Automatic Multi-Modality Segmentation of White Matter Hyperintensities Using a Random Forests Classifier

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1. Methods

1.1. Pre-processing:

All the images are first preprocessed in three steps: I) noise reduction [1], II) intensity non-uniformity correction [2] and III) linear intensity normalization into range (0-100) using an intensity histogram matching technique. The T1w and FLAIR images are linearly co-registered using a 6 parameter rigid registration [3]. The T1w images are first linearly and then nonlinearly registered to an average template created based on data from the ADNI1 study [4], enabling the use of anatomical priors in the segmentation process. A brain mask is created by warping the template mask back to the individual's native space.

1.2. Features:

The following location and intensity features are created using information from the training data as well as the individual's T1w and FLAIR images. These features have been previously validated and verified to be informative in detecting WMHs [5], [6].

1. Voxel intensity from T1w and FLAIR images
2. Average voxel intensity of non-WMH tissue from T1w and FLAIR images for a specific voxel location obtained from averaging non-WMH voxels of the training subjects in stereotaxic space.
3. Probability of voxel being a lesion (P_{WMH}) obtained by creating a probability distribution function (PDF) based on the intensity histogram of the WMH labels from manually segmented training data across all WMH voxels
4. Probability of voxel being healthy tissue (P_H) obtained by creating a PDF of Non-WMH voxels from manually segmented training data across all non-WMH voxels
5. Ratio of P_H / P_{WMH}
6. Spatial WMH probability map created by averaging the WMH maps from the training dataset
7. Ratio of T2w/T1w, PD/T1w, FLAIR/T1w

The segmentations are performed in native FLAIR space to avoid the blurring caused by resampling. To achieve this, all images are non-linearly transformed to the ADNI template space, and all the priors and averages are calculated and then registered back in the native space using the inverse nonlinear transformations. Therefore, the FLAIR image is not resampled and only a 6-parameter rigid transformation is applied to the T1w image.

1.3. Classification:

Random decision forests perform classification by constructing a series of independent decision trees and voting between their predictions to obtain the classification output. Here, Scikit-learn Python library implementation of random forests classifier is used [7] with 100 estimators. Ten-fold cross validation across subjects was used to validate the performance of the classifiers. The spatial WMH probability maps, average intensities, and P_{WMH} and P_H were also calculated through the cross-validation to avoid overfitting.

2. References

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