

Comparison of Brain Segmentation Results Using Automated FSL-FAST With DTI Channel Inputs

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Introduction

A well-recognized algorithm for image segmentation is the Expectation-Maximization (EM) algorithm. [1] The freely distributed FSL-FAST program is designed to perform automated segmentation using the EM algorithm on T1W, T2W, or proton-density weighted images. However, Diffusion Tensor Imaging (DTI) offers unique information on white matter tractography by tracking the magnitude and direction of the diffusion of water molecules. In white matter tracts, diffusion is anisotropic, with water molecules diffusing preferentially along the direction of the white matter pathway. Therefore, it is desirable to use the information DTI gives us to perform white matter segmentation. The aim of this investigation was to compare the performance of methods of adapting the FSL-FAST algorithm on DTI data to each other and to manual segmentation.

Materials and Methods

Five datasets were used from healthy subjects, collected at 3.0T using an 8-channel receiver coil, DW-EPI with SENSE undersampling of 2, $b = 1000\text{s/mm}^2$, 12 encoding directions, 3 averages, and $2 \times 2 \times 2.5\text{ mm}$ voxels. Each included T1W and T2W images, along with fractional anisotropy (FA) and apparent diffusion coefficient (ADC) maps, and the three eigenvector images. T1-W and T2-W images from the same subjects were coregistered to DTI images using an affine transformation in FSL. Manual segmentation by an expert was performed as a gold standard on selected slices of T2W images for each dataset (except one dataset in which ADC and FA maps were used for segmentation). A mask to remove the skull and boundary noise was created, in addition to separate WM, GM, and CSF images. The expert was blinded to the FSL-FAST segmentation results. Spmalyze [2] software was used for the manual segmentation for evaluations. Automated segmentation was performed using FSL-FAST [3] in the following methods: (a) 2-channel segmentation into three classes, using ADC and FA maps as inputs, (b) 2-channel segmentation into three classes, using the first and third eigenvectors (ev1 and ev3) as inputs, (c) 2-step segmentation first segmenting the ADC map (1-channel input) into three classes, then using the class CSF as a mask applied to the FA image, and finally segmenting WM from GM using the masked FA image (1-channel input), and (d) the same method as in (c), but using the third eigenvector (ev3) to create the CSF mask and the first eigenvector (ev1) to segment GM from WM. We have called the method used in (c) and (d) "stepped masking" in Figure 1. These data types were chosen because ADC has high contrast between the CSF and other regions, and FA has a high contrast between WM and other regions. [3]

Results and Discussion

Each of the four approaches to automated segmentation was compared to the manually segmented WM maps. The manual image was overlaid onto the automated result image (Figure 1), and the true positive and true negative rates were calculated from histograms of the overlaid image (Figure 2). While the performance of each method compared to the others varied by subject, we see that in general the 2-channel input segmentation outperforms the stepped masking in at least some respect, but that within the 2-channel segmentation, the method using ADC and FA maps tends to over estimate the white matter area, while the method using ev1 and ev3 maps tends to slightly underestimate the white matter area. The stepped masking using the ev1 and ev3 maps is more consistently poor in matching the manual results.

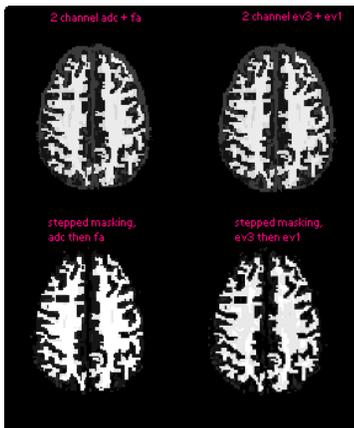


Figure 1: FAST-segmented image overlaid with manually segmented white matter image. Shown is one slice in one subject.

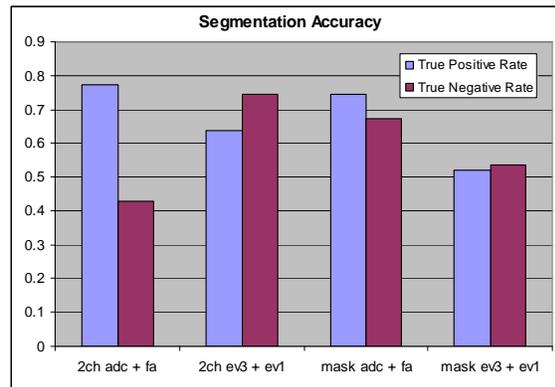


Figure 2

Conclusion

FSL-FAST is a well-respected program within the community for segmenting MRI brain image data. However, this is the first case (that we know of) in which its performance using DTI datasets as inputs has been evaluated. We hope in the future to compare these methods more thoroughly to other segmentation methods. The results of this investigation, in the mean time, should provide information for researchers to be aware of when applying FSL-FAST to their own DTI brain tissue segmentation projects.

References

[1] Liu T, et al. NeuroImage vol.31,pp:51-65 (2006). [2] brainimaging.waisman.wisc.edu/~oakes/spam. [3] www.fmrib.ox.ac.uk/fsl. [4] Pierpaoli C, et al. Radiology vol.201,No.3,pp:637-648 (1996).