Automatic Fuzzy Algorithms for Reliable Image Segmentation

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Abstract

The problem of classifying an image into different homogeneous regions is viewed as the task of clustering the pixels in the intensity space. In particular, medical image segmentation is complex, and automatically detecting regions or clusters of such widely varying sizes is a challenging task. In this paper, we present automatic fuzzy *k*-means, and kernelized fuzzy *c*-means algorithms by considering some spatial constraints on the objective function. The proposed algorithm incorporates spatial information into the membership function and the validity procedure for clustering. It starts by partitioning the given data into an arbitrary number of clusters. These clusters are considered as an initial partition of the data. The similar clusters that satisfy the validity function are merged into one cluster. The proposed validity function is based on the intra-cluster distance measure, which is simply the distance between the center of the cluster and its neighbor cluster center multiplied by the objective function. A first cluster is fetched; the second cluster is selected if it has the shortest distance between their two centers. These clusters are merged together into one cluster if they satisfy the validity function; else the next cluster is fetched, and so on. The process stops only when all clusters are checked. The number of clusters increases automatically according to the decision of validity function. The most important aspect of the proposed algorithms is actually to work automatically to improve automatic image segmentation. The proposed methods are evaluated and compared with the existing methods by applying them on various test images, including synthetic images corrupted with noise of varying levels and simulated volumetric Magnetic Resonance Image (MRI) datasets.

Key Words: Image segmentation, medical imaging, fuzzy clustering.

1 Introduction

Clustering is one of the most popular classification methods and has found many applications in pattern classification and image segmentation [2, 6, 8-10, 12, 16]. Clustering algorithms attempt to classify a voxel to a tissue class by using the notion of similarity to the class. Unlike the crisp k-means clustering algorithm [10], the FCM algorithm allows partial membership in different tissue classes. Thus, FCM can be used to model the partial volume averaging artifact, where a pixel may contain multiple tissue classes [8-9]. The fuzzy *c*-means clustering (FCM) algorithms have recently been applied to MRI segmentation [6, 16]. Unlike the crisp *k*-means clustering algorithm (FKM) [2, 8-10, 12], the FCM algorithm allows partial membership in different tissue class. Thus, FCM can be used to model the partial volume averaging artifact, where a pixel may contain multiple tissue classes [6]. A method of simultaneously estimating the intensity non-uniformity artifact and performing voxel classification based on fuzzy clustering has been reported in [6] where intermediate segmentation results are utilized for the intensity non-uniformity estimation. The method uses a modified FCM cost functional to model the variation in intensity values and the computation of the bias field is formulated as a variation problem. However, in conventional FCM clustering algorithm, there is no consideration of spatial context between voxels since the clustering is done solely in the feature space.

The kernelized fuzzy *c*-means (KFCM) [6-7, 16] used a kernel function as a substitute for the inner product in the original space, which is like mapping the space into higher dimensional feature space. There have been a number of other approaches to incorporating kernels into fuzzy clustering algorithms. These include enhancing clustering algorithms designed to handle different shape clusters [7]. More recent results of fuzzy algorithms have been presented in [15] for improving automatic MRI image segmentation. They used the intra-cluster distance measure to give the ideal number of clusters automatically; more discussion can be found in [15]. Also, possibilistic clustering which is pioneered by the possibilistic *c*-means (PFCM) algorithm was developed in [5, 11, 17]. They had been shown that PFCM is more robust to outliers than FCM. However, the robustness of PFCM comes at the expense of the stability of the algorithm [17]. The PCM-based algorithms suffer from the coincident cluster problem, which makes them too sensitive to initialization [5].

Although fuzzy methods have several advantages such as: (1) it yields regions more homogeneous than those of other

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methods, (2) it reduces the spurious blobs, (3) it removes noisy spots, and (4) it is less sensitive to noise than other techniques. The final number of clusters is still always sensitive to one or two user-selected parameters that define the threshold criterion for merging. Though some compatibility or similarity measure can be applied to choose the clusters to be merged, no validity measure is used to guarantee that the clustering result after a merge is better than the one before the merge. Partial results were stated in [4, 14] to answer the questions: "Can the appropriate number of clusters be determined automatically? And if the answer is yes, how?" The number of clusters is determined by operating index procedures to whole data to determine the number of clusters before starting fuzzy methods. This will consume much time for finding the suitable number of clusters. Therefore, two major problems are known with the fuzzy methods: (1) How to determine the number of clusters. (2) The computational cost is quite high for large data sets.

In this paper, we develop the *k*-means, FCM, KFCM, and SKFCM algorithms that could improve MRI segmentation. The algorithms incorporate spatial information into the membership function and the validity procedure for clustering. The most important aspect of the proposed algorithm is actually to work automatically. The alternative is to improve automatic image segmentation. The performance of the proposed method is illustrated using synthetics and simulated volumetric MRI. The rest of the paper is organized as follows. In Section 2, the cluster number is optimized. The fuzzy validity function is stated in Section 3. The proposed *k*-means clustering algorithm is presented in Section 4. Section 5 presents the FCM method. In Section 6, KFCM is proposed. SKFCM is presented in Section 7. Experimental results are presented in Section 8. In Section 9 we present our conclusions and future work.

2 Optimization of Cluster Number

Clustering analysis aims to place similar objects in the same groups. The purpose is to get an idea about the sample dispersions and about the correlations between variables in the samples which include huge data. However, many clustering algorithms necessitate pre-knowledge of the number of clusters. The fact that the researchers do not have pre-knowledge of the number of clusters in many studies make it impossible to know whether the end number of clusters is more or less than the actual number of clusters. If the end number of clusters turn out to be less than the actual number of clusters, then one or more of the present clusters will have to unite; if it turns out to be more, then one or more of the present clusters will be divided. The process of determining the optimal cluster number is called cluster validity in general. Thus, the accuracy of the end cluster number can be determined.

Recall that fuzzy algorithms seek to minimize the following objective function [8]:

$$d_{ij} = \left\| x_i - c_j \right\|^2$$

$$p = \sum_{i=1}^{n} \sum_{j=1}^{k} u_{ij}^{m} d_{ij} \quad (1)$$

Where $u_{ij} = u_j(x_i)$ is the membership of the *i-th* object x_i in the *j-th* cluster, and c_i is the *j-th* center. In the commonly employed probabilistic version of fuzzy *c*-means [16], it is required that

$$\sum_{j=1}^{k} u_{ij} = \sum_{j=1}^{k} u_j(x_i) = 1 \quad (2)$$

The constant $m>1$ in (1) is called the fuzzifier and controls the overlap ("smoothness") of the clusters (a common choice is $m=2$). As mentioned before, the simple enumeration strategy for optimizing the cluster number, as outlined in the introduction, is not practicable in an online setting as it requires the consideration of too large a number of candidate values and, hence, applications of the clustering algorithm.

3 Fuzzy Validity Function

Since the fuzzy method aims to minimize the sum of squared distances from all points to their cluster centers, this should result in compact clusters. The proposed method starts to subdivide the data a set of N vector $X = \{x_j, j = 1, \ldots, N\}$ into M clusters using well-known fuzzy methods [2, 8-9]. Assume the data is divided into M cluster, $R_1, R_2, .., R_M$ with centers $c_1, c_2, .., c_M$ respectively. The proposed algorithm processes every two neighbor clusters individually, i.e., if we have three clusters A, B, C with centers c_A, c_B, and c_c. We start to hold our validity function between clusters A and B if

$$\| c_A - c_B \| < \| c_A - c_c \| \quad (3)$$

Our validity function is proposed to use the intra-cluster distance measure, which is simply the distance between a center of cluster A and cluster center B multiplied by the objective function of fuzzy. We can define the validity function as:

$$V_1 = \left\| c_A - c_B \right\|^2 \frac{1}{n} \sum_{i=1}^{n} u_i^m (d_{iA} + d_{iB})$$

$$(4)$$

$$V_2 = (Max(A) - Min(B)) \sum_{i=1}^{n} \sum_{k=1}^{2} u_{ik}^m d_{iA \cup B}$$

Where $Max(B)$ and $Min(B)$ are the maximum and minimum values of clusters A and B, respectively. While $C_{A \cup B}$ is the center of the data x_i (of number *n*) of A union B i.e., $A \cup B$.

4 The Proposed *K*-Means Clustering Algorithm

K-means clustering is one of the simplest unsupervised classification algorithms [2, 8-9]. The procedure follows a simple way to classify the dataset through a certain number of clusters. The algorithm partitions a set of N vector $X = \{x_j, j = 1, \ldots, N\}$ into C classes v_i, $i = 1, \ldots, C$, and finds a cluster center for each class c_i denotes the centroid of cluster v_i such that an objective function of dissimilarity, for example a distance measure, is minimized. The objective function that should be minimized, when the Euclidean distance is selected as a dissimilarity measure, can be described as:

$$P = \sum_{i=1}^{C} \sum_{k, x_k} d_{ki} \tag{5}$$

where $\sum_{k,x_k} \|x_k - c_i\|^2$ is the objective function within group i, and $\|x_k - c_i\|$ is a chosen distance measure between a data point x_k and the cluster center c_i. The partitioned groups are typically defined by a $(C \times N)$ binary membership matrix $U = (u_{ij})$, where the element u_{ij} is 1 if the j^{th} data point x_j belongs to group i, and 0 otherwise. This means:

$$u_{ij} = \begin{cases} 1 & if \|x_j - c_i\|^2 \leq \|x_j - c_k\|^2 \quad \forall k \neq i \\ 0 & otherwise \end{cases} \tag{6}$$

$$c_i = \frac{\sum_{j=1, x_j \in c_i}^{N} x_j}{R_i} \tag{7}$$

where R_i is number of data point in class v_i.

The following algorithm starts by partitioning the given data into arbitrary M clusters. It can find the optimal cluster number with associated partition clusters R_k, k=1,2,.., M with centers $c_1, c_2, .., c_M$ and membership u_{ij} respectively using the *k*-means clustering algorithm.

The proposed *k*-means clustering algorithm is described as follows:

Algorithm1

Initial: Subdivided the data into arbitrary M cluster using *k*-means method.
Input: data, R_k, k=1,2,.., M.
Output: optimal cluster number.
Put: k=1, t=2.
Repeat
  Fetch R_k and R_t satisfy Equation (3)
  While R_k and R_t satisfy Equation (3)
    $S = R_k U R_t$
    Apply Equation (4) on R_k and R_t
    Evaluate V_1, V_2
    If $V_2 \geq V_1$
      R_k and R_t are merged into R_k cluster and
      Delete R_t.
    Else still without merging
    Estimate the center of new cluster (R_k) c_k using Equations (7) and (6).
    t=t+1
  End While
  Update: k=k+1
End Repeat until for checked all regions.
End

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5 The Proposed Fuzzy *C*-Means Algorithm

Fuzzy *c*-means clustering (FCM), also known as fuzzy ISODATA, is a data clustering algorithm in which each data point belongs to a cluster to determine a degree specified by its membership grade. Bezdek [2, 8-9] has proposed this algorithm as an alternative to earlier *k*-means clustering. FCM partitions a collection of *N* vector x_i, $i = 1, \ldots, N$ into C fuzzy groups, and finds a cluster center in each group such that an objective function of a dissimilarity measure is minimized. The major difference between FCM and *k*-means is that FCM employs fuzzy partitioning such that a given data point can belong to several groups with the degree of belongingness specified by membership grades between 0 and 1. In FCM, the membership matrix *U* is allowed to have not only 0 and 1 but also the elements with any values between 0 and 1. This matrix satisfies the constraints:

$$\sum_{i=1}^{C} u_{ij} = 1, \quad \forall j = 1, \ldots, N \tag{8}$$

The objective function of FCM can be formulated as follows:

$$p(u, v_1, \ldots v_c) = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^m d_{ji} \tag{9}$$

Where u_{ij} is between 0 and 1; c_i is the cluster center of fuzzy group i, and the parameter m is a weighting exponent on each fuzzy membership (in our implementation, we set it to 2). Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, updating of membership u_{ij} and the cluster centers c_j by:

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m} \tag{10}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| x_j - c_i \|}{\| x_j - c_k \|} \right)^{2/(m-1)}} \tag{11}$$

Similar to the *k*-means method, we use the validity measure, which is simply based on the intra-cluster distance measure, which is simply the distance between a center of cluster and its neighbors cluster center multiplied by the objective function as shown in Equations (3) and (4).

The proposed algorithm is described as follows:

Algorithm2

Initial: Subdivided the data into arbitrary M cluster using *c*-means method.
Input: data, R_k, k=1,2,.., M .
Output: optimal cluster number.
Put: k=1, t=2.
Repeat
  Fetch R_k and R_t satisfy Equation (3)
  While R_k and R_t satisfy Equation (3)
   $S=R_k U R_t$
    Apply Equation (4) on R_k and R_t
   Evaluate V_1, V_2
   If $V_2 \geq V_1$
    R_k and R_t are merged into R_k cluster and
    Delete R_t.
   Else still without merging
  Estimate the center of new cluster (R_k) c_k
     using Equations (10) and (11).
    t=t+1
  End While
 Update: $k=k+1$
End Repeat until for checked all regions.
End

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6 Kernelized Fuzzy *C*-Means Method

The kernel methods [5-7, 11, 15, 17] are one of the most researched subjects within the machine learning community in recent years and have widely been applied to pattern recognition and function approximation. The main motives of using the kernel methods consist of: (1) inducing a class of robust non-Euclidean distance measures for the original data space to derive new objective functions and thus clustering the non-Euclidean structures in data; (2) enhancing robustness of the original clustering algorithms to noise and outliers, and (3) still retaining computational simplicity. The algorithm is realized by modifying the objective function in the conventional fuzzy *c*-means (FCM) algorithm using a kernel-induced distance instead of Euclidean distance in the FCM, and thus the corresponding algorithm is derived and called as the kernelized fuzzy *c*-means (KFCM) algorithm, which is more robust than FCM. In FCM, the membership matrix U is allowed to have not only 0 and 1 but also the elements with any values between 0 and 1, this matrix satisfies the constraints:

$$\sum_{i=1}^{C} u_{ij} = 1, \forall j = 1,..., N \tag{12}$$

In this work, the kernel function $K(x,c)$ is taken as the Gaussian radial basic function (GRBF):

$$K(x,c) = \exp\left(\frac{-\|x-c\|^2}{\sigma^2} \right), \tag{13}$$

where σ is an adjustable parameter. The objective function is given by:

$$j_m = 2 \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^m (1 - K(x_j, C_i)) \tag{14}$$

The fuzzy membership matrix u can be obtained from:

$$u_{ij} = \frac{\left(1 - K(x_j, c_i)\right)^{-1/(m-1)}}{\sum_{k=1}^{C} \left(1 - K(x_j, c_k)\right)^{-1/(m-1)}} \tag{15}$$

The cluster center c_i can be obtained from:

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^{\,m} K(x_j, c_i) x_j}{\sum_{j=1}^{N} u_{ij}^{\,m} K(x_j, c_i)} \tag{16}$$

Similar to algorithm 2, the proposed KFCM clustering algorithm is composed of the following steps:

Algorithm3

Initial: Subdivided the data into arbitrary M cluster using c-means method.
Input: data, R_k, k=1,2,.., M .
Output: optimal cluster number.
Put: k=1, t=2.
Repeat
Fetch R_k and R_t satisfy Equation (3)
While R_k and R_t satisfy Equation (3)
$S=R_k U R_t$
Apply Equation (4) on R_k and R_t
Evaluate V_1 , V_2
If $V_2 \geq V_1$
R_k and R_t are merged into R_k cluster and
Delete R_t.
Else still without merging
Estimate the center of new cluster (R_k) c_k
using Equations (15) and (16).
t=t+1
End While
Update: k=k+1
End Repeat until for checked all regions.
End

7 Spatial Constrained SKFCM Method

Since SKFCM is applied directly to image segmentation like KFCM, it would be helpful to consider some spatial constraints on the objective function [14]. This penalty term contains spatial neighborhood information, which acts as a regularizer and biases the solution toward piecewise-homogeneous labeling. Such regulization is helpful in segmenting images corrupted by noise. The objective function is as follows:

$$j_m = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^m \left(1 - K(x_j, c_i)\right) + \frac{\alpha}{N_R}\sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^m \sum_{r \in N_j} (1 - u_{ir})^m \quad (17)$$

Where N_j stands for the set of neighbors that exist in a window around x_j (do not include x_j itself) and N_R is the cardinality of N_j. The parameter α controls the effect of the penalty term and lies between zero and one inclusive. An iterative algorithm for minimizing Equation (17) is derived by evaluating the centroids and membership functions that satisfy a zero gradient condition like the KFCM. A necessary condition on u_{ij} for Equation (17) to be at a local minimum or a saddle point is:

$$u_{ij} = \frac{\left((1-K(x_j,c_i)) + \left(\alpha \sum_{r \in N_j} (1-u_{ir})^m / N_R\right)\right)^{-1/(m-1)}}{\sum_{k=1}^{C}\left((1-K(x_j,c_k)) + \left(\alpha \sum_{r \in N_j} (1-u_{kr})^m / N_R\right)\right)^{-1/(m-1)}} . \quad (18)$$

The proposed SKFCM algorithm is almost identical to the KFCM, except, Equation (18) is used instead of Equation (15) to update the memberships.

8 Experimental Results

The experiments were performed with several data sets. The first experiment consists of two simple synthetic images (synthetic1 and synthetic2), one corrupted by 9 percent salt and pepper noise, and another corrupted by gaussian noise of standard deviation 50 respectively, and the image size is 142×145 pixels, as shown in Figure 1a, and Figure 1b, respectively. The second set includes simulated volumetric MR data consisting of 10 classes. The advantages for using digital phantoms rather than real image data for validating 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. We used a high-resolution T1-weighted MR phantom with slice thickness of 1mm, 3 percent noise and no intensity in homogeneities, obtained from the classical simulated brain database of McGill University [3]. Two slices drawn from the simulated MR data is shown in Figure 1d and 1e.

The quality of the segmentation algorithm is of vital importance to the segmentation process. The comparison score S for each algorithm is proposed in [1, 13, 16], which defined as:

$$S = \left| \frac{A \cap A_{ref}}{A \cup A_{ref}} \right| \quad (19)$$

where A represents the set of pixels belonging to a class as found by a particular method and Aref [1] represents the set of pixels belonging to the very same class in the reference segmented image (ground truth).

Another accuracy measure, segmentation accuracy (overall accuracy) S' is computed by dividing the total number of correct number of correct classified pixels over the total number of pixels [1, 13,16].

The measure S is more conservative than defined S' in evaluating the segmentation quality as shown in the following example. Assume we have a simple synthetic data set with 10 pixels, which is plotted in Figure 2, and contains two classes, with 5 pixels in each class. Assume the segmentation method is applied to these datasets, where the segmentation results gives 6 pixels in class1 and 4 pixels in class2. The two measures will yield S=9/11, S'=9/10. The value of S is lower as it penalizes the misclassification of the pixels more. Thus we will use S in our experiments.

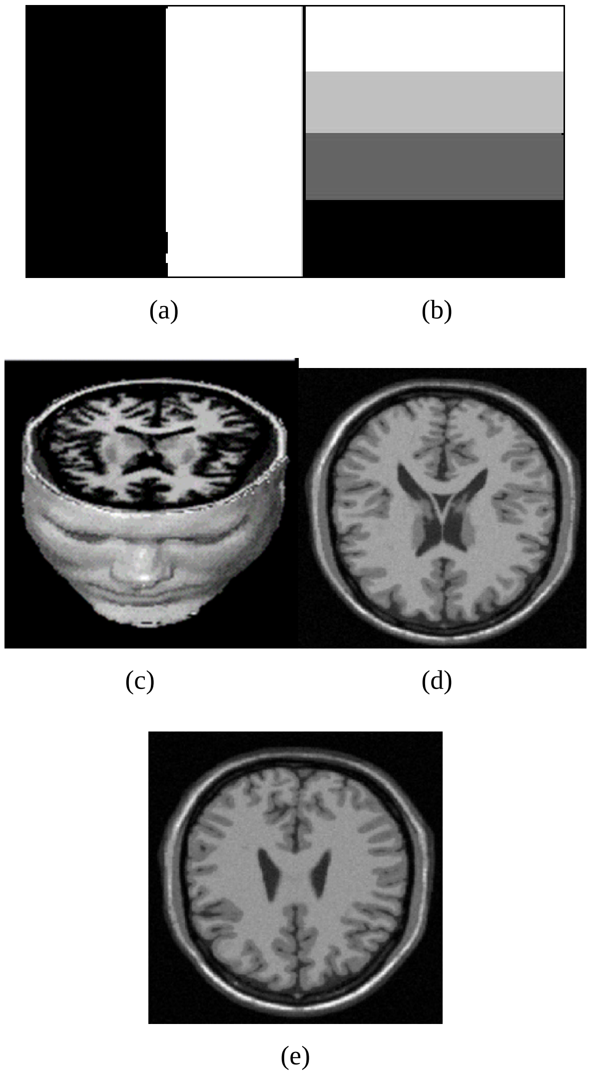


Figure 1: Test images: (a) Synthetic 1, (b) Synthetic 2, (c) 3D simulated data, (d) and (e) two original slices from the 3D simulated data (slice91 and slice100)

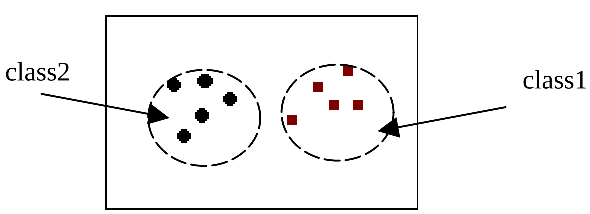


Figure 2: Two accuracy measure evaluated on a two-class example

The proposed fuzzy methods have been implemented. The Gaussian RBF kernel is used for KFCM and SKFCM. We set the parameters M=100, m=2, σ=150, α=0.7 and N_R =26 when using 3D MR phantom image, because the add noise is relatively big, otherwise we use α=0.1, and N_R=8 (a 3 $\times$ 3 window centered around each pixel). These values will be used in the rest of this work if no specific value is explicitly stated.

8.1 Experiment on Synthetic1

We applied these algorithms to a synthetic test image; the synthetic image contains two class patterns corrupted by 9 percent salt and pepper noise. The performance of each segmentation method on this dataset is reported in the upper part of the first column of Table 1.

The table shows that the highest segmentation accuracy is obtained using SKFCM. After that, KFCM gives better results than the other methods, as shown in Figure 3d.

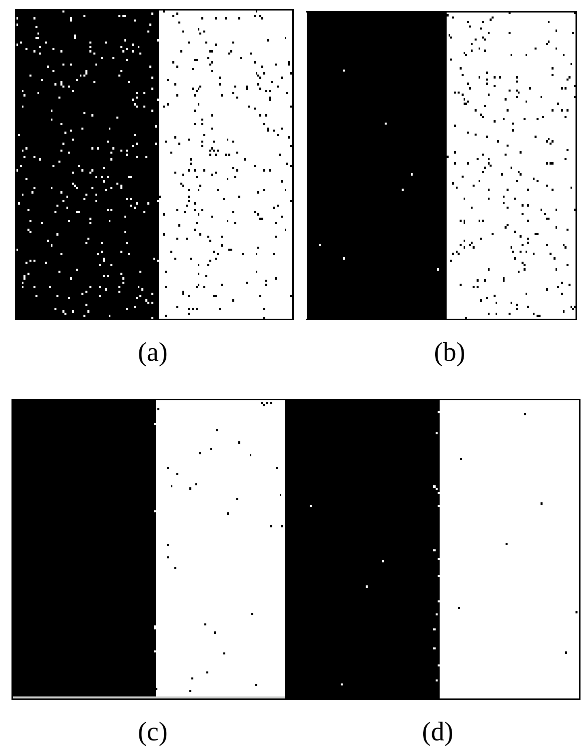


Figure 3: Segmentation results for the synthetic1 using methods: (a) *k*-means, (b) FCM, (c) KFCM, (d) SKFCM

8.2 Experiment on Synthetic2

The performance of each segmentation method on the 4-class synthetic image synthetic2 is reported in the upper part of the second column of Table 1. Obviously, FCM gives the best segmentation performance, as shown in Figure 4b, and the least segmentation accuracy is obtained by applying the FKM. Note KFCM and SKFCM give similar accuracy.

We tested the efficiency of the accuracy for a synthetic2 image with various degrees of standard deviation of gaussian noise. Figure 5 depicts the relationship between accuracy results when the proposed FKM, FCM, KFCM, and SKFCM

Table 1: Segmentation accuracy of individual methods and performance of implemented fusion techniques on synthetic1, synthetic2, and MRI volume dataset

	Methods	Synthetic1	Synthetic2	MRI volume
The established methods	FCM	0.91615	0.832537	0.52531
	KFCM	0.91597	0.835839	0.53341
	SKFCM	0.95286	0.835316	0.54708
	k-means	0.926	0.8501	0.55394
The proposed methods	FCM	0.99123	0.8699	0.664
	KFCM	0.9895	0.8702	0.5987
	SKFCM	0.999	0.8821	0.231
	k-means	0.999	0.8976	0.432

are applied to the synthetic2 image and various degrees of standard deviation of gaussian noise.

8.3 Experiment on the Simulated 3D Data.

Table 1 shows the corresponding accuracy scores of the individual proposed methods after applying them on simulated data. Obviously, the proposed *k*-mean and FCM give the best segmentation performance, as shown in Figures 6a, 6b, 7a, and 7b, and the other methods gave similar accuracy.

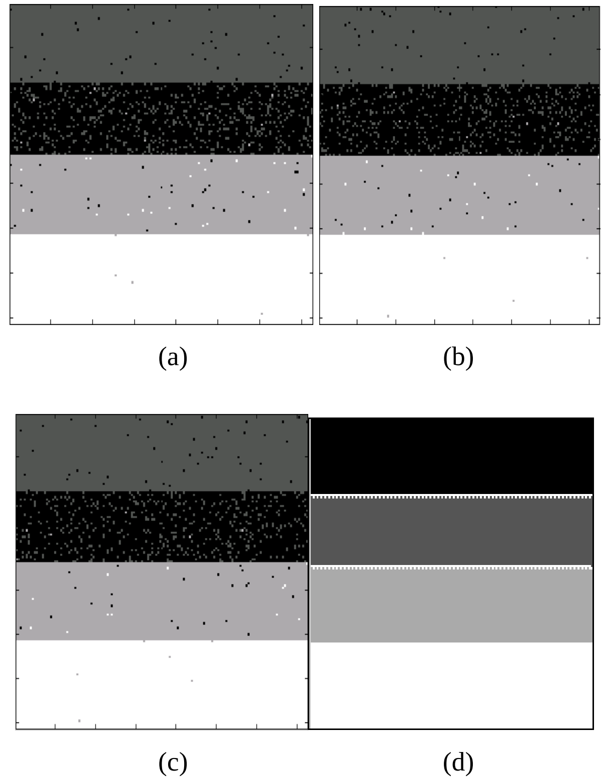


Figure 4: Segmentation results for the synthetic2 using methods: a) *k*-means, (b) FCM, (c)KFCM, (d) SKFCM

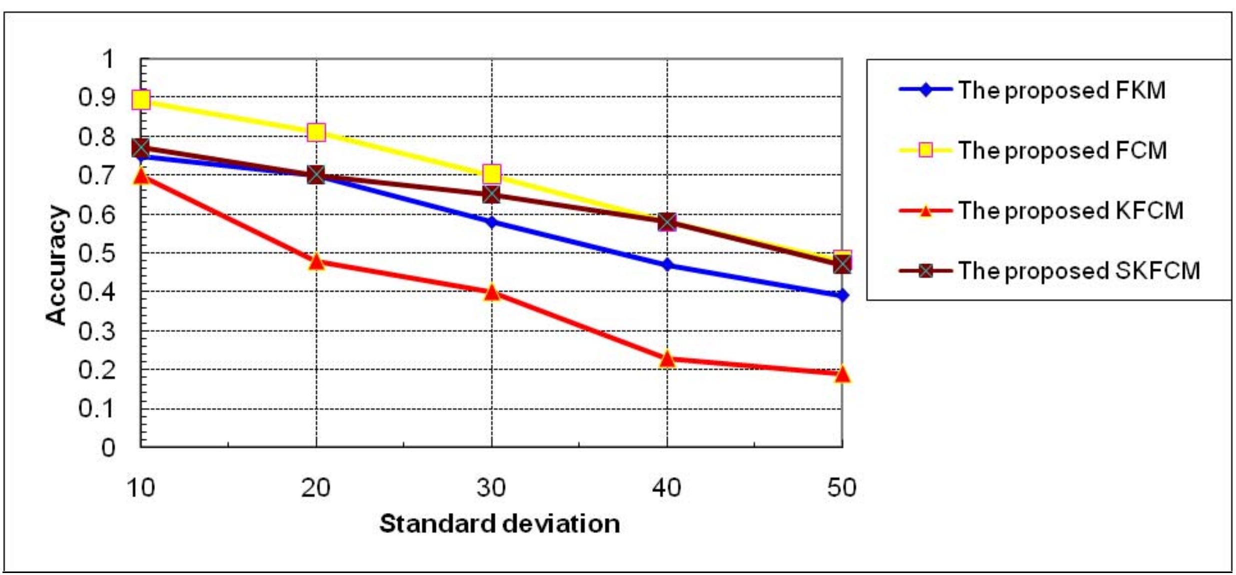
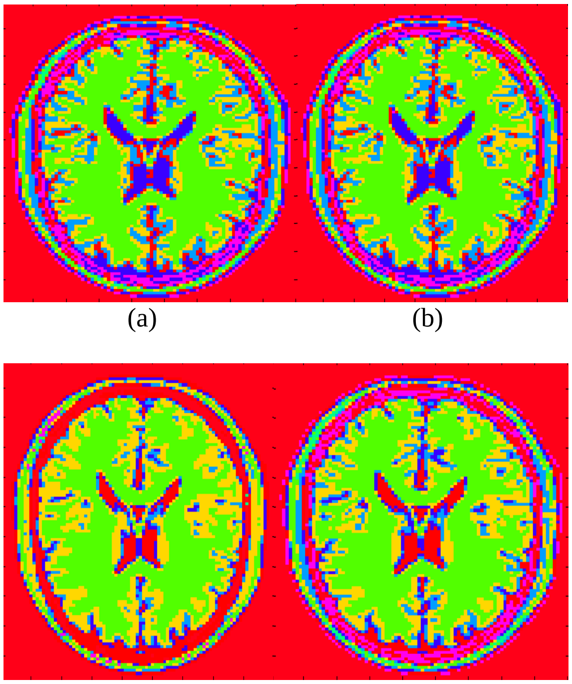
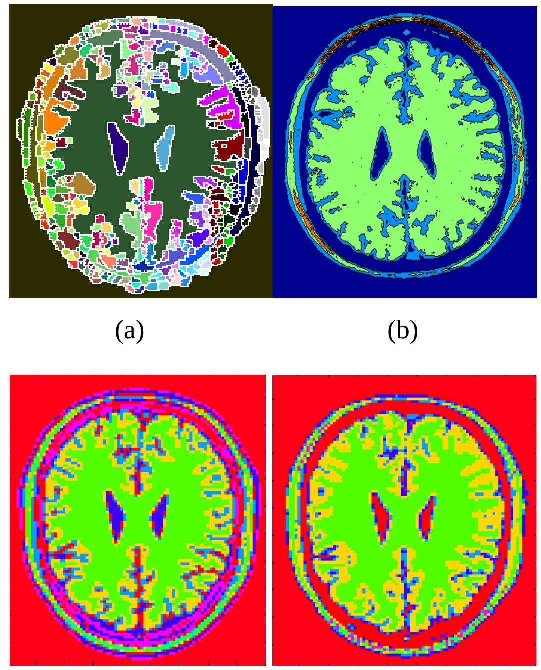


Figure 5: The relation between accuracy and standard deviation, when the proposed FCM, KFCM, and SKFCM are applied on synthetic2 image



(a) (b) (c) (d)

Figure 6: Segmentation results for the slice (z=91) on a simulated data using methods: (a) *k*-means, (b) FCM, (c) KFCM, (d) SKFCM



(a) (b) (c) (d)

Figure 7: Segmentation results for the slice (z=100) on a simulated data using methods: (a) *k*-means, (b) FCM, (c) KFCM, (d) SKFCM

8.4 Experiment on the Real MR Data

Table 2 shows the corresponding accuracy scores of the eight methods for the nine classes of real images (real brain image with nine classes). Obviously, the proposed SKFCM acquires the best segmentation performance. The proposed

Table 2: Segmentation accuracy (%) of eight methods on real brain classes

Method	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Overall
K-means	62..96	57..53	77.84	91.61	66.47	77.18	85.96	43.6	99.15	73.47
FCM	53..52	64.38	75.19	89.3	62.76	29.09	83.09	6.76	98.95	63.37
KFCM	67.55	51.14	58.83	88.54	67.96	21.87	59.21	11.27	97.26	58.18
SKFCM	75.46	71.88	88.65	93.76	96.63	82.31	55.70	1.50	96.82	73.64
The proposed *k*-means	66.76	63.76	77.65	89.54	67.96	65.43	90.43	51.27	99.54	74.70
The proposed FCM	67.87	67.16	78.34	88.54	98.65	94.65	87.43	55.32	99.43	81.92
The proposed KFCM	71.65	69.65	66.54	99.65	88.65	88.54	66.32	62.87	98.51	79.15
The proposed SKFCM	79.14	81.87	92.76	100.0	98.65	90.65	73.43	69.43	97.43	87.04

Table (3): Comparisons of running time of eight algorithms on synthetic, phantom, and real images (seconds)

Method	FKM	The proposed FKM	FCM	The proposed FCM	KFCM	The proposed KFCM	SKFCM	The proposed SKFCM
Phantom image	90.65	100.65	105.87	144.76	118.54	155.76	287.43	24.43
Real image	144.8	155.76	116.54	166.76	223.87	104.87	154.76	287.9

SKFCM is the best, and then the traditional SKFCM and KFCM. The proposed KFCM and SKFCM methods are still more stable and achieve much better performance than the others for different classes.

8.5 Time Overhead

These times have been computed from the time average of all given images that have same type. For example, the time of phantom image using FKM 88.90 is obtained by computing the average of nine class times. From this table, the established methods are much faster than the proposed methods for all tested data sets, due to the proposed methods consuming some time for obtaining the true number of segments but this time is acceptable for automatic medical image segmentation.

9 Conclusion

The results of the proposed fuzzy segmentation methods have been presented. Rather than tuning a method for the best possible performance, it works automatically and can indeed improve the segmentation accuracy over the existing methods. The algorithms incorporate spatial information into the membership function and the validity procedure for clustering. They have estimated accurate clusters automatically even without prior knowledge of the true tissue types and the number of cluster of given images. Extensive experiments using MR images generated by the BrainWeb simulator [3] and real MR data have been used to evaluate the proposed methods. Due to the use of soft segmentation, the proposed FCM algorithm is able to give a good estimation of tissue volume in the presence of inaccurate tissues. It is observed that the proposed methods have shown higher robustness in discrimination of regions because of the low signal/noise ratio characterizing most of medical images data. By comparing the proposed methods with established ones, it is clear that our algorithms can estimate the correct tissues much more accurately than the established algorithms. Although the number of clusters are varied according to noise factor, we have shown that the proposed SKFCM gives a correct number of clusters with high noise levels. On the other hand, the established KFCM and SKFCM are much faster than the proposed methods for all tested data sets, due to the proposed methods that consume much time for obtaining the true number of segments. These times are acceptable for achieving more accurate and automatic MRI segmentation. Future research in MRI segmentation should strive toward improving the accuracy, precision, and computation speed of the segmentation algorithms, while reducing the amount of manual interactions needed. This is particularly important as MR imaging is becoming a routine diagnostic procedure in clinical practice. It is also important that any practical segmentation algorithm should deal with 3D volume segmentation instead of 2D slice by slice segmentation, since MRI data is 3D in nature.

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