2},
\]

For each given sulcus (CS, STS, SFS, or CMF) we define the average and the standard deviation of each measure across the \( N_s \) subjects:

\[
\bar{HS}_{av} = \frac{1}{N_s} \sum_{s=1}^{N_s} HS_{av}(S_{suj}, G_{suj}),
\]

\[
\sigma_{av} = \sqrt{\frac{\sum_{s=1}^{N_s} (HS_{av}(S_{suj}, G_{suj}) - \bar{HS}_{av})^2}{N_s - 1}},
\]

\[
\bar{HS}_{wor} = \frac{1}{N_s} \sum_{s=1}^{N_s} HS_{wor}(S_{suj}, G_{suj}),
\]

\[
\sigma_{wor} = \sqrt{\frac{\sum_{s=1}^{N_s} (HS_{wor}(S_{suj}, G_{suj}) - \bar{HS}_{wor})^2}{N_s - 1}},
\]

<table>
<thead>
<tr>
<th></th>
<th>PDPDM</th>
<th>Snake</th>
</tr>
</thead>
<tbody>
<tr>
<td>( HS_{av} )</td>
<td>( \sigma_{av} )</td>
<td>( HS_{wor} )</td>
</tr>
<tr>
<td>CMF</td>
<td>1.666</td>
<td>0.614</td>
</tr>
<tr>
<td>CS</td>
<td>1.503</td>
<td>0.699</td>
</tr>
<tr>
<td>SFS</td>
<td>1.410</td>
<td>0.286</td>
</tr>
<tr>
<td>STS</td>
<td>1.679</td>
<td>0.496</td>
</tr>
</tbody>
</table>

Table 1

Results of the average Hausdorff-based measures on four sulci, for both methods (25 subjects).
**Table 2**

Results of the worst Hausdorff-based measures on four sulci, for both methods (25 subjects).

<table>
<thead>
<tr>
<th></th>
<th>GPDM</th>
<th>Snake</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(h_{\text{worst}})</td>
<td>(h_{\text{worst}})</td>
</tr>
<tr>
<td>CMF</td>
<td>6.294</td>
<td>3.883</td>
</tr>
<tr>
<td></td>
<td>(\alpha_{\text{worst}})</td>
<td>(\alpha_{\text{worst}})</td>
</tr>
<tr>
<td>CS</td>
<td>7.949</td>
<td>2.678</td>
</tr>
<tr>
<td></td>
<td>9.115</td>
<td>3.802</td>
</tr>
<tr>
<td>SFS</td>
<td>6.176</td>
<td>2.036</td>
</tr>
<tr>
<td></td>
<td>11.261</td>
<td>3.582</td>
</tr>
<tr>
<td>STS</td>
<td>8.250</td>
<td>2.643</td>
</tr>
<tr>
<td></td>
<td>11.687</td>
<td>5.240</td>
</tr>
</tbody>
</table>

\(h_{\text{worst}}\) is an overall measure of precision, it shows the quality of the average match between the two lines, whereas \(\alpha_{\text{worst}}\) indicates how far apart the two lines are at their worst match, hence often indicating the maximum distance between corresponding extremities. Results given by these measures are presented in next section.

**Results and discussion**

Table 1 shows the values of \(h_{\text{av}}\) and \(\alpha_{\text{av}}\) on the four sulci under study, for our method (GPDM) and the snake-based method in (Clouchoux et al., 2010) (snake), while Table 2 shows the same results for \(h_{\text{worst}}\) and \(\alpha_{\text{worst}}\). Fig. 7 presents these results in a graphical form and shows the clear overall superiority of the GPDM method over the snake-based method. The ‘average’ measure \(h_{\text{av}}\) is lower for all sulci \((p=2.7e^{-10})\), showing a better precision of the sulcal line extraction and a better robustness with a lower inter-subject standard deviation. At the sulcus level, the advantage of the GPDM method is significant for the CS \((p=0.0222)\), SFS \((p=2.6e^{-8})\), and STS \((p=0.0017)\), and almost significant for the CMF \((p=0.0622)\).

The ‘worst’ measure also shows the superiority of our method for all sulci \((p=4.1e^{-8})\). At the sulcus level, the advantage of the GPDM method is significant for the CMF \((p=0.0095)\), SFS \((p=6.7e^{-7})\), and STS \((p=0.0031)\), but not for the CS \((p=0.6632)\), where the two methods have similar performances. Fig. 8 shows that for the CS the snake-based method tends to extract sulcal lines that are slightly longer than their reference while the GPDM-based method extract lines that are often shorter than their reference, resulting in a slightly poorer performance with \(h_{\text{worst}}\). This difference in length between the GPDM-based CS lines and their reference is due to the adaptive threshold selection algorithm and concerns mostly the CS. In the case of a long uninterrupted sulcal basin (like the CS), the first mode of the GPDM histogram contains a higher than normal proportion of points and it takes a high threshold to come down to \(N_e=2\) extremities, resulting in a shorter line. Nevertheless it is not a very important problem and the GPDM-based method produces conservative results in terms of overall length of the lines: at the extremities where variability is higher, where depth decreases, and where sometimes a sulcus opens into a small fork (e.g. at the ventral extremity of the CS), the GPDM thresholding selects points that are deep enough for most geodesic paths to go through, a safer approach in our framework of inter-subject cortical surface matching. On the other hand, the snake-based method suffers from an extremity selection process with a low performance, which explain the poor results of the ‘worst’ measure: end points were chosen by considering the 3D sulcal ribbon, and projecting its extremities onto the closest mesh node that has a high curvature.

The conservative property of our method that provides sometimes shorter but more stable sulcal lines is an important point. It removes an element of inter-subject variability at the extremities of sulcal basins, but also at the junction of several sulci that can meet within the same negative curvature region. In this case, the region is oversegmented by our algorithm. This oversegmentation aims at providing different sulcal lines for sulci that have been identified as different, although they meet in the same basin. The behavior of the algorithm around the meeting point depends largely on the local geometry or depth. For instance if two sulci that share the same negative curvature region are separated by an annectant gyrus, associated with a lower depth (Cunningham and Horsley, 1892), the two resulting sulcal lines will probably be quite distant. On the other hand, if the two sulci meet in a zone were depth does not change, the two resulting sulcal lines will be closer. The significant invariant behavior in both cases is that they will be disjoint. Again this behavior is conservative with respect to our application: if two sulci have a junction on one subject, they do not necessarily have one on another subject and the inter-subject homology model should include only the common features, i.e. without the junction.

![Fig. 7. Average (left) and worst (right) Hausdorff-based measures for 4 different sulci and two methods, computed across 25 subjects.](image1)

![Fig. 8. Extracted sulci for 4 of the 25 subjects, using the expert manual delineation (green), the GPDM algorithm (blue), and the snake-based method (red).](image2)
The segmentation in sulcal basins of the cortical surface also leads to a major difference with other methods, in particular the snake-based one: a sulcus that goes across several sulcal basins will be represented with several sulcal lines, whereas the snake-based method will represent it with a single line. A good example of this is illustrated in Fig. 8 with the SFS. There is evidence in the literature that this is a good way to deal with variability (see for instance (Régis et al., 2005; Lohmann et al., 2008; Im et al., 2010)) and it is relevant for inter-subject matching. Nevertheless, in another context one might need a continuous line. If for instance the segmentation of a fold in two sulcal basins is due to an annectant gyrus (Cunningham and Horsley, 1892) buried in the depth of the fold, representing the whole fold instead of the two basins could be of interest if one has a prior on the variability of this specific fold, or in order to perform measurements along the entire fold. In such case, besides using another method it is possible to use the output of our method and join the two sulcal lines by means of an additional geodesic path.

In terms of precision along sulcal lines, Fig. 8 shows that our method behaves a lot better than the snake-based one: the extracted lines are very close to the reference and the number of connected components (i.e. the number of sulcal basins) is always correct, whereas by nature the snake-based method always leads to a single connected component. As shown in Fig. 8 for the SFS, this artificial connection of distinct sulcal basins sometimes forces the snake-based sulcal line to interpolate between two ideal lines in order to preserve a good regularity, resulting in a lower precision. Besides, the tradeoff between precision and regularity of the snake is performed at a global level and is harder to achieve at a local level. Finally, the regularity of the snake is controlled using an isotropic length that is in competition with locations of maximal depth or curvature, whereas for the GPDM method the cost function is only based on depth, and regularity is intrinsic to the nature of geodesic paths.

Precision results of the GPDM ‘average performance’ are better than those reported in (Bao et al., 2011), in which a comparison between several methods and ground truth reports errors around 4 mm, and comparable to the training error reported in Tu et al. (2007), where the deviation to the ground truth on three sulci is in the range 2–4 mm. In this paper, the authors also acknowledge the influence of sulcal line extremities on the larger error measurements and the ‘worst’ Hausdorff measures. In comparison to Tu et al. (2007), our method does not need a learning process to optimize the choice of the end points: for a given sulcal basin, our method is entirely data-driven. Although providing statistically meaningful results, the learning approach has the drawback to depend on the training population, and for developmental pathologies that disrupt the folding process this would probably require a new training. Fig. 9 shows the result of the process on the cortical surface of a specific subject for all 25 left-hemisphere sulci that are part of the model presented in (Auzias et al., 2011b) for cortical surface matching. The figure shows a close up on the frontal lobe and the temporal lobe, the two regions were the density of landmarks is the highest.

Finally, in terms of computation time the GPDM algorithms is obviously not optimal because it has to compute for all points on the boundary of a sulcal basin their distance to all other points on this boundary. This rather high complexity could probably be improved, nevertheless we have measured that for a single subject it takes about 30 minutes to compute all sulcal lines.

Conclusion

In this paper we have presented a fully automatic method for extracting sulcal lines on high-resolution triangular meshes of the cortical surface. The method is entirely data-driven and relies on the definition of a new function, the Geodesic Path Density Map, computed using shortest paths based on a geometry-driven anisotropic distance function. It was validated on real data and experiments on a set of 25 subjects showed that the algorithm is efficient and robust, with an average error below 2 mm, providing a clear improvement compared to the snake-based algorithm presented in Clouchoux et al. (2010). In the context of inter-subject cortical surface alignment, the method will be used to automatically extract landmarks that are part of the model, as defined in Auzias et al. (2011b).

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