Segmentation of MR Brain Images with Intensity Correction and Partial Volume Averaging

S. Datta[1], B. R. Sajja[1], R. He[1], J. M. Dieber[1], and P. A. Narayana[1]

[1]Diagnostic and Interventional Imaging, Medical School, University of Texas Health Science Center at Houston, Houston, Texas, United States

Introduction:

Classification of brain tissues is important in a number of neurological disorders, such as multiple sclerosis and Alzheimer's. However, the intensity non-uniformity and the partial volume averaging (PVA) within voxels affect tissue classification. An iterative technique based on expectation-maximization that includes the bias field correction and PVA is presented for improving the segmentation and volumetric measurements.

Image Acquisition:

MR brain images of 13 healthy volunteers with median age 31 yrs (range: 24-57 yrs) were acquired on a 3T Philips intera scanner with a dual quaser gradient system with a SENSE factor of 2. Dual fast spin echo (FSE) images with TE1/TE2/TR = 9.2 ms/90 ms/6800 ms, contiguous and interleaved 3 mm slices, and matrix 256x256 with a field of view 240 mm x 240 mm were acquired.

Methods:

Extrameningeal tissues in the FSE images were removed using in-house developed, semi-automated software followed by bias field correction using the module in SPM2 [1]. An anisotropic diffusion filter was applied to minimize the noise while preserving the edges in the images [1]. The whole brain was segmented into GM, WM, and CSF iteratively based on the expectation-maximization (EM) procedure along with the bias field correction. In order to account for the PVA, we assume L predefined labels into which the whole brain was classified. It was assumed that the observed intensity at voxel i with a known class label x follows multivariate Gaussian distribution

$$p(y_i \mid x_i) = G_{\Sigma_j}(y_i - \mu_j)$$

with parameters $\theta(x_i = j) = \{(\mu_j, \Sigma_j), j \in L\}$, where, $\mu_j = \alpha\mu_a + (1-\alpha)\mu_b$ and $\Sigma_j = \alpha\Sigma_a + (1-\alpha)\Sigma_b$, α and $(1-\alpha)$ are the fractions corresponding to tissues 'a' and 'b' present in class j. The parameters μ_a, μ_b, Σ_a, and Σ_b represent the mean vectors and covariance matrices corresponding to tissues 'a' and 'b'. In the present study, L is 6 (GM, WM, CSF, GM-WM, GM-CSF, WM-CSF) with α = 0, 0.5, or 1. Expectation maximization algorithm was used to estimate the class parameters with expectation step calculating the conditional expectation $Q(\theta|\theta^{(m)}) = E[\log p(y, x|\theta)|y, \theta^{(m)}]$ and maximization step for maximizing the function $Q(\theta|\theta^{(m)})$. The estimated class parameters were obtained as $\theta^{(m+1)} = \arg\max_\theta Q(\theta|\theta^{(m)})$. A Markov Random Field (MRF) model was used for the class labels with prior probability $p(x) = \exp(-U(x))/Z$, where Z is a normalizing constant [2]. Class labels were estimated using a *maximum a posteriori* principle, $\hat{x} = \arg\max_x p(y|x)p(x)$. In the presence of bias field, for a known class label x, it is assumed that the observed intensity y_i at voxel i follows the Gaussian distribution. Bias field was modeled as a linear combination of polynomials [3].

$$p(y_i \mid x_i, \theta_j, b_i) = G_{\Sigma_j}(y_i - \mu_j - b_i) = G_{\Sigma_j}(y_i - \mu_j - \sum_k c_k \phi_k(x_i)), \qquad k = 1, \ldots, q.$$

The probability density of an observed intensity can be written as

$$p(y_i \mid x_i, b_i) = G_{\Sigma_j}(y_i - \mu_j - \sum_k c_k \phi_k(x_i))\, p(x_i).$$

The coefficients c_k were obtained by maximizing the likelihood function $\prod_i p(y_i|\theta_j, b_i)$, which was obtained by taking partial derivative of $-\Sigma_i \log p(y_i|\theta_j, b_i)$ with respect to c_k and equating it to zero,

$$\left(\sum_i \log(G_{\Sigma_j}(y_i - \mu_j - \sum_k c_k \phi_k(x_i))\, p(x_i)) \right) = 0, \qquad k = 1, \ldots, q.$$

The class parameters, class labels, and coefficients of polynomials were estimated iteratively based on EM algorithm until the mean square error of mean vectors of tissue classes at consecutive iterations is minimized.

Results and Discussion:

Figure 1 shows the short echo FSE (proton density or PD) (A), long echo FSE or T2 (B) images, segmented images without (C) and with (D) the inclusion of PVA correction. The three mixed tissue classes, GM-WM, GM-CSF, and WM-CSF were included in classification. An important conclusion of these studies is the need to perform bias field correction twice (SPM2 and interleaved correction as a part of EM algorithm). This is demonstrated in Fig. 2 at the cerebellar level of the brain. Segmentation without any bias field correction resulted in poor tissue classification (Fig. 2C) which was further improved either by the application of SPM2 or interleaved intensity correction (Figs. 2D and 2E). Inclusion of both SPM2 and interleaved bias field correction remarkably improved the classification of tissues (Fig. 2F). Presumably the interleaved correction does a better job in reducing the in-plane inhomogeneity compared to SPM2 which is a 3D correction method. This is consistent with earlier report that suggests that the in-plane intensity inhomogeneity is important when images are acquired in an interleaved fashion [4] as is the case in the current studies.

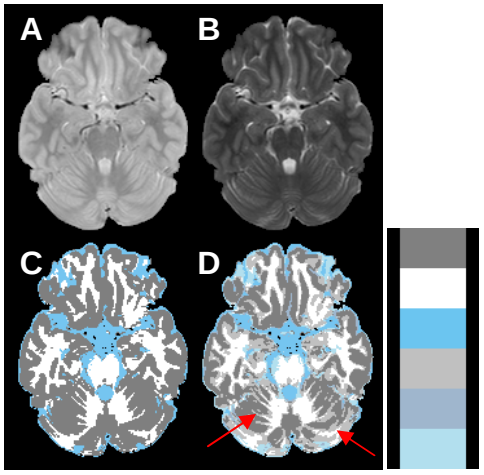

Fig. 1: A: PD and B: T2 of a normal brain. C: Segmented image: GM, WM and CSF without partial volume effect (PVA) correction. D: Segmented image: GM (grey), WM (white), CSF (blue), GM-WM (light grey), GM-CSF (violet) and WM-CSF (light blue) with PVA correction. [The color bar on right shows grey, white, blue, light grey, violet and light blue]. The arrows indicate the significant improvement in the tissue classification by considering the PVA.

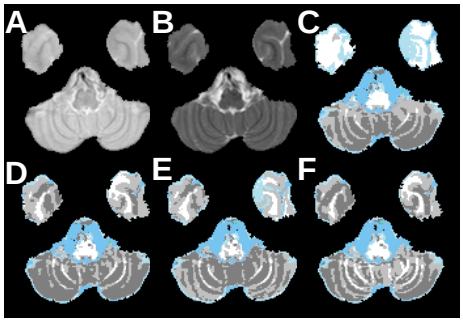

Fig. 2: Effect of bias field correction at the cerebellum of the brain

Conclusions:

We have presented a method for improving the segmentation of tissue with intensity non-uniformity correction and including partial volume averaging effect. This method results in more accurate tissue segmentation. These studies also suggest the importance of in-plane bias field correction.

Acknowledgment: This work was supported by the NIH Grsant EB002095.

References:

[1] Sajja BR, Datta S, He R, Mehta M, Gupta RK, Wolinsky JS, Narayana PA. Ann. Biomed. Engg. 2006;34:142-151.

[2] Leemput VK, Maes F, Vandermeulen D, Suetens P. IEEE Trans Med Imag 2003;22:105-119.

[3] Leemput VK, Maes F, Vandermeulen D, Suetens P. IEEE Trans Med Imag 1998;18:885-896.

[4] Dawant BM., Zijdenbos AP, Margolin RA., 1993. IEEE Trans Med Imag 1993;12:770-781.