Brain MRI Segmentation for Focal Cortical Dysplasia Lesion Detection

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Introduction

Focal cortical dysplasia (FCD), a malformation of the cortical development in the brain, is a major cause of refractory epilepsy. In clinical treatments, FCD lesions often have to be removed by surgery and before this can be done, it is necessary to detect and delineate the lesions. However, identification of FCD lesions is a very challenging task and standard radiological MRI evaluation still fails in many cases, because of the complexity of the cortex and subtle behavior of the lesions. On T1-weighted MRI sequence, FCD is usually characterized by increased cortical thickness and blurring between cortex and white matter junction. Therefore, to automatically detect FCD lesion, it is necessary to calculate cortical thickness and intensity map, which often require accurate MRI cortex segmentation. To date, the most popular methods for brain MRI segmentation are the histogram-based method with automated threshold (HTR), Functional MRI of the Brain (FMRIB) Automated Segmentation Tool (FAST) [1] and Statistical Parametric Mapping (SPM) [2]. Although all of these techniques are fast, reproducible and require minimum human intervention, their outcome may be influenced by image noise, bias field and partial volume effects. Thus, to improve the accuracy of cortex segmentation, in this work we propose a 3D brain MRI segmentation technique based on graph cuts algorithm [3]. The novelty of our approach is automatic initialization of the voxel probabilities using Gaussian Mixture Model (GMM) and a 3D instead of 2D segmentation using three labels: gray matter, white matter and cerebrospinal fluid (CSF).

Methods

Our algorithm incorporates intensity, local boundary and spatial neighborhood information in a graph cuts energy function using T1-weighted MRI. Image segmentation is formulated as a problem of energy minimization $E(A) = \alpha\, D(A) + S(A)$ that consists of a data term $D(A)$ and a smoothness term $S(A)$. The data term estimates how well the label can be assigned to the voxel based on GMM. The smoothness term includes the spatially dependent interaction between neighboring voxels. Minimization of the energy occurs by setting up a graph and calculating the minimum cost cut. The graph consists of nodes (for each voxel and label) and edges (to connect nodes). The voxel nodes are connected with two types of edges: to the neighboring voxels (included in the smoothness term) and to the label nodes (included in the data term). In the first set of edges, gradients are also incorporated to include boundary information.

Results

The performance of the proposed algorithm is tested on both phantom [4] and real T1-weighted MRI data (recorded at the Ghent University Hospital). Using phantom MRI data with different noise levels, we quantitatively compare our results with HTR, FAST and SPM methods. The Dice coefficient is used as a similarity measure. The results of gray matter segmentation are shown in Fig. 1a and indicate that our method has the best performance for 5% and 7% noise levels, while for the highest noise level FSL gives the same result and for the lowest noise level HTR performs better. The qualitative validation was done on eight FCD patients where all lesions, delineated by expert physician, were detected and segmented as part of the cortex. In all cases segmentation showed an increased cortical thickness at the place of the lesion (see Fig. 1b).
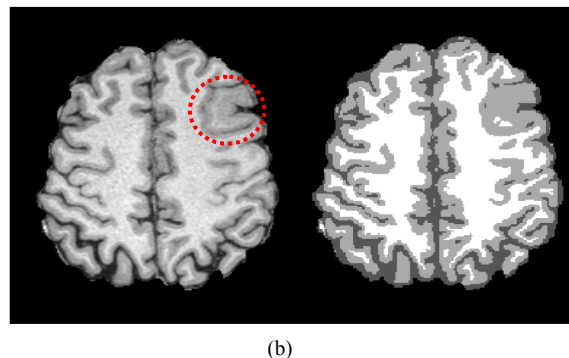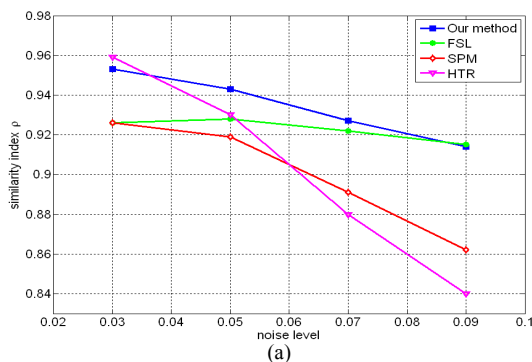

Fig. 1. (a) Comparison of the gray matter segmentation results using brain MRI phantom with different noise levels; (b) Left: a real brain MRI with an FCD lesion in a red circle. Right: 3D graph cuts segmentation using three labels: white matter (white), gray matter (light gray) and CSF (dark gray).

Conclusion

Based on the quantitative and qualitative validation, we showed that our method outperforms FSL, SPM and HBM algorithms for a wide range of noise levels and can successfully segment FCD lesions with the brain cortex, indicating the cortical deformations. Future work will include further refinement of the algorithm and incorporating multi-modal information (combining T1-weighted and FLAIR volumes).

References

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