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Segmentation of Tissues from Brain MRI Using Fuzzy Local Gaussian Mixture Model

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Abstract
Magnetic Resonance Imaging (MRI) is the heart of medical imaging technology, providing high resolution three dimensional images of soft tissues in human brain. Segmentation of brain tissue in MRI is a crucial preprocessing step in several medical research and clinical applications. Many methods were developed to classify the tissues from the MRI images. MRI medical imaging uncertainty is widely presented in data because of the noise and blurs in acquisition and the partial volume effects originating from the low resolution of the sensors. In particular, borders between tissues are not clearly defined and memberships in the boundary regions are intrinsically fuzzy. The conventional (hard) clustering methods restrict each point of the data set to exactly one cluster. Fuzzy sets give the idea of uncertainty of belonging described by a membership function. Therefore, fuzzy clustering methods turn out to be particularly suitable for the segmentation of MRI medical images. In this paper we focus the attention on the GMM and FLGMM methods for tissue segmentation from MRI Brain images.

Keywords: *MRI, Imaging, Brain, Segmentation, Fuzzy, GMM, FLGMM*

1. Introduction

Magnetic resonance imaging (MRI) is one of the most significant diagnostic imaging techniques, often used for the early detection of anomalous changes in tissues and organs and also it allows a radiologist to produce an image covering the internal features of living tissue [1]. MRI reveals fine details of anatomy, and yet is non invasive and does not require ionizing radiation such as x-rays. It is a highly flexible technique where contrast between one tissue and another in an image can be varied simply by varying the way the image is made.

Brain tissue segmentation is usually concerned with the delineation of 3 types of brain matters, i.e., GM, WM and CSF. Because most brain structures are anatomically defined by boundaries of these tissue classes, accurate segmentation of brain tissues into one of these categories is an important step in quantitative morphological study of the brain. It is well-known that the brain has a complicated structure, thus accurate segmentation of brain is very decisive for detecting tumors, edema, necrotic tissues, white matter, gray matter, cerebrospinal fluid (CSF) or vasculature in order to provide proper treatment [2].

A technique to segment tissues into these categories is a vital step in quantitative morphology of brain because most brain structures are defined by boundaries of these tissue classes [3]. Furthermore, manual detection and analysis of lesions from MR brain images are normally time consuming, expensive, and can produce unacceptably high intra-observer and inter-observer variability.

MR-image segmentation methods are often analyzed in terms of their potentiality to discriminate i) between cerebro-spinal fluid (CSF), white matter, and gray matter, and ii) between normal tissues and abnormalities.MRI Tissue Classification and Bias Field Estimation describes an important characteristic of local image intensities of different tissues within a neighborhood forming separable clusters, and the center of each cluster can be well approximated by the product of the bias within the neighborhood and a tissue-dependent constant [4].

However, due to the non uniform magnetic field or susceptibility effects, brain MR images may contain a smoothly varying bias field, which is also referred to as the intensity in homogeneity or intensity non uniformity. As a result, the intensities of the same tissue vary across voxel locations and may lead to segmentation be interleaved in an iterative process so that they can benefit from each other and yield better results.

In this paper, we review some of the current approaches in the tissue segmentation of MR brain images. Then, we provide some experimental results indicating the superior performance of FLGMM approach. We conclude this review by pointing out some possible future directions.

2. Literature Review

The image segmentation approaches can be divided into four categories: thresholding, clustering, edge detection and region extraction. In this paper, a clustering based method for image segmentation will be considered. Three commonly used clustering algorithms are the K-means, the fuzzy C-means algorithm, and the expectation-maximization (EM) algorithm.

The K-means clustering algorithm clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with the closest mean [5]. K-means clustering algorithm is a simple clustering method with low computational complexity as compared to FCM. The clusters produced by K-means clustering do not overlap.

The fuzzy set theory [6], which involves the idea of partial membership described by a membership function, fuzzy clustering as a soft segmentation method has been widely studied and successfully applied to image segmentation [7, 8]. Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm [9] is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods.

FCM allows pixels to belong to multiple clusters with varying degrees of membership. One of the main disadvantages of FCM is that sensitive to noise; therefore, standard FCM algorithm has proven to be problematic because medical images always include considerable uncertainty and unknown noise caused by operator performance, equipment, and the environment [10].

The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (M) estimate in the presence of missing or hidden data. It classifies [11] data using membership function as a weighted sum of a number of Gaussian distributions which called a Gaussian Mixture Model (GMM). It used intensity distribution as normal distribution of image, its result affected by noisy images.

Inspired from the mechanism of FCM, the weighting exponent on the fuzzy membership is introduced into generalized GMMs in order to improve the efficiency of convergence [10]. It is evident that GMMs are mixtures of Gaussian distributions, the dissimilarities of individual cluster points are defined in the form of certain exponential function of the distances.

3. Methodology

3.1. Fuzzy C-Means Algorithm

Fuzzy c-means algorithm allows data to belong to two or more clusters with different membership coefficient. Fuzzy C-Means clustering is an iterative process.

- Step-1: the initial fuzzy partition matrix is generated
- Step-2: the initial fuzzy cluster centers are calculated.
- Step-3: In each step of the iteration, the cluster centers and the membership grade point are updated and the objective function is minimized to find the best location for the clusters.
- Step-4: The process stops when the maximum number of iteration is reached, or when the objective function improvement between two consecutive iterations is less than the minimum amount of improvement specified.

3.2. Gaussian Mixture Model

Each brain tissue is modeled with multiple four-dimensional Gaussians, where each Gaussian represents a localized region and the intensity characteristic per region. Gaussian in the set has similar intensity characteristics with minimal overlapping spatial supports. The hypothesis is that all the Gaussians within the same class represent the same physical tissue with the same mean intensity and the same intensity covariance.

- Step-1: K-means clustering is done based only on the intensity feature in order to extract a rough segmentation into 6 tissue Classes (WM, GM, CSF, WM+GM, WM+CSF, GM+CSF) .
- Step-2: split regions until we obtain convex regions that are suitable for Gaussian modeling.
- Step 2.1-Regions with less voxels than a user defined threshold are deleted and their voxels are marked as background noise, thus avoiding redundant Gaussians caused by noise.
- Step-2.2: the region is marked for further splitting.
- Step-3: A marked region is further split using K-means on the spatial features, into two distinct subregions. The splitting algorithm iteratively pro-ceeds as long as at least one region is marked for partitioning. Once the regions are determined, each region is modeled with a single Gaussian.
- Step-4: The Gaussian's spatial parameters are estimated using the spatial features of the voxels supported by the region, while the intensity parameters are estimated using all the voxels supported by all the regions of the same tissue.
- Step-5: Thus, Gaussians from the same tissue receive the same initial intensity parameter.

3.3. Fuzzy Local Gaussian Mixture Model

The objective function of Fuzzy Local GMM algorithm is defined as the integration of the weighted GMM energy functions over the entire image. In the objective function, a truncated Gaussian kernel function is used to impose the spatial constraint, and fuzzy memberships are employed to balance the contribution of each GMM to the segmentation process. The proposed algorithm has been compared with other segmentation algorithms in brain MR images.

- Step 1: Preprocessing using Weiner Filter
- Step 2: Bias Field Estimation
- Step 3: Initialize the number of clusters, standard deviation, and neighborhood radius of the truncated Gaussian kernel, cluster centroids, and bias field at each voxel.
- Step 4: Update the parameters.

- Step 4.1: Update the membership function
- Step 4.2: Update the covariance matrix
- Step 4.3: Update the bias field
- Step 4.4: Update the mixture weight
- Step 4.5: Update the centroids
- Step 5: Check the termination condition.

If the distance between the newly obtained cluster centers and old ones is less than a user-specified threshold ε, stop the iteration; otherwise, go to step 3.

4. Results and Evaluation

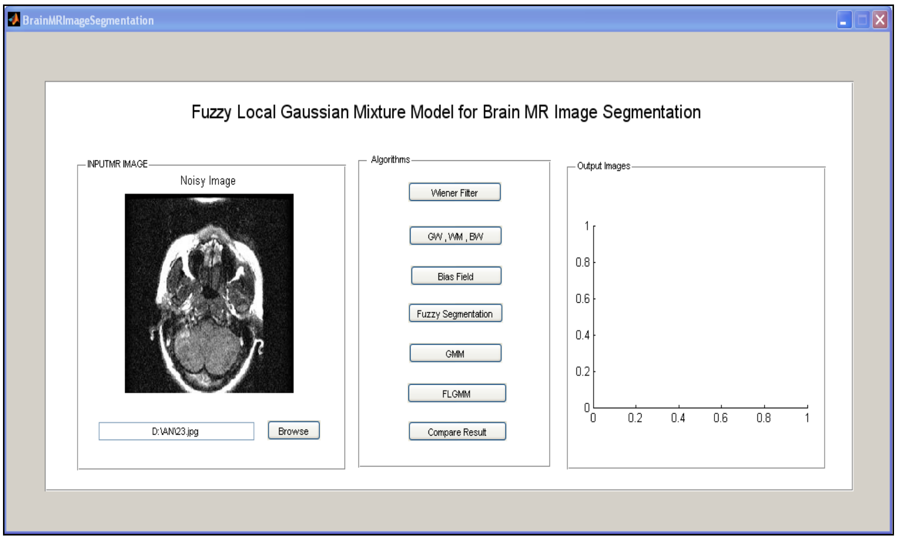

Figure 1: Noisy Image

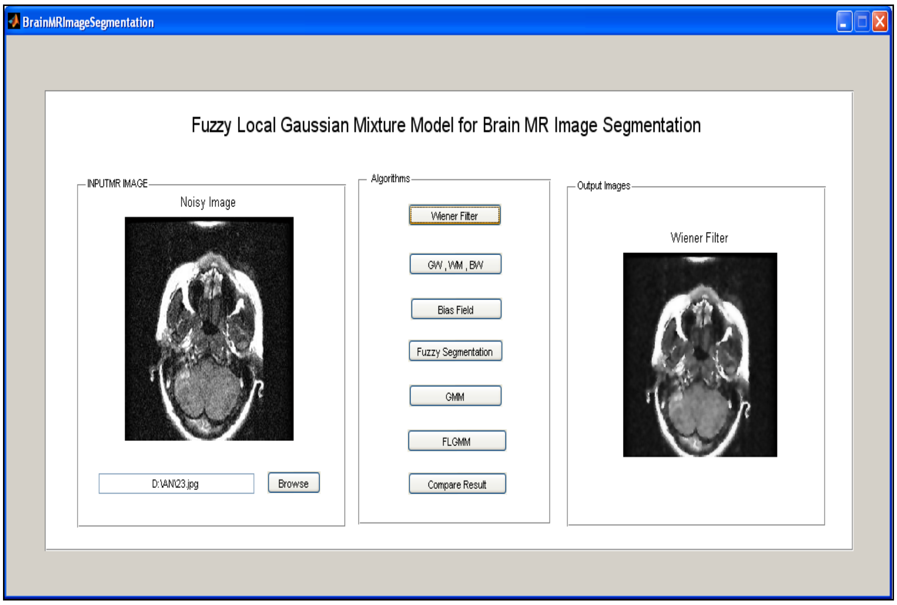

Figure 2: Denoised Image

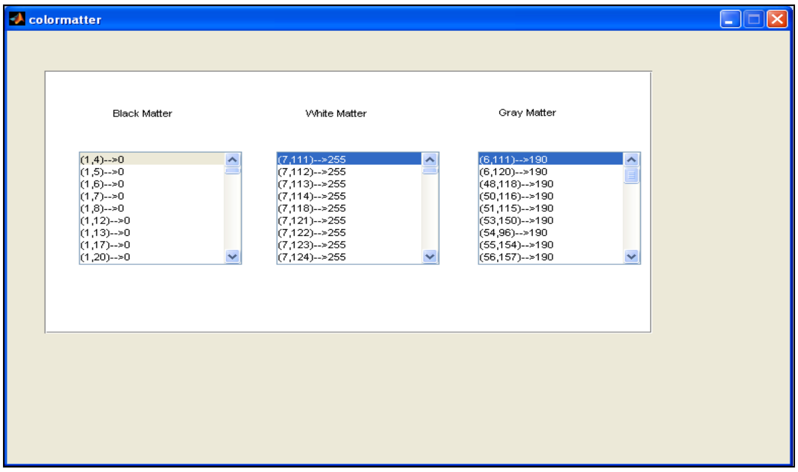

Figure 3: Color Matter

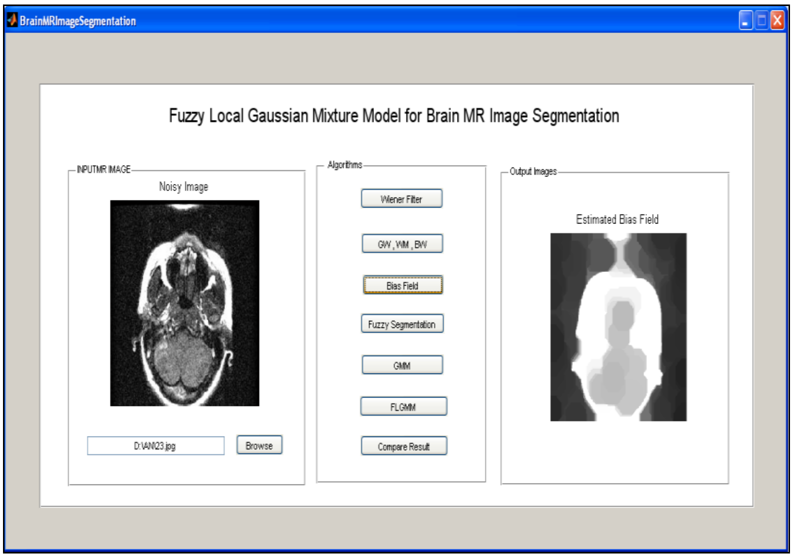

Figure 4: Bias Field Estimation

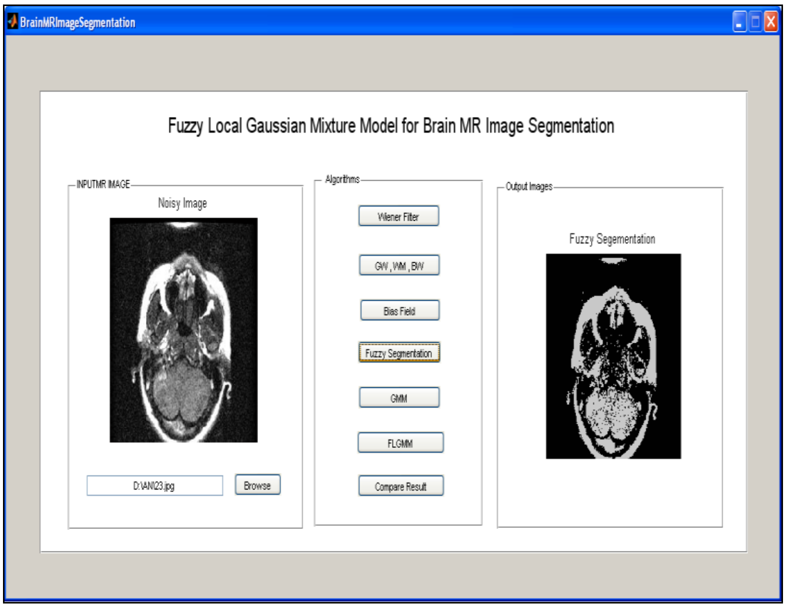

Figure 5: Fuzzy Segmentation

Figure 6: Gaussian Mixture Model

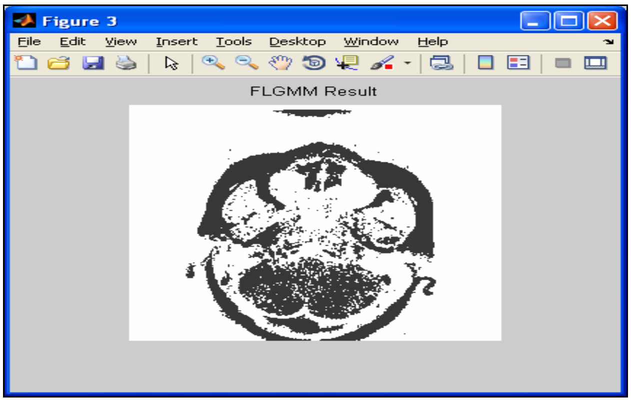

Figure 7: FLGMM

Sl. No	Segmentation Techniques	Percentage
1	FCM	53.52
2	GMM	71.24
3	FLGMM	84.22

Table 1: Percentage of Segmentation Accuracy

5. Conclusion & Future Work

The results shows that the FCM algorithm can largely overcome the difficulties raised by low contrast, and bias fields and is capable of producing more accurate segmentation results than several state-of-the-art algorithms. However FCM- and EM-based segmentation results are affected by noisy images. The results obtained by FLGMM algorithm overcome the existing limitations. FLGMM image segmentation method can be used to identify particular cases of medical pathology such as Acoustic Neuroma and Parkinson's diseases there by helping in proper diagnosis and preventing disabilities such as hearing loss and dizziness.

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