Modeling non-central Chi distributed noise in T1-weighted MR images: brain tissue segmentation using partial volume densities

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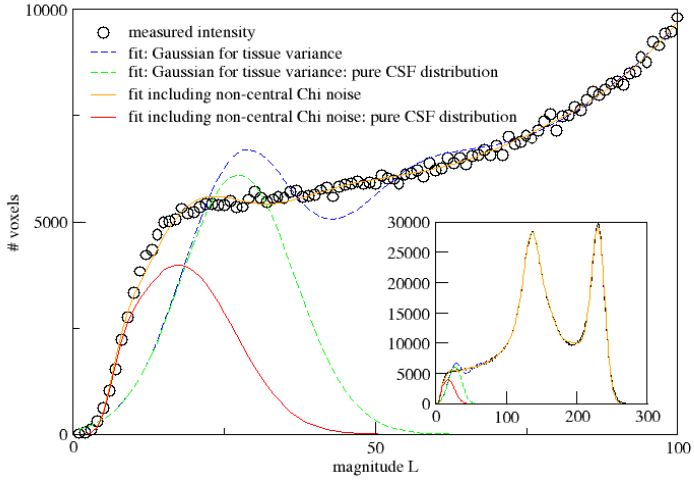
Noise in MR magnitude images follows a Rician distribution, or, in the case of parallel signal acquisition using multiple reciever coils, a non-central Chi distribution. The deviation of these distributions from Gaussian distributions becomes visible at low intensities (compared to the standard deviation of the noise). Although several schemes have been proposed to correct for the non-normality of the noise distribution [1,2], these rely on the possibility to analyze a (large enough) homogeneous dark region in the image, to estimate intensity and variance. In T1-weighted images of the (healthy) human brain with dark cerebrospinal fluid (CSF) signals, the estimation of its mean intensity is complicated, because pure CSF voxels are scarce (and not easily determined). It is therefore necessary to include pure CSF and partial volume voxels, containing CSF and brain tissue, for simultaneous estimation of mean intensities, variance, and partial volume distribution. We developed an algorithm that includes the three main brain tissue types, gray matter (GM), white matter (WM), and CSF, models their partial volume distributions, and a non-central Chi noise distribution. The model is fitted to the measured magnitude histogram of the intracranial region. From the fitted parameters a partial volume or binary segmentation is constructed, which can be used to calculate tissue volumes, or serve as inputs for further analyses such as cortical thickness measurements.

Methods

We started from our partial volume segmentation algorithm [3], which models the mean tissue intensities μ_{CSF}, μ_{GM}, μ_{WM}, their standard deviation σ_{tis}, and the non-uniform partial volume densities $n_{cg}(x)$, $n_{gw}(x)$, with x the fraction of gray matter in a voxel. The 'true' intensity distribution was convolved with a non-central Chi distribution, representing MR scanner noise with standard deviation σ_{MRI} and a parallel acquisition with N_q quadrature coils. The modeled magnitude histogram was fitted to the measured intensity distribution from the intracranial space. The algorithm was applied to T1-weighted scans of 16 healthy subjects (scan parameters were: TE=4.6 ms, TR=10 ms, flip angle 90º) and simulated brain images (MNI phantom [4]). Fits including non-central Chi noise were performed as well as fits modeling Gaussian noise only.



Results

Modeling both Gaussian (tissue) variation and non-central Chi distributed (MR scanner) noise result in better fits to measured magnitude histograms than Gaussian-only fits. As expected, the improvements were located in the darker regions, where the signal-to-noise ratios were low (see Fig. 1). Apart from a better fit to the histogram, the estimation of μ_{CSF} changed: The asymmetry of the non-central Chi distribution lead to lower values of μ_{CSF}, as compared to those from Gaussian-only fits. The mean relative difference was 24%±20%, which was reflected by a 6.1±5.9 ml change in CSF volume, and a -7.2±5.6 ml GM volume difference. Rician fits to the MNI images showed a smaller relative error in the determination of μ_{CSF} (1.0%) than Gaussian fits (1.5%), compared to the truth.

Fig. 1. Intensity histogram with model fits. Non-central Chi (red) fits better than Gaussian (green dashed).

Discussion

We developed a partial volume brain tissue segmentation algorithm that incorporates the effect of non-Gaussian MR scanner noise. By including this type of noise in the model better fits to measured magnitude histograms were obtained, leading to improved estimations of mean CSF intensities. The gray matter volumetric differences of up to 2.3% (17 ml) are of the order of changes found in psychiatric diseases such as schizophrenia, showing the importance of modeling the noise correctly.

References

1. Gudbjartsson H and Patz S, MRM 34:910-914 (1995); 2. Koay CG and Basser PJ, JMR 179: 317-322 (2006); 3. Brouwer et al., NeuroImage 49: 467-477 (2010); 4. http://www.bic.mni.mcgill.ca/brainweb/