Automated Segmentation of MS Lesions in FLAIR, DIR and T2-w MR images via an Information Theoretic Approach

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INTRODUCTION

Problem: automated segmentation of T2-weighted (T2-w), Fluid Attenuated Inversion Recovery (FLAIR)[1] & Double Inversion Recovery (DIR)[2] Magnetic Resonance Images (MRIs) with Multiple Sclerosis (MS) lesions[3] of various severity.

Our Approach: The Improved "Jump" Method (IJM)[4-8,14-16] clustering, assisted by edge suppression, is applied to the segmentation of brain tissues, in a subset of slices determined to be the best MS lesion candidates via Otsu's method[9]. From this preliminary clustering, the mode values for the tissues are determined. A Euclidean distance is then used to estimate the fuzzy memberships of each brain voxel for all tissue types and their 50%/50% partial volumes (PVs) for improved segmentation.

Validation: the segmentation of labeled benchmark MRI datasets of brains with MS lesions[10].

Goal: the automated segmentation of brain MR images for detection and tracking of MS[3].

METHODOLOGY

MRI Simulation

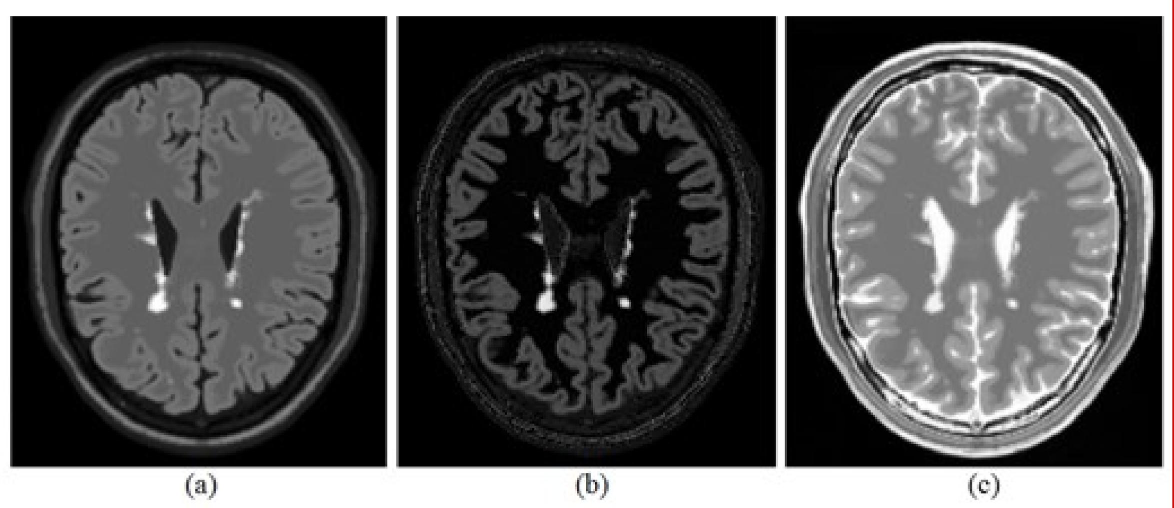
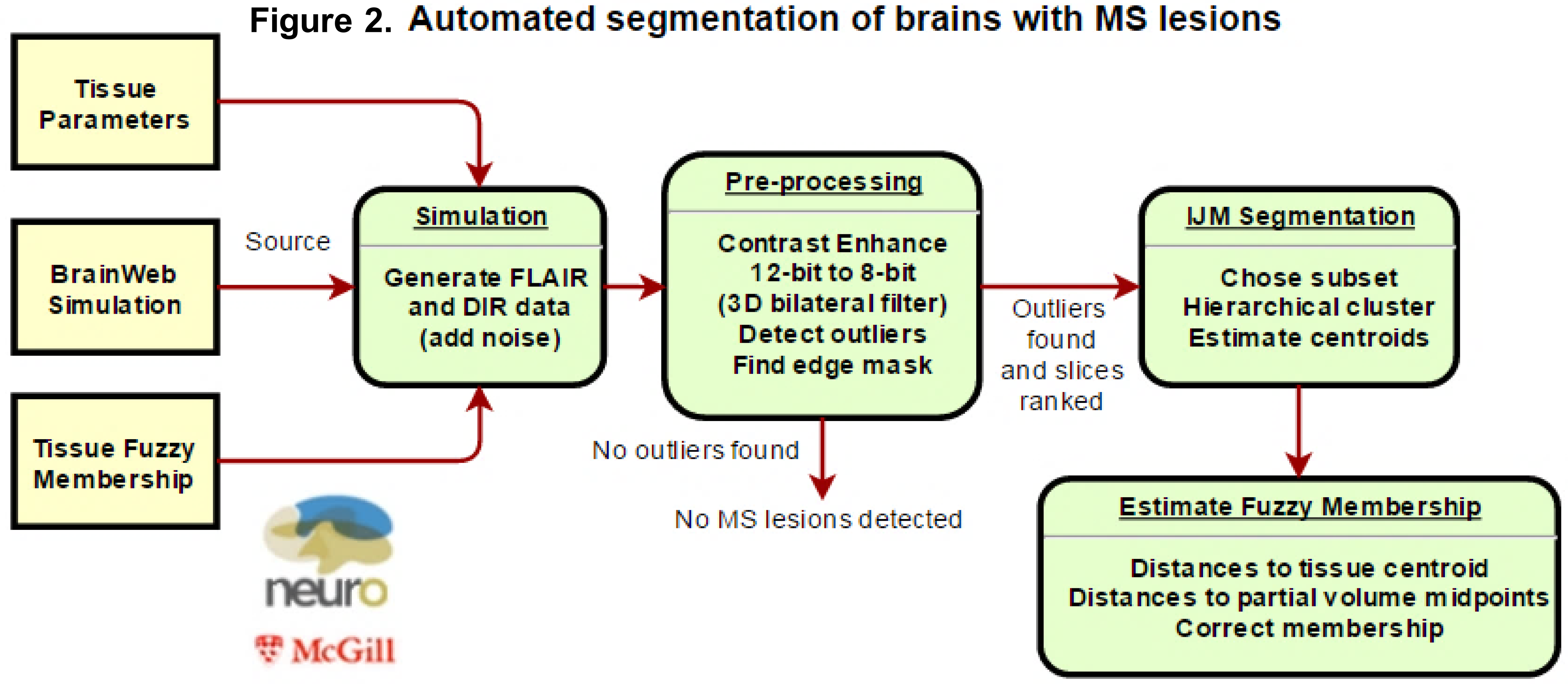


Figure 1. FLAIR (a) and T2-w (c) MRIs are obtainable from BrainWEB[10], and DIR (b) is a simulated signal[13] derived from the Bloch equation.

Figure 2. Automated segmentation of brains with MS lesions



Preprocessing

The 12-bit data are converted to 8-bit after screening for outliers and contrast enhancement.

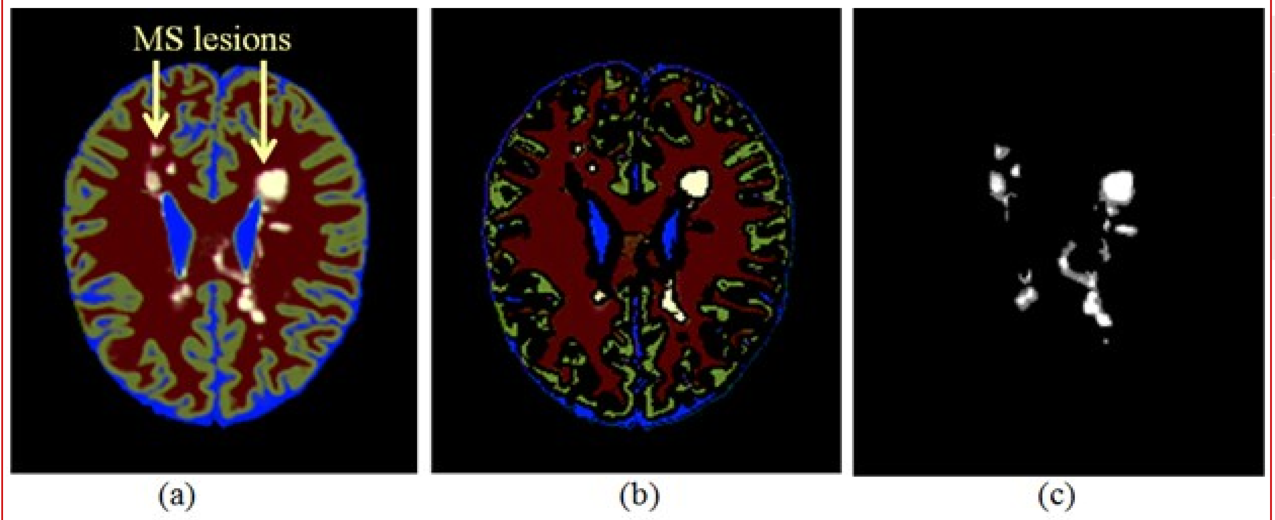


Figure 3. The data are combined into colorized images (a) with FLAIR (red), DIR (green) and T2-w (blue). To remove the affect of the PVs, the edges are suppressed (b) for the input of the segmentation process; severe MS result shown (c).

The Improved "Jump" Method (IJM)

Goal: to cluster p-dimensional data with n points.

Definitions (applied to quantized images):

- Distortion: measures within cluster dispersion,

$$d_K = \frac{1}{p} \min_{c_1, c_2, \ldots c_K} \left\{ \frac{1}{n} \sum_{k=1}^{K} \sum_{i \in k} (\boldsymbol{x}_i - \boldsymbol{c}_k)^{\mathrm{T}} \boldsymbol{\Sigma}^{-1} (\boldsymbol{x}_i - \boldsymbol{c}_k) \right\},$$

- The Jump Statistic: $J_K^Y = \dfrac{1}{d_K^Y} - \dfrac{1}{d_{K-1}^Y}$
- Effective Dimension: p_{eff}, allowing $Y = p_{\mathrm{eff}}/2$
- Margin Operator: $M_K^Y = \dfrac{J_K^Y}{\max_{\beta \neq K} \left\{ J_\beta^Y \right\}}$
- χ^2 score of features: $\chi_{ij}^2 = \dfrac{1}{2} \sum_{k=1}^{K} \dfrac{\left[h_i(k) - h_j(k) \right]^2}{h_i(k) + h_j(k)}$
- Estimation: $M_K^* = \max_{Y>0} \left\{ M_K^Y \right\}$, $K^* = \max_K \left\{ J_K \right\}$

RESULTS

Determination of tissue centroids by IJM

Table 1. IJM results for the estimated centroids for the four tissue types in the form of RBG triples across all three MS severities obtained from BrainWeb.

	WM	GM	CSF	MS lesions
mild	(85, 0, 0)	(107.1, 137, 43.2)	(0, 30, 255)	(255, 255, 186)
moderate	(79, 0, 0)	(99.4, 98, 67.1)	(0, 21.3, 255)	(255, 255, 232)
severe	(80, 0, 0)	(101.1, 120, 44.1)	(0, 26.5, 255)	(255, 255, 202)

Estimation of fuzzy memberships

- The Fuzzy Membership: $\mu_k(\vec{x}_i) = \dfrac{\left[d_E^{-2}(\vec{c}_k, \vec{x}_i) \right]^\beta}{\sum_{n=1}^{K} \left[d_E^{-2}(\vec{c}_n, \vec{x}_i) \right]^\beta}$.

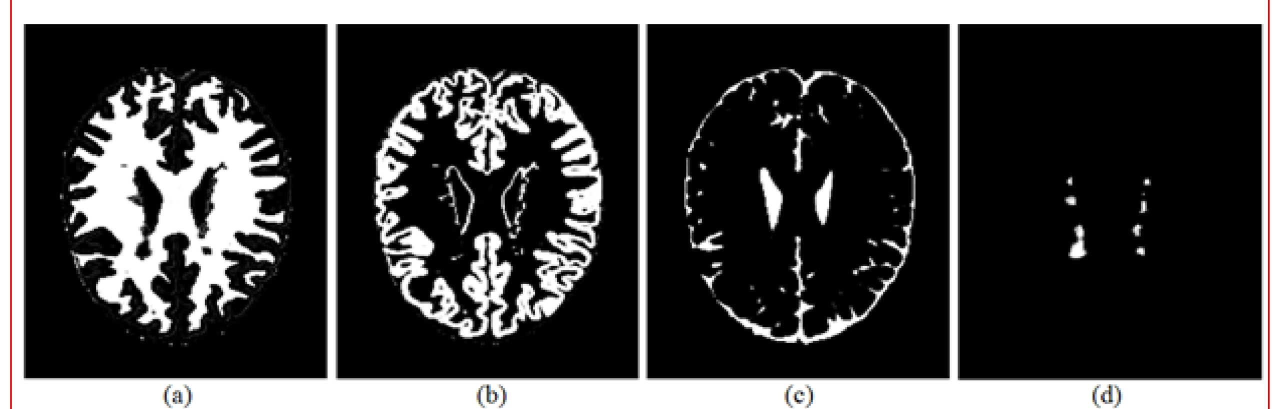


Figure 4. Estimated fuzzy memberships from a Euclidean distance ($\beta = 3$) of (a) the WM; (b) the GM; (c) of the CSF; (d) MS lesions.

Table 2. Results of the discrete binary labels for all three MS lesion severities.

	True Positive	True Negative	False Positive	False Negative	Ground Truth (GT=TP+FP)	Sensitivity TP/GT
mild	402	1958463	295	20	422	95.26%
moderate	3153	1955199	359	359	3512	89.78%
severe	9746	1946937	2138	358	10104	96.46%

Table 3. Comparison measures for discrete and fuzzy results across severities.

	Specificity TN/(TN+FP)	Reliability TP/(TP+FP)	Dice S. C.	Under Estimation	Over Estimation	Fuzzy SSIM
mild	99.98%	57.68%	0.7185	0.0010%	0.0151%	0.9621
moderate	99.92%	68.22%	0.7753	0.0184%	0.0752%	0.9277
severe	99.89%	82.01%	0.8865	0.0184%	0.1100%	0.9422

CONCLUSIONS

Segmentation of MS lesions in FLAIR, DIR & T2-w MR images without prior knowledge of the disease presence or severity is done via a clustering technique based on an information theoretic approach. This yields a sensitivity of ~90-95% and a reliability of ~58-82%; consistently deems a normal brain as MS lesion-free; is robust with respect to noise[17] up to levels of about 2% of the peak amplitude of T2-w image; is extendable to higher noise levels with a 3D bilateral filter.

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