Improving Fuzzy Algorithms for Automatic Image Segmentation

E. A. Zanaty
College of computers and Information Technology,
Taif University, Taif, Saudi Arabia
n.allam@tu.edu.sa

Sultan Aljahdali
College of computers and Information Technology,
Taif University, Taif, Saudi Arabia
aljahdali@tu.edu.sa

Abstract- This paper seeks an answer to the question: Can the fuzzy k-means (FKM), c-means (FCM), kernelized FCM (KFCM), and spatial constrained (SKFCM) work automatically without pre-define number of clusters. We present automatic fuzzy algorithms with considering some spatial constraints on the objective function. The algorithms incorporate spatial information into the membership function and the validity procedure for clustering. We use the intra-cluster distance measure, which is simply the median distance between a point and its cluster centre. The number of the cluster increases automatically according the value of intra-cluster, for example when a cluster is obtained, it uses this cluster to evaluate intra-cluster of the next cluster as input to the fuzzy method and so on, stop only when intra-cluster is smaller than a prescribe value. The most important aspect of the proposed algorithms is actually to work automatically. Alternative is to improve automatic image segmentation The proposed methods are evaluated and compared with the established 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.

Keywords: **Image segmentation, Medical imaging, Fuzzy clustering.**

I. INTRODUCTION

Clustering, from a machine learning perspective, is a popular unsupervised classification method and has found many applications in pattern classification and image segmentation [1-7]. Clustering aims to organise data into groups called clusters, such that data within a cluster are more similar to each other than they are to data in other clusters [2]. This notion of similarity can be expressed in very different ways, according to the application, and can include domain-specific assumptions and prior knowledge. The fuzzy c-means clustering (FCM) algorithms have recently been applied to MRI segmentation [6-7]. Unlike the crisp k-means clustering algorithm (FKM) [1-5], 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 [7]. A method of simultaneously estimating the intensity non-uniformity artifact and performing voxel classification based on fuzzy clustering has been reported in [7], 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 problems. 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 FCM (KFCM) [8-12] 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 [8]. The objective function for FCM then has a new form. 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 [12]. An approach which is designed for incomplete data [11] and a different formulation of a centroid-based clustering algorithm [11]. More recent results of fuzzy algorithms have been presented in [12] for improving automatic MRI image segmentation. They use the intra-cluster distance measure to give the ideal number of clusters automatically; more discussion can be shown in [12].

Although fuzzy methods have several advantages such as: (1) it yields regions more homogeneous than those of other methods, (2) it reduces the spurious blobs, (3) it removes noisy spots, and (4) it is less sensitive to noise than other techniques. 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 [13] 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 cluster. Therefore, two major problems are known with the fuzzy methods: (1) How to determine the number of clusters. (2) The computational cost is quit high for large data sets.

In this paper, we develop the FKM, FCM, KFCM, and SKFCM algorithms that could improve MRI segmentation. Since the fuzzy methods aims to minimize the sum of squared distances from all points to their cluster centres, this should result in compact clusters. Therefore the distance of the points from their cluster centre is used to determine whether the clusters are compact. For this purpose, we use the intra-cluster distance measure, which is simply the median distance between a point and its cluster centre. The intra-cluster is used to give us the ideal number of clusters automatically; i.e a centre of the first cluster is used to estimate the second cluster, while an intra-cluster of the second cluster is obtained. Similar, the third cluster is estimated based on the second cluster information (centre and intra cluster), so on, and only stop when the intra-cluster is smaller than a prescribe value.

The rest of the paper is organized as follows. The proposed k-means clustering algorithm is presented section II. Section III presents the proposed FCM method. In section IV, KFCM is proposed. The proposed SKFCM is presented in section V.

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Experimental results are presented in section VI. In section VII, we present our conclusions and future work.

II. THE PROPOSED K-MEANS CLUSTERING ALGORITHM

K-means clustering is one of the simplest unsupervised classification algorithms [1-3]. 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 classes $v_i,\ i = 1,\ldots,C$, and finds a cluster centre 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:

$$P = \sum_{i=1}^{C}\left(\sum_{k,x_k}\left\|x_k - c_i\right\|^2\right) \tag{1}$$

where $\sum\left\|x_k - c_i\right\|^2$ is the objective function within group i, and $\left\|x_k - c_i\right\|$ is a chosen distance measure between a data point x_k and the cluster centre c_i. The partitioned groups are typically defined by a $(N \times C)$ 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:

$$u_{ij} = \begin{cases} 1 & if \left\|x_j - c_i\right\|^2 \le \left\|x_j - c_k\right\|^2 \quad \forall k \ne i \\ 0 & otherwise \end{cases} \tag{2}$$

$$c_i = \sum_{j=1, x_j \in c_i}^{N} x_j / R_i \tag{3}$$

where R_i is number of data point in class v_i. Since the k-means method aims to minimize the sum of squared distances from all points to their cluster centers, this should result in compact clusters. We use the intra-cluster distance measure, which is simply the median distance between a point and its cluster centre. The equation is given as:

$$Intra = midean\left(\sum_{i=1}^{C}\sum_{x\in ci}\left\|x - c_i\right\|^2\right) \tag{4}$$

Therefore, the clustering which gives a minimum value for the validity measure will tell us what the ideal value of k is in the k-means. Then the number of cluster is known before estimating the membership matrix. The proposed k-means clustering algorithm is described as follows:

1. Select a subset from the dataset instead of using all of them.
2. Set $C = 2$ the initial number of cluster, and $C_{\max}$ =the maximum number of cluster (it is selected arbitrary).
3. Determine the membership matrix U according to Equation 2 using C is set $C_{\max}$.
4. Compute the objective function according to Equation
5. Go to step 6, if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold.
6. Update the cluster centres $c_i,\ i = 1,\ldots,C$ using Equation 3, then go to step 3.
7. Obtain the centre v_1.
8. Apply step 3 and use v_1 centers as input C number of cluster to obtain center v_2.
9. Use c_2 to calculate the intra distance according to the Equation 4. Stop if intra is smaller than a prescribe value else set $C = C + 1$, return to step.

III. 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 [1-3] 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 centre 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:

$$\sum_{i=1}^{C} u_{ij} = 1, \quad \forall j = 1,\ldots,N \tag{5}$$

The objective function of FCM can be formulated as follows:

$$p(u, v_1, \ldots v_c) = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m}\left\|x_j - c_i\right\|^2 \tag{6}$$

Where u_{ij} is between 0 and 1; c_i is the cluster centre 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 centres c_i by:

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \tag{7}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_j - c_i\right\|}{\left\|x_j - c_k\right\|}\right)^{2/(m-1)}} \tag{8}$$

Similar to k-means method, we use the intra-cluster distance measure, which is simply the median distance between a point and its cluster centre as shown in Equation 4. The proposed algorithm is described as follows:

1. Select a subset from the dataset.
2. Set $C = 2$ the initial number of cluster, and $C_{\max}$ = the maximum number of cluster (it is selected arbitrary).
3. Initialize the membership matrix U with random values between 0 and 1 such that the constraints in Equation 5 are satisfied.
4. Calculate fuzzy cluster centers $c_i,\ i = 1,\ldots,C$ using Equation 7.
5. Compute the objective function according to Equation 6. Go to step 7, if either it is below a certain tolerance value or its improvement over previous

iteration is below a certain threshold.

6. Compute a new membership matrix U using Equation 8, then go to step 2.
7. Obtain the centre v_1 .
8. Apply step 3 on the subset with C number of cluster to obtain centre v_2 .
9. Use v_2 to calculate the intra distance according to the Equation 4. Stop if intra is smaller than a prescribe value else set $C = C + 1$, return to step.

IV. THE PROPOSED KERNELIZED FUZZY C-MEANS METHOD

The kernel methods [7-12] are one of the most researched subjects within machine learning community in the recent few 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 to be 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:

$$\sum_{i=1}^{C} u_{ij} = 1, \forall j = 1, ..., N \tag{9}$$

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

$$K(x,c) = \exp\left(-\|x-c\|^2 / \sigma^2\right) \tag{10}$$

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

$$J_m = 2\sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}{}^{m} (1 - K(x_j, c_i)) \tag{11}$$

The fuzzy membership matrix U can be obtained from:

$$u_{ij} = \frac{\sum_{k=1}^{C} (1 - K(x_j, c_k))^{1/(m-1)}}{(1 - K(x_j, c_i))^{1/(m-1)}} \tag{12}$$

The cluster centre c_i can be obtained from:

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^m K(x_j, c_i) x_j}{\sum_{j=1}^{N} u_{ij}^m K(x_j, c_i)} \tag{13}$$

Since the K-means method aims to minimize the sum of squared distances from all points to their cluster centres, this should result in compact clusters. We use the intra-cluster distance measure in Equation (4), which is simply the median distance between a point and its cluster centre.

Therefore, the clustering which gives a minimum value for the validity measure will tell us what the ideal value of the clusters. Then the number of cluster is known before estimating the membership matrix.

The proposed KFCM clustering algorithm is composed of the following steps:

1. Select a subset from the dataset and initialize the cluster centres c_i, $i = 1, \ldots, C$
2. C =2 the initial number of cluster, $C_{\max}$ = the maximum number of cluster, it is selected arbitrary.
3. Initialize the membership matrix U with random values between 0 and 1 such that the constraints in Eq.(9) are satisfied.
4. Calculate fuzzy cluster centers c_i, $i = 1, \ldots, C$ using Eq. (13).
5. Compute the cost function (objective function) according to Eq.(11). Go to step 9, if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold.
6. Compute a new membership matrix U using Eq.(12).
7. Obtain centre c_1 .
8. Goto step3 on the subset with C number of cluster to obtain centre c_2 .
9. Use c_2 to calculate the intra distance according to the above equation (13), stop if intra is smaller than a prescribe value.
10. $C = C + 1$, return to step 3.
11. Stop.

V. SPATIAL CONSTRAINED SKFCM METHOD

SKFCM is applied directy 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 regualization is helpful in segmenting images corrupted by noise. The objective function is as follows:

$$J_m = 2\sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}{}^{m} (1 - K(x_j, c_i)) + \frac{\alpha}{N_R} \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^m \sum_{r \in N_j} (1 - u_{ir})^m \tag{14}$$

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.

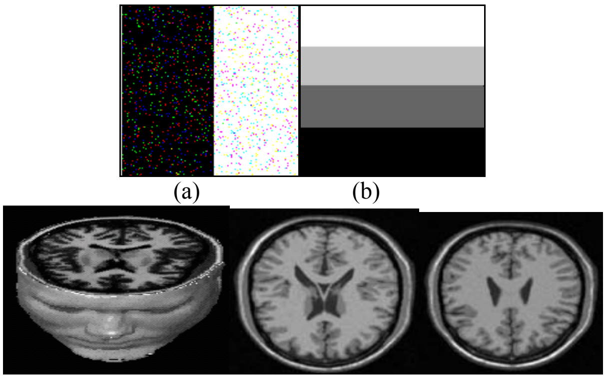
An iterative algorithm for minimizing Eq.(14) is derived by evaluating the centroids and membership functions that satisfy a zero gradient condition like the proposed KFCM. A necessary condition on u_{ij} for Eq.(12) to be at a local minimum or a saddle point is:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\dfrac{(1 - K(x_j, c_i)) + \frac{\alpha}{N_R} \sum_{r \in N_j} (1 - u_{ir})^m}{(1 - K(x_j, c_k)) + \frac{\alpha}{N_R} \sum_{r \in N_j} (1 - u_{ir})^m} \right)^{1/(m-1)}} \tag{15}$$

The proposed SKFCM algorithm is almost identical to the proposed KFCM, except in Step 4, Eq.(15) is used instead of Eq.(13) to update the memberships.

VI. 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% 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 Fig.1(a), and Fig.1(b), respectively. The second set includes simulated volumetric MR data consisting of ten 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 inhomogeneities. We used a high-resolution T1-weighted MR phantom with slice thickness of 1mm, 3% noise and no intensity inhomogeneities, obtained from the classical simulated brain database of McGill University [15]. Two slices drawn from the simulated MR data is shown in Figs. 1(d) and 1(e). The quality of the segmentation algorithm is of vital importance to the segmentation process.



(a) (b)

(c) (d) (e)

Fig.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).

The comparison score S for each algorithm is proposed in [16-18], which defined as:

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

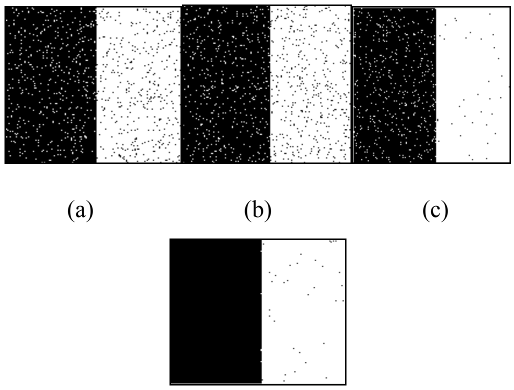
where A represents the set of pixels belonging to a class as found by a particular method.

The proposed fuzzy methods have been implemented. The Gaussian RBF kernel is used for KFCM and SKFCM. We set the parameters 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 3×3 window centred on each pixel). These values will be used in the rest of this work if no specific value is explicitly stated.

Experiment on synthetic1

We applied these algorithms to a synthetic test image; the synthetic image contains two classes pattern corrupted by 9% salt and pepper noise. The performance of the established and proposed methods on this dataset is reported in 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 Fig.2 (c).



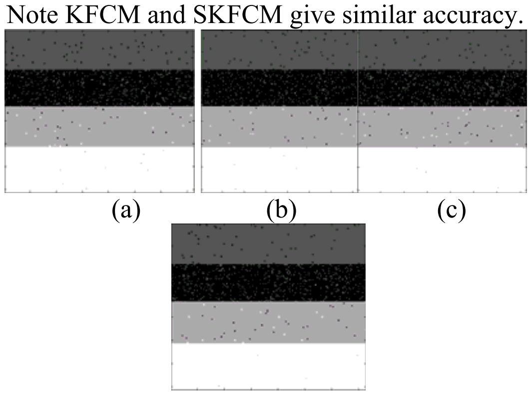
(a) (b) (c)

(d)

Fig.2: Segmentation results for the synthetic1 using methods: (a) K-means, (b) FCM, (c) KFCM, (d) SKFCM.

Experiment on synthetic2

The performance of each segmentation method on the 4-class synthetic image synthetic2 is reported in the second column of Table 1. Obviously, the proposed FCM gives the best segmentation performance, as shown in Fig.3 (b), and the least segmentation accuracy is obtained by applying the FKM. Note KFCM and SKFCM give similar accuracy.



(a) (b) (c)

(d)

Fig.3: Segmentation results for the synthetic2 using methods: a) K-means, (b) FCM, (c)KFCM, (d) SKFCM.

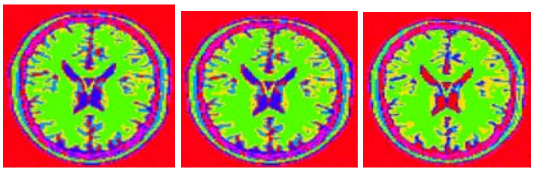
We tested the efficiency of the accuracy for a synthetic2 image with various degrees of standard deviation of gaussian noise. Fig.6 depicts the relationship between accuracy results when the proposed FKM, FCM, KFCM, and SKFCM are applied to synthetic2 image and various degree of standard deviation of gaussian noise.

Experiment on the simulated 3D data.

Table 1 shows the corresponding accuracy scores of the individual the proposed methods after applying them on the simulated data. Obviously, the proposed k-mean, SKFCM, and FCM give the best segmentation performance, as shown in Figs.4 (f) and 5(f), and the other methods gave similar accuracv.

Table1: Segmentation accuracy of individual methods and performance of implemented fusion techniques on synthetic1, synthetic2, and MRI volume dataset.

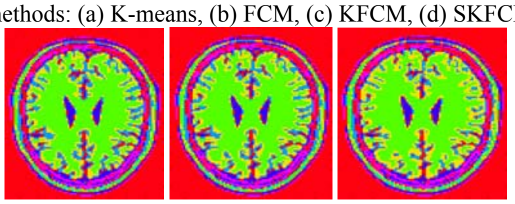
	methods	Synthetic1	Synthetic2	MRI volume
The established methods	FCM	0.91615	0.832537	0.52531
	KFCM	0.91597	0.835839	0.53341
	SKFCM	0.95286	0.835316	0.54708
	K-means	0.91776	0.826830	0.55394
The proposed methods	FCM	0.99389	0.878961	0.56309
	KFCM	0.99854	0.870248	0.57182
	SKFCM	0.99438	0.870338	0.53433
	K-means	0.99980	0.830148	0.57075



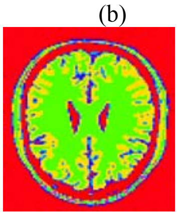
(a) (b) (c)

(d)

Fig.4: 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)

Fig.5: Segmentation results for the slice (z=100) on a simulated data using methods: (a) K-means, (b) FCM, (c) KFCM, (d) SKFCM.

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

Time overhead

Table (3) shows the comparison of the CPU time for the three test images, synthetic, simulated MR images, and real MR images. 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's times. From this table, the established methods are much faster than the proposed methods for all tested data sets, due the proposed methods consume some time for obtaining the true number of segments but this time is acceptable for automatic medical image segmentation.

VII. Conclusion and Future Work

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 [15] 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 characterising most of medical images data.

By comparing the proposed methods with established one, 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, but we have shown that the proposed SKFCM gives a correct number of clusters with high noise level. In other hand, the established KFCM and SKFCM are much faster than the proposed methods for all tested data sets, due

the proposed methods consume much time for obtaining the true number of segments. 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. These times are acceptable for achieving more accurate and automatic MRI segmentation.

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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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	77.36
FCM	53.52	64.38	75.19	89.3	62.76	29.09	83.09	6.76	98.95	73.73
KFCM	67.55	51.14	58.83	100.0	67.96	21.87	59.21	11.27	97.26	59.454
SKFCM	75.46	71.88	99.98	100.0	96.63	82.31	55.70	1.50	96.82	75.58
The proposed k-means	67.55	61.14	78.83	100.0	67.96	61.87	89.21	51.27	97.27	66.55
The proposed FCM	64.92	87.64	77.84	86.18	66.17	89.18	99.95	20.3	99.03	80.46
The proposed KFCM	66.87	55.77	59.087	100.0	70.32	37.96	63.99	10.12	97.99	62.456
The proposed SKFCM	79.54	77.55	98.34	100.0	98.65	81.98	55.70	9.54	99.54	77.87

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	88.9	99.68	102.98	130.98	108.883	154.87	286.98	20.654
Real image	122.96	153.87	112.87	188.99	285.98	100.876	1.765e+003	2.654e+003

Fig.6: The relation between accuracy and standard deviation, when the proposed FCM, KFCM, and SKFCM are applied on synthetic2 image.