A METHOD FOR SEGMENTATION OF MULTIPLE SCLEROSIS LESIONS ON MAGNETIC RESONANCE IMAGES

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INTRODUCTION and PURPOSE

The identification and segmentation of focal hyperintense lesions on Magnetic Resonance Images (MRI) are essential steps in multiple sclerosis (MS) patients [1]. Despite many automatic methods for MS lesion segmentation have been proposed in the last 15 years, manual segmentation is still considered the gold standard. This is due to the fact that not all lesions are correctly identified employing automated techniques [2, 3].

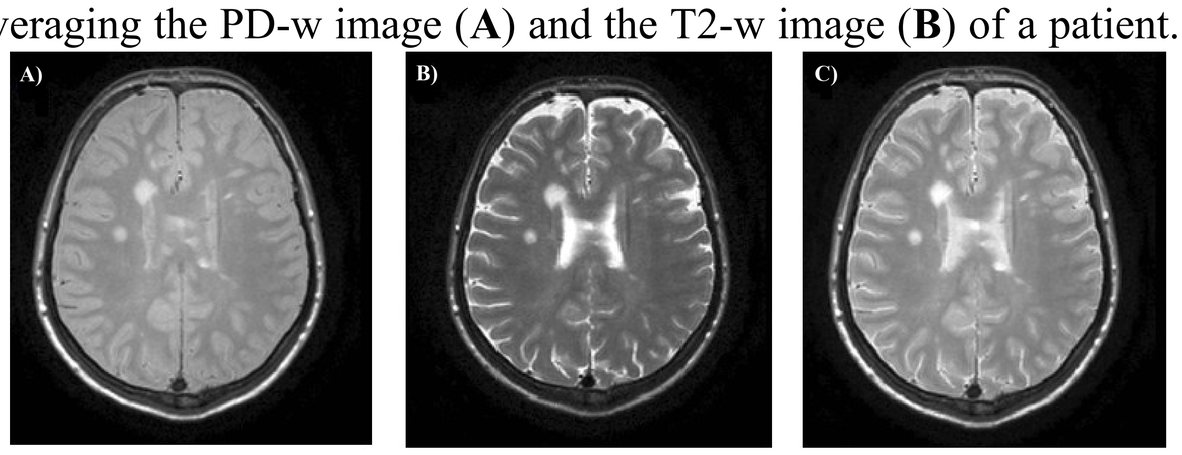
Purpose: Aim of this study was to develop a method for MS lesion segmentation based on Dual-Echo (DE) MRI, initialized by manual identification of lesions and *a priori* information, that provides high similarity with the manual segmentation performed by an expert operator, as well as low misclassification of lesions and a considerable reduction in time required for the analysis.

METHODS

Patients: The dataset consisted of 10 MS patients used for the training set and 20 MS patients with variable T2-hyperintense lesion load [0.3-9.0 ml] used for the validation. For each patient, a brain DE turbo spin-echo MRI sequence was obtained using a 3.0 Tesla scanner (Achieva Philips Medical Systems, Best, The Netherlands), (TR/TE = 2910/16-80 msec, ETL=6; flip angle=90, matrix size=256x256, FOV=240x240mm², 50 axial 3mm-thick slices).

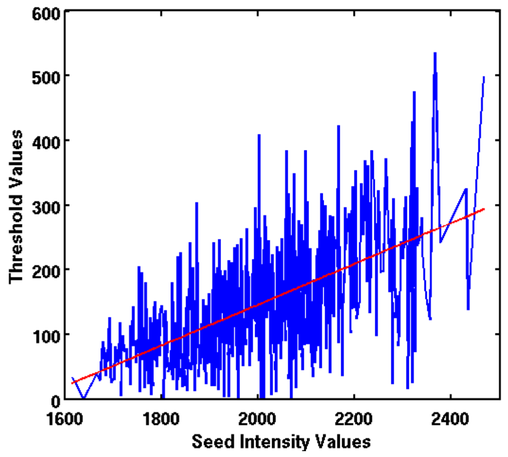
Methods: Preprocessing. In the first step, PD-weighted (PD-w) image intensity values are standardized to correct for the arbitrary intensity scaling for different acquisitions [4]. Then, a half-way contrast image is obtained by averaging the not standardized PD-w and T2-w images to take advantage of both images tissue contrasts (Figure 1). This "mean image" is subsequently high-pass filtered to amplify high-frequency components. The edge-enhanced image is subtracted from the original one to obtain an image in which the inside of the lesion assumes negative values, while lesion edges are zero-crossing points easily recognizable by the algorithm.

Figure 1. An example of a half-way contrast image (**C**) obtained averaging the PD-w image (**A**) and the T2-w image (**B**) of a patient.



Region Growing and Training. The core of the algorithm is the pixel-based region growing segmentation method, that starts from the seed point manually identified by an expert neurologist. Region growing stops when the intensity of all new adjacent voxel exceeds a certain threshold. Such a threshold depends on seed intensity following a curve (Figure 2) estimated during the training process, using the manually segmented lesions.

Figure 2. Threshold values extracted after a training process on the manual segmented lesions. The red line is the fitting curve used as threshold function.



Segmentation. Starting from the seed point, the expansion of the segmented region continues to the adjacent pixels until, for all neighbouring pixels:

- an edge is reached, based on the high-pass filtered image;
- the intensity of the new voxel is dissimilar to that of the seed point.

Refinement step. After an initial segmentation, a more robust intensity threshold is estimated, considering the percentiles of the distribution of intensity values for each lesion. This new threshold is used to proceed the region growing and refine the initial segmentation. **Validation.** Manual segmentations by an expert operator are used as the gold standard. The metrics evaluated are Dice Similarity Coefficient (DSC), Root Mean Square Error of lesion load (RMSE), True Positive Fraction (TPF), False Positive Fraction (FPF), and False Negative Fraction (FNF) for each patient.

RESULTS

The results obtained are represented in Figure 3. Averaging the metrics over all patients, the following values are obtained: **DSC=0.78**; **RMSE=0.17 ml**; **TPF=0.81**; **FPF=0.14**; **FNF=0.20**. Figure 4 shows an example of lesion segmentation.

Figure 3. A: scatter plot of the automatic segmented volume compared to the gold standard. **B:** the DSC evaluated for each patient. **C:** TPF (blue squares), FPF (red crosses) and FNF (black circles) for each patient.

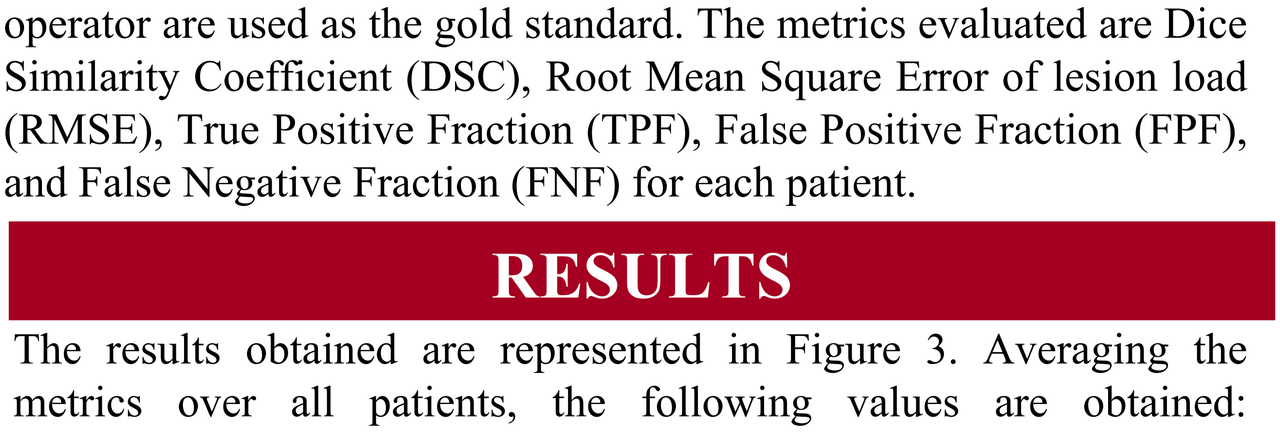
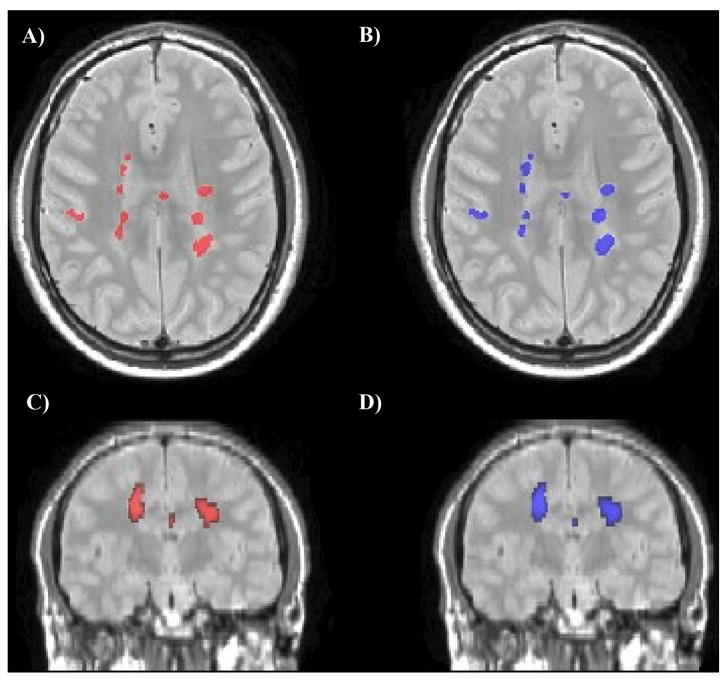


Figure 4. Example of lesion segmentation performed with the new method (**A-C**), compared to the manual one (**B-D**) in axial and coronal plans.



CONCLUSIONS

- Lesion segmentation performed using the new method was very similar to the ground truth.
- FPF and FNF values indicated low misclassification of lesions.
- Process time was drastically reduced of about 39 minutes for the average lesion load quantification.

REFERENCES

[1] Filippi et al., Arch Neurol 2011; [2] Garcia-Lorenzo et al., Med Image Anal 2013; [3] Schmidt et al., Neuroimage 2012; [4] Nyul and Udupa, Magn Reson Med, 1999.

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DISCLOSURES.

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