

A Geo Cut Algorithm For Brain MRI Segmentation

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INTRODUCTION

Segmentation of MR brain images is an important step in many clinical applications, but is challenging due to the vast amount of fine structures. Conventional EMS algorithm [1] fails in presence of noise, partial voluming or fine details and textures. Recent improvement were reported using graph cuts [2] but standard inter-voxel edge weighting in graph cuts fails near small structures. We propose a graph-based combinatorial algorithm called geo-cuts, where image gradient magnitudes and gradient directions determine the weighting, to overcome this problem. Our results show that the overall percentage of correctly classified voxels is higher using the geo-cuts method except when noise is present. The Dice Similarity Measure indicates that both methods work well with geo-cuts generally outperforming standard graph cuts for white matter and CSF and vice versa for gray matter. Visually, geo-cuts gives better performance on both real and synthetic images with respect to fine structures of white matter and CSF.

METHOD

We incorporate geo-cuts in a Expectation Maximization (EM)-style framework [3], where we iteratively estimate the intensity probability distributions of the different brain tissues and classify the voxels into different tissues. The intensity probability distribution is modeled using a Gaussian mixture (GMM). The geo-cuts output labeling is used to classify the voxels, using prior intensity probability distribution and the MNI brain atlas as regional prior information. Synthetic images from the Brainweb data (MNI, Montreal) with and without noise and intensity inhomogeneities are tested to assess the robustness of the methods. On the synthetic data, we perform quantitative assessments using the percentage of voxels correctly classified and the Dice Similarity Measure with respect to the ground truth. Real MPRAGE brain data was obtained from a Siemens/Bruker 4 Tesla scanner. We compare the segmentation results of real images through a visual assessment.

RESULTS

Percentage of voxels miss-classified on synthetic images (Table 1), and Dice Similarity Measure with respect to ground truth is shown in Table 1. Visual comparison with conventional EMS technique is shown in fig 1.

Table 1. Quantitative results on synthetic images with no noise and no intensity inhomogeneities (NOBF0), with no noise and 20% of intensity inhomogeneities (NOBF20) and with 7% noise and no intensity inhomogeneities (N7BF0). Misclassification percentage and Dice Similarity Measure are shown for each tissue with respect to the ground truth. WM1, GM1, CSF1 etc are the measures for the standard graph cuts method and WM2, GM2, CSF2 are those for the geo-cuts method.

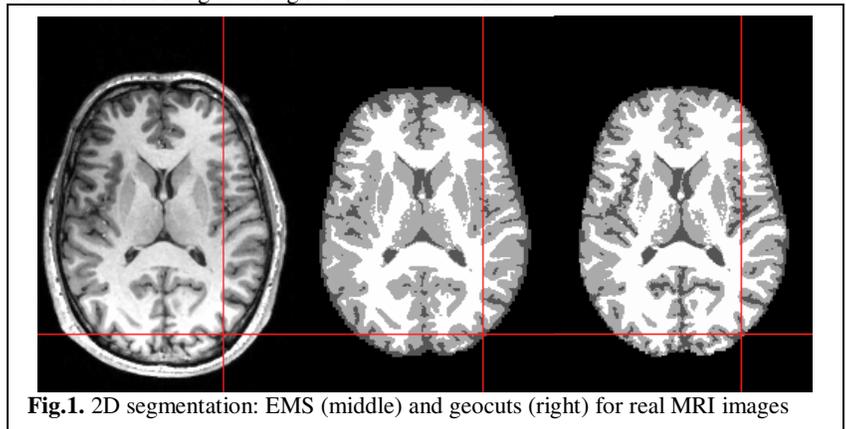


Fig.1. 2D segmentation: EMS (middle) and geocuts (right) for real MRI images

	Misclass 1	DSM-WM1	DSM-WM2	DSM-GM1	Misclass 2	DSM-GM2	DSM-CSF1	DSM-CSF2
NOBF0	0.103586	0.816449	0.902594	0.95406	0.0762035	0.923463	0.965167	0.97288
NOBF20	0.159059	0.82432	0.869258	0.79524	0.116573	0.860761	0.967626	0.960032
N7BF0	0.136134	0.798941	0.824457	0.902836	0.147791	0.841027	0.935762	0.93730

CONCLUSION

Results show that the overall percentage of correctly classified voxels is higher using the geo-cuts method except when noise is present. This is not unexpected since geo-cuts method is theoretically more susceptible to salt and pepper noise, which will not be discussed here due to, limited spacing. The Dice Similarity Measure indicates that both methods are working well with geo-cuts generally outperforming standard graph cuts for white matter and CSF and vice versa for gray matter. This fact is likely caused by partial white matter/gray matter voxels more evenly classified as both tissue types using geo-cuts and heavily classified as gray matter by standard graph cuts. Visually, the geo-cuts method gives better performance on both real and synthetic images with respect to fine structures of white matter and CSF.

REFERENCES

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