Comparison of three Gaussian mixture modeling and spatial encoding methods for segmenting human brain MRI

MAHMOOD ZEYDABADI-NEJAD,[1] REZA A. ZOROOFI,[1] HAMID SOLTANIAN-ZADEH[1,2]
[1]Control and Intelligent Processing Center of Excellence, Electrical and Computer Engineering Department, Faculty of Engineering, University of Tehran, Tehran 14395-515, Iran
[2]Image Analysis Lab., Radiology Department, Henry Ford Health System, Detroit, MI 48202, USA
zeydabadi@yahoo.com

Abstract: - We propose a method to improve performance of image segmentation methods that are based on Gaussian mixture models and spatial encoding, and then compare them on T1-weighted MR images. Three approaches are considered for this study. The first one 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 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 nearly 4000 synthetic and real images.

Key-Words: - Brain MRI segmentation, Gaussian Mixture Modeling, Multi-resolution Analysis.

1 Introduction

Segmentation of brain soft tissues from magnetic resonance (MR) images is crucial to many medical imaging applications such as study of anatomical structures, localization of pathology, treatment planning, and computer integrated surgery [1, 2].
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 some artifacts such as additive noise, intensity non-uniformity and partial volume effect. Different approaches are published in the literature to deal with this problem.
The Gaussian mixture modeling (GMM) is a well-known and widely used statistical method for segmentation of soft brain tissues on T1-weighted MR images [3, 4]. One of the drawbacks with the GMM is its disability to consider the spatial relation between image pixels. In this paper, we study the issue of introducing of 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 segmentation methods compared. Section 4 is devoted to validation study and we conclude in section 5.

2 Image model

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 [5]:

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

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 [5]. This algorithm consists of two steps;