IMPROVED FUZZY POSSIBLISTIC C-MEANS (IFPCM) ALGORITHMS FOR MAGNETIC RESONANCE IMAGES SEGMENTATION

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Abstract: In this paper, we propose a new method called "improved fuzzy possiblistic c-means (IFPCM)" which could improve medical image segmentation. The proposed method combines the fuzzy c-means (FCM) and possiblistic c-means (PCM) functions without considering any spatial constraints on the objective function. It is realized by modifying the objective function of the conventional PCM algorithm with Gaussian exponent weights to produce memberships and possibilities simultaneously, along with the usual point prototypes or cluster centers for each cluster. IFPCM avoids various problems of existing fuzzy clustering methods solves the noise sensitivity defect of FCM and overcomes the coincident clusters problem of PCM.

The proposed algorithm is evaluated and compared with the most popular modified possibilistic c-means techniques via application to simulated MRI brain images corrupted with noise. The quantitative results suggest that the proposed algorithm yields better segmentation results than the others for all tested images.

Keywords: Fuzzy c-means clustering, possiblistic c-means, medical image segmentation.

INTRODUCTION

Applications that use the morphologic contents of magnetic resonance image (MRI) often require segmentation of the image volume into tissue types [1]. For example, accurate segmentation of magnetic resonance images (MRIs) of the brain is of interest in the study of many brain disorders [2]. There are many types of image segmentation techniques [3-10]. Among them, the fuzzy clustering methods are of considerable benefits for MRI brain image segmentation [2-4, 5] because the uncertainty of MRI image is widely presented in data. For example, the fuzzy c-means (FCM) can be seen as the fuzzified version of the k-means algorithm [5]. The fuzzy c-means clustering algorithms fall into two categories: fuzzy c-means *(FCM)* and *possibilistic c-means (PCM)*.

Many extensions of the *FCM algorithm* have been proposed to overcome above mentioned problem and reduce errors in the segmentation process [8,10-13]. Shen et al. [9] introduced a new similarity measure that depends on spatial neighborhood information. In the work, the degree of the neighborhood attraction is optimized by a neural network. There are also other methods for enhancing the FCM performance. For example, to improve the segmentation performance, one can combine the pixel-wise classification with pre-processing (noise cleaning in the original image) [11,13] and post-processing (noise cleaning on the classified data). Xue et al. [13] proposed an algorithm where they firstly denoise images and then classify the pixels using the standard FCM method. These methods can reduce the noise to a certain extent, but still have some drawbacks such as increasing computational time [8], complexity [8,9,12] and introducing unwanted smoothing [11, 13]. Liew et al. [16] proposed a spatial FCM clustering algorithm for clustering and segmenting the images by using both the feature space and spatial information. Another variant of FCM algorithm

called the robust fuzzy c-means (RFCM) algorithm was proposed in [17].

Pham and Prince [18] modified the FCM objective function by introducing a spatial penalty for enabling the iterative algorithm to estimate spatially smooth membership functions. Ahmed et al. [8] introduced a neighborhood averaging additive term into the objective function of FCM. They named the algorithm bias corrected FCM (BCFCM). Liew and Yan [19] introduced a spatial constraint to a fuzzy cluster method where the in homogeneity field was modeled by a B-spline surface. The spatial voxel connectivity was implemented by a dissimilarity index, which enforced the connectivity constraint only in the homogeneous areas. This way preserves significantly the tissue boundaries. Cai et al. [11] introduced a new local similarity measure by combining spatial and gray level distances. They used their method as an alternative pre-filtering to an enhanced fuzzy c-means algorithm (EnFCM) [20]. Kang et al. [21] proposed a spatial homogeneity-based FCM (SHFCM). Wang et al. [22] incorporated both the local spatial context and the non-local information into the standard FCM cluster algorithm. They used a novel dissimilarity measure in place of the usual distance metric.

The main disadvantages of FCM is sensitivity to noise; therefore, the 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. To address this problem, possibilistic c-means algorithm (PCM) was developed in [23]. This technique combines FCMand logic with some modification in its membership function for removal of noise from the MRI brain images. It has been shown to be more robust to outliers than FCM. However, the robustness of PFCM comes at the expense of the stability of the algorithm [24]. The PCM-based algorithms suffer from the coincident cluster problem that makes them

too sensitive to initialization [24]. Many efforts have been presented to improve the stability of possibilistic clustering [25-27].

Krishnapuram et al., [23] proposed PCM, that relaxes the column sum constraint so that the sum of each column satisfies the looser constraint. They suggested that the PCM objective function optimization sometimes helps to identify outliers (noise points) [25-27]. Other methods were introduced in [24-25, 28] to modify the PCM algorithms to segment the brain into different tissue effectively. In those methods, effect of noise is overcome by incorporating possibility (typicality) function in addition to membership function.However the algorithm still has some problems: It is very sensitive to initialization and sometimes coincident clusters will occur. To address the problems of FCM and PCM a new fuzzy possibilistic c-mean (FPCM) algorithm was proposed in [7] by combining these two algorithms. These algorithmsinclude several limitations including: accuracy, misclassification in noise affected image, etc., and theyare very sensitive to initialization and sometimes coincident clusters will occur.

In this paper, we introduce an improved fuzzy possibilisticc-mean (IFPCM) for overcoming the shortcomings of existing modified possibilistic c-mean (PCM). In order to reduce the noise effect during segmentation, IFPCM algorithm combines the objective functions of conventional FCM algorithm and PCM algorithm. To overcome the problem of coincident clusters of PCM and also for combination the objective FCM and PCM, a new weight function is proposed that is based on Gaussian membership. In this method the effect of noise is overcome by incorporating possibility (typicality) function in addition to membership function. Consideration of these constraints can greatly control the noise in the image as shown in our experiments. The efficiency of the proposed algorithm is demonstrated by extensive segmentation experiments using real MRIs and comprising with other state of the art algorithms.

The rest of this paper is organized as follows: We discuss the limitations of existing fuzzy c-means and its generalization in Section 2.In Section 3, the proposed IPFCMalgorithm is presented. Experimental comparisons are given in section 4. Finally, Section 5 gives our conclusions.

FCM AND PCM ALGORITHMS AND THEIR LIMITATIONS

The FCM algorithm is an iterative clustering method that produces optimal C partitions by minimizing the weighted within the group sum of squared error objective function J_{FCM}:

$$J_{FCM}(V,U,X) = \sum_{i=1}^{C}\sum_{j=1}^{n} u_{ij}^{m} d^{2}(x_j,v_i), 1 < m < +\infty \quad (1)$$

Where $X = \{x_1, x_2,..., x_n\} \subseteq R^p$ is the data set in the p-dimensional vector space, p is the number of data items, $C$is the number of clusters with $2 < C < n$ - 1. $V = \{v_1, v_2, . . . , v_C\}$ is the C centers or prototypes of the clusters, $v_i$is the p-

dimension center of the cluster i, and $d^2(x_j,v_i)$ is a square distance measure between object x_j and cluster centre v_i, $U = \{u_{ij}\}$ represents a fuzzy partition matrix with $u_{ij} = u_i(x_j)$ is the degree of membership of x_j in the i^{th}cluster; x_j is the $j^{th}$of p-dimensional measured data. The fuzzy partition matrix satisfies:

$$0 < \sum_{j=1}^{n} u_{ij} < n, \forall i \in \{1,......,C\} \quad (2)$$

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j \in \{1,.....,n\} \quad (3)$$

The parameter m is a weighting exponent for each fuzzy membership and determines the amount of fuzziness of the resulting classification; it is a fixed number greater than one. The objective function J_{FCM} can be minimized under the constraint of U.

The objective function J_{FCM} is minimized with respect to u_{ij} and v_i, respectively:

$$u_{ij} = \left[\sum_{k=1}^{C} \left(\frac{d^2(x_j,v_i)}{d^2(x_j,v_k)} \right)^{2l(m-1)} \right]^{-1} \quad 1 \le i \le C, i \le j \le n. \quad (4)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}}, 1 \le i \le C. \quad (5)$$

Although FCM and the modified FCM [18, 20, 22] are useful clustering methods, their memberships do not always correspond well to the degree of belonging of the data, and may be inaccurate in a noisy environment, because the real data unavoidably involves noise. To alleviate weakness of FCM, and to produce memberships that have a good explanation for the degree of belonging of the data, Krishnapuram and Keller [23] relaxed the constrained condition (3) of the fuzzy C-partition to obtain a possibilistic type of membership function and propose PCM for unsupervised clustering. The component generated by the PCM corresponds to a dense region in the data set; each cluster is independent of the other clusters in the PCM strategy. The objective function of the PCM can be formulated as follows:

$$J_{PCM}(V,U,X) = \sum_{i=1}^{C}\sum_{j=1}^{n} u_{ij}^{m} d^2(x_j,v_i) + \sum_{i=1}^{C} \eta_i \sum_{j=1}^{n} (1-u_{ij})^{m} \quad (6)$$

Where

$$\eta_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} d^2(x_j,v_i)}{\sum_{j=1}^{n} u_{ij}^{m}} \quad (7)$$

is the scale parameter at the ith cluster, and

$$u_{ij} = \frac{1}{1 + \left(\dfrac{d^2(x_j, v_i)}{\eta_i} \right)^{\frac{1}{m-1}}} \quad (8)$$

is the possibilistic typicality value of training sample x_j

belonging to the cluster $i, m \in 1, \infty$ is a weighting factor called the possibilistic parameter. Typical of other cluster approaches, the PCM also depends on initialization. In PCM techniques, the clusters do not have a lot of mobility, since each data point is classified as only one cluster at a time rather than all the clusters simultaneously. Therefore, a suitable initialization is required for the algorithms to converge to nearly global minimum.

Rajendranand Dhanasekaran[28] define a clustering algorithm that combines the characteristics of both fuzzy and possibilistic c-means: Memberships and typicalities are important for the correct feature of data substructure in clusteringproblems. Thus, an objective function in the FPCM that depends on both memberships and typicalities can be shown as:

$$J_{FPCM}(U, T, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^m + t_{ij}^{\eta}) d^2(x_j, v_i) \quad (9)$$

With the following constraints:

$$\sum_{i=1}^{C} u_{ij} = 1, \forall j \in \{1, \dots, n\}$$

$$\sum_{j=1}^{n} t_{ij} = 1, \forall i \in \{1, \dots, C\} \quad (10)$$

A solution of the objective function can be obtained via an iterative process where the degrees of membership, typicality and the cluster centers are updated as follows:

$$u_{ij} = \left[\sum_{k=1}^{C} \left(\frac{d^2(x_j, v_i)}{d^2(x_j, v_k)} \right)^{2/(m-1)} \right]^{-1} 1 \le i \le C, 1 \le j \le n$$

$$t_{ij} = \left[\sum_{k=1}^{n} \left(\frac{d^2(x_j, v_i)}{d^2(x_j, x_k)} \right)^{2/(\eta-1)} \right]^{-1}, 1 \le i \le C, 1 \le j \le n \quad (11)$$

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik}^m + t_{ik}^{\eta}) x_k}{\sum_{k=1}^{n} (u_{ik}^m + t_{ik}^{\eta})}, 1 \le i \le C \quad (12)$$

The objective function in [28] is called the modified fuzzy possiblistic c-means (MFPCM)function composed of two expressions: the first is the fuzzy function and it uses a fuzziness weighting exponent, the second is possiblistic function and it uses a typical weighting exponent; but the two coefficients in the objective function are only used as exhibitor of membership and typicality. The objective function of the modified fuzzy possiblistic c-means (MFPCM) can be formulated as follows:

$$J_{MFP|CM} = \sum_{i=1}^{C} \sum_{j=1}^{n} (u_{ij}^m \omega_{ji}^m d^{2m}(x_j, v_i) + t_{ij}^{\eta} \omega_{ji}^{\eta} d^{2m}(x_j, v_i)) \quad (13)$$

Where

$U = \{ u_{ij} \}$ represents a fuzzy partition matrix and is defined by:

$$u_{ij} = \left(\sum_{k=1}^{C} \left(\frac{d^2(x_j, v_i)}{d^2(x_j, v_k)} \right)^{2m/(m-1)} \right)^{-1} \quad (14)$$

$T = \{t_{ij}\}$ represents a typical partition matrix, and is defined by:

$$t_{ij} = \left(\sum_{k=1}^{n} \left(\frac{d^2(x_j, v_i)}{d^2(x_j, v_k)} \right)^{2\eta/(\eta-1)} \right)^{-1} \quad (15)$$

$V = \{v_i\}$ represents c centers of the clusters, and is defined by:

$$v_i = \frac{\sum_{j=1}^{n} (u_{ij}^m \omega_{ji}^m + t_{ij}^{\eta} \omega_{ji}^{\eta}) * x_j}{\sum_{j=1}^{n} (u_{ij}^m \omega_{ji}^m + t_{ij}^{\eta} \omega_{ji}^{\eta})} \quad (16)$$

Where

$$\omega_{ij} = \exp\left(-\frac{d^2(v_i, v_j)}{\left(\sum_{j=1}^{n} d^2(x_j, \bar{x}_j) \right) * v/n} \right), \bar{x} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (17)$$

The above equations indicate that membership u_{ij} is influenced by all C cluster centers, while possibility t_{ij} is influenced just by the i-th cluster center c_i. The possibilistic term distributes the t_{ij} with respect to every n data points, but not by means of every C clusters. Thus, membership can be described as relative typicality, it determines the degree to which a data fit in to cluster in accordance with other clusters and is helpful in correctly labeling a data point. Possibility can be observed as absolute typicality, it determines the degree to which a data point belongs to a cluster correctly, and it can decrease the consequence of noise. Joining both membership and possibility can yield to good clustering result.

THE PROPOSED IFPCM ALGORITHM

The choice of an appropriate objective function is a key to the success of cluster analysis and to obtain better quality clustering results; hence, clustering optimization is based on the objective function [31]. To identify a suitable objective function, one may start from the following set of requirements: the distance between the data points assigned to a cluster should be minimized and the distance between clusters should to be maximized [26]. To obtain an

appropriate objective function, we take into consideration the following:

   a. The distance between clusters and the data points allocated to them must be reduced.
   b. Coincident clusters may occur and must to be controlled.
   c. Selecting the initialization sensitive parameters for decreasing noises affect.

The desirability between data and clusters is modeled by the objective function. Hung et al [30] provides a modified PCM technique which considerably improves the function of FCM because of a prototype-driven learning of parameter ω_{ij} (see Eq. (17)). The learning procedure of ω_{ij} is dependent on an exponential separation strength between clusters and is updated at every iteration.

As for the common value used for this parameter by every data for iterations, we propose a new weight function W_{ij} which is based on Gaussian membership of a point p. achieving every point of the data set has a weight in relation to every cluster. The usage of weights produces good classification particularly in the case of noisy data. The weight is calculated as follows:

$$w_{ij} = \frac{1}{\sqrt{2\Pi}\sigma_i} e^{\frac{-(p_j - \mu_i)^2}{2\sigma_i^2}} \quad ; \tag{18}$$

where $\mu_i = \dfrac{\sum\limits_{j=1}^{n} x_j}{n}$, $\quad \sigma_i^2 = \dfrac{\sum\limits_{j=1}^{n} (p_j - \mu_i)}{n}$

and W_{ij} is the weight of the point j in relation to class i. This weight is used to modify the fuzzy and typical partition. To classify a data point, the cluster centroid has to be closest to the data point, it is membership; and for estimating the centroids, the typicality is used for alleviating the undesirable effect of outliers. The objective function is composed of two expressions: the first is the fuzzy function and it uses a fuzziness weighting exponent, the second is possiblistic function and it uses a typical weighting exponent; but the two coefficients in the objective function are only used as exhibitor of membership and typicality. A new relation, lightly different, enabling a more rapid decrease in the function and increase in the membership and the typicality when they tend toward 1 and decrease this degree when they tend toward 0. This relation is to add weighting Gaussian exponent as exhibitor of distance in the two under objective functions.

To solve the noise sensitivity defect of FCM which has an influence on the estimation of centroids, and to overcomethe coincident clusters problem of PCM, the hybridization of possibilistic c-means (PCM) and fuzzy c-means (FCM) is proposed that often avoids various problems. We will use the proposed weight W_{ij} and the term $(1-t_{ij})^{\eta}$ in the objective function for alleviating the noise affect and to decrease the distances between clusters and centers and to

avoidcoincident clusters. Thus the objective function of the proposed method (IFPCM) can be formulated as follows:

$$L_m = \sum_{i=1}^{C}\sum_{j=1}^{N}(u_{ij}^m + t_{ij}^m)w_{ij}^m d(x_j, v_i)^{2m} + \sum_{i=1}^{C}\sum_{j=1}^{n}u_{ij}^m(1-t_{ij})^{\eta}w_{ij}^m d(x_j, v_i)^{2m} \tag{19}$$

$$\sum_{i=1}^{C} u_{ij} = 1, \forall j \in \{1,......,n\}, t_{ij} \le 1, 1 \le j \le n, 1 \le i \le C$$

where $\eta \ge 1$ are user defined constants and the parameter m is a weighting exponent for each fuzzy membership.More datasets are tested in [30], they proved that there is a relation between the data shape and m. For instance, the triangular shape will fit better if $m=3$ is used, more discussion can be found in [10]. Therefore we take into account the data shape in the objective function and to be general for all tested data sets. This penalty term also contains spatial neighborhood information, which acts as a regularizer and biases the solution toward piecewise-homogeneous labeling. Such regularization is helpful in segmenting images corrupted by noise. The objective function J_m under the constraint of u_{ij} and v_i can be obtained by using the following theorem [25]:

Theorem: Let $X = \{x_i, i = 1,2,..., N \mid x_i \in R^d\}$ denotes an image with n pixels to be partitioned into C classes (clusters), where x_i represents feature data. The algorithm is an iterative optimization that minimizes the objective function defined by Eq.(19) with the constraints $\sum\limits_{i=1}^{C} u_{ij} = 1, \forall j \in \{1,...,n\}$.Then u_{ij} t_{ij} and v_i must satisfy the following equalities:

$$u_{ij} = \left[\frac{\sum\limits_{i=1}^{c} w_{ij}^m d(x_j, v_i)^{2m} + (1-t_{ij})^{\eta} w_{ij}^{\eta} d(x_j, v_i)^{2m}}{w_{ij}^m d(x_j, v_i)^{2m} + (1-t_{ij})^{\eta} w_{ij}^{\eta} d(x_j, v_i)^{2m}}\right]^{\frac{1}{m-1}} \tag{20}$$

$$v_i = \left(\frac{\left(\sum\limits_{i=1}^{c}\sum\limits_{j=1}^{n}(u_{ij}^m + t_{ij}^m)w_{ij}^m + \sum\limits_{i=1}^{c}\sum\limits_{j=1}^{n}u_{ij}^m(1-t_{ij})^{\eta}w_{ij}^m\right)x_j}{\sum\limits_{i=1}^{c}\sum\limits_{j=1}^{n}(u_{ij}^m + t_{ij}^m)w_{ij}^m + \sum\limits_{i=1}^{c}\sum\limits_{j=1}^{n}u_{ij}^m(1-t_{ij})^{\eta}w_{ij}^m}\right)^{\frac{1}{2m-1}} \tag{21}$$

$$t_{ij} = \left(\frac{\sum\limits_{i=1}^{c}\sum\limits_{j=1}^{n}u_{ij}^m w_{ij}^m d(x_j, v_i)^{2m}}{\sum\limits_{i=1}^{c}\sum\limits_{j=1}^{n}w_{ij}^m d(x_j, v_i) + \sum\limits_{i=1}^{c}\sum\limits_{j=1}^{n}u_{ij}^m w_{ij}^m d(x_j, v_i)^{2m}}\right)^{\frac{1}{\eta-1}} \tag{22}$$

Proof: The minimization of constraint problem J_m in Eq.(19) under the given constraints can be solved of using the Lagrange multiplier method. We define a new objective function with the constraint condition of (Eq.(10)) as follows:

$$L_m = \sum_{i=1}^{C}\sum_{j=1}^{N}(u_{ij}^m + t_{ij}^m)w_{ij}^m d(x_j, v_i)^{2m} + \sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^m(1-t_{ij})^{\eta}w_{ij}^m d(x_j, v_i)^{2m} + \sum_{j=1}^{n}\lambda_j(1-\sum_{i=1}^{c}u_{ij})$$

Taking the partial derivative of L_m with respect to u_{ki} and λ_i and then setting them to equal to zero, we have

$$\frac{\partial L_m}{\partial U_m} = 0 \Rightarrow mu_{ij}^{m-1} w_{ij}^m d(x_j, v_i)^{2m} + mu_{ij}^{m-1}(1-t_{ij})^\eta w_{ij}^\eta d(x_j, v_i)^{2m} + \lambda_i(-1) = 0$$

(23)

$$\frac{\partial L_m}{\partial \lambda_i} = 0 \Rightarrow \sum_{k=1}^{c} u_{ki} - 1 = 0$$

(24)

From Eq.(14), we get:

$$u_{ij} = \left(\frac{\lambda_i}{m\left(w_{ij}^m d(x_j, v_i)^{2m} + (1-t_{ij})^\eta w_{ij}^\eta d(x_j, v_i)^{2m} \right)} \right)^{\frac{1}{m-1}}$$

(25)

By substitution from Eq.(23) into Eq.(24), we get

$$\left(\frac{\lambda_i}{m} \right)^{\left(\frac{1}{m-1}\right)} \sum_{i=1}^{c} \left(\frac{1}{\left(w_{ij}^m d(x_j, v_i)^{2m} + (1-t_{ij})^\eta w_{ij}^\eta d(x_j, v_i)^{2m} \right)} \right)^{\left(\frac{1}{m-1}\right)} = 1$$

$$\left(\frac{\lambda_i}{m} \right)^{\left(\frac{1}{m-1}\right)} = \frac{1}{\sum_{i=1}^{c} \left(\left(w_{ij}^m d(x_j, v_i)^{2m} + (1-t_{ij})^\eta w_{ij}^\eta d(x_j, v_i)^{2m} \right) \right)^{\left(\frac{-1}{m-1}\right)}}$$

$$u_{ij} = \left[\frac{\sum_{i=1}^{c} w_{ij}^m d(x_j, v_i)^{2m} + (1-t_{ij})^\eta w_{ij}^\eta d(x_j, v_i)^{2m}}{w_{ij}^m d(x_j, v_i)^{2m} + (1-t_{ij})^\eta w_{ij}^\eta d(x_j, v_i)^{2m}} \right]^{\frac{1}{m-1}}$$

(26)

$$\frac{\partial L_m}{\partial t_{ik}} = 0 \Rightarrow \eta \sum_{i=1}^{c} \sum_{j=1}^{n} t_{ij}^{\eta-1} w_{ij}^m d(x_j, v_i)^{2m} - \eta \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m (1-t_{ij})^{\eta-1} w_{ij}^\eta d(x_j, v_i)^{2m} = 0$$

$$t_{ij} = \left(\frac{\sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m w_{ij}^\eta d(x_j, v_i)^{2m}}{\sum_{i=1}^{c} \sum_{j=1}^{n} w_{ij}^m d(x_j, v_i) + \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m w_{ij}^\eta d(x_j, v_i)^{2m}} \right)^{\frac{1}{\eta-1}}$$

$$\frac{\partial L_m}{\partial v_i} = 0 \Rightarrow -2m \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^m + t_{ij}^m) w_{ij}^m \| x_j - v_i \|^{2m-1} - 2m \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m (1-t_{ij})^\eta w_{ij}^\eta \| x_j - v_i \|^{2m-1} = 0$$

(27)

$$v_i = \left(\frac{\left(\sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^m + t_{ij}^m) w_{ij}^m + \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m (1-t_{ij})^\eta w_{ij}^\eta \right) x_j}{\sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^m + t_{ij}^m) w_{ij}^m + \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m (1-t_{ij})^\eta w_{ij}^\eta} \right)^{\frac{1}{2m-1}}$$

(28)

The process of finding the best clusters is continued to update the centres c_i and the membership u_{ij} using Eqs.(20) and (21), respectively.

EXPERIMENTAL AND COMPARATIVE RESULTS

The experiments were performed ontwo differentsets: one corrupted by 6% salt and pepper noise and the image size is 129×129 pixels which are shown in Fig. 1(b) [32]. The second set includes simulated volumetric MR data consisting of ten classes as shown in Figure (1a). The advantages of using digital phantoms rather than real image data for soft segmentation methods include prior knowledge of the true tissue types and control over image parameters such as modality, slice thickness, noise, and intensity in homogeneities. The quality of the segmentation algorithm is of vital importance to the segmentation process. The comparison score S for each algorithm as proposed in [8] is defined as follows:

$$S = \left| \frac{A \cap A_{ref}}{A \cup A_{ref}} \right|$$

Where A represents the set of pixels belonging to a class as found by a particular method and A_{ref} represents the reference cluster pixels.
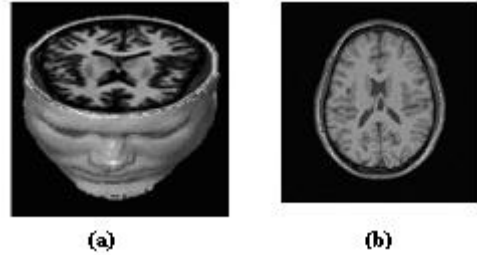

Figure.(1): Test images: (a) 3D simulated data, (b) original slice from the 3D simulated data (slice91).

Experiments on the real image:

We used a high-resolution T1-weighted MR phantom (with slice thickness of 1mm, 6% noise and no intensity in homogeneities) obtained from the classical simulated brain database of McGill University [32].

The test slicesare drawn from the simulated MR data, for example slice 91is shown in Fig. 1(b). In this test, beside the proposed method, the standard FCM [8] and the most popular modified possibilistic c-means such as: Zhang and Leung [27], Rajendran and Dhanasekaran[28], andFadhel et al. [29] are implemented and applied on slice 91 (as in Fig. 1(b)) to prove the efficiency of the proposed method. Five segments (as shown in figs.(2-6))are obtained after applyingthese methods to this slice. Evaluating the accuracy of the existing methods and the proposed method is shown in Table 1. Through our implementation, we set the following parameters: $m = 2$ and $\eta = 2$.Obviously, the proposed method acquires the best segmentation performance. Rajendran and Dhanasekaran[39] gave satisfactory result comparing toFCM [8]. The proposed methods appear to be stable and achieve better performance than the others.

Table 1: Accuracy of the segmentation results.

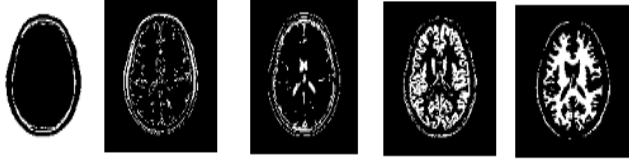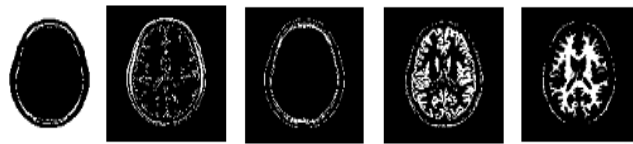| Methods	Segments					average
	a	b	C	d	E	
FCM[8]	99%	50.07%	63.89%	64%	41.23%	64%
Zhang and Leung [27]	99.273%	50.12%	73.87%	71.73%	80.39%	75.08%
Rajendran and Dhanasekaran [28]	99%	40.55%	87.23%	85%	79.65%	80%
Fadhel et al. [29]	99.1%	73.98%	79.54%	66.54%	77.98%	79.43%
The proposed method	99.88%	77.47%	84.86%	88.43%	87.64%	87.66%

Figure. (2): Results of segmentation using FCM[8].

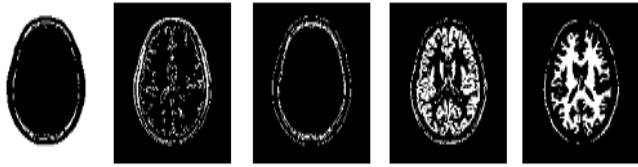Figure. (3): Results of segmentation using Zhang and Leung. method[27].

Figure. (4): Results of segmentation usingRajendran and Dhanasskaran method [28].

Figure. (5): Results of segmentation using Fadhel et al. method [29]

Figure. (6): Results of segmentation using the proposed method.

Experiment on the simulated MR data:

Table (2) shows the corresponding accuracy scores (%) of the proposed and four other methods: standard FCM [8], Zhang and Leung [27], Rajendran and Dhanasekaran[28], and fadhel et al. [29] for the nine classes. Obviously, the FCM gives the worst segmentation accuracy for all classes, while other methods give satisfactory results. On the other hand, the method of Zhang and Leung [27], Rajendran and Dhanasekaran[28], and Fadhel et al. [29] acquire the good segmentation performance in case of classes 9,4, and 1 respectively. Overall, the proposed method is more stable and achieves much better performance than the others in all different classes even with misleading of true tissue of validity indexes.

Table 2. Segmentation accuracy (%) of the proposed and the existing methods on brain classes.

Method	Class1	Class2	Class3	Class4	Class5	Class6	Class7	Class8	Class9	Overall
Standard KFCM	66.87	68.77	65.087	68.0	75.32	45.96	71.99	20.12	95.11	64.136
Zhang Leung [27]	68.55	63.14	82.83	78.88	73.96	67.87	96.21	23.27	96.97	72.409
Rajendran and Dhanaskaran[28]	80.54	70.55	81.34	86..01	83.65	87.98	88.70	27.54	93.54	77.761
Fadhel et al. [29]	57.87	62.43	69.98	91.54	81.09	51.98	73.87	24.43	84.09	66.364
The proposed method	84.76	80.45	83.09	94.34	88.56	70.12	96.64	67.34	97.98	84.808

CONCLUSION

Image enhancement in the medical field is a wide problem because of the noise occurrence in the captured image due to some faults in the capturing device. It helps doctors to better analyze better the image and for providing better diagnosis. This can be done with the help of image segmentation techniques. This paper focuses on brain image enhancement with the help of image segmentation. Clustering is considered to be better segmentation technique because of its advantages. FCM and PCM are a popular clustering method and have been widely applied for medical image segmentation. However, traditional FCM always suffers from noise in the images. Although many researchers have developed various extended algorithms based on FCM, none of them are flawless. A new approach called IFPCM combines FCM and PCM has been proposed in this paper.

The proposed algorithm works without manual parameters as FCM method. The algorithm is formulated by modifying the objective function of PCM algorithm to allow the labeling of a pixel to be influenced by other pixels and to suppress the noise effect during segmentation. We tested our algorithm on real MRI images with 6% noise. The

superiority of the proposed algorithm is demonstrated by comparing its performance againstthe existing FCM [8], Zhang and Leung [27], Rajendran and Dhanasekaran[28], and fadhel et al. [29]. In addition, quantitative resultsare also given in our experiments. We noted that the segmentation accuracy of the proposed method is increased over the existing methods between49% and 7% for one slice and9% for volumetric MR data (nine slices) over the best one. From the quantitative evaluation and the visual inspection, we conclude that our proposed algorithm IFPCM yields a robust and precise segmentation.Through the quantitative evaluation and the visual inspection, we can conclude that IFPCM algorithm yields more superior segmentation result than other two methods for all tested images.

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