International Journal of Electronics Communication and Computer Engineering
Volume 5, Issue 5, ISSN (Online): 2249–071X, ISSN (Print): 2278–4209

Performance Evaluation of Segmentation Algorithm for MR Images

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***Abstract* – MRI intensity inhomogeneities can be attributed to imperfections in the RF. The result is slowly-varying shading artifact over the image that can produce errors with conventional intensity-based classification. Intensity inhomogeneity often occurs in real-world images, which presents a considerable challenge in image segmentation. The most widely used image segmentation algorithms are region-based and typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to provide accurate segmentation results due to the intensity inhomogeneity In order to decrease the noise effect during image segmentation, the proposed method incorporates both the local spatial context and the non-local information into the standard FCM cluster algorithm using a novel dissimilarity index in place of the usual distance metric. Therefore a modified FCM algorithm is used to segment the image in this paper. In this paper results obtained from the proposed algorithm is compared with those obtained by using FLGMM, Level set method, and BCFCM and AFCM with raw image as input data and same is analyzed. Thus concluding that the proposed algorithm can largely overcome the difficulties raised by noise, low contrast, and bias field, and improves the accuracy of brain MR image segmentation.**

***Keywords* – Bias field correction, Fuzzy C-means (FCMs), Level Set Function, MRI.**

I. Introduction

For some of the application, such as image recognition or compression, it may be difficult to process the whole image directly for the reason that it is inefficient and unpractical. Therefore, it becomes necessary to partition image into small meaningful sub-groups. Hence many image segmentation algorithm were developed to segment an image into several parts (region) based on the feature of image like pixel value or histogram of image etc. Image Segmentation is useful in many applications, to identify and demark area of interest or annotate the data. On a broad level image segmentation process can be classified under following headings- Thresholding based, Clustering based, Histogram based, Edge detection, region-growing method etc.

Medical image segmentation is the task of classifying image components (pixels or voxels) into relevant anatomical components or describing the structural and intensity changes in terms of the underlying functional process. The knowledge of the location, size, and shape of different anatomical structures is a fundamental step in understanding and analyzing medical images. Explicit knowledge of the segmented structures in medical images allows us to do more than qualitative visual assessment, as in the following examples-. The location of pathology relative to healthy anatomical structures is useful in planning radiological treatments and surgeries, growth patterns can be determined by analyzing changes of segmented structures of a population group over time, analysis of the shape of the segmented brain structures can be used to find characteristics or markers of neurological disorders, etc.

The image segmentation is a challenging problem that has received an enormous amount of attention by many researchers [1-4]. Pham et al. and James et al. have presented various techniques used in medical image segmentation and analysis [5, 6]. The segmentation problem can be categorized as supervised and unsupervised problem.

Segmentation of major brain tissues, including gray matter (GM), white matter (WM), and cerebrospinal fluid, from magnetic resonance (MR) images plays an important role in both clinical practice and neuroscience research. 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 inhomogeneity or intensity non-uniformity [7]. As a result, the intensities of the same tissue vary across voxel locations and may lead to segmentation errors.

Therefore, bias field correction and segmentation should be interleaved in an iterative process so that they can benefit from each other and yield better results. Many brain MR image segmentation approaches with bias field correction have been proposed in the literature [8]–[18]. Among them, those based on the expectation-maximization (EM) algorithm [8, 10] and fuzzy Cmean (FCM) clustering [9, 18] are the most popular ones. Variants of Fuzzy Cmean clustering like AFCM [19], BCFCM [20], and SFCM [21] have been proposed till date.

In fuzzy clustering process, the input MRI image and number of clusters are to be initialized. In this process, fuzzy objective function, membership function and weights are calculated. To separate the partition matrix with help of cluster centroid value, the distance matrix is used to find the similarity index value of black and white pixels of the image. In the last iteration, the final partitioned objective function is derived.

The most important shortcoming of standard FCM algorithm is that the objective function does not think about the spatial dependence therefore it deal with image as the same as separate points. In order to decrease the noise effect during image segmentation, the proposed method incorporates both the local spatial context and the non-local information into the standard FCM cluster algorithm using a novel dissimilarity index in place of the usual distance

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metric. Therefore a modified FCM algorithm is used to segment the image in this paper. The membership value decides the segmentation results and hence the membership value is evaluated by the distance measurement. Therefore in this approach the distance measurement parameter is modified.

In this paper an alternate method of image segmentation is presented. The results obtained by proposed method have been compared with those obtained by using FLGMM [1], Level Set Method [22], BCFCM and AFCM on same set of input MR images.

II. Related Work

A. Bias Field Generation

The bias field in a brain MR image can be modeled as a multiplicative component of an observed image, as shown in the following:

$$I = bJ + n \tag{1}$$

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 objective of bias field estimation and correction is to gauge and eliminate the bias field b from the observed image I. In broader perspective, the bias field b is assumed to be a slowly varying entity in the entire image domain. Ideally, the intensity J in each tissue should take a specific value z_i, reflecting the physical property being measured. This property, in concurrence with the spatially coherent nature of each tissue type, implies that the true signal *J* is approximately a piecewise constant map.

B. Fuzzy C-Mean

Let $I = \{I(k) \in Rd;\ 1 \le k \le n\}$ be a set of *d*-dimensional image features. The FCM [23] partitions this feature set into *c* clusters based on minimizing the Euclidian distance of each feature to every cluster centroid weighted by its corresponding membership. Let the membership nction be $M = \{u_i(k)\} \in R^{c\times n}$, where $ui(k) \in [0, 1]$ is the degree of feature $I(k)$ belonging to cluster i and follows the constraint $\sum ui(k) = 1$ for i=0 to c. The quadratic objective function [1] to be minimized is

$$J_{\mathrm{FCM}} = \sum_{i=1}^{c} \int u_i(k)^m \left|I(k) - v_i\right|^2 dk \tag{2}$$

where vi is the centroid of cluster i, and $m \in (1,\infty)$ is the fuzzy coefficient.

C. Bias Corrected Fuzzy Cmeans

The most important shortcoming of standard FCM algorithm is that the objective function does not think about the spatial dependence therefore it deal with image as the same as separate points. In order to decrease the noise effect during image segmentation, this method incorporates both the local spatial context and the non-local information into the standard FCM cluster algorithm using a novel dissimilarity index in place of the usual distance metric. The bias-corrected FCM (BCFCM) by regularizing the FCM objective functions with a spatial neighbourhood regularization term. It is especially effective for image segmentation.

D. FLGMM

Image segmentation aims to partition the image domain Ω into c disjoint regions, such that $\Omega = \{\Omega_i\}$, i=1 to c. For each voxel x, if its neighbourhood region is denoted by Ox, $\{\Omega_i \cap O_x\}$ c, i=1 forms a partition of Ox. It is assumed that the local image data within Ox satisfy the GMM.

The FLGMM energy [1] over voxel x in the image domain Ω is defined as follows:

$$E_x^{\mathrm{FLGMM}} = \sum_{i=1}^{c} \int_{\Omega} -u_i(y)^m K(x-y) \ln[p_i(x) N(I(y)|b(x)v_i, |\Sigma_i(x))] dy \tag{3}$$

To minimize the GMM energy E^{FLGMM} x over every voxel x in the image domain Ω, following objective function [1]:

$$J^{\mathrm{FLGMM}} = \sum_{i=1}^{c} \int_{\Omega}\int_{\Omega} -u_i(y)^m K(x-y) \ln[p_i(x) N(I(y)|b(x)v_i, \Sigma_i(x))] dy dx. \tag{4}$$

E. Kmeans

K-means algorithm is one of the most referred data clustering algorithm. It basically partitions a collection of n vector x_j , j = 1, 2,……, n into C bins C_i , i = 1, 2, …, C and finds the cluster centre in each group such that a cost (or objective) function of dissimilarity measure is minimized. Different types of objective function which may be considered are Manhattan distance, hamming distance, inner product space etc. When the Euclidean distance is chosen as a dissimilarity measure between a vector x_k in group j and the corresponding cluster center C_i, the cost function is given by Eq. 5.

$$j = \sum_{i=1}^{C} V_i = \sum_{i=1}^{C} \left(\sum_{k,\, x_k \in G_i}^{C} \left\| x_k - C_i \right\|^2 \right) \tag{5}$$

III. Proposed Algorithm

A. Spatial Fuzzy Cmeans

A conventional FCM algorithm does not fully utilize the spatial information in the image. In this paper, we present a fuzzy c-means (FCM) algorithm that incorporates spatial information into the membership function for clustering. The spatial function is the summation of the membership function in the neighborhood of each pixel under consideration. The advantages of the new method are the following: (1) it yields regions more homogeneous than those of other methods, (2) it reduces the spurious blobs, (3) it removes noisy spots, and (4) it is less sensitive to noise than other techniques. This technique is a powerful method for noisy image segmentation and works for both single and multiple-feature data with spatial information.

A traditional approach to segmentation of magnetic resonance (MR) images is the Fuzzy C - Means (FCM) clustering algorithm. However, the conventionally standard FCM algorithm is sensitive to noise. To overcome the above problem, a modified FCM algorithm Spatial FCM for MRI brain image segmentation is

International Journal of Electronics Communication and Computer Engineering
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presented in this paper. The algorithm is realized by incorporating the spatial neighborhood information into the standard FCM algorithm and modifying the membership weighting of each cluster. In The proposed algorithm every point of the data set has a weight in relation to every cluster. Therefore this weight permits to have a better classification especially in the case of noise data.

$$S_{ij}^{*} = \sum_{k \in H(x_j)} U_{ik}\beta_{k1} + \frac{\sum_{k \in H(x_j)} U_{ik}\beta_{k2}}{\sum_{t=1}^{c} \sum_{k \in H(x_j)} U_{tk}} \quad (6)$$

B. Jaccard index

The segmentation accuracy was measured by the Jaccard similarity (JS) [1], which is the ratio between intersection and union of the segmented volume S1 and ground truth volume S2

JS (S1, S2) = | (S1 ∩S2)| / | (S1 U S2)| (7)

The value of JS ranges from 0 to 1, and a higher JS represents more accurate segmentation.

Jaccard's similarity for White Matter (WM) and Grey Matter (GM) for each of the images with respect to the input is calculated independently and the results have been compared.

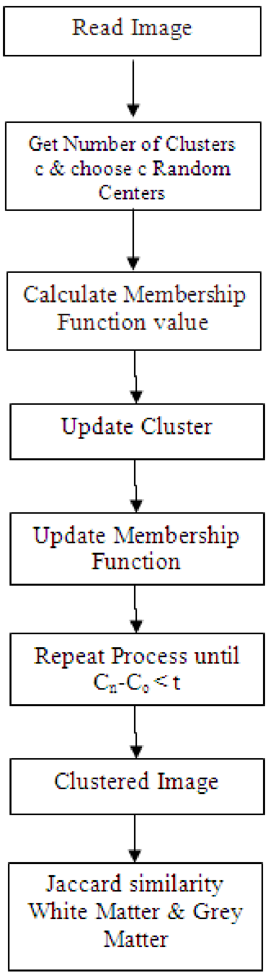


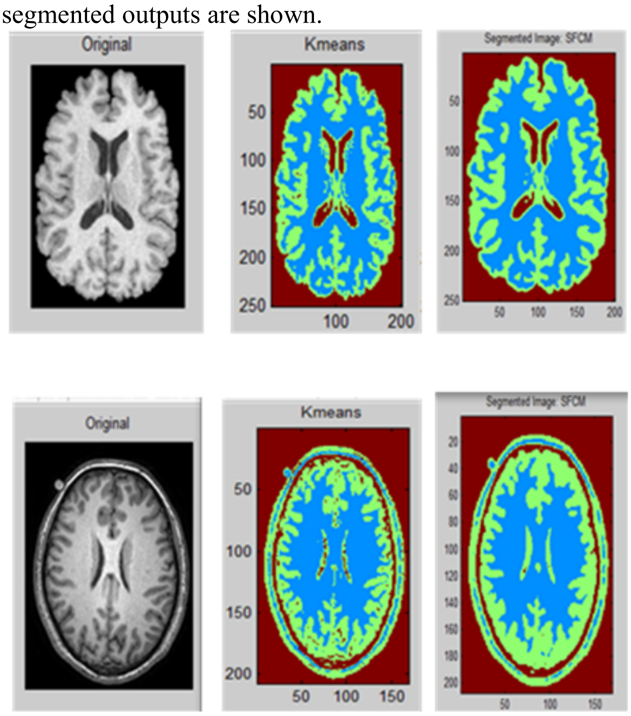
Fig.1. Block Diagram of Proposed Algorithm

The flow of proposed algorithm for image segmentation can be depicted by Figure 1. Using equation (6) membership function for each cluster and corresponding centroid is defined and calculated. Based on this each pixel is assigned to cluster and thus each cluster centre is updated. Now membership for each cluster is updated iteratively. The stopping criterion for the process is when the difference between new cluster centroid and previous centroid is less than a certain preselected threshold t. The output of this iterative process is a segmented image. Jaccard's index for WM & GM is computed for both input as well as segmented image.

IV. Experimental Results

A. Segmentation of Brain MR Images

The first experiment was performed in two images with different intensity inhomogeneity; these are displayed in the first column of Fig. 2. Column 2 depicts the probability image of respective input, and in column 3 segmented outputs are shown.



(a) (b) (c)

Fig. 2 (a). Original Image, (b). Kmeans , (c). Segmented Image using proposed method

B. Comparative Results

Here the proposed algorithm is compared to state-of the-art segmentation algorithms like FLGMM, Level Set, and Bias corrected FCM for brain MR images.

The parameters used herein are empirically set as follows: the fuzzy factor $m = 2$, standard deviation of the kernel function $\tau = 4$ and neighbourhood radius of the kernel function $\rho = 10$.

The results obtained by using different MR images are depicted in Fig 3.

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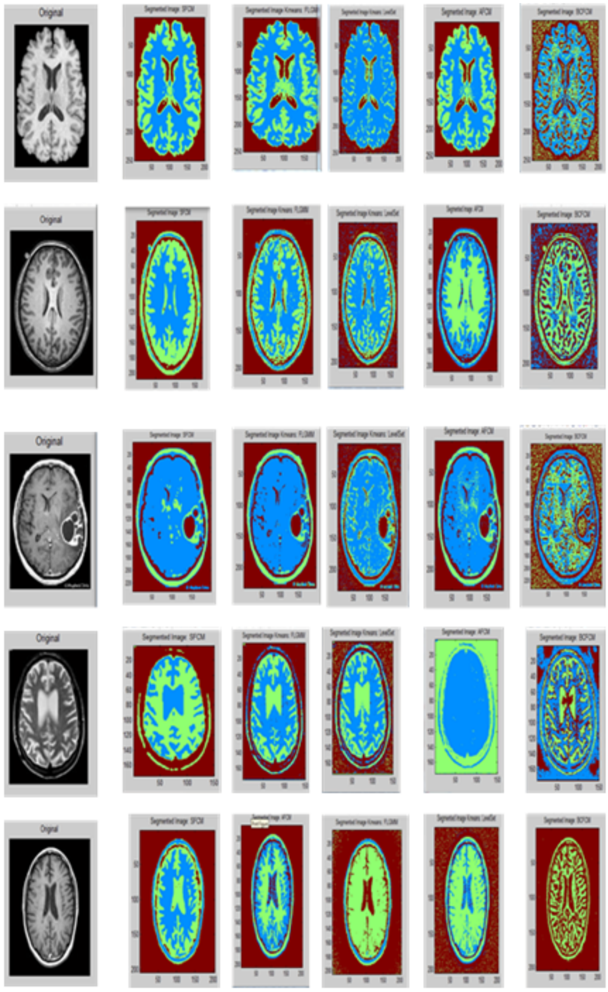

(a) (b) (c) (d) (e) (f)

Fig.3. (a) Original Image, Segmented image using algorithm, (b) SFCM, (c) FLGMM, (d) Level Set, (e) AFCM, (f) BCFCM

Jaccard's similarity (JS) value for Grey Matter & White Matter, of segmented images obtained by applying four segmentation algorithms to brain MR images are computed and listed in Table 1.

V. Conclusion

It can be concluded that Spatial Fuzzy C-means algorithm is a robust segmentation method for segmenting brain MR Images. In comparison to other standard segmentation algorithms provides better results for both normal as well as noise induced MR images. Experimental results obtained indicate that the proposed method is more accurate over the standard segmentation algorithms. The segmented images are then compared to that of variational level set framework for segmentation, FLGMM and Bias corrected FCM method. For quantitative analysis Jaccard's similarity parameter is calculated for the tissue types for similarity between the segmented and input image. Based on figure 2 and figure 3 it can be concluded that proposed algorithm is a better image segmenting algorithm as compared to other four standard algorithms. With reference to results tabulated in table 1 it is fairly clear that the proposed method for segmenting white matter, works better in 75 percent of cases and 67 percent in case of grey matter in comparison to other algorithms. Results obtained from this experiment concludes that it is possible to largely overcome the difficulties raised by noise, low contrast, and bias fields for brain MR images by using the proposed image segmentation method.

Table 1: JS value for GM & WM segmentation obtained by applying four segmentation algorithms to brain MR images.

Image S.No.	Tissue	Proposed Method	FLGMM	Level Set	BCFCM	AFCM
1	White Matter	0.936565	0.814788	0.655322	0.521049	0.90897
	Grey Matter	0.889686	0.621544	0.338693	0.155921	0.86579
2	White Matter	0.895328	0.82017	0.693566	0.179377	0.00000
	Grey Matter	0.898132	0.460697	0.608835	0.224133	0.29217
3	White Matter	0.808634	0.677591	0.607226	0.328752	0.92541
	Grey Matter	0.924794	0.543888	0.006259	0.007501	0.81094
4	White Matter	0.832777	0.744231	0.704829	0.003732	0.36874
	Grey Matter	0.843431	0.344766	0.717845	0.087612	0.00655
5	White Matter	0.87592	0.791246	0.694333	0.674081	0.55591
	Grey Matter	0.762386	0.778161	0.707566	0.511896	0.01778

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