WMH Segmentation Challenge: a Texture-based Classification Approach (ID: textclass)

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1. INTRODUCTION

We propose an automated method to segment WMH that uses no *a priori* information and performs a texture-based classification of pixels within the brain white matter.[1] The main goal is to compute the probability of each pixel being normal tissue or white matter hyperintensity (WMH), by generating a probability map. Based on this probability map, we can automatically segment the WMHs.

2. METHODOLOGY

The proposed methodology is performed on a slice-by-slice basis and has four key steps (outlined in Fig. 1). Step 1 is image pre-processing and 1a) crops the image to just fit the brain, 1b) resizes it to 200x200 (on a per slice basis) using a bicubic interpolation, 1c) segments the white matter, and 1d) normalize image intensities to the range $[0, 255]$ (Fig. 2). The white matter segmentation is automatically performed by using a max-tree structure. The max-tree node corresponding to the connected component with largest rectangularity ratio, *i.e.*, volume of the object divided by the volume of its bounding-box, is selected as being the most appropriate white-matter segmentation. Only nodes with volumes ranging between 200 ml and 500 ml are considered.

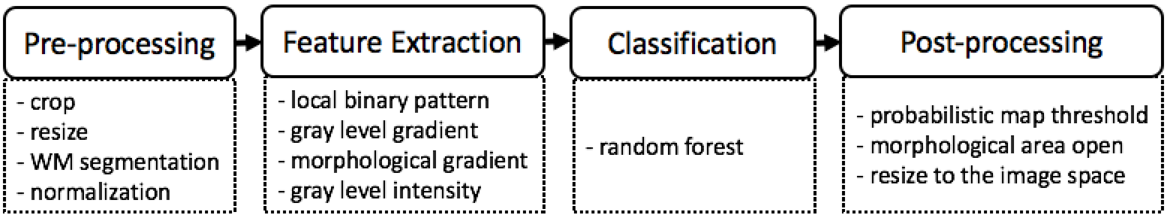
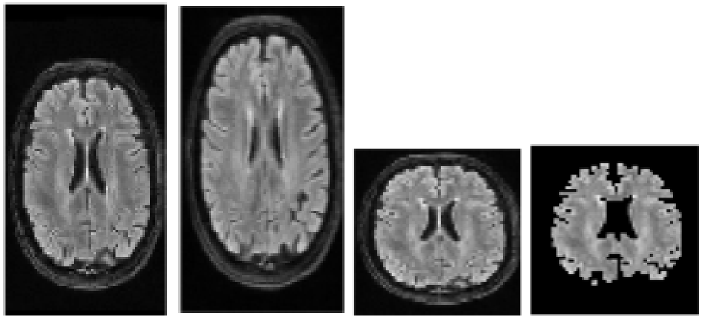


Figure 1: Methodology overview: pre-processing and feature extraction, are followed by the probabilistic random forest classification and post-processing (Steps 1 to 4)

In Step 2, feature extraction is performed. First 2a) the local binary pattern (LBP), and both 2b) structural and 2c) morphological gradients are computed for each slice (Fig. 3). Then for each pixel within the white matter, a feature vector is computed containing 2d) the intensity value of that pixel in the following images: T1, FLAIR, next most anterior FLAIR slice, next most posterior FLAIR slice, LBP, gradient, morphological gradient; and the mean white matter intensity (to provide overall information about the slice). A total of eight features are extracted for each pixel within the white matter.

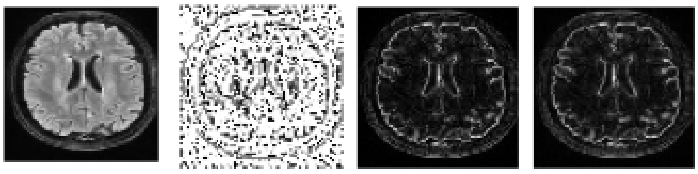
In Step 3, the training dataset is used to train a probabilistic random forest classifier.[2] The output of this classifier is a probabilistic map, containing the probability that each pixel is WMH. Images within the testing dataset are then tested using this classifier.

The WMH segmentation is achieved after post-processing (Step 4). First 4a) the WMH probabilistic map is thresholded. After the probability map thresholding (≥ 0.7), the resulting connect components serve as regions



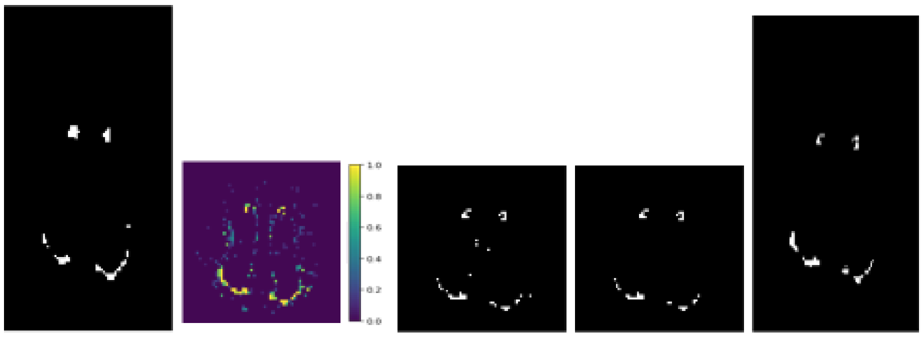
(a) (b) (c) (d)

Figure 2: Pre-processing step (Step 1 in Fig. 1): (a) original FLAIR image; (b) cropped image; (c) resized (to 200×200) image; (d) mask containing only white matter.



(a) (b) (c) (d)

Figure 3: Feature extraction (Step 2 in Fig. 1) on a pixel-by-pixel basis showing intensity values in: (a) original FLAIR image; (b) local binary pattern; (c) structural gradient; (d) morphological gradient images.



(a) (b) (c) (d) (e)

Figure 4: Post-processing step (Step 4 in Fig. 1): (a) ground truth; (b) WMH probability map; (c) threshold probabilistic map; (d) morphological area open; (e) final result after resizing to the original image space.

of interest (ROIs) (*i.e.*, they contain pixels with high probability of being WMH). Then, 4b) a morphological area open operator is applied to the ROIs to remove noise and small regions (*i.e.*, ROIs of < 10 pixels are removed). The resulting segmentation is 4c) resized back to the original image space, giving the final WMH segmentation result (Fig. 4).

REFERENCES

[1] Bento, M., Sym, Y., Frayne, R., Lotufo, R., and Rittner, L., "Probabilistic segmentation of brain white matter lesions using texture-based classification," *Lecture Notes in Computer Science* **10317**, 71–78 (2017).

[2] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E., "Scikit-learn: Machine learning in python," *Journal of Machine Learning Research* **12**(1), 2825–2830 (2011).