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# AUTOMATIC PARCELLATION OF CORTICAL SURFACES USING RANDOM FORESTS

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## Abstract

Automatic and accurate parcellation of cortical surfaces into anatomically and functionally meaningful regions is of fundamental importance in brain mapping. In this paper, we propose a new method leveraging random forests and graph cuts methods to parcellate cortical surfaces into a set of gyral-based regions, using multiple surface atlases with manual labels by experts. Specifically, our method first takes advantage of random forests and auto-context methods to learn the optimal utilization of cortical features for rough parcellation and then the graph cuts method to further refine the parcellation for improved accuracy and spatial consistency. Particularly, to capitalize on random forests, we propose a novel definition of Haar-like features on cortical surfaces based on spherical mapping. The proposed method has been validated on cortical surfaces from 39 adult brain MR images, each with 35 regions manually labeled by a neuroanatomist, achieving the average Dice ratio of 0.902, higher than the-state-of-art methods.

### Index Terms

Cortical surface parcellation; random forests; context feature; graph cuts; Haar-like features

## 1. INTRODUCTION

Automatic and accurate parcellation of cortical surfaces into anatomically and functionally meaningful regions is of fundamental importance in human brain mapping [1]. The major challenge for accurate cortical surface parcellation is attributable to the fact that the human cerebral cortex is highly convoluted and extremely variable in shape across individuals [1]. In neuroimaging studies, several methods have been proposed for parcellation of cortical surfaces based on either concave sulci or convex gyri [1–8]. As sulci are typically bounded by gyral crests, the sulcal-based parcellation can be achieved by purely using the geometric features of cortical folding, such as the curvature and sulcal depth [2, 6]. In contrast, the gyral-based parcellation is a much more complicated task, because most gyri are connected together on the cortical surface and there is no clear boundary between these connected gyri [7]. Therefore, prior information is highly needed for assisting gyral-based parcellation of cortical surfaces. For example, FreeSurfer performs gyral-based parcellation of cortical surfaces based on a Bayesian model of position-specific prior statistics of geometric features of cortical folding and also class-conditional densities in the surface atlas space, which are learned from the manually labeled cortical surfaces by experts [1, 7]. However, one limitation of this method is that it cannot learn to optimally utilize geometric features of the variable cortical folding for surface parcellation.

Recently, random forests draw great attention in image segmentation [9–11], due to its powerful capability of learning optimal image features. Therefore, in this paper, we are motivated to leverage this method for the challenging problem of cortical surface parcellation. However, these techniques cannot be directly applied to cortical surface parcellation. This is because pixel-comparison features in [10–12] rely on the relationships between local relative positions, which can be uniformly defined and used across the whole image, since all the pixels/voxels are in a regular grid. However, for the highly convoluted cortical surface manifold represented by triangular meshes, no such regular grid is available. Note that we use cortical surface to represent the cortex rather than using 3D image-based representation, because surface-based analysis respects the inherent topology of the cortex, and facilitates the normalization, analysis, measurement, and visualization of folded cortical regions [1, 2]. Since each cortical surface has its own triangular mesh configuration, it is difficult to uniformly define local relative positions. To deal with this issue, we propose a new method for defining Haar-like features on the cortical surface based on spherical mapping. Capitalizing on these Haar-like features of cortical geometric attributes, such as curvature and convexity, we propose to leverage random forests and auto-context methods to effectively parcellate cortical surfaces, using multiple surface atlases manually labeled by experts. However, because random forests classify each vertex independently, the parcellation result is inherently spatially-inconsistent, especially near the boundaries of different cortical regions, although adding auto-context features in random forests leads to improved accuracy and spatial consistency. To address this problem, we further integrate random forests with the graph cuts method [13] for further improving both the accuracy and spatial consistency of the parcellation. Specifically, we consider the parcellation as a Markov random field problem, and then define an energy function considering both the fitness of label probabilities derived from random forests and the spatial smoothness of boundaries. Our method has been validated on cortical surfaces from 39 adult brain MR images, each with 35 regions manually defined by a neuroanatomist, achieving a higher accuracy than the-state-of-the-art FreeSurfer and Spherical Demons methods [14].

## 2. METHOD

The proposed method for cortical surface parcellation consists of two main steps: rough parcellation using random forests and auto-context, and further refinement using graph cuts. Each step is detailed in the following sections.

### 2.1. Deriving Label Probability Maps by Random Forests

**2.1.1 Random forests—**A random forest consists of a number of binary decision trees, which are trained with randomness on features and corresponding thresholds [15]. Each tree is trained independently to learn a mapping from the feature space to a label probability distribution. The final result is the average over the label probability distributions of all individual trees. Compared to the case of using only one decision tree, a forest yields more accurate and robust results.

**2.1.2. Cortical features for parcellation—**For cortical surface parcellation, Random forests need appropriate features. As mentioned, it is difficult to directly derive cortical features encoding relative positions on the original cortical surface. To deal with this issue, before computing cortical features, all individual cortical surfaces are mapped onto a spherical space and further registered onto a spherical surface atlas using Spherical Demons [14]. Then each cortical surface is resampled as a standard mesh tessellation based on the registration results, thus vertex-to-vertex cortical correspondences are established across all subjects. For each vertex on the cortical surface, we compute three types of features: 1) spatial positions in the aligned spherical space, 2) geometric features of cortical folding, and 3) auto-context features of nearby labels. Specifically, spatial positions encode the spatial prior information. The geometric features of cortical folding are the Haar-like features extracted from the mean curvature map and the average convex map of the original cortical surface. Auto-context features are the Haar-like features extracted from the label probability maps derived from random forests. Note that auto-context features are not available in the first iteration of training or testing.

The Haar-like features are defined in a local circular neighborhood on the spherical surface, as shown in Fig. 1. Specifically, given a vertex $v_x$ on the standard spherical surface with $v_0$ as the origin, a local 2D coordinate system with the center as $v_x$ is built on its tangential plane. Assuming that the normal vector from $v_0$ to $v_x$ is $\vec{r_x}$, the direction of $X'$ axis is determined by $\vec{Z} \times \vec{r_x}$, and the direction of $Y'$ axis is then determined by $\vec{r_x} \times \vec{X'}$. All $N$-ring neighboring vertices of $v_x$ are projected to the tangential plane along $\vec{r_x}$. We further divide the circular neighborhood into 4 different ways to generate 4 types of Haar-like features, as shown in Fig. 2. The value of the feature in each case is computed as the summation of the cortical attribute values (i.e., mean curvature, average convexity, or label probability) of all vertices in the white region subtracting that in the black region. For features A and B, rotating around the center by an angle will produce different feature values, thus we calculate 8 feature values at 8 rotation angles at $n\pi/8$, $n$=0,…,7. For feature C, 16 successive values are computed at 16 rotation angles at $n\pi/8$, $n$=0,…,15. For features B and C, the width of the black region is defined as one-third of the diameter of the circle. Note that changing the size of the circle produces different feature values. In our implementation, for computing features A, B, and C, we use 4 different sizes of circles, including 7-ring, 11-ring, 15-ring, and 19-ring neighborhoods, on the resampled spherical surface with 163,842 vertices. For feature D, we use 7-ring as the inner circle and 15-ring as the outer circle, and also 11-ring as the inner circle and 19-ring as the outer circle.

**2.1.3. Training and testing of random forests—**In the first round of training, spatial positions and geometric features are used to train a forest. Then the training subjects are sent to the forest to obtain initial label probability maps, from which auto-context features are computed for further usage. In the next round of training, the auto-context features are used jointly with spatial positions and geometric features to train a new forest. Because geometric features of local cortical folding are quite similar, auto-context features can greatly help reduce the ambiguity and thus increase the accuracy of the parcellation. Sending the training subjects to this new forest, new label probability maps can be obtained accordingly, and new auto-context features can be computed consequently. By repeating the above process, the gradually refined forests can be iteratively trained. The testing process follows the same way as the training process. Specifically, given a testing subject, the spatial positions and geometric features are sent to the first forest to obtain initial label probability maps. Then auto-context features are computed from the label probability maps, and sent with spatial positions and geometric features to the second forest for obtaining more accurate label probability maps. This process repeats until the final label probability maps are obtained from the last forest.

### 2.2. Integrating Label Probability Maps into Graph Cuts

By using random forests with auto-context features, each vertex $x$ on the cortical surface is assigned a probability vector $P_x=[p_{x,1},\ldots,p_{x,l},\ldots,p_{x,N}]$, indicating the probability of each vertex belonging to a label $l$, $l=1,\ldots,N$. An intuitive way to label a vertex is to assign it with a label $l$ that has the maximum probability. However, because random forests classify each vertex independently, this will lead to spatially inconsistent parcellation, although adding auto-context features in random forests leads to improved accuracy and spatial consistency (Figs. 3(c)), comparing with the results without using auto-context features (Figs. 3(b)). To further improve the accuracy and spatial smoothness of the parcellation, we explicitly formulate it as a problem of minimizing a Markov random field energy function $E$:

$$E=E_d+\lambda E_s \quad (1)$$

where $E_d$ is the data fitting term, $E_s$ is the spatial smoothness term, and $\lambda$ is a weight. The data fitting term, which reflects the sum of the cost of labeling each individual vertex on the cortical surface, is defined as:

$$E_d=\sum_x -\log(p_{x,l}) \quad (2)$$

where $p_{x,l}$ is the probability of assigning label $l$ to a vertex $x$, obtained from random forests with auto-context features as described in **Section 2.1**. Intuitively, assigning a label with a higher probability to a vertex leads to a lower energy value of $E_d$. The spatial smoothness term, which reflects the sum of the cost of labeling the spatially neighboring vertices on the cortical surface, is defined as:

$$E_s=\sum_{(x,y)\in N_s} C_{x,y}(l_x,l_y) \quad (3)$$

where $N_s$ is a set of all one-ring neighboring vertex pairs on the cortical surface. $C_{x,y}(l_x,l_y)$ indicates the cost of labeling vertex $x$ as $l_x$ and labeling vertex $y$ as $l_y$. Of note, in the manual parcellations by experts, different cortical regions are usually divided at the highly bended areas (i.e., regions with high magnitudes of curvatures), such as sulcal fundi or gyral crests [7]. Therefore, in those highly bended areas, the cost of assigning two different labels to $x$ and $y$ should be low to encourage the dividing. On the other hand, in the flat areas, this cost should be high to prevent from dividing. Based on the above analysis, $C_{x,y}(l_x,l_y)$ is designed adaptively to the cortical folding geometry as below:

$$C_{x,y}(l_x, l_y) = \frac{1+(\overrightarrow{n}_x \cdot \overrightarrow{n}_y)}{2} \times \frac{e^{-|H_x|}+e^{-|H_y|}}{2} \times \delta(l_x, l_y) \quad (4)$$

where $\overrightarrow{n_x}$ and $H_x$ are the normal direction and mean curvature at vertex $x$, respectively. If $l_x \neq l_y$, $\delta(l_x,l_y)=1$; otherwise, $\delta(l_x,l_y)=0$. Of note, the value of $C_{x,y}(l_x,l_y)$ is in the interval of [0, 1]. If $x$ and $y$ are in the flat cortical areas, their normal directions are similar and their magnitudes of mean curvature are close to 0, thus the cost value will be close to 1. On the other hand, if $x$ and $y$ are in the highly bended cortical areas, their magnitudes of mean curvatures are large, thus the second term in Eq. (4) is small. Therefore, if $x$ and $y$ belong to different cortical regions, their normal directions will have large difference, and thus the first term in Eq. (4) is also small, leading to a small cost when assigning $x$ and $y$ with different labels. However, when $x$ and $y$ belong to the same cortical region, their normal directions tend to be similar, thus the first term in Eq. (4) is large, leading to a large cost when assigning $x$ and $y$ with different labels. This energy function is effectively minimized by the alpha-expansion graph cuts method, which guarantees to achieve a strong local minimum [13].

## 3. RESULTS

The proposed method has been applied to the NAMIC cortical surface dataset [8], which includes the cortical surfaces reconstructed from 39 adult brain MR images by FreeSurfer [16]. Each cortical surface was manually labeled into 35 gyral-based regions by a neuroanatomist, based on the mean curvature map of the cortical folding [7]. In all our experiments, 10 trees (each with 15 layers) were used in random forests, and the weight $\lambda$ in graph cuts was set as 1.0 experimentally. 4-fold cross-validation of the proposed method was performed, in order to directly compare with the results in [14], where the same dataset and same validation strategy were used. In each iteration of cross-validation, 10 subjects were used as testing data and the remaining subjects were used as training dataset.

Fig. 3 provides an illustration of different stages in the proposed method. As we can see, the surface parcellation results were gradually improved by adding auto-context features into random forests, and by using graph cuts. Fig. 4 displays the parcellation results of four randomly selected subjects. For better inspection of the surface parcellation accuracy of the whole dataset, an inflated cortical surface was color-coded by the average Dice ratio of each structure in Fig. 5(a). Dice ratios were relatively low in small regions, such as frontal and temporal poles, due to lacking of reliable cortical geometries in those regions. The improvement of Dice ratio with auto-context feature is shown in Fig. 5(b), and the improvement of Dice ratio by integration of random forests with graph cuts is shown in Fig. 5(c), compared with the sole use of random forests. These results further demonstrated the effectiveness of using auto-context features and graph cuts.

In summary, the average Dice ratio was 0.896±0.014 by using random forests without auto-context features, 0.900±0.015 by using random forests with auto-context features, and 0.902±0.015 by integration of random forests with graph cuts. Of note, our results were higher than the reported average Dice ratio of 0.889 by FreeSurfer and 0.896 by Spherical Demons in [14]. Fig. 6 further showed the mean and standard error of the Dice ratio for each of the 35 cortical structures in the left hemisphere by using FreeSurfer, Spherical Demons, and the proposed method, demonstrating the superior performance of the proposed method. Note that the proposed method shows much improvement especially in small cortical regions without clear boundaries, such as rostral anterior cingulate (region 27, 4.6%), fusiform gyrus (region 8, 3.1%), corpus callosum (region 5, 3.0%), entorhinal cortex (region 7, 2.3%), isthmus cingulate (region 11, 1.4%), frontal pole (region 33, 1.3%), and bank of the superior temporal sulcus (region 2, 1.3%).

## 4. CONCLUSION

The major contributions of this paper are: 1) we propose a novel method for computing Haar-like features on the cortical surface; 2) we propose to jointly use auto-context features and geometric features in random forests for surface parcellation; 3) we integrate label probability maps derived from random forests with graph cuts for accurate and spatially consistent surface parcellation. In future work, we will validate our method on more subjects and also explore other useful features for parcellation.

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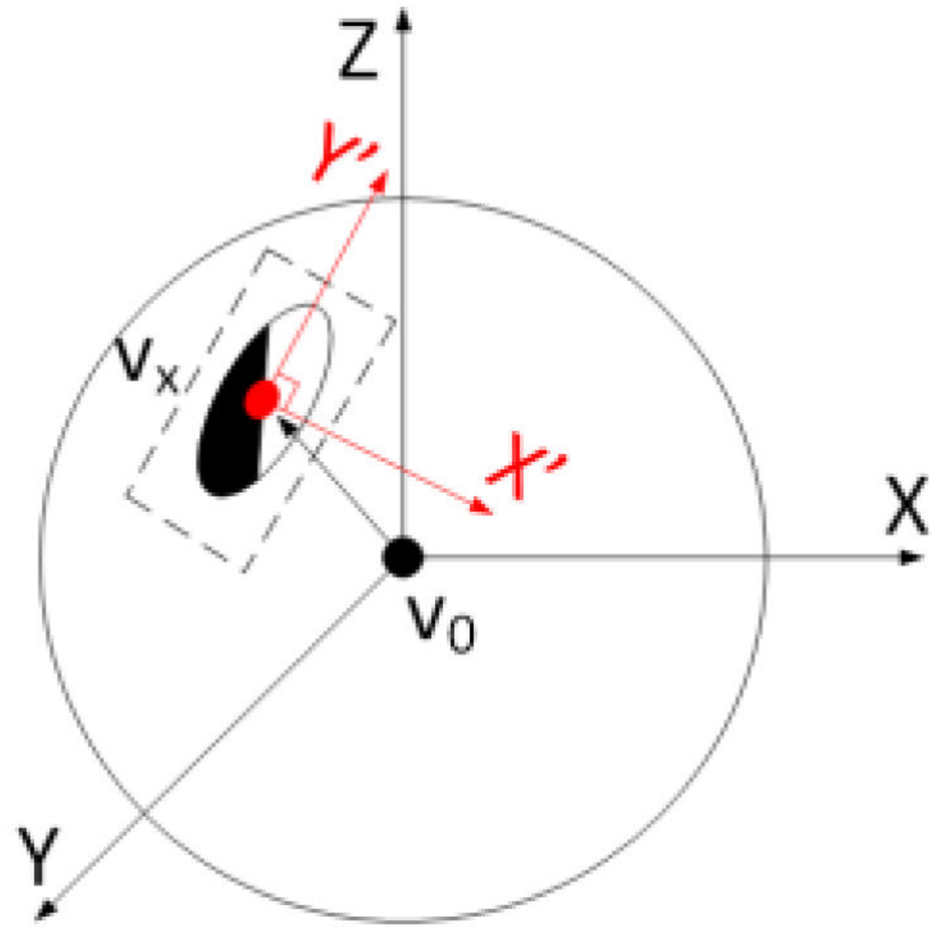


**Fig. 1.**
Illustration of projecting *N*-ring neighboring vertices on the spherical space of $v_x$ onto its tangential plane for computing Haar-like features on the cortical surface.

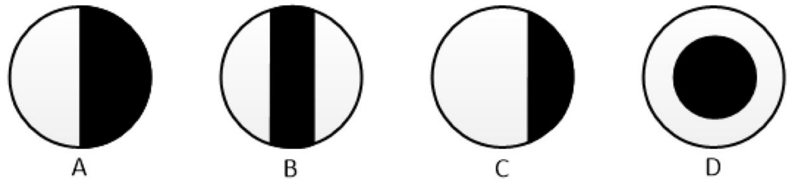


**Fig. 2.**
Illustration of Haar-like features used for cortical surface parcellation. Each circle represents an *N*-ring neighborhood of a given center vertex. Features A, B, and C can capture ridges and valleys, and feature D can capture concave and convex peaks.

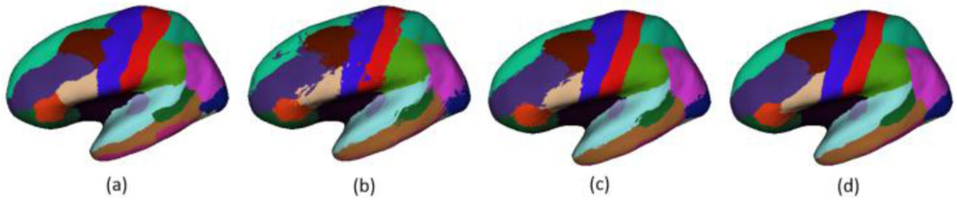


**Fig. 3.**

An illustration of different stages in the proposed method for cortical surface parcellation. (a) Ground truth. (b) Parcellation by using random forests without auto-context features. (c) Parcellation by using random forests with auto-context features. (d) Final parcellation by integration of random forests with graph cuts.

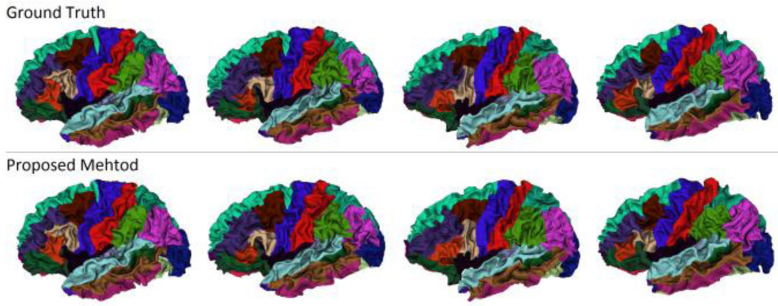


**Fig. 4.**
The parcellation results of four individual subjects.

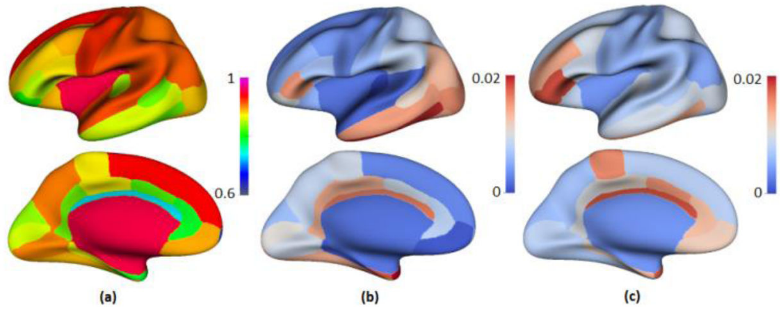


**Fig. 5.**

(a) Average Dice ratio by integration of random forests with graph cuts. (b) Dice ratio improvement between random forests with and without auto-context features. (c) Dice ratio improvement before and after integration of random forests with graph cuts.

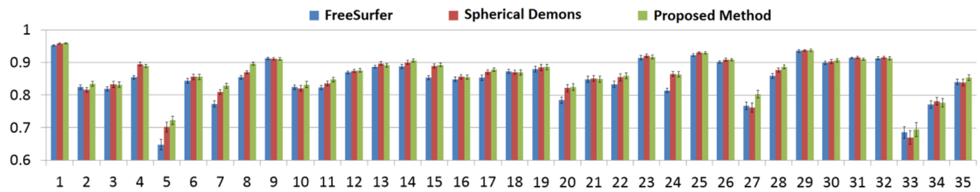


**Fig. 6.**

Mean and standard error of Dice ratio of each of 35 cortical structures on the left hemisphere by using FreeSurfer, Spherical Demons, and the proposed method.