Comparison of Normalized DTI analytical methods II: Detection powers of voxel-based, atlas based, and sub-atlas based analysis

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INTRODUCTION

The voxel-based group analysis (VBA) is one of the most effectual assessment methods of the entire white matter (WM) of brain. However, the VBA often suffers from high false discovery rate (FDR), which caused by embedded noise in voxels and imperfect registration. To surmount this problem, the combination of the VBA with a pre-segmented WM has already been proposed [1]. On the other hand, 3D whole brain WM atlas (ABA: atlas-based analysis) was proposed to achieve statistical power on the examination of the WM analysis [2]. We also have proposed alternative way to analyse WM by sub-atlas based analysis (SBA) [3]. In this paper, we attempted to ascertain the statistical detection power and the features of VBA, ABA, and SBA.

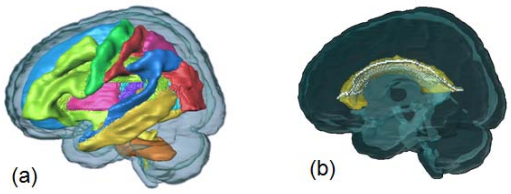

Figure 1. WM atlas(a) and the sub-atlas of CC (white colored plane) (b)

METHODS

Subjects: ICBM-152 normal subjects data (n=21) [4], which were randomly selected from data set, were used. We performed dual channel (b0 and FA) affine transformation and a large deformation diffeomorphic metric mapping (LDDMM) for alignment [2] and computed FA values.

Creation of a sub-atlas: Fig.1b shows the sub-atlas of corpus callosum (CC) [3]. A 3D plane was fit to each portion of parceled WM atlas (Fig.1a) and trimmed the hanging out portions of fitted plane. This process was applied to every parceled WM region and combined to create whole brain WM atlas plane. All voxels within a parceled atlas were projected to the nearest voxel on sub-atlas plane. The averaged value of the all projected voxels was assigned as the value of voxel on the sub-atlas.

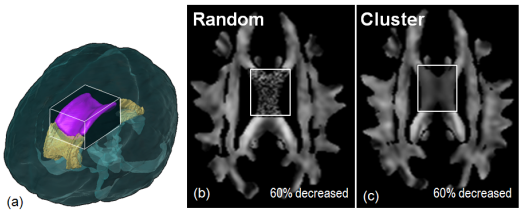

Figure 2. Embedded abnormal area (a) and arrangements of abnormality(b, c)

Embedding abnormal value: We embedded abnormal values within the rectangle area which covers body of CC (bCC, Fig.2a, purple colored). We set this rectangle was 100% abnormal area, which included 22 portions of parceled WM (fornix, anterior limb of internal capsule left (-L), right (-R), posterior limb of internal capsule-L, -R, cingulum-L, -R, superior fronto-occipital fasciculus-L, -R, superior frontal blade-L, -R, post-central blade-L, -R, CC, corona radiata-L, -R). We changed abnormality covering area based on this rectangle from 10 to 100%. We also changed FA value of each voxel from 10 to 100% based on original values. Fig. 2(b and c) shows slices of 60% abnormal area 60% decreased FA (b: randomly arranged abnormal values, c: cluster arranged abnormal values).

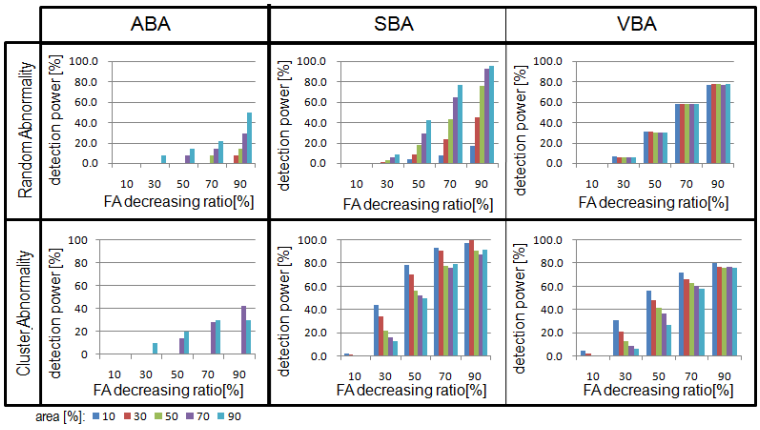

Figure 3. Results of outlier test

Comparison of detection power: We detected abnormality as the outlier of FA values on the same spatial position across the subjects (VBM-style analysis [1]) by using Grubbs-Smirnov (GS) test. The detection power of each method was defined as percentage of detected outliers per embedded abnormalities. In the case of VBA and SBA, the abnormalities were counted by voxels, whereas, the numbers of abnormal area were counted in the ABA.

RESULTS AND DISCUSSION

Fig.3 shows the results of outlier test. The horizontal axis of the charts indicate the decreasing percentage of original FA value. Each bar shows the percentages of abnormal area, based on Fig.2a. The vertical axis shows the detection power. In the case of random abnormality, the detection power of ABA and SBA were clearly affected by both abnormal area and its value (Fig3, upper left, middle). On the other hand, the detection power of VBA was not affected abnormal area and it was only affected by abnormal values (Fig4, upper right). These results clearly reflect the features of each method on the detection problem. In the case of cluster abnormality, the detection power of ABA and SBA were also affected by both abnormal area and value (Fig3, lower left, middle). The detection power of VBA was affected by both abnormal area and value as well (Fig3, lower right). The reason of this discrepancy on VBA seemed to be based on the smoothed out by cluster abnormality. From the results, SBA and VBA showed better detection power on the cluster abnormal arrangement than the random abnormal arrangement. This means that the distribution of abnormal values affects the detection power of VBM-style examination methods. The extension of the area covered by abnormal values in the region of interest also affected the detection power of these methods. In the case of ABA, the cluster abnormal arrangement was well detected in higher detection power than in the case of random. On the other hand, the random abnormal arrangement was better detected in its lower area by ABA than cluster arrangement. The reason was that the abnormalities were higher value than the threshold of outlier which defines the ability of the test. When abnormal values covered relatively narrow area, the detection power was relatively higher than the wide-covered area by abnormal value on SBA and VBA (Fig3, middle and right). The reason was the averaging, which decides each voxel value, on the SBA. On the VBA, when abnormal values cover relatively wide area, wide-value-distribution occurs. This wide-value-distribution range across the subjects make hard to detect the abnormality by GS test.

CONCLUSION

The features of VBA, ABA, and SBA on the abnormality-detection problem were generally grasped. We attempt to compare ABA, VBA, and SBA. Nevertheless, there is still no direct way to compare ABA and other methods. Further study was required to create the method that can conquer both the smoothed-out problem of ABA and the FDR of VBA and SBA. The combination of ABA and VBA might confer us a new point of view.

References [1] Smith et al., NeuroImage 31(2006), 1487-1505, [2] Mori et al., NeuroImage 40 (2008), 570-582, [3] Sakai et al., ISMRM2009 XXX, [4] http://www.loni.ucla.edu/ICBM/Downloads/Downloads_Atlases.shtml