Parcellating Brain Cortical Regions at Multiple Levels of Granularity using the Weighted K-means Algorithm

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Introduction

Studies on brain structural and functional connectivity using modern neuroimaging methods have caught great attention in neuroscience research. Among these methods, brain network analysis with graph theory has been increasingly employed to layout the connective characteristics between different cortical regions and provide a global view of how brain works internally. Although the brain network analysis is potentially useful and powerful, the connective characteristics highly depend on the definition of cortical regions (i.e. nodes in graph theory). Conventionally, the anatomically and functionally cortical parcellations, such as Automatic Anatomical Labeling (AAL) and Brodmann atlases, have been used in most previous studies. In order to investigate the brain networks at different scales, a number of recent studies have attempted to divide the cortical regions of a given brain atlas into smaller parcels at multiple levels of granularity [1-3]. Although these proposed methods have opened a window to depict brain networks at multiple scales, a systematic parcellation approach with robustness and repeatability is still lacking. Therefore, in this study, we proposed a parcellation method based on the weighted k-means algorithm which has the following desirable features, including similar subdivision volume size over the whole brain, not fragmented, fully deterministic and highly reproducible. This method will be potentially helpful to provide a reliable and systematic approach to conduct the subsequent analyses of connectivity and investigate the brain networks at multiple scales.

Materials and Methods

To divide the cortical regions in original brain atlas into parcels with similar volumes, we proposed a weighted k-means clustering algorithm in this study. Compared with conventional k-means algorithm, the distance measure is weighted by an additional weighting parameter to adaptively adjust the volume of each parcel. The parcellation method was implemented in a region-by-region fashion. For each cortical region pair in both hemispheres, the first step was to determine the number of parcels, which was the ratio of the minimum region volume of this pair to a user-specific parcel volume. A constraint that the same number of parcels was used in both hemispheres was imposed. For each region, the initial center positions of all parcels were deterministically assigned along the first principal component axis uniformly. Starting with these initial center positions, the weighted k-means clustering algorithm was then performed recursively to minimize the deviation of volume between all parcels. After the clustering was done, a region-growing algorithm was used to avoid fragmentation. The reassignment of those fragmented voxels was done by using a k-nearest neighbor algorithm. To obtain parcellated brain atlases with different levels of granularity, an iterative splitting algorithm was applied to the coarsest parcel, i.e. the original region. Any parcellation with intermediate level of granularity was obtained by merging a part of the finest parcels to form a subset of the coarsest parcel. To demonstrate our proposed parcellation method, three widely used brain atlases were tested in this study, i.e. AAL, SRI24 and Destrieux atlases [4-6]. With the spatial resolution of 1×1×1 mm^3 voxel size, the numbers of cortical regions for AAL, SRI24 and Destrieux atlases are 90, 90 and 148. For each atlas, a total of 4 or 5 levels of granularity including the original one were obtained, and the number of parcels in finest level of granularity we specified was approximately 1000. Coefficient of variance (COV) of parcel volumes was calculated for each parcellation to evaluate the parcel-wise volume deviations.

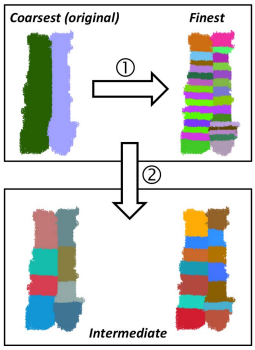

Figure 1. The parcellations at different levels of granularity in frontal superior cortex in AAL atlas. The weighted k-means algorithm and the iterative splitting algorithm were used in steps 1 and 2 respectively.

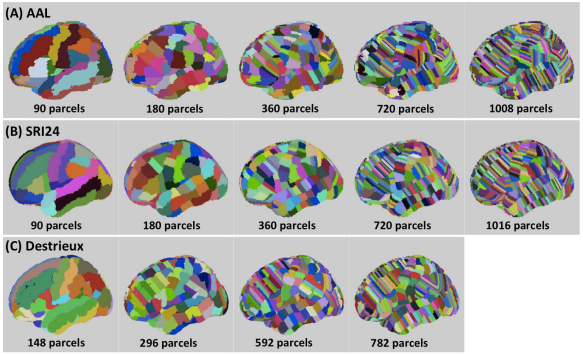

Figure 2. Parcellation results at different levels of granularity. (A) AAL atlas and its parcellation results with 180, 360, 720 and 1008 parcels. (B) SRI24 atlas and its parcellation results with 180, 360, 720 and 1016 parcels. (C) Destrieux Atlas and its parcellation results with 296, 592 and 782 parcels.

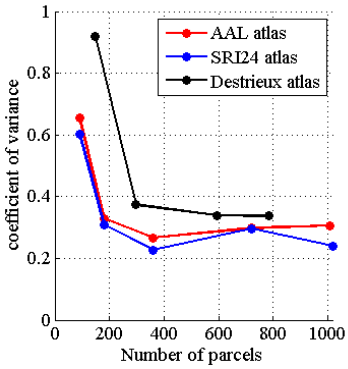

Figure 3. Plots of COV against different numbers of parcels among different brain atlases (AAL in red, SRI24 in blue and Destrieux in black).

Results

Figure 1 shows the parcellations of the frontal superior medial cortex in AAL atlas at different levels of granularity. Our results demonstrate the high spatial correspondence between the parcels in left and right hemispheres. It also shows that all the boundaries in intermediate-level parcels match well to those in finest-level parcels, providing a systematic approach for future large-scale network analysis. The parcellation results from coarsest to finest levels for AAL, SRI24 and Destrieux atlases are shown in figure 2. By visually inspection, no fragmentation exists among all parcellated regions. Figure 3 shows the plots of COV against different numbers of parcels among these three brain atlases. As shown, the variances significantly drop to approximately 0.3 between intermediate to finest levels, suggesting that the clustering sizes become more uniform after employing the proposed weighted k-means algorithm.

Discussion and Conclusions

In this study, we demonstrated our proposed method could be employed on different brain atlases to generate the parcellations at different levels of granularity. Preliminary results suggest that this method is fully deterministic and highly reproducible. However, due to the tradeoff between the left-to-right symmetry and the volume uniformity, the convergence of COV is constrained by the volume difference between the left and right regions in original brain atlas. Another obstacle is that no biologically or functionally relevant prior information is included in our method. The above issues need further consideration with an application-driven thinking. Future works include developing more quantitative evaluation parameters, demonstration on other brain atlases and application on brain network analysis at multiple scales.

Reference [1] Cammoun et al. Journal of neuroscience methods 203(2), 386-397, 2012. [2] Zalesky et al. Neuroimage 50(3), 970-983, 2010. [3] Bassett et al. Neuroimage 54(2), 1262-1279, 2011. [4] Tzourio-Mazoyer et al. Neuroimage 15(1), 273-289, 2002. [5] Rohlfing et al. Human brain mapping 31(5), 98-819, 2010. [6] Fischl et al. Cerebral Cortex 14(1), 11-22, 2004.