AN AUTOMATED METHOD FOR FINDING CURVES OF SULCAL FUNDI ON HUMAN CORTICAL SURFACES

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ABSTRACT

We present a method for automatically finding curves representing the sulcal fundi on the human brain cortex. A flattened map of the cortical surface is used as the reference space in which the curves are modeled. The map is also used to transfer planar curves back to the cortical surface to extract sulcal fundal curves. Instead of modeling the curves by densely sampled landmark points, as it is done in the traditional active shape models, we model sulcal curves by a small number of anchor points that correspond to salient features, such as end points or points of intersections. The full sulcal curves connecting the anchor points are reconstructed by an extension of the fast marching method. Each anchor point carries a wavelet based attribute vector whose goal is to provide a distinctive morphological signature for the anchor point. This allows us to efficiently solve the problem in a low-dimensional space. Moreover, because each anchor point has this signature, and because anchor points are chosen to be salient features, the cost function defined in this low-dimensional space is presumed to have few local minima. Experimental results show that the sulcal curves extracted using the automatic method agrees well with the manually drawn sulcal curves.

1 Introduction

The cortex of the human brain is a thin convoluted sheet of gray matter. The outwards folds of the cortex are called gyri, and the cortical grooves are called sulci. Cortical sulci and gyri are important anatomical features that have been used in spatial normalization algorithms [1, 2, 3]. Previous attempts to build statistical models of the cortical sulci have relied on graphs constructed from 3D point-sets [4, 5], on ribbons used to model the space between opposite sides of sulci [6, 7, 8, 9], or on curves located on the outer cortex [1, 10], which is a shrink wrap surface that does not represent the buried cortex. In our previous work [10], we modeled and automatically extracted sulcal curves lying on the outer cortex using a statistical shape model [11].

In this paper, we model sulci as curves running along the deepest part of sulci, also known as the sulcal fundi, because they are believed to be less variable than other part of the

Fig. 1. (a) A schematic drawing of the left brain hemisphere with seven major sulci indicated, and (b) a flattened map of one training example with the sulcal curves. The gray level in (b) reflects the mean curvature of the cortical surface. The light regions are gyri and dark regions are buried cortex. The crosses indicate the locations of the anchor points.

sulci, and are suitable to be used as features for registering cortical surfaces. We will present a new method for automatically finding the sulcal fundal curves on the full cortex. We introduce the concept of anchor points, which are points with prominent features on the desired sulcal curves. The full curves are reconstructed from the set of anchor points using an extension of the fast marching method [12, 13].

2 Method

We use a flattened map of the left cortical hemisphere (Fig. 1) as the reference space. The modeling and reconstruction of the sulcal curves are performed in this reference space. The flattened map is derived from a conformal spherical map [14] by projecting all the cortical features to the plane tangent to the sphere at a fixed point to get the same view of the spherical maps for all the subjects. The spherical map, together with the projection, establish a one-to-one correspondence between points on the cortical hemisphere and these on the tangent plane, which enables us to map the planar curves representing sulcal fundi back to the cortical surface to extract fundal curves on the folded cortical surface.

The method consists of two stages (Fig. 2): the training stage and the testing stage. During the training stage

Fig. 2. The block diagram of the proposed method.

(Sec. 2.1), we find the set of anchor points on the sulcal curves in the training sets and build the models for the anchor points and the sulcal curves. Our models include: statistics of the attribute vector for each anchor point, statistical prior of the shape formed by the anchor points, and statistics of the geometric properties along the curves (e.g. mean curvature of the cortical surface). In the testing stage (Sec. 2.2), the models are applied to a new image. The set of anchor points deforms under the influence of external forces, which seek to find matches with similar attribute vectors. This deformation is further constrained by the shape prior of the anchor points. After an optimal set of anchor points is found, the curves of sulcal fundi are constructed via the extended fast marching method, and by taking into consideration statistics of geometric properties of these fundi. The details of each of these steps are described next.

2.1 Building the models

Suppose we have N training samples, each one consisting of an image $I_i(\mathbf{p}) : \Omega \rightarrow \mathcal{R}$, which is the mean curvature of the cortical surface mapped to the unit sphere and projected to the tangent plane, and M sulcal curves on the image $c_{ij}(t) : [0, 1] \rightarrow \Omega$, $i = 1, \dots, N$, $j = 1, \dots, M$ [See Fig. 1 (b)]. The curves are parameterized using uniform speed parameterization. This setup gives us a natural point correspondence between curves in different images.

For any point $\mathbf{p} \in \Omega$ in an image I , we define an attribute vector $V(\mathbf{p})$, which is a vector of the wavelet coefficients of the sub images of I of different sizes around $\mathbf{p}$. The sub image of size r around $\mathbf{p}$ is defined as $I^{(sub)}(\mathbf{x}) = I(\mathbf{x} + \mathbf{p})$, $\|\mathbf{x}\| \leq r$. The attribute vectors encode the average image value at different location and information of the location and strength of the edges in the neighborhood of each point in different scales. They provide a multi-scale description of the image around each point in I . We compute attribute vectors for all points on the sulcal curves in the training datasets and use these attribute vectors to determine the set of anchor points.

The anchor points are obtained as follows: 1. All the end points and intersections of sulcal curves are automatically anchor points; 2. If a curve segment cannot be reconstructed accurately from its end points for any training example, we select a point along that curve segment to be an anchor point, and divide the curve segment into two segments. The point selected to be the new anchor point is the one that the covariance matrix of whose attribute vector has the smallest trace among all the non-anchor points on the same curve segment. The second step is iterated until all curves can be accurately reconstructed by only their anchor points.

The above process generates a set of anchor points with following desired properties: the set is minimal in that the number of anchor points is the smallest possible; the anchor points have the most distinctive morphological attributes because of the way we select anchor points in step 2 above; and the set of anchor points is complete in that they give faithful reconstruction of the sulcal curves in the training sets. This process yields K anchor points, $\mathbf{a}_{ik} = (a_{ik}^x, a_{ik}^y)$, $k = 1, \dots, K$ (see Fig. 1 (b), for example). The attribute vector for the k -th anchor point in the i -th image is denoted as $\mathbf{v}_{ik}$. The statistics of the attribute vectors for the anchor points consists of the means and covariance matrices of the attribute vectors, $\bar{V}_k$ and Σ_k , $k = 1, \dots, K$.

The other model for the anchor points is a statistical shape model for the shape formed by the anchor points. A standard procedure is applied to get the mean shape and a number of eigenvariations for the shape formed by the anchor points. We denote the mean shape vector, the matrix of eigenvariations, and the corresponding eigenvalues, $\boldsymbol{\mu}$, $\boldsymbol{\Psi} = [\psi_1 | \dots | \psi_L]$, and $\lambda_1, \dots, \lambda_L$, respectively, where L is the number of significant eigenvariations. The shape statistics together with the statistics of the attribute vectors are used to find the candidates for the anchor points.

In addition to the models for the anchor points, we compute the statistics of the geometric properties, the mean curvature of the cortical surface in particular, along the sulcal curves in the training sets. The statistics includes the average mean curvature and point-wise variance for each point on the curves. The extension from point-wise variance to the covariance of the mean curvature along curves is straightforward. This statistical information is used by the fast marching method to reconstruct curves connecting anchor points.

2.2 Finding sulcal curves on test data

For a new image I , we compute the attribute vector for every point $\mathbf{p} \in \Omega$ in the new image, $V(\mathbf{p})$, and define a similarity measure between $V(\mathbf{p})$ and the attribute vector of the k -th anchor point. The similarity measure is the Mahalanobis distance between $V(\mathbf{p})$ and $\bar{V}_k$:

$$d_k(\mathbf{p}) = (V(\mathbf{p}) - \bar{V}_k)^T \Sigma_k^{-1} (V(\mathbf{p}) - \bar{V}_k). \quad (1)$$

When Σ_k is not invertible, we use a lower dimensional distribution in the space spanned by the eigenvectors of Σ_k corresponding to the non-zero eigenvalues, which are obtained using standard principal component analysis. We label all points $\mathbf{p}$ such that $d_k(\mathbf{p})$ achieve local minima and are below a given threshold the candidates for the k -th anchor point. This step results in n_k candidates for the k -th anchor point, $\{\mathbf{p}_{k1}, \dots, \mathbf{p}_{kn_k}\}$.

In this step, we do not constrain the location of the candidates to follow any spatial distribution, neither do we require the candidates for all anchor points follow the shape statistics. Some of the candidates are obviously in the wrong part of the image and some combinations of the candidates for anchor points do not form feasible shapes according to the shape statistics. A two-step process is then used to eliminate the infeasible candidates.

First we find the candidates of the anchor points that minimizes the following cost function:

$$C(\mathbf{s}) = \alpha \sum_{l=1}^L \frac{((\mathbf{s} - \boldsymbol{\mu})^T \boldsymbol{\psi}_l)^2}{\lambda_l} + \sum_{k=1}^K d_k(\mathbf{p}_{kj_k}) \quad (2)$$

where $\mathbf{s}$ is the vector formed by the coordinates of the candidates of the anchor points, $\mathbf{s} = [\mathbf{p}_{1j_1}, \dots, \mathbf{p}_{Kj_K}]^T$, $j_k = 1, \dots, n_k$, $k = 1, \dots, K$, and α is a weighting factor. The cost function in Eq. (2) has two terms, the first one penalizes the deviation from the mean shape computed from the training samples, and the second one penalizes the deviation from the mean attribute vectors for anchor points.

The problem of minimizing $C(\mathbf{s})$ in Eq. (2) is a combinatorial problem. Exhaustive searching method is prohibitive even for relatively small K and n_k 's. In order to solve the problem, we use a discrete version of the coordinate descent optimization algorithm. We first set α to be 0, and find the anchor points that minimize only the second term in Eq. (2). This step gives us the initial configuration $\mathbf{s}^{(0)}$. We set $\alpha = 1$, $l = 1$, and iterate the following:

1. Loop through all the K anchor points. For the k -th anchor point, we perform the following:
 - 1.a. Evaluate $C(\mathbf{s})$ for all the n_k candidates with the configuration of the rest anchor points fixed;
 - 1.b. Find the candidate point that has minimal cost, and update the candidate for this anchor point if it differs from the previous configuration;
2. If all the anchor points have been processed, call the resulting coordinate vector of anchor points $\mathbf{s}^{(l)}$;
3. If $\mathbf{s}^{(l)}$ is the same as $\mathbf{s}^{(l-1)}$, stop the iteration and set $\mathbf{s}^{(init)} = \mathbf{s}^{(l)}$, which is the optimal configuration from the candidates of the anchor points. Otherwise, set $l = l + 1$ and go to step 1.

Second we use $\mathbf{s}^{(init)} = [\mathbf{p}_{10}, \dots, \mathbf{p}_{K0}]$ and the shape statistics to eliminate the infeasible candidates. For the k -th anchor point, we keep only the candidates that, together

with $\mathbf{p}_{10}, \dots, \mathbf{p}_{k-1,0}, \mathbf{p}_{k+1,0}, \dots, \mathbf{p}_{K0}$, form a shape that is within a prescribed "distance" from the mean shape $\boldsymbol{\mu}$. Mathematically, the set of candidate points we keep for the k -th anchor point is the following:

$$\mathcal{A}_k = \left\{ \mathbf{p}_{kj} \left| \frac{1}{L} \sum_{l=1}^L \frac{((\mathbf{s}(\mathbf{p}_{kj}) - \boldsymbol{\mu})^T \boldsymbol{\psi}_l)^2}{\lambda_l} \leq d_0^2 \right. \right\} \quad (3)$$

where

$$\mathbf{s}(\mathbf{p}_{kj}) = [\mathbf{p}_{10}, \dots, \mathbf{p}_{k-1,0}, \mathbf{p}_{kj}, \mathbf{p}_{k+1,0}, \dots, \mathbf{p}_{K0}]^T$$

and d_0 is the parameter that controls how strictly we impose the shape prior on the candidate points.

After we find the candidates for anchor points in the test image, we use an extension of the fast marching method to reconstruct the full sulcal curves connecting the anchor points [12, 13]. The statistics of the mean curvature of the cortical surface along sulcal curves are used for the fast marching method to find the curves that have the desired local and global properties.

3 Experimental Results

We manually labeled seven major sulci on the flat maps of 26 left cortical hemispheres (Fig. 1). We used leave-one-out method to test our models and the method for automatically finding sulcal curves.

Fig. 3 shows four typical results on the flat maps. The thin dashed curves are curves manually extracted. The thick solid curves are sulcal curves extracted using the automated method, which match well with the curves manually drawn in most parts. In Fig. 3, we see a couple of cases where large errors occur, indicated by arrows. In these cases, the errors are caused by mistakes in locating the anchor points. But with the shape model for anchor points and the curve reconstruction method, we can still find part of the sulcal curve accurately even when relatively large anchor point location errors exist. Fig. 4 shows two views of the partially flattened map [15] of a subject with automatically extracted sulcal curves overlaid. The gray level on the partially flattened map indicates the mean curvature of the original cortical surface.

In order to validate our method, we computed the Euclidean distances between corresponding points in the automatically extracted curves and the manually extracted ones. The average distance is 2.95 mm, with a standard deviation of 3.11 mm.

4 Summary and Discussion

We presented a method for building statistical models for the curves representing sulcal fundi on the cortical surfaces. The models can be used to automatically find and label sulcal curves on cortical surface. The method combines the use of a wavelet based attribute vector, a statistical model

Fig. 3. Four typical results on flat maps. See text for details.

for the shape formed by anchor points, and an extension of fast marching method for reconstructing sulcal curves between anchor points. Experimental results show that the sulcal curves extracted using the automatic method agrees well with the manually extracted sulcal curves.

Future work includes building models for a richer set of sulci that cover the entire cortical surface. In the models presented in this paper, the sulcal curves on the sphere are close to the tangent plane in 3D. If the set of sulci is enriched, one tangent plane is not able to capture all the curves, in which case we may need to use multiple tangent planes [10]. Also, by iteratively refining the anchor points in a gradually localized neighborhood, it is possible to reduce the kind of errors shown in Fig. 3. Further validation is also needed to compare the errors between results of the method and the manually extracted curves with the inter-rater errors.

Fig. 4. Two views of the automatically extracted curves on the partially flattened surface of one subject.

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