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Novel segmentation algorithm in segmenting medical images

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ABSTRACT

The aim of this paper is to develop an effective fuzzy c-means (FCM) technique for segmentation of Magnetic Resonance Images (MRI) which is seriously affected by intensity inhomogeneities that are created by radio-frequency coils. The weighted bias field information is employed in this work to deal the intensity inhomogeneities during the segmentation of MRI. In order to segment the general shaped MRI dataset which is corrupted by intensity inhomogeneities and other artifacts, the effective objective function of fuzzy c-means is constructed by replacing the Euclidean distance with kernel-induced distance. In this paper, the initial cluster centers are assigned using the proposed center initialization algorithm for executing the effective FCM iteratively. To assess the performance of proposed method in comparison with other existed methods, experiments are performed on synthetic image, real breast and brain MRIs. The clustering results are validated using Silhouette accuracy index. The experimental results demonstrate that our proposed method is a promising technique for effective segmentation of medical images.

1. Introduction

Cluster analysis (Dunn, 1973; Runkler and Bezdek, 1999; Ruspini, 1969) is playing an important role in solving many problems in medical field, psychology, biology, sociology, pattern recognition (Bezdek, 1981; Bezdek and Pal, 1992) and image processing. Clustering is the process of partitioning a given set of objects into clusters. This is done in such a way that objects within a given cluster have a high degree of similarity, whereas objects belonging to different clusters have a high degree of dissimilarity. There are two main approaches in the clustering: Hard or non-fuzzy clustering and fuzzy clustering. In hard clustering, the dataset is partitioned into clusters, where one object belongs to only one cluster. In practice, the class attributes of most objects are not strict but uncertain; hence it is suitable for soft or fuzzy partitioning. Auspiciously, Zadeh (1965) proposed the fuzzy set theory which provides a powerful tool for such soft partitioning. Thus, people began to deal the clustering techniques with fuzzy approach and named them as fuzzy cluster analysis (Ruspini, 1970). Since fuzzy clustering obtains the degree of uncertainty of samples belonging to each class and expresses the intermediate property of their memberships, it can more objectively reflect the real world. Especially, fuzzy clustering is an effective tool for image segmentation (Acton et al., 1999; Bezdek et al., 1993; Boudraa et al., 2000).

Image segmentation (Clark et al., 1998; Fletcher-Heath et al., 2001; Gering et al., 2002) is the process to partition the image into non-overlapping, constituent regions which are homogeneous with respect to some characteristics such as intensity or texture. There are many methods available for segmenting the medical images into different regions or tissues such as thresholding, edge detection, region growing techniques, region based technique and clustering technique. Among them fuzzy clustering techniques (Al-Sultan and Selim, 1993; Al-Sultan and Fedjki, 1997; Boudraa et al., 1996; Yang, 2002) are receiving much attention to segment medical images, since these techniques preserve a lot more information from the original image than other segmentation methods. Because of the additional flexibility, FCM has been widely used in applications of MR image segmentation (Ketsetzis et al., 2004; Wu et al., 2006; Chen, 2006). However, the standard FCM algorithm is noise sensitive, because of not considering the spatial information in the image. To overcome the above problem, many researchers recently introduced many modified fuzzy c-means algorithms for MRI segmentation. Ahmed et al. (2002) first developed a bias-corrected FCM (BCFCM) by normalizing the objective function of FCM with a spatial neighborhood regularization term and then the proposed technique successfully applied in the segmentation of MRI dataset. A shortcoming of the BCFCM is that it consumes more time than FCM for completion of the algorithm. To rectify this, Zhang and

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Chen (2004) enhanced the objective function of BCFCM to reduce the computational time by replacing the euclidean distance using kernel-induced distance and the methods are named as KFCM_S_1 and KFCM_S_2.

However, the main drawback of BCFCM, KFCM_S_1 and KFCM_S_2 is that their parameters heavily affect the final clustering results. In order to avoid the problems in the final clusters, Yang et al. (2005) and Chuang et al. (2006) have proposed fuzzy c-means clustering algorithm with Spatial constraints for image segmentation. But still the methods fail to completely remove the problems in final clusters which affected by the parameters of FCM with Spatial constraints. Yang and Tsai (2008) introduced Gaussian kernel-based fuzzy c-means (GKFCM) algorithm with a spatial bias correction to solve the drawbacks of BCFCM, KFCM_S_1 and KFCM_S_2. Jiayin Kang et al. (2009) proposed Novel modified fuzzy c-means algorithm (called FCM-AWA) which is modified by incorporating the spatial neighborhood information into the standard FCM algorithm to avoid the problems cause by BCFCM, KFCM_S_1 and KFCM_S_2. Zanaty et al. (2009) presented alternative Kernelized FCM algorithms (named as SKFCM) that could improve MRI segmentation. This method was constructed by incorporating spatial information into the membership function.

Even though these algorithms are performed well on medical image segmentation, they have two important drawbacks: (1) unsuitable initialization of cluster center. In iterative clustering algorithms, the proper initial cluster center is very important to lead the algorithm to the best fuzzy partition of dataset. (2)These algorithms could not succeed completely to segment the images which are corrupted by heavy noise, outliers and other imaging artifacts, such as the intensity inhomogeneity induced by the radio-frequency coil in MRI.

In order to rectify the drawbacks of recent fuzzy c-means algorithms in medical image segmentation, we propose effective computer assisted Kernalized fuzzy c-means with bias field information and center initialization algorithm, for robust image segmentation. To show the effectiveness of our proposed algorithm, the proposed method is compared with the recent FCM algorithms such as BCFCM, GKFCM with Spatial constraints, FCM-AWA and SKFCM.

The rest of this paper is organized as follows: Section 2 describes the formulation of proposed method. Section 3 presents center initialization method and proposed method. The experimental results are given in Section 4. Conclusions are made in Section 5.

2. Formulation of proposed method

2.1. Kernel method

Recently, a number of powerful kernel-based learning machines were proposed and have found successful applications such as pattern recognition and image processing (Zhang and Chen, 2003). A common philosophy behind these algorithms is based on the following kernel (substitution) trick, that is, a nonlinear map which is defined from the data space to the higher dimensional feature space S is used to have the proper structure for nonlinear dataset.

Kernel method studies often employ a high-dimensional feature space S for having nonlinear classification boundaries. For this purpose a mapping

$$\varphi : R^p \to S \tag{1}$$

is used whereby an object x is mapped into S:

$$\varphi(x) = (\varphi_1(x), \varphi_2(x), \ldots\ldots) \tag{2}$$

Although x is the p-dimensional vector, $\varphi(x)$ may have the infinite dimension. In the nonlinear classification method, an explicit form of $\varphi(x)$ is unavailable, but the inner product is denoted by:

$$K(x, y) = \left\langle \varphi(x), \varphi(y) \right\rangle \tag{3}$$

The function $K(x, y)$ is called a kernel function, and assumed as known. Three commonly used kernel functions are:

(1) Gaussian radial basis function (GRBF) kernel:

$$K(x, y) = \exp\left(-\frac{\|x-y\|^2}{\sigma^2} \right) \tag{4}$$

(2) Polynomial kernel:

$$K(x, y) = (1 + \langle x, y \rangle)^d \tag{5}$$

(3) Sigmoid kernel:

$$K(x, y) = \tan h(\alpha \langle x, y \rangle + \beta) \tag{6}$$

where σ, d, α, β are the adjustable parameters of the above kernel functions. For the sigmoid function, only a set of parameters satisfying the Mercer theorem can be used to define a kernel function.

2.2. Notion of Kernelized fuzzy c-means with weighted bias field information

The standard FCM objective function for partitioning a dataset $\left\{x_i\right\}_{i=1}^{n}$ into c clusters is given by:

$$J_{\text{FCM}}(U, V) = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^m d_{ik}^2, \quad \text{where} \quad d_{ik} = \left\| x_i - v_k \right\| \tag{7}$$

Here $\left\{v_k\right\}_{k=1}^{c}$ are centers or prototypes of the clusters and the array $\left\{u_{ik}\right\}(=U)$ represents the partition matrix satisfying:

$$u_{ik} = \left\{ U = (u_{ik}) : \sum_{k=1}^{c} u_{ik} = 1,\ 1 \le i \le n;\ u_{ik} \in [0, 1],\ 1 \le i \le n,\ 1 \le k \le c \right\} \tag{8}$$

The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. In image clustering, the most commonly used feature is the gray-level value, or intensity of image pixel. Thus, the objective function of FCM is minimized when high membership values are assigned to pixels whose intensities are close to the cluster center of its particular class, and low membership values are assigned when the point is far from the cluster center.

The Lagrangian of objective function J_{FCM} of FCM is given by:

$$J_{\text{LFCM}}(U, V, \xi) = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^m d_{ik}^2 - \sum_{i=1}^{n} \xi_i \left(\sum_{k=1}^{c} u_{ik} - 1 \right) \tag{9}$$

where ξ_i's are the Lagrangian multipliers.

The fuzzy membership functions u_{ik} and cluster center v_k of J_{LFCM} as follows:

$$u_{ik} = \frac{\left(\dfrac{1}{d^2(x_i, v_k)} \right)^{\frac{1}{m-1}}}{\sum_{j=1}^{c} \left(\dfrac{1}{d^2(x_i, v_j)} \right)^{\frac{1}{m-1}}} \qquad \begin{array}{l} i = 1, 2, \ldots, n \\ k = 1, 2 \ldots, c \end{array} \tag{10}$$

$$v_k = \frac{\sum_{i=1}^{n} u_{ik}^m x_i}{\sum_{i=1}^{n} u_{ik}^m} \tag{11}$$

A common ground of the algorithms is to represent the clustering center as a linearly-combined sum of all $\varphi(x_i)$, i.e. the clustering centers lie in feature space. Now we introduce the notion of kernelized fuzzy c-means algorithm with the above objective function as follows:

$$J_{\mathrm{KFCM}}(U, V, \xi) = \sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^{m} \left\| \varphi(x_i) - \varphi(v_k) \right\|^2 - \sum_{i=1}^{n} \xi_i \left(\sum_{k=1}^{c} u_{ik} - 1 \right) \tag{12}$$

since

$$\left\| \varphi(x_i) - \varphi(v_k) \right\|^2 = \left\langle \varphi(x_i) - \varphi(v_k), \varphi(x_i) - \varphi(v_k) \right\rangle \tag{13}$$

and

$$\left\langle \varphi(x_i), \varphi(v_k) \right\rangle = K(x_i, v_k) \tag{14}$$

$$\left\| \varphi(x_i) - \varphi(v_k) \right\|^2 = K(x_i, x_i) + K(v_k, v_k) - 2K(x_i, v_k) \tag{15}$$

We obtain the following objective function using GRBF kernel given in Eqs. (4) and (12) can be simplified as:

$$J_{\mathrm{KFCM}}(U, V, \xi) = \sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^{m}(1 - K(x_i, v_k)) - \sum_{i=1}^{n} \xi_i \left(\sum_{i=1}^{c} u_{ik} - 1 \right) \tag{16}$$

In a similar way to the standard FCM algorithm, the objective function (16) can be minimized under the constraints of U. Specifically, taking the first derivatives of Eq. (16) with respect to u_{ik} and v_k, and zeroing them, respectively, two necessary but not sufficient conditions for J_{KFCM} to be at its local extrema is obtained as follows:

$$u_{ik} = \frac{\left(\frac{1}{1-K(x_i, v_k)} \right)^{\frac{1}{m-1}}}{\sum_{j=1}^{c} \left(\frac{1}{1-K(x_i, v_j)} \right)^{\frac{1}{m-1}}} \tag{17}$$

$$v_k = \frac{\sum_{i=1}^{n} u_{ik}^{m} K(x_i, v_k) x_i}{\sum_{i=1}^{n} u_{ik}^{m} K(x_i, v_k)} \tag{18}$$

Although KFCM can be directly applied to image segmentation like FCM, it would be helpful to consider some weighted bias field information on the objective function.

We introduce weighted bias field information with the objective function of J_{KFCM} as follows:

$$J_{\mathrm{KFCM\_wBI}}(U, V, \beta, \xi) = 2\sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^{m}((1 - K(y_i - w_i\beta_i, v_k)) - \sum_{i=1}^{n} \xi_i \left(\sum_{k=1}^{c} u_{ik} - 1 \right) \tag{19}$$

This objective function is minimized with respect to β_i and hence we get bias field estimation term as:

$$\beta_i = \frac{1}{w_i} \left[y_i - \frac{\sum_{k=1}^{c} u_{ik}^{m} v_k}{\sum_{k=1}^{c} u_{ik}^{m}} \right] \tag{20}$$

2.3. Bias field

Our aim of this paper is to achieve a novel segmentation algorithm in order to segment or differentiate the tissue classes in given medical images. Intensity inhomogeneity or bias field in MRI images affects the process of differentiating different tissue classes during medical image segmentation. So, in order to deal the bias field in the brain MRIs, this section proposes additive bias field to the novel fuzzy c-means of this paper. There are three commonly used bias models of how the bias interacts with noise. The bias filed model (Ye Xing et al., 2007) used in this paper is defined by:

$$y_i = x_i + w_i\beta_i \quad \forall i \in \left\{ 1, 2, \ldots, n \right\}$$

where x_i and y_i are the true and observed log-transformed intensities at the ith voxel, respectively, w_i is the weight at the ith voxel and β_i is the bias field at the ith voxel. If the gain field is known, then it is relatively easy to estimate the tissue class by applying a conventional intensity-based segmentation method to the corrected data.

3. Proposed method

In this section, we present an automatic center initialization algorithm for assigning the initial cluster center and introduce a novel objective function for proposed FCM, called effective kernelized fuzzy c-means with weighted bias field information (EKFCM_wBI). The objective function of proposed method is minimized based on the membership function and cluster center, and hence the equation for updating membership grade and cluster center are obtained in this section.

3.1. Method for cluster center initialization

In this subsection, we present the center initialization algorithm in order to avoid the random initialization which consumes more time period for the completion of algorithms.

3.1.1. Cluster center initialization algorithm

Step 1: Find $m_i = \sum_{s=1}^{p} x_{is}/P$, $i = 1, 2, \ldots, n$ for p-dimensional dataset $X = \{x_1, x_2, \ldots, x_n\} \subset R^p$. Sort m_i's in ascending order.

Step 2: Rearrange the data matrix in respect of its relabeling mean value (i.e.) $X' = [x_1', x_2', \ldots x_n']$. Partition the data into c groups.
Find $r = \lfloor n/c \rfloor$, where r is the number of elements in each group. The number of cluster ``c'' is specified according to the nature of the dataset.
Case 1: Suppose r is an integer, then r elements exist in each cluster.
Case 2: Suppose r is not an integer. Consider $r = r{\cdot}d$, where d is decimal point. If the decimal $d < 0.5$, then $r{\cdot}d$ has been rounded as r. If the decimal $d \geq 0.5$, then $r{\cdot}d$ has been rounded as $r+1$.
First group contains first r data of X'. Second group contains second r data of X'

⋮

$(c-1)$th group contains remaining $(c-1)$th r data of X'.
cth group contains remaining all the elements.

Step 3: Computing the distance between each data points of qth ($q = 1, \ldots, c$) data group in step 2 and all other data points in the same qth data group.

Step 4: Find the furthest pair of data points for each group and assign the each mean value of that pair of data points as initial cluster center for concern group.

3.2. Effective kernelized fuzzy c-means with bias field information

In this subsection, we propose effective Kernelized fuzzy c-means with weighted bias field information by incorporating normed kernel function with weighted bias field information that allows the clustering of objects to be more reasonable. We have constructed the objective function of EKFCM_wBI as in Section 2.2.

The objective function of Effective Kernelized fuzzy c-means is given by:

$$J_{\text{EKFCM\_wBI}}(U,V,\beta,\xi) = 2\sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^{m}(\delta - K(y_i - w_i\beta_i, v_k)) - \sum_{i=1}^{n}\xi_i\left(\sum_{k=1}^{c}u_{ik} - 1\right) \tag{21}$$

Here we introduce the kernel function with weighted bias field information as:

$$K(x_i, v_k) = -\frac{\left\|y_i - w_i\beta_i - v_k\right\|^2}{\eta} + \delta \tag{22}$$

where η and δ are the adjustable parameter.

The proposed partition matrix in an objective function satisfies the following conditions:

$$0 \le u_{ik} \le 1, \quad \text{for} \quad \mathbf{1} \le \boldsymbol{i} \le \boldsymbol{n}, \mathbf{1} \le \boldsymbol{k} \le \boldsymbol{c} \tag{23}$$

$$0 < \sum_{i=1}^{n} u_{ik} < n, \quad \text{for} \quad \mathbf{1} \le \boldsymbol{k} \le \boldsymbol{c} \tag{24}$$

$$\sum_{k=1}^{c} u_{ik} = 1, \quad \text{for} \quad \mathbf{1} \le \boldsymbol{i} \le \boldsymbol{n} \tag{25}$$

3.2.1. Bias field estimation

Taking the derivative of (21) with respect to β_i and setting the result to zero we have:

$$\frac{\partial J_{\text{EKFCM\_wBI}}(U,V,\beta,\xi)}{\partial \beta_i} = 2\sum_{k=1}^{c}\frac{\partial}{\partial\beta_i}\sum_{i=1}^{n}u_{ik}^{m}(\delta - K(y_i - w_i\beta_i, v_k)) \tag{26}$$

Since only the $\boldsymbol{i}$th term in the second summation depends on β_i we have:

$$2\sum_{k=1}^{c}\frac{\partial}{\partial\beta_i}u_{ik}^{m}\frac{\left\|y_i - w_i\beta_i - v_k\right\|^2}{\eta} = 0 \tag{27}$$

$$\frac{-4}{\eta}\sum_{k=1}^{c}u_{ik}^{m}(y_i - w_i\beta_i - v_k)(w_i) = 0 \tag{28}$$

$$\sum_{k=1}^{c}u_{ik}^{m}y_i - \sum_{k=1}^{c}u_{ik}^{m}w_i\beta_i - \sum_{k=1}^{c}u_{ik}^{m}v_k = 0 \tag{29}$$

$$(y_i - w_i\beta_i)\sum_{k=1}^{c}u_{ik}^{m} = \sum_{k=1}^{c}u_{ik}^{m}v_k \tag{30}$$

The zero-gradient condition for the bias- field estimator is expressed as:

$$\beta_i = \frac{1}{w_i}\left[y_i - \frac{\sum_{k=1}^{c}u_{ik}^{m}v_k}{\sum_{k=1}^{c}u_{ik}^{m}}\right] \tag{31}$$

Here, $w_i \in (0, 1)$ is the weight. Suppose taking 10 data points, we can define $w_1 = 0.008$ and $w_2, \ldots, w_{10}$ by increasing 0.001 with w_1. The bias field estimation enables the proposed algorithm to deal the intensity inhomogeneity and heavy noise during the segmentation of MRIs.

3.2.2. Membership grades and centers of clusters

We minimize the objective function (21) with respect to u_{ik}, subject to the constraints in Eq. (25), and thus we can obtain membership grade evaluation.

Taking the derivative of (21) with respect to u_{ik} and setting the result to zero, we have:

$$\frac{\partial J_{\text{EKFCM\_wBI}}(U,V,\beta,\xi)}{\partial u_{ik}} = 2mu_{ik}^{m-1}(\delta - K(y_i - w_i\beta_i, v_k)) - \lambda_i = 0 \tag{32}$$

Solving u_{ik} we have:

$$u_{ik} = \left(\frac{\lambda_i}{m}\right)^{\frac{1}{m-1}}\frac{1}{((\delta - K(y_i - w_i\beta_i, v_k))^{\frac{1}{m-1}}} \tag{33}$$

Since $\sum_{k=1}^{c}u_{ik} = 1$, $\forall i$ we have:

$$\left(\frac{\lambda_i}{m}\right)^{\frac{1}{m-1}} = \frac{1}{\sum_{j=1}^{c}(\delta - K(y_i - w_i\beta_i, v_j))^{\frac{1}{m-1}}} \tag{34}$$

Substituting the above equation into Eq. (33), the zero-gradient condition for the membership grade estimator can be rewritten as:

$$u_{ik} = \frac{\left[\frac{1}{(\delta - K(y_i - w_i\beta_i, v_k))}\right]^{\frac{1}{m-1}}}{\left[\frac{1}{\sum_{j=1}^{c}(\delta - K(y_i - w_i\beta_i, v_j))}\right]^{\frac{1}{m-1}}} \tag{35}$$

The general equation is used to obtain membership grades for objects in data for finding meaningful groups. By minimizing the objective function:

$$J_{\text{EKFCM\_wBI}}(U,V,\beta,\xi) = 2\sum_{i=1}^{n}\sum_{k=1}^{c}u_{ik}^{m}\frac{\left\|y_i - w_i\beta_i - v_k\right\|^2}{\eta} \tag{36}$$

with respect to v_k, we can obtain cluster center updating:

$$\frac{\partial J_{\text{EKFCM\_wBI}}(U,V,\beta,\xi)}{\partial v_k} = 2\sum_{i=1}^{n}\frac{\partial}{\partial v_k}\sum_{k=1}^{c}u_{ik}^{m}\frac{\left\|y_i - w_i\beta_i - v_k\right\|^2}{\eta} \tag{37}$$

$$2\sum_{i=1}^{n}\frac{\partial}{\partial v_k}u_{ik}^{m}\frac{\left\|y_i - w_i\beta_i - v_k\right\|^2}{\eta} = 0 \tag{38}$$

$$\frac{-4}{\eta}\sum_{i=1}^{n}u_{ik}^{m}(y_i - w_i\beta_i - v_k)(-1) = 0 \tag{39}$$

$$v_k = \frac{\sum_{i=1}^{n}u_{ik}^{m}(y_i - w_i\beta_i)}{\sum_{i=1}^{n}u_{ik}^{m}} \quad \boldsymbol{k = 1, 2, \ldots, c} \tag{40}$$

3.2.3. Algorithm for robust image segmentation

Step 1: Fetch the data from image.
Step 2: Set the number of clusters c and assign the initial centers using Center Initialization algorithm. Initialize the value for $\{\beta_i\}_{i=1}^{n}$.
Step 3: Compute the partition matrix U using (35).
Step 4: Update the cluster centers using (40).
Step 5: Update the weighted bias field information using (31).
Step 6: Repeat Steps (3)--(5) until the following termination criterion is satisfied: $\left\| J_{(t)}(U, V, \beta) - J_{(t-1)}(U, V, \beta) \right\| < \varepsilon$, where t is the iteration count and ε is a thresholding value lies between 0 and 1.

4. Results and discussions

To validate the effectiveness of our proposed method, the experiments are performed on PC Intel core 2 dual processor 2.93 GHZ CPU, 500 GB of HDD, 2 GB of RAM and performed in R programming. The proposed method and existed methods such as BCFCM, GKFCM with Spatial constraint, FCM-AWA, SKFCM are implemented on synthetic image which is (given in Fig. 1(b)) corrupted by Gaussian noise, and then implemented on real breast and brain MRIs. The synthetic test image includes three classes with intensity values taken from 0 to 100 given in Fig. 1(a). The segmentation results of five algorithms on synthetic image are shown in Fig. 1(c–g). As shown in Fig. 1(c), BCFCM has not succeeded well in correcting and clustering the data in the presence of "Gaussian" noise on synthetic image. From Fig. 1(d and e) the GKFCM with Spatial constraint and FCM-AWA achieve nearly the same result as BCFCM, and both the algorithms have failed to reduce "Gaussian" noise in the image. Fig. 1(f) shows the better segmentation result than previous algorithms, but it also failed to remove the noise effectively. On the other hand, the proposed effective fuzzy c-means is having superior result given in Fig. 1(g) to the corresponding classical algorithms, especially on the Gaussian corrupted synthetic image.

The second experimental works of this paper are performed on Gaussian corrupted real left & right breast images given in Figs. 2 and 3(a) and brain T1 & T2 weighted images given in Fig. 4(a and b) by using BCFCM, GKFCM with Spatial constraint, FCM-AWA, SKFCM and proposed method. In nature, the MRIs do not suffer from "Gaussian" noise, and we add such type of noise for the comparison of robustness to noises of proposed algorithm. For the experimental purpose we use two image slices of right and left breast with thickness of 3 and 1.5 mm space between slices in the axial plane. The flip angle is 10° and the repetition time: TR = 8.9 ms; echo time: TE = 4.2 ms. The brain image T1 with TR (200–400 ms) & TE (20 ms) have involved for the purpose of experimental works. The breast image can be divided by the algorithm into four tissue classes. They are fat, normal tissue, benign lesions and malignant lesions. The identification of different tissues are indicated by varying colors such as grey for fat tissue, blue for normal tissue, red for benign lesions and green for malignant lesions. And also, the brain image are discriminate by using the algorithm into four tissue classes such as cerebrospinal fluid, grey matter, white matter fluid and background. From the resulted images given in Fig. 2(b–d), Fig. 3(b–d) and Fig. 4(c–h), BCFCM gives bad segmentation performance in the presence of "Gaussian" noise and GKFCM with Spatial constraint, FCM-AWA, produce almost the same result of BCFCM. Though SKFCM algorithm has provided better segmentation result in Fig. 2(e) than other existed algorithms, it has still lacks in robustness for removing the noise. Figs. 2 and 3(f) and Fig. 4(l–m) show the results of applying the proposed new effective fuzzy c-means for the segmentation of noisy breast and brain images. Notice that the proposed new effective fuzzy c-

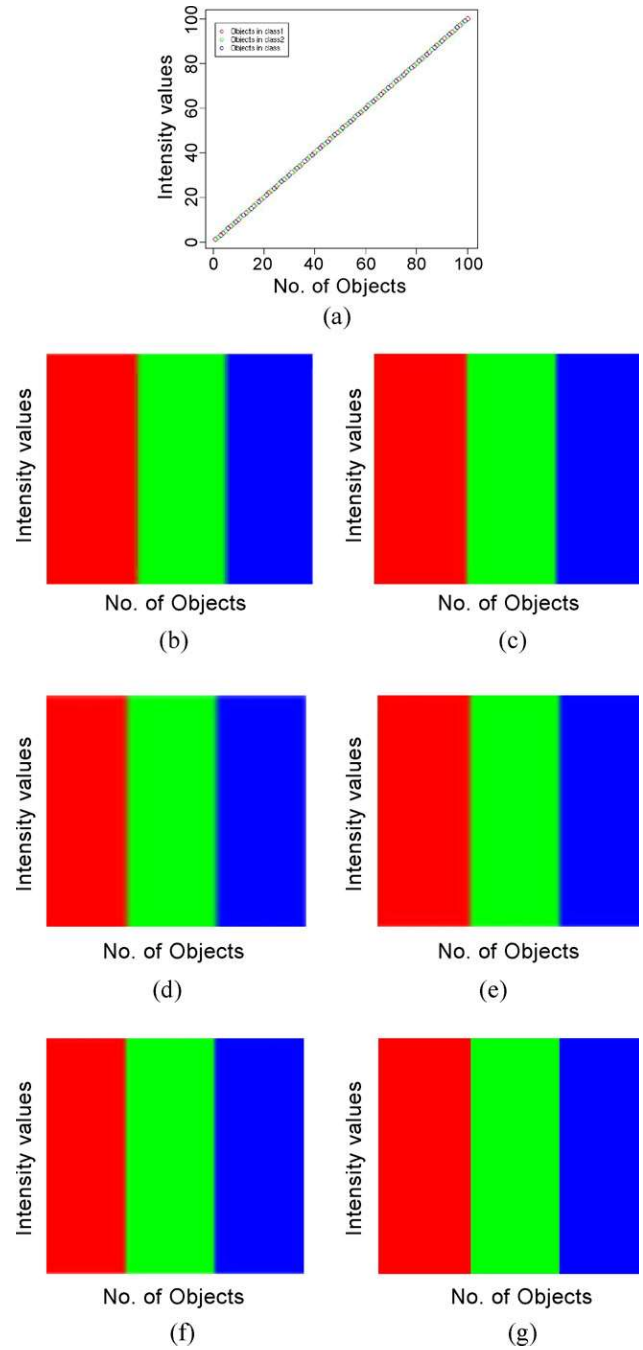

Fig. 1. Comparison of segmentation results on Synthetic image. (a) Artificial data. (b) Synthetic image corrupted by Gaussian noise. (c) Result by BCFCM. (d) Result by GKKFCM with Spatial constraint. (e) Result by FCM-AWA. (f) Result by SKFCM. (g) Result by proposed method.

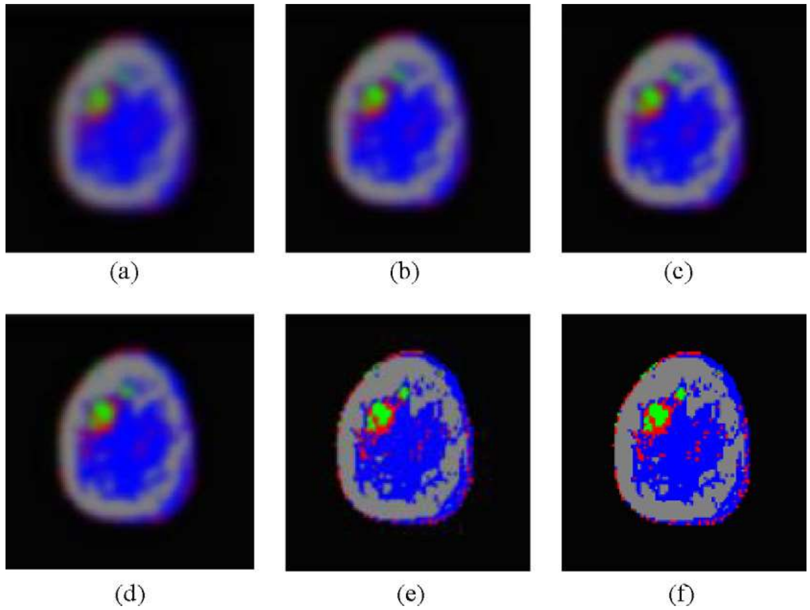

Fig. 2. Comparison of segmentation results on original MRI image. (a) Original left breast MRI corrupted by Gaussian noise. (b) Result by BCFCM. (c) Result by GKKFCM with Spatial constraint. (d) Result by FCM-AWA. (e) Result by SKFCM. (f) Result by proposed method.

means algorithm, which uses the weighted bias field effect, is much less fragmented than the existed fuzzy c-means approaches. As the level of noises increases, performance of the existed algorithms gradually degrade, but the proposed new effective fuzzy c-means algorithms still surpass the corresponding existed algorithms.

Finally, the efficiency of proposed algorithm has been proven through the experimental work on real image which is corrupted by real noise such as intensity inhomogeneity. The five algorithms have been executed on the noisy image and the segmented results are given in Fig. 5(c–g). From Fig. 5(c–g), we can observe that the existed algorithms are very sensitive to noises while the proposed algorithm still more stable and achieves the best performance among the five algorithms.

To show the quantitative evaluation of performance of proposed algorithm, the segmentation accuracies are validated by using well known Silhouette method and Hausdorff distance method. Table 1 gives the segmentation accuracy of the five algorithms on two different noisy images, where segmentation accuracy (SA) is defined using silhouette average value measure of silhouette method in Kannan (2008) and Kannan et al. (2009). The silhouette method measures the degree of confidence in the clustering assignment of a particular observation, with well-clustered observations having values near 1 and poorly clustered observations having values near -1. The silhouette width $s(i)$ of the object i is obtained using the equation $s(i) = b(i) - a(i)/ \max\left\{a(i), b(i)\right\}$. $a(i)$ is the average distance between the ith data and all other data in the same cluster. $b(i)$ is the smallest average distance between the ith data and all

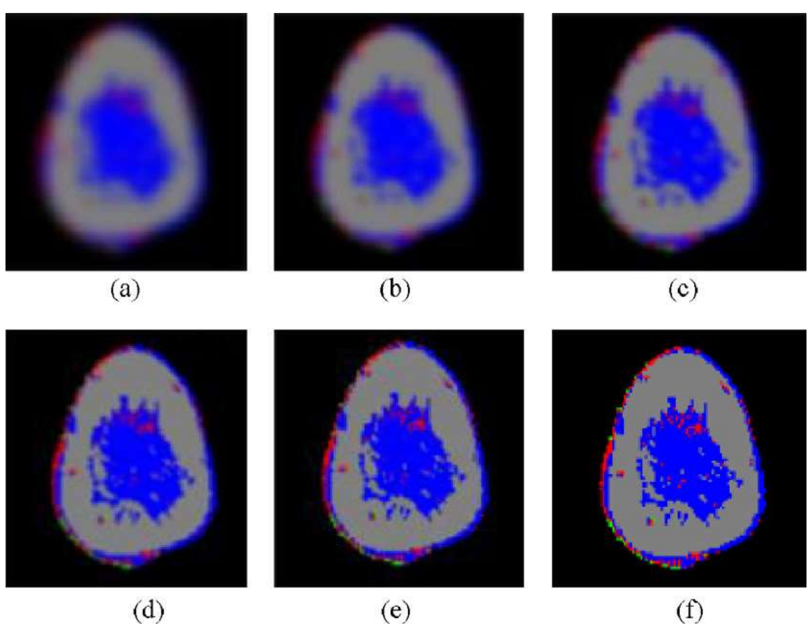

Fig. 3. Comparison of segmentation results on original MRI image. (a) Original right breast MRI corrupted by Gaussian noise. (b) Result by BCFCM. (c) Result by GKKFCM with Spatial constraint. (d) Result by FCM-AWA. (e) Result by SKFCM. (f) Result by proposed method.

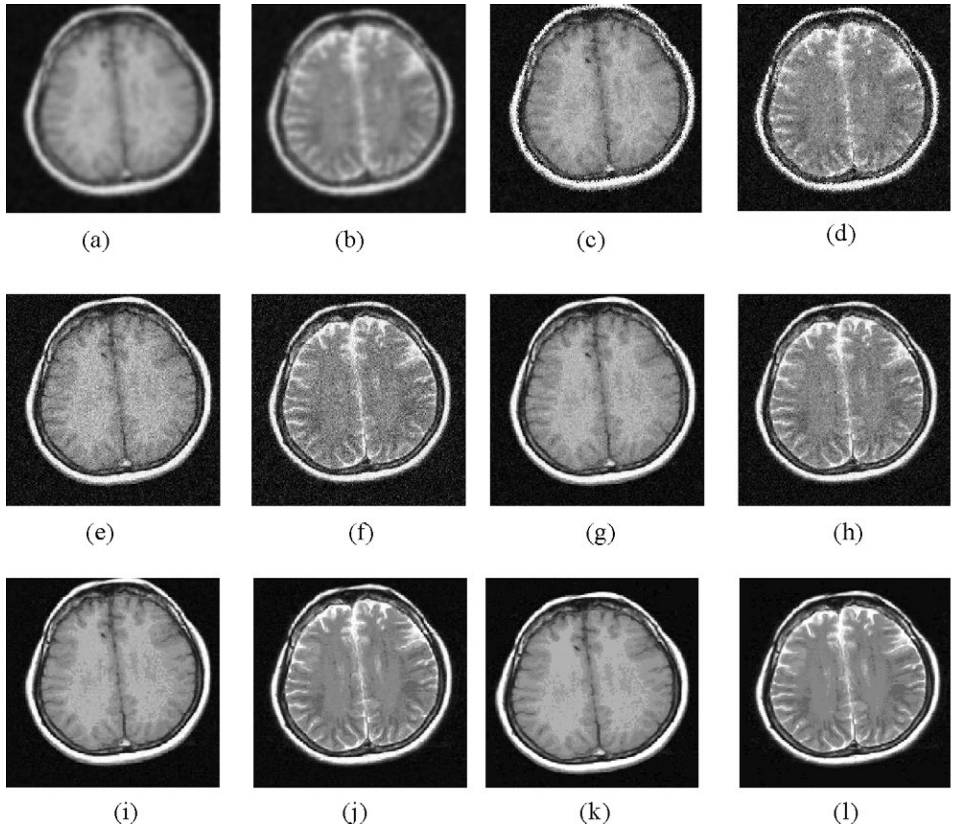

Fig. 4. Comparison of segmentation results on brain MRI. (a and b) T1 & T2 corrupted by Gaussian noise. (c and d) Result by BCFCM. (e and f) Result by GKKFCM with Spatial constraint. (g and h) Result by FCM-AWA. (i and j) Result by SKFCM. (k and l) Result by proposed method.

other data of other clusters. The obtained silhouette accuracy of each method is listed in Table 1. From Table 1, the best segmentation accuracy is obtained for proposed robust fuzzy clustering algorithms during the experimental study on breast and brain MRIs. Since the validation of segmentation methods is very important, we concentrate on other specific method Hausdorff Distance (H.D.) (Morra et al., 2008), for validating the algorithms. The segmentation accuracies of Hausdorff distance on breast, T1 & T2 brain images, and real noised image are reported in Table 2. The maximum of H.D. represents the well clustered structure in the given dataset. The

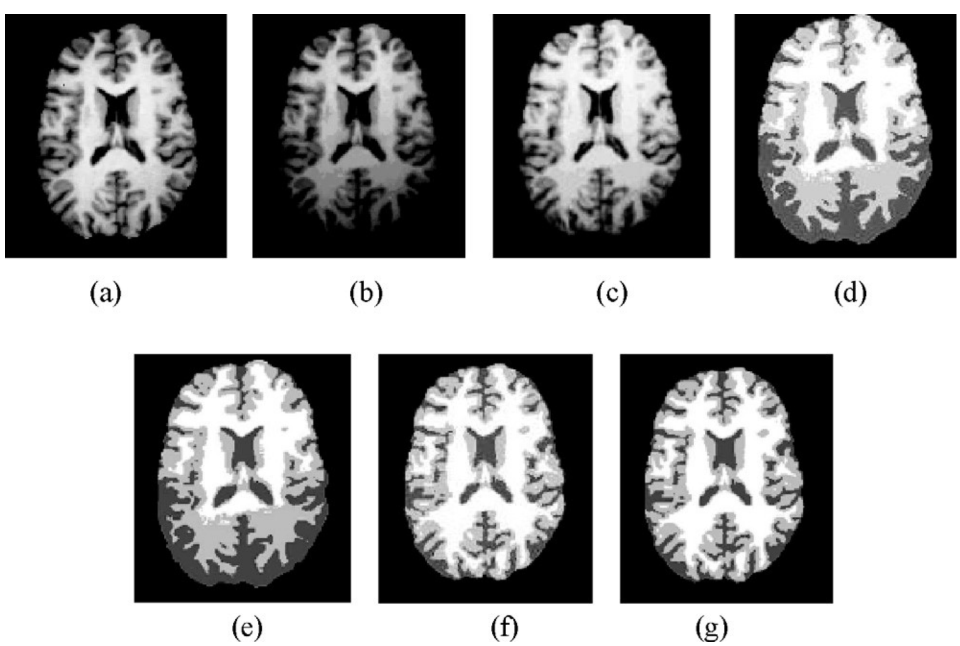

Fig. 5. Comparison of segmentation results on brain MRI with intensity inhomogeneity. (a) Real brain MRI. (b) Image corrupted by intensity inhomogeneities. (c) Segmented image by BCFCM. (d) Segmented image GKKFCM with Spatial constraint. (e) Segmented image by FCM-AWA. (f) Segmented image by SKFCM. (g) Segmented image by proposed method.

Table 1
Segmentation accuracy.

Name of the algorithms	Real breast MRI with Gaussian noise			Real brain MRI with Gaussian noise			Real brain MRI with intensity inhomogeneity		
	No. of Clusters	Silhouette value	Accuracy (%)	No. of clusters	Silhouette value	Accuracy (%)	No. of clusters	Silhouette value	Accuracy (%)
BCFCM	4	0.46	46	4	0.41	41	4	0.40	40
GKFCM with Spatial constraint	4	0.49	49	4	0.49	49	4	0.48	48
FCM-AWA	4	0.75	75	4	0.74	74	4	0.72	72
SKFCM	4	0.80	80	4	0.81	81	4	0.83	83
Proposed FCM	4	0.89	89	4	0.86	86	4	0.88	88

Table 2
Hausdorff distance.

Name of the algorithms	Real breast MRI with Gaussian noise		Real brain MRI with Gaussian noise		Real brain MRI with intensity inhomogeneity	
	No. of clusters	HD value	No. of clusters	HD value	No. of clusters	HD value
BCFCM	4	0.169424362	4	0.130874665	4	0.141774324
GKFCM with Spatial constraint	4	0.185963215	4	0.153923162	4	0.172810752
FCM-AWA	4	0.229917506	4	0.248910569	4	0.262576073
SKFCM	4	0.292413681	4	0.293612719	4	0.295373198
Proposed FCM	4	0.357943548	4	0.319432108	4	0.348363096

Table 3
Running time and number of iterations: minutes [min], seconds[s] and iterations [Its].

Name of the algorithms	Real breast MRI with Gaussian noise		Real brain MRI with Gaussian noise		Real brain MRI with intensity inhomogeneity	
	Running time	No. of Its	Running time	No. of Its	Running time	No. of Its
BCFCM	2.34 min	64	2.25 min	63	2.4 min	66
GKFCM with Spatial constraint	1.8 min	52	1.85 min	54	1.9 min	55
FCM-AWA	1.05 min	41	1 min	43	1.3 min	42
SKFCM	55 s	30	53 s	29	57 s	28
Proposed FCM	30 s	14	28 s	13	24 s	11

best segmentation accuracy of H.D. is occurred for the proposed method. In order to show the robustness of our proposed algorithm, the number of iterations and running time of our proposed method and other existed methods are listed in Table 3. Since our proposed algorithm assigned initial cluster center using the center initialization algorithm, it reduced the running time and number of iterations to converge the algorithm. Table 3 shows that our proposed algorithm works very faster than other existed algorithms. On the whole, proposed effective robust FCM algorithm provides better segmentation results under both synthetic and MRI breast and brain images.

5. Conclusions

This paper proposed an effective Kernelized fuzzy c-means with weighted Bias field Information for robust automatic segmentation of MRIs. The method was originated by incorporating the concept of Kernel function and weighted bias field estimation in order to deal the general shaped MRI dataset which is corrupted by intensity inhomogeneities and other artifacts during segmentation of MRI. Further, the proposed method initialized the initial cluster centers by using center initialization algorithm and hence the random initialization which consumes more time period for completion of clustering process was avoided. The performance of proposed method in comparison with other existed methods was assessed through the experimental work on synthetic image, real breast and brain MRIs. For comparative study, the existed methods BCFCM, GKFCM with Spatial constraint, FCM-AWA, and SKFCM were used in the experimental work. And, the clustering accuracies were validated using Silhouette accuracy index and Hausdorff distance. The experimental results showed that the proposed method provided much better segmentation results than other existed methods and achieved high segmentation accuracy. Finally, based on the experimental results, this work hopes that our proposed method is a promising technique for effective segmentation of medical images.

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