

Four Tissue Segmentation in ADNI II

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Summary

While Alzheimer's disease (AD) is the most common cause for dementia among older individuals^{1,2} and the primary goal of ADNI, the lifetime risk for stroke equals and may exceed the risk of AD in some circumstances³. In addition, MRI evidence of asymptomatic cerebrovascular disease (CVD) occurs in one-third of older individuals⁴. In community based studies, mixed pathologies account for the most common cause of dementia⁵ and the impact of cerebrovascular and AD pathology is additive, particularly when the AD pathological burden is mild⁶. Similarly, MRI community based studies have shown that white matter hyperintensities (WMH) increase with advancing age and associated vascular risk factors^{4,7} and are associated with an array of cognitive deficits in cross-sectional studies⁸⁻¹⁰. Similar cross-sectional differences are also seen with clinically silent brain infarctions noted on MRI^{4,11,12}. Importantly, community based studies show that both WMH and SBI are associated with cognitive decline and *incident* MCI and dementia^{13,14}.

These results strongly suggest that vascular brain injury (WMH, SBI) occurs commonly amongst older community dwelling cognitively normal individuals and is associated with subtle cognitive impairment, including memory impairment. Importantly, increasing survival from vascular disease including hypertension, diabetes, myocardial infarction and stroke is likely to increase the prevalence of asymptomatic vascular brain disease thereby increasing the public health consequences of cognitive impairment related to these disorders. Furthermore, the age of onset of these diseases is quite early and cognitive effects appear to begin similarly early in life, possibly before age 60^{10,14,15}.

Method

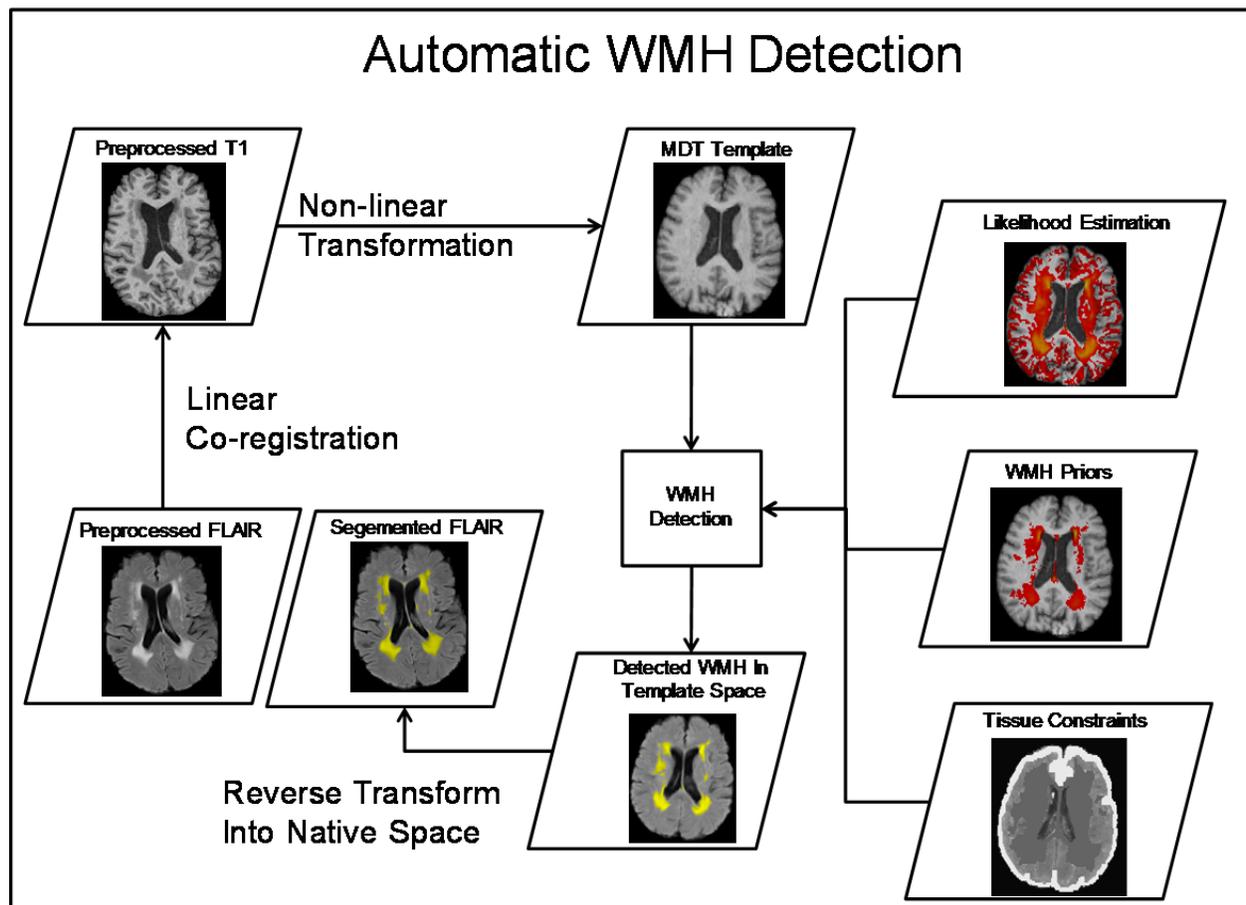
WMH Measurement

For ADNI 2, our WMH measurement approach is based a Bayesian approach to segmentation of high resolution 3D T1 and FLAIR sequences. In brief, non-brain structures are excluded from the 3D T1 images prior to measurement using an automated atlas based method. The FLAIR image is the affined transformed to the 3DT1 image using the FLIRT method from the FSL tool box, with error estimation based on correlation ratio. Inhomogeneity correction of the 3D T1 is performed using interleaved bias estimation and B-Spline deformation with a template¹⁶. This multiple iteration method updates a B--spline intensity deformation between an unbiased



template image and the subject image with an estimation of a bias field based on the current template-to-image alignment. The bias field is modeled using a spatially smooth thin-plate spline interpolation based on ratios of local image patch intensity means between the deformed template and subject images. FLAIR inhomogeneity corrections after co-registration of the FLAIR to the 3D T1 image is based on a previously published local histogram normalization method¹⁷. Prior to WMH calculation, each 3D T1 image is non-linearly aligned to a common template atlas and each of the accompanying images are transformed onto the same atlas using the same transformation parameters.

Figure 1 WMH Segmentation Pipeline



Estimation of WMH is then performed using a modified Bayesian probability structure based on a previously published method of histogram fitting¹⁸. Prior probability maps for WMH were created from more than 700 individuals with semi-automatic detection of WMH followed by manual editing. Likelihood estimates of the native image are calculated through histogram segmentation and thresholding. All segmentation is initially performed in standard space resulting in probability likelihood values of WMH at each voxel in the white matter (Figure 1). These probabilities are then thresholded at 3.5 sd above the mean to create a binary WMH mask. Segmentation is based on a modified Bayesian approach that combines image likelihood

estimates, spatial priors and tissue class constraints. The segmented WMH masks are then back-transformed in to native space for tissue volume calculation. Since image segmentation occurs in a common template space, group statistics using previously reported methods¹⁹⁻²¹ can be applied.

Gray, White and CSF Measurement

The primary segmentation mechanism is an Expectation-Maximization (EM) algorithm that iteratively refines its segmentation estimates to produce outputs that are most consistent with the input intensities from the native-space T1 images and a model of image smoothness^{22,23}. Like all EM algorithms, the system must be initialized with a reasonable estimate. We produce this initial estimate from the template-space warps used for WMH detection; because locations of WM/GM/CSF tissues are known in the template space, transforming these masks back to the each image's native space produces rough estimate 3-tissue segmentations (Figure 2). We then calculate the mean and standard deviation of the image intensities in locations labeled as each tissue type, and in the main segmentation method these values form the initial parameters for a Gaussian model of image intensity for each class. At each iteration, the segmenter uses a Gaussian model of T1-weighted image intensity for each tissue class, in order to produce a segmentation. In the first iteration, these models are estimated as described above. The segmentation yielded by these appearance models alone is then refined using a Markov Random Field (MRF) model, a computational statistical method that efficiently produces a label map consistent with both the input intensities and image smoothness statistics. Inference in the MRF is computed using an adaptive priors model²³. This refined segmentation from the MRF is then used to compute new Gaussian intensity models for each tissue class, and the algorithm repeats, iteratively switching between calculating Gaussian appearance models and MRF-based segmentation, until convergence. The MRF-based segmentation at the final iteration is used as the final output segmentation.

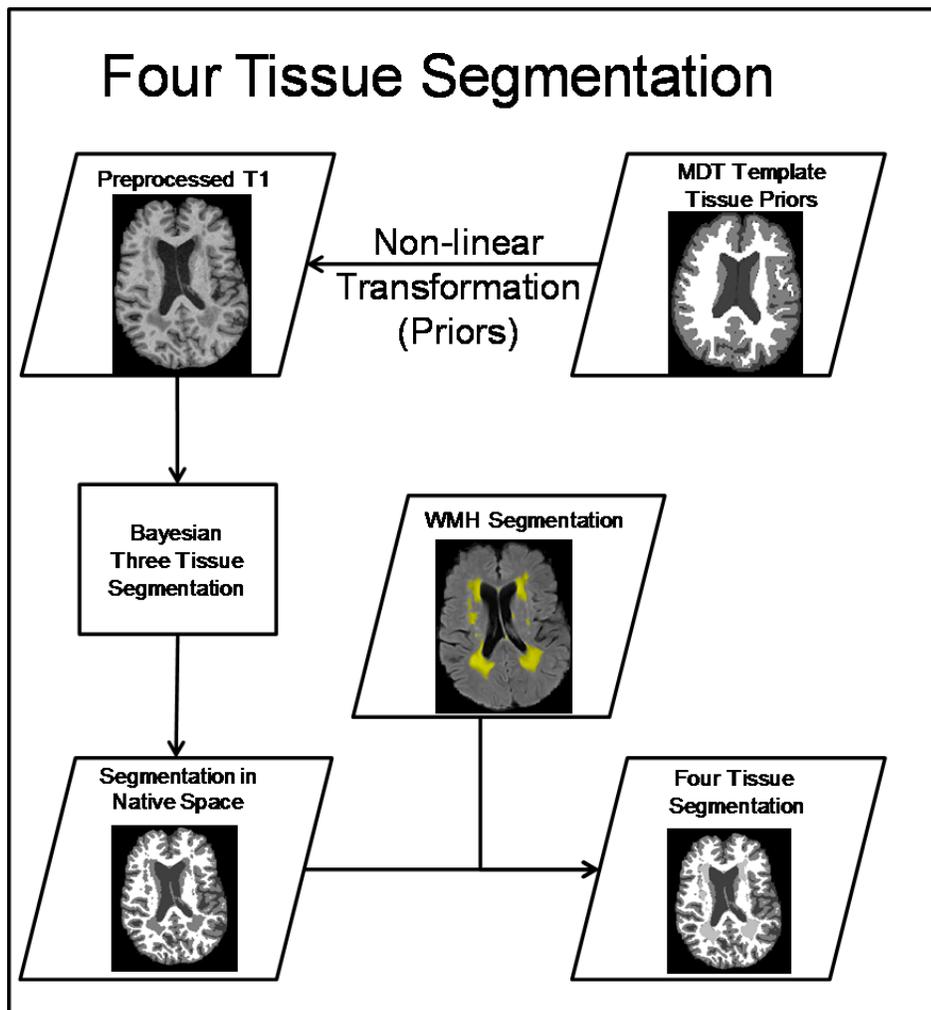
Final Four Tissue Segmentation

Final four tissue segmentation consists of substitution of voxels within the three tissue segmented image with voxels identified as WMH from the automatic WMH segmentation algorithm. Results are reported in native space as volumes in cubic centimeters. Total intracranial volume based on automatic segmentation is also included (Figure 2).

Robustness

Irregularities and variance in image intensities are corrected for in preprocessing by the best available methods. WMHs, a difficult problem for many similar segmenters, are detected using a dedicated specialized method to ensure their proper handling. While the method is sensitive to being given poor quality initial estimates, those we use are generated in a very sophisticated and robust automated fashion. The mathematical methods used are both state of the art and strongly validated.

Figure 2 Three and Four Tissue Segmentation



About the Authors

This document was prepared by Charles DeCarli, University of California at Davis. For more information please contact Charles DeCarli at cdecarli@ucdavis.edu.

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