Method for Improving Segmentation of Multispectral brain MRI by a Supervised Hybrid Classifier</sub>

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INTRDOCUTION

Multispectral MRI data have been commonly used for brain quantitative volumetric measurement by using meaningful segmentation techniques. However, there is a lack of effective techniques that can be used to perform quantification of normal brain tissue and brain pathologies simultaneously because of different MR characteristics from normal and pathological components. In our previous work, a supervised technique has been proposed for effective quantification of brain normal tissues and hyperintense white matter lesions (WML) simultaneously by using independent component analysis (ICA) coupled with support vector machine (SVM) for slice-by-slice segmentation of multispectral MRI [1]. The method only needed a small set of training samples selected from each of the multislice MR data to effectively classify the individual image slice. Actually, the method was applicable in its clinical applicability. But the practicality might be hampered by the limitations of the slice-by-slice segmentation, because of a burden on training sample selection of multislice image data, sensitivity from different sets of training samples for individual slices and computational complexity. In this paper, we attempted to implement a hybrid classifier derived from iterative Fisher's linear discriminant analysis (IFLDA) [2] coupled with the volume sphering analysis (VSA) and SVM to effectively segment multi-slice MRI brain data by using only one set of training samples.

MATERIALS and METHODS

Synthetic data from the BrainWeb Simulated Brain Database [3] and real normal brain MR data of twenty healthy volunteers were used to conduct an objective assessment on accuracy and reproducibility of the proposed method. The hybrid classifier approach consists of four stage processes to analyze three sets of T1-weighted, T2-weighted and proton density images. First, the entire volume data cube of multislice MR images is sphered by removing the first two order statistics. The data sphering is a crucial preprocessing step for ICA for image enhancement by capturing data samples with non-Gaussian statistics. Second, a small set of training samples, containing a 3x3 matrix of 9 pixels of GM, WM, CSF and background (BG), were depicted by an experienced radiologist from any one of multislice images for SVM to classify GM, WM and CSF in the sphered MR images. Third, the results of SVM classification, after removal of the extrameningeal structures, served as the training samples of FLDA to classify tissue substances. Forth, the classified results from FLDA were used as the training samples of the next FLDA to classify tissue substances repeatedly. The iterative process was terminated when two FLDA-classification results produced by two consecutive iterations are identical. Tanimoto index was used to evaluate quantification results of brain volume measurements of synthetic data. The intra- and inter-operator variability was analyzed to evaluate reproducibility of quantification results of clinical brain data.

RESULTS

The results showed an improvement of the mean *Tanimoto* indexes of GM/WM segmentation in the synthetic normal brain data, as table 1. As for clinical MR data experiments, the hybrid classifier performed as well as does that using the slice-by-slice method in quantification of GM/WM volume, and was much superior in consistency of intra- and interoperator measurements. Coefficients of variation of GM/WM volume measurements of twenty volunteers were listed as Table 2.

Table 1. The Tanimoto indexes of GM and WM quantification in the synthetic MRI at various parameter settings

Tanimoto index		GM		WM	
		Hybrid classifier	Slice-by-slice	Hybrid classifier	Slice-by-slice
0% of intensity nonuniformity	Noise 0%	0.88	0.82	0.92	0.89
	Noise 1%	0.86	0.77	0.90	0.85
	Noise 3%	0.81	0.73	0.86	0.80
	Noise 5%	0.78	0.68	0.81	0.78
20% of intensity nonuniformity	Noise 1%	0.83	0.74	0.88	0.81
	Noise 3%	0.80	0.72	0.85	0.83
	Noise 5%	0.75	0.67	0.80	0.77

CONCLUSIONS

The proposed hybrid classifier has several advantages. One was a reduction of computational cost in data processing since it only needs one set of training samples to process the entire multislice images. Besides, the same saving is also applied in minimizing operator burden. The uppermost benefit is to avoid potential operator interferences from selecting training samples and improve the reproducibility of the supervised classifier. This supervised hybrid classifier would be explicitly applicable in clinical applications to segmentation of brain MRI.

References

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Table 2. GM and WM volume quantification in twenty healthy volunteers by three operators and three measurements by one operator.

	Measurements by three operators				Three measurements by one operator			
	Hybrid classifier		Slice-by-slice		Hybrid classifier		Slice-by-slice	
	Mean	CV.%	Mean	CV.%	Mean	CV.%	Mean	CV.%
GM	615.3±63.91	1.0±0.9	629.0±76.6	4.3±1.8	617.0±63.9	0.6±0.5	632.0±79.1	3.2±1.7
WM	437.9±65.7	1.7±1.5	445.5±65.1	7.2±3.0	444.6±64.6	1.0±0.7	456.4±67.9	5.6±3.5
GM+WM	1053.2±109.0	0.2±0.2	1074.5±130.8	3.4±1.6	1071.6±107.6	0.3±0.5	1088.4±137.5	2.0±1.4