Histogram-based acceleration on EM algorithm for segmentation of multi-spectral MRI with contextual constrains

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Introduction: Expectation maximization (EM) is a powerful method for image segmentation. However, it tends to be slow, particularly, when applied to multi-spectral segmentation. Here we propose a histogram-based EM (HEM) technique that increases the speed of conventional EM considerably. HEM, unlike the EM technique, performs the clustering on the gray level, rather on each voxel. The idea is similar to that used in the histogram-based fast FCM [1][2]. In addition, we also incorporate the contextual constraints into the HEM algorithm [3]. This combination results in a faster and more reliable method compared to conventional segmentation using EM algorithm for finding maximum likelihood mixture density parameters [4]. We apply this method for segmenting dual fast spin echo MR images of human brain.

Image Acquisitions: MR images were acquired on a Philips 3.0T MR scanner. The protocol includes the acquisition of dual FSE and FLAIR images with slice thickness of 3 mm, FOV of 240mm·240mm, and image matrix of 256·256 with 44 slices.

Methods and Materials: The preprocessing steps include registration of FLAIR images with FSE images, bias field correction, anisotropic diffusion filtering, brain stripping, and intensity standardization. Let L be the predefined number of clusters, and x be the observed intensity on FSE images with occurrences $H(x_i)$, $i = 0, 1, \ldots, N-1$. Based on the EM algorithm [4], the expected value of the log-likelihood log $p(x, y|\Theta)$ with respect to the clusters y, and the cluster parameters $\Theta_l = \{(\mu_l, \Sigma_l): 2 \le l \le L\}$, given the observed intensity, is defined as $Q(\Theta, \Theta^{(m+1)}) = E[\log p(x, y|\Theta)|x, \Theta^{(m)}]$. The function $p(x, y|\Theta)$ represents the joint distribution as $p(x, y|\Theta) = p(y|x, \Theta)p(x|\Theta)$, where $p(x|\Theta)$ is modeled as the mixture of cluster densities,

$$p(x\mid\Theta)=\sum_{j=1}^{L}\alpha_j p_j(x\mid\Theta_j),$$

such that $\alpha_1 + \alpha_2 + \ldots + \alpha_L = 1$. The maximization step, $\Theta^{(m+1)} = \arg\max_\Theta Q(\Theta, \Theta^{(m)})$, yields

$$\alpha_l^{(m+1)}=\frac{1}{N}\sum_{i=1}^{N}H(x_i)p(l\mid x_i,\Theta),\quad \mu_l^{(m+1)}=\frac{\sum_{i=1}^{N}H(x_i)x_i p(l\mid x_i,\Theta)}{\sum_{i=1}^{N}H(x_i)p(l\mid x_i,\Theta)},\ \text{and}\quad \Sigma_l^{(m+1)}=\frac{\sum_{i=1}^{N}H(x_i)p(l\mid x_i,\Theta)\left(x_i-\mu_l^{(m+1)}\right)\left(x_i-\mu_l^{(m+1)}\right)^T}{\sum_{i=1}^{N}H(x_i)p(l\mid x_i,\Theta)}.$$

The proposed EM algorithm was applied iteratively until there is no change in likelihood value. The classification was done based on the estimated cluster Gaussian mixtures using maximum likelihood (ML). To minimize the misclassification, the HEM was followed by region growing technique such as contextual based classification that classifies each spatial region on the basis of its class affinity as well as other local information. The acceptance of the cluster classification generated after a HEM stage, is based on the contextual affinity function defined in a 3D neighborhood of a voxel in the cluster.

Results and Discussion: HEM on FSE can speed up to 5 times with rebinning each echo to 256 levels and re-label the 2D index into 1D as x_i, using IDL to program without any optimization over the code. Test on FSE+Flair is undergoing. For contextual based classification, shape, geometry or topology of regions can be taken into account by considering contextual information, as suggested by [3]. Fig. 1, 2 and 3 demonstrated the results on brainweb data (http://www.bic.mni.mcgill.ca/brainweb/) and clinical FSE image.

For dual-echo MRI, H is 2D histogram, while 3D histogram seems getting even complicated, it could be greatly simplified by taking advantage of the sparse distribution of high dimensional histogram. Further, increasing the bin size along each dimension of histogram can reduce the complexity considerably.

Conclusion: HEM is efficient for single channel and dual-echo MRI; for multi-spectral MRI, compression on the high dimensional feature space is required to keep the efficiency of HEM.

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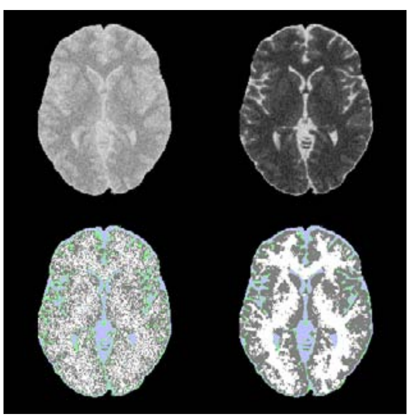

Fig. 1: Segmentation of brainweb image. 1st row are PD and T2 normal images, with noise=7 and RF=0, 2nd row are the segmentations, left is ML segmentation based on HEM, right is the segmentation based on contextural constraints, with 4 clusters.

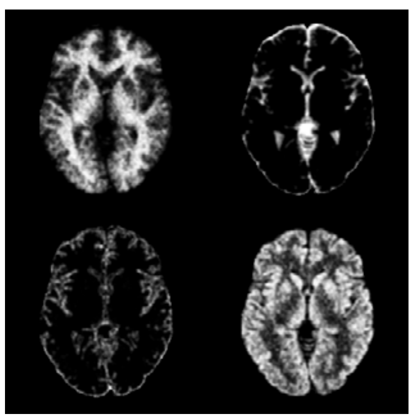

Fig. 2: Segmentation of brainweb image with contextural constraints, the probability map for 4 clusters is displayed for left to right, and from up to down, in the order of WM, CSF,CSF+GM, and GM.

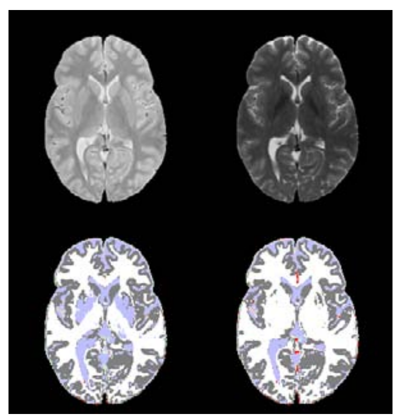

Fig. 3: Segmentation of FSE image. 1st row are PD and T2 images after imhomogeneity correction, 2nd row are segmentations, left is the segmentation based on $p\left(l\middle|x_i,\Theta\right)$, right is the ML segmentation based on HEM, with 6 clusters.