BRIAN MR IMAGE SEGMENTATION BY GUASSIAN MIXTURE MODLEING

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ABSTRACT

Magnetic resonance (MR) image data are of increasing importance in biomedical and biological science. We propose an evaluation study and a method to improve performance of brain tissue segmentation methods on T1-weighted MR brain images. Three approaches which are considered for this study, are based on Gaussian mixture models (GMM) and spatial encoding. The first method considers a simple neighborhood system to encode the spatial relation between image pixels. The second one uses a multi-resolution neighborhood system to take into account the spatial information. The third one is a new segmentation algorithm, which we proposed, and uses a wavelet based multi-resolution scheme to include the spatial consideration into the standard Gaussian mixture model. The methods are tested on a large amount of synthetic and real images.

1. INTRODUCTION

Magnetic resonance imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. Many clinical and research applications using magnetic resonance (MR) images require a segmentation into different intensity classes which are regarded as the best available representations for biological tissues [1]. Because of importance of the segmentation task, an expert in the clinical environment usually does it. Manual segmentation has several disadvantages. It is time consuming and costly because of the large amount of data and is non-repeatable and case dependent because of human interpretation. Hence, there is a strong motivation toward automatic segmentation of brain soft tissues from MR images.

Automated and robust brain tissue segmentation is complicated due to imaging artifacts. Methods for performing medical image segmentation vary widely depending on the specific application, imaging modality, and other factors.

The Gaussian mixture modeling (GMM) is the most commonly used model for statistical segmentation of brain MR images because of its simple mathematical form and the piecewise constant nature of ideal brain. However, being a pixel based model, the GMM has an intrinsic limitation: no spatial information is taken into account [2, 3]. This causes the GMM to work only on well-defined images with low levels of noise; unfortunately, this is often not the case due to artifacts such as bias field distortion and partial volume effect. In view of these, we study the issue of introducing the spatial relation into the standard GMM using three approaches.

In section 2, we introduce the fundamentals of GMM. In section 3, we describe the three compared segmentation methods. Section 4 is devoted to validation study. A brief discussion is presented in section 5 and we conclude in section 6.

2. PROBLEM FORMULATION

A statistical model of the image pixels is in form of a probability density function (*pdf*) of the pixel intensities. A finite mixture model (FMM) with K >1 components is defined as follows [4]:

$$f(y_j) = \sum_{k=1}^{K} \rho_k f_k(y_j \mid \theta_k). \qquad \forall \mathrm{y_j} \in R^n, n \geq 1 \quad (1)$$

Where $\rho_k \in (0,1)\ (\forall k = 1,2,...,K),\ \sum_{\mathrm{k=1}}^{\mathrm{K}} \rho_k = 1$ are the mixing proportions. For the GMM, each component is a normal *pdf:*

$$f_k(y_j \mid \theta_k) = \frac{1}{\sqrt{(2\pi)^n \det(\Sigma_k)}} \times \exp\{\frac{-1}{2}(y_j - \mu_k)^T \Sigma_k^{-1}(y_j - \mu_k)\}. \quad (2)$$

Where $\theta_k = (\mu_k, \Sigma_k)$ is the parameter set of the ***k***-th normal *pdf.* We define the set of all model parameters as $\Phi = \{\theta_1, \theta_2, ..., \theta_K, \rho_1, \rho_2, ..., \rho_K\}$. In practice, the model parameters are not known a priori. An attractive method to estimate the GMM unknown parameters is the expectation maximization (EM) algorithm [4]. This algorithm consist of two steps: The Expectation step (E-step) and the Maximization step (M-step).