Brain MR Image Segmentation using Fuzzy Local Gaussian Mixture Model

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Abstract- Image segmentation is a major problem in computer vision and is most importance to medical imaging. The segmentation is perplexed due to clarity and overlap of intensities and many other elements. Though there are many brain image segmentation techniques proposed, accuracy in these lags, so the main aim of this paper is to improve the accuracy of segmentation. The Fuzzy Local Gaussian Mixture Model(FLGMM)algorithm forecasts the segmentation result that maximizes the posterior probability by minimizing an objective energy function, where the truncated Gaussian kernel function is used to enforce the spatial constraint and fuzzy memberships are employed to balance the contribution of each GMM(Gaussian Mixture Model).The proposed algorithm depict that this algorithm can predominately overcome the difficulties evoked by noise, low contrast, and bias field and considerably increase the accuracy of brain MR image segmentation for accurate result.

Key Words - Fuzzy C-means, Gaussian Mixture Model, Image Segmentation, Kernel function, MRI.

I. INTRODUCTION

Brain image segmentation is one of the most-valuable parts of clinical diagnostic segmentation. Brain images generally contain noise, in homogeneity and Bias field. Therefore, exact segmentation of brain images is a very difficult task. Nevertheless, the procedure of accurate segmentation of these images is very important and essential for a correct diagnosis by clinical tools. This paper survey of the methods used in brain segmentation and deals bias field estimation and its correction, magnetic resonance imaging and use methods for noise reduction, in homogeneity correction, segmentation and enhancement of the image by using fuzzy local Gaussian mixture model.

The advance growth in computers and technology, significant efforts have been taken in computer-aided diagnosis using medical images to develop the analysis of medical images. Computer-aided design analysis of medical images received from different imaging systems such as MRI (Magnetic Resonance Imaging), CT (Computer Aided Tomography) scan, ultrasound B-scan involves four basic steps: a) image filtering or preprocessing Technique, b) image segmentation, c) feature extraction, and d) classification of extracted features by classifier or pattern recognition system. The main objective of image preprocessing is to inhibit unwanted noise and to enhance image depending upon the type of noise present in the image. Image Segmentation is very important step in image analysis. Segmentation is a process of splitting an image into regions having similar attributes, such as gray level, color, texture, brightness and contrast, etc.

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II. RELATED WORK

Segmentation of major brain tissues, containing gray matter (GM), white matter (WM), and cerebrospinal fluid, from magnetic resonance (MR) images acts an important role in both clinical and neuroscience research. Nevertheless, due to the non-uniform magnetic field or susceptibility effects, brain MR images may contain a smoothly changing bias field, which is also denoted to as the intensity in -homogeneity or intensity non-uniformity [1]. Most of the brain MR image segmentation comes near with bias field correction has been proposed. Among them, those based on the expectation-maximization (EM) algorithm [2]–[4] and fuzzy C-mean (FCM) clustering [5]–[8] are the most popular ones.

Pham and Prince.[8] Proposed an adaptive FCM (AFCM) algorithm, which incorporates a spatial penalty term into the objective function to enable the estimated membership functions to be spatially smoothed. Ahmed [9] added a neighbor- hood averaging term to the objective function, and thus developed the bias-corrected FCM (BCFCM) algorithm. Brain MR images can be segmented by using the Gaussian mixture model (GMM), where the voxel intensities in each target region are modeled by a Gaussian distribution. The GMM parameters are usually estimated by maximizing the likelihood of the observed image via the EM algorithm.

Tran proposed the fuzzy GMM (FGMM) model to address the uncertainty of data and improve parameter estimation. Based on the fact that the bias field varies very slowly and can be ignored within a small window, in this paper, we assume that the local image data within the neighborhood of each voxel follow the GMM, in which the mean of each Gaussian component is approximated as a tissue- dependent constant multiplied by the bias field estimated at this voxel. Thus, we propose the fuzzy local GMM (FLGMM) algorithm for brain MR image segmentation. The proposed algorithm has been compared to other state-of-the-art segmentation algorithms in both simulated and clinical brain MR images.

III. EXISTING SYSTEM

This section describes some of the various methods that are used to produce the quality of the images given by the previous methods that are used to find the accurate brain images using some of the new methods.

A. Bias Field Formulation

This technique is based on the idea that plotted although number of cluster increases. The bias field in a brain MR image can be modeled as a multiplicative component of an observed image, as shown in the following:

$$I = bJ + n, Eqn\ (3.1)$$

Where I is the observed image, J is the true image to be restored, b is an unknown bias field, and n is the additive zero-mean Gaussian noise. The goal of bias field correction is to estimate and eliminate the bias field b from the observed image I. Without each tissue type, implies that the true signal J is approximately a piecewise constant map. Each tissue type, implies that the true signal J is approximately a piecewise constant map. This algorithm works by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center. Clearly, summation of membership of each data point should be equal.

B. Fuzzy C- Means

Let $I = \{I(k) \in R^d; 1 \le k \le n\}$ be a set of dimensional image features. The FCM partitions this feature set into c clusters based on minimizing the sum of distances from each feature to every cluster centroid weighted by its corresponding membership. Let the membership function be $U = \{u_i(k)\} \in R^{c \times n}$, where $u_i(k) \in [0,1]$is the degree of feature I(k) belonging to cluster i and follows the constraint $\sum_{i=1}^{c} u_i(k) = 1$. The quadratic function to be minimized is

$$J_{FCM} = \sum_{i=1}^{c} \int u_i(k)^m |I(k) - v_i|^2 dk\, , (Eqn\ 3.2)$$

Where v_i is the centroid of cluster i, and m ∈(1,∞) is the fuzzy coefficient.

C. Gaussian Mixture Model

The GMM is a weighted sum of c Gaussian density distributions. With the GMM, the likelihood of the observed data $I(k)$ is as follows:

$$P(I(k)|\Theta_i) = \sum_{i=1}^{c} p_i N(I(k)|\mu_i, \Sigma_i)\, , (Eqn\ 3.3)$$

Where Θ_i={p_i, μ_i, Σ_i} is the assembly of parameters, and p_i is the mixing coefficient of ith Gaussian component N(I(k)| μ_i ,Σ_i) and follows the constraint $\sum_i^c p_i = 1$The parameters involved in the GMM are denoted by $\Theta = \{\Theta_i, i = 1, \dots, c\}$, and are usually estimated through maximizing the likelihood of observed data via the EM algorithm.

IV. PROPOSED SYSTEM

The given input of brain MR images first sent to the Bias field it will segment the image with various distances and partition the image using FCM. The finding the neighborhood voxels based on the Gaussian Mixture model .

Step 1: Initialization.

Initialize the number of clusters, standard deviation and neighborhood radius of the truncated Gaussian kernel, cluster centroids, and bias field at each voxel.

Step 2: Updating parameters.

$$u_i(y) = (\sum_{i=1}^{c} (\frac{d_i(I(y))}{d_j(I(y))})^{1/m-1})^{-1}, (Eqn\ 4.1)$$

Step 2.1: Updating membership function

$$\sum_i (x) = \frac{\int u_i(y)^m K(x-y)((I(y) - b(x)v_i)(I(y) - b(x)v_i)^T)\, dy}{\int u_i(y)^m K(x-y) dy}, (Eqn\ 2)$$

Step 2.2: Updating covariance matrix

$$b(x) = \frac{\sum_{i=1}^{c} \int K(x-y) u_i(y)^m (I(y)^T \sum_i (x)^{-1} v_i) dy}{\sum_{i=1}^{c} \int K(x-y) u_i(y)^m (v_i{}^T \sum_i (x)^{-1} v_i) dy}, (Eqn\ 4.3)$$

$$p_i = \frac{K * u_i^m}{\sum_{j=1}^{c} K * u_i^m}, (Eqn\ 4.4)$$

Step 2.3: Updating bias field

$$(\iint u_i(y)^m K(x-y) b(x)^2 (\sum_i (x)^{-1}) dxdy)^{-1} \times (\iint u_i(y)^m K(x-y) b(x) \sum_i (x)^{-1}) dxdy)\, .\ (Eqn\ 4.5)$$

Step 2.4: updating mixture weight

Step 2.5: Updating centroids

Step 3: Checking the termination condition.

If the distance between the newly obtained cluster centers and old ones is less than a user-specified small threshold ε, stop the iteration .

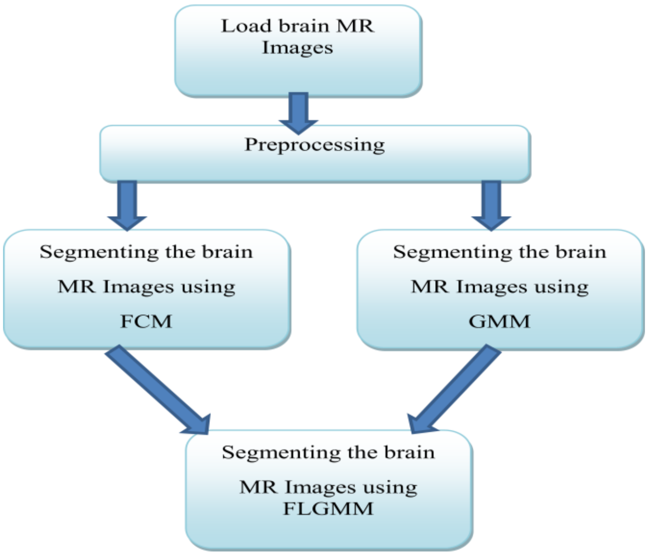


Fig. 4.2.1 System Architecture

- Load input image: First loading the Brain MR image.
- Preprosessor: The Preprocessing technique is done based on the Bias Field Formulation.
- Segmentation using FCM: Once the preprocessing technique over then segmentation is done based on the fuzzy C-Means algorithm.
- Segmentation using GMM: After finishing the preprocessing technique then segmenting is done based on Gaussian Mixture Model.
- Segmentation using FLGMM: After finishing the fuzzy c means and Gaussian Mixture Model then combing will produce FLGMM algorithm.

We compared the proposed FLGMM algorithm to state-of- the-art segmentation algorithms in both synthetic and clinical brain MR images.

A. Segmentation of Synthetic Images

The first experiment was performed in three synthetic images, which were displayed in the first column of Figure 4. 2.2 In the first image, the intensities of the star-shaped object and background have the same mean but different variances. The images in the middle and bottom rows were corrupted by intensity in-homogeneity. The intermediate segmentation results obtained by running the proposed algorithm for different numbers of iterations were shown in the second to fourth columns, and the final results obtained after the convergence of our algorithm were shown in the fifth column. It is revealed from Figure 4.2.3 that the result gradually improves during the iterative segmentation process.

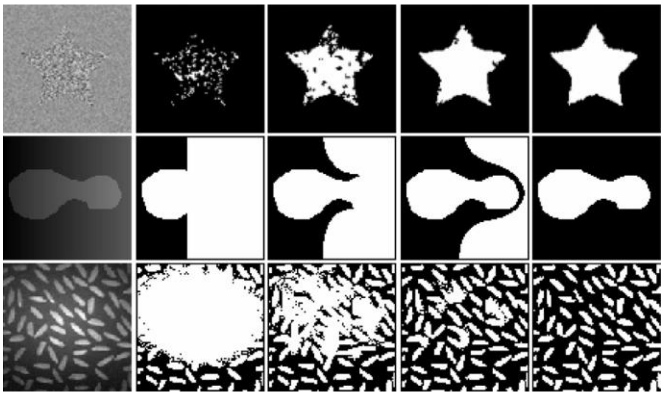


Fig. 4.2.2. Illustration of (first column) three synthetic image and their (second to forth columns) intermediate and (fifth column) final segmentation results.

B. System Architecture

The second experiment was carried out in 3T- weighted clinical brain MR images. Fig. 4.2.3 shows three 3T-weighted clinical brain MR images that were used in [5], together with the estimated bias fields and segmentation results.

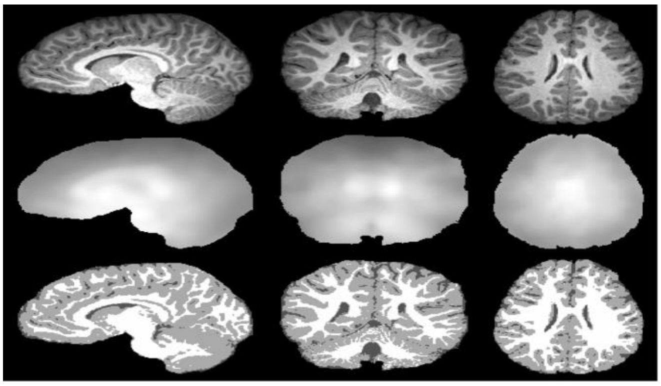


Fig. 4.2.3. Illustration of (top row) three 3T-weighted brain MR images, (middle row) the estimated bias field, and (bottom row) segmentation results.

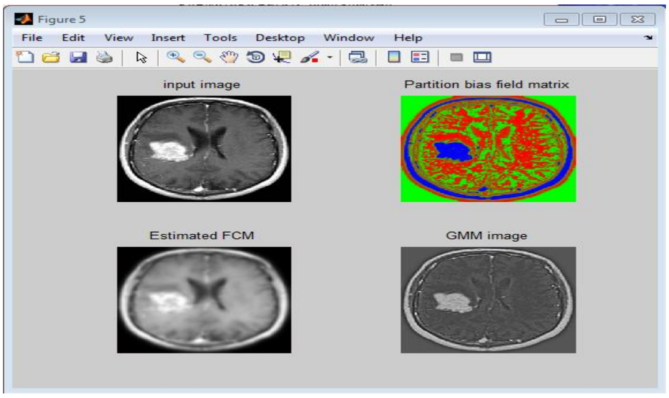


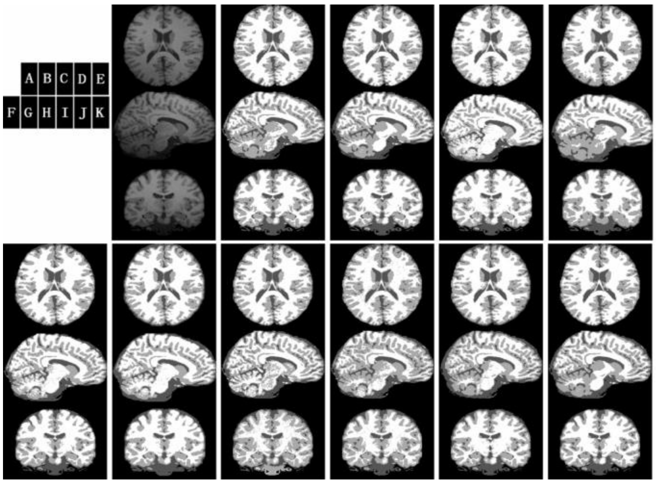
Fig 4.2.4. Illustration of Brain images partition bias field, estimated FCM, Gaussian Mixture Model image segmentation results.

It is clear from this figure that in spite of the quite obvious bias field and noise in these images, the proposed algorithm can estimate the bias field and achieves satisfactory segmentation results.

C. Quantitative Comparison

In the third experiment, we quantitatively compared the proposed FLGMM algorithm to eight existing segmentation approaches, including two FCM-based algorithms (AFCM and BCFCM), two kernel FCM- based algorithms , two EM-based algorithms proposed by Wells and Leemput and two fuzzy member membership and local-information-based algorithms (CLIC and MPFCM). To make a fair comparison, all algorithms were initialized by using the *k*-means clustering. The segmentation accuracy was measured by the Jaccard similarity (JS), which is the ratio between intersection and union of the segmented volume $S1$ and ground truth volume $S2$

$$JS(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}.$$



4.2.5. Illustration of (a) three slices extracted from a simulated T1-weighted MR study, (b) their ground truth, and segmentation results obtained by using(c) the proposed, (d) AFCM, (e) BCFCM, (f) GKFCM, (g) SFKFCM, (h) Wells',(i) Lemmput's, (j) CLIC, and (k) MPFCM algorithms.

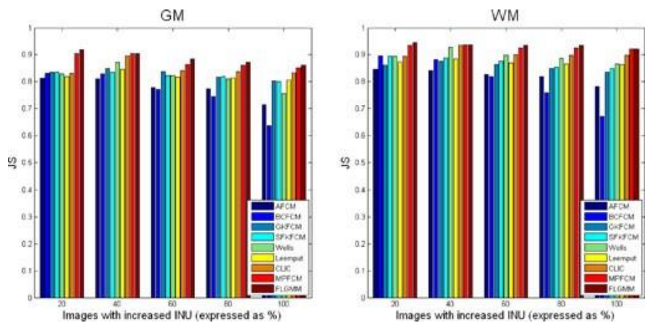


Fig. 4.2.6. Average JS of (left) GM segmentation and (right) WM segmentation obtained by applying nine segmentation algorithms to simulated brain MR images with increasing levels of intensity in-homogeneity.

V. CONCLUSION

In this paper, we take over that the local image within the neighborhood of each voxel follows the GMM, and thus propose the FLGMM algorithm for brain MR image segmentation. This algorithm uses a truncated Gaussian kernel function to incorporate spatial constraints into local GMMs, and employs the fuzzy membership function to balance the contribution of each GMM to the segmentation process. The proposed algorithm can largely overcome the difficulties raised by noise, low contrast, and bias fields, and is capable of producing more accurate segmentation results.

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