Clustering of Ultrasound Cervix Image Using Objective Function

R Jemila Rose R, S Allwin

ABSTRACT

Objective: The purpose of this study was to evaluate a clustering method that gets the similarity between the classes, where the comparison measure controls how the clusters are formed.

Methods: The clinical ultrasound images of the cervix were obtained by C.S.I. Mission Hospital- International Cancer Center, Neyyoor. The regular ways of arranging the image in the format of bmp and the dimensions of 256× 256.For investigation, different ultrasound cervix images were tested with the maximum iteration.

Results: This provides the information pattern with the missing values so that the clustering results are enhanced.

Conclusion: The kernel based clustering method and the objective function gives healthier information and also greatest outcome for overlapped information set.

Keywords: Cervix, clustering, objective function, ultrasound

From: [1]St. Xavier's Catholic College of Engineering, Chunkankadai. Nagercoil, Tamil Nadu, India, 629 003. [2]Professor, Infant Jesus College of Engineering, Keelavallanadu, Tamil Nadu, 628 851, India.

Correspondence: Dr R Rose, St. Xavier's Catholic College of Engineering, Chunkankadai, Nagercoil. Tamil Nadu, India, 629 003.

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INTRODUCTION

Clustering is the process of dividing data elements into classes or clusters so that objects in the identical class are as similar as possible, and objects in different classes are as dissimilar as possible. Depending on the nature of the data and the purpose for which clustering is being used, different measures of similarity may be used to place items into classes, where the comparison measure controls how the clusters are formed. Some examples of measures that can be used as in clustering include distance, connectivity, and intensity.

Elnomery (1) proposed Fuzzy c-means (FCM) is one of the information clustering techniques in which information is grouped into n clusters belonging to every group to a certain quantity. For instance, a certain data point that comes near to the center of a cluster will have a maximum level of relation or membership to that cluster and other data point that comes far away from the center of a cluster will have a minimum level of relation or membership to that cluster.

The Fuzzy Logic Toolbox function fcm performs FCM clustering. It starts with a primary assumption for the cluster centers, which are projected to note the mean position of all clusters. The primary assumption for these cluster centers is most probably inaccurate. Next, fcm assigns every data point a relationship score for each cluster. By frequently updating the cluster centers and the relationship scores for each data point, fcm frequently moves the cluster centers to the right position within a data set. This movement is based on reducing an objective function that indicates the distance from any assigned data point to a cluster center weighted by that data point's relationship score. The function fcm takes a data set and a desired number of clusters and returns optimal cluster centers and relationship scores for each data point. Use this information to build a fuzzy inference system by creating membership functions that represent the fuzzy qualities of each cluster.

Fuzzy c-means (FCM) clustering technique that has been effectively applied to feature investigation, clustering and classifier designs in fields such as medical imaging and image segmentation. An image can be represented in various characteristic spaces, and the FCM algorithm classifies the image by grouping related data points in the feature area into clusters. This clustering is achieved by iteratively reducing a cost functionality that is related on the distance of the pixels to the cluster groups in the characteristic domain.

Dorin and Peter (2) KFCM adopts a new kernel-induced metric in the data space to change the innovative Euclidean norm metric in FCM and the clustered prototypes still lie in the data space so that the clustering outcome can be reformulated and interpreted in the innovative space. This investigation shows that KFCM is healthy to noise and outliers and also tolerates unequal sized clusters. And finally this property is utilized to group incomplete data.

K-means is the simplest unsupervised learning algorithms that answer the well- known clustering dilemma. The process follows an easy and a simple way to categorize a specified information set through a certain amount of clusters (assume k clusters) fixed a priori. The key initiative is to describe k centroids, one for each cluster. These centroids should be located in a cunning way because of dissimilar position causes dissimilar outcome. So, the enhanced choice is to situate them as much as possible far away from each other. The subsequent step is to obtain each point belonging to a given information set and relate it to the adjacent centroid. When no point is awaiting, the initial step is finished and an early group age is done. At this point it requires to re-estimate k new centroids as bary centers of the clusters resulting from the earlier step. After these k new centroids, a novel binding has to be done between the same information set points and the nearby new centroid. A loop has been generated.

As a result of this loop it may observe that the k centroids adjust their location step by step until no more changes are done. In other words centroids do not progress any more. Place K points into the space represented by the substances that are being clustered. These points represent primary group centroids. Allocate each object to the group that has the closest centroid. When all objects have been assigned, recalculate the k-centroid. Repeat the above steps till the centroids no longer move. This produces the partition of the substance into groups from which the metric to be reduced to be designed.

METHODS

FCM clustering

Fuzzy c-means (FCM) is a way of clustering that supports one portion of data belongs to two or more clusters. This technique is often used in pattern recognition. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{n} \sum_{j=0}^{c} U_{ij}^{m} \, ||x_i - c_j||^2, \quad 1<m<\infty \qquad [1]$$

where m is any valid number greater than 1, u_{ij} is the measure of relationship of x_i in the cluster j, x_i is the i^{th} of d-dimensional calculated data, c_j is the d-dimension midpoint of the cluster, and ||*|| is any standard specifying the match between any calculated data and the center. Fuzzy partitioning is approved out during an iterative optimization of the objective function exposed above, with the revise of membership u_{ij} and the cluster centers c_j by

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\left\|\frac{x_i - c_j}{x_i - c_k}\right\|\right)^{\frac{2}{m-1}}} \quad [2]$$

$$C_j = \frac{\sum_{i=1}^{N} \mathbf{U_{ij}^{m}}.\mathbf{X_i}}{\sum_{i=1}^{N} u_{ij}^{m}} \quad [3]$$

This iteration will stop when, $\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \delta$ where δ is an execution condition between 0 and 1, whereas *k* are the execution steps. This process converges to a local minimum or a load point of J_m.

The algorithm is composed of the subsequent steps:

Initialize $U = [u_{ij}]$ matrix, $U^{(0)}$

At k-step: calculate the centers vectors $C^{(k)} = [c_j]$ with $U^{(k)}$

Update U(k), U(k+1)

If $\| U^{(k+1)} - U^{(k)} \| < \delta$ then STOP; otherwise return to step 2.

KFCM clustering

Step 1: Select the cluster number C_k for the preparation samples of the k-th category and the execution condition $\varepsilon \in (0, 1)$, maximal number of iteration Tmax. Set the iteration count t=0.

Step 2: Choose kernel function K ( ) and its parameters.

Step 3: Initialize centers v(t) j, and Calculate uji(t),j=1,2,…,C_k, i=1,2,..,N_k.

Step 4 : t=t+1, update vj (t) and update uji (t).

Step 5 : Calculate $E^{(t)}=\max_{j,i}|u_{ji}^{(t)}-u_{ji}^{(t-1)}|$. If $E(t)\leq\varepsilon$, or t=Tmax next Stop, or else, go to Step 4.

In fuzzy clustering (also referred to as soft clustering), information elements can belong to more than one group, and connected with each part is a set of membership levels. These specify the power of the relationship between that information element and a particular cluster. Fuzzy clustering is a method of defining these membership values, and then using them to allocate information elements to individual or more than one clusters.

The normalized ultrasound cervix image segmentation problem is formulated as an objective function and implemented by using an iterative method. Also, Centroid description of cluster analysis is proposed which makes use of an image segmentation technique of ultrasound cervix.

Fuzzy c-means (FCM) clustering evaluates n vectors in p-space as information input, and uses them, in combination with first order required conditions for reducing the FCM objective functional, to get evaluation for two sets of unknowns. Fuzzy K-means clustering algorithm is a familiar approach for exploring the structure of a set of patterns, particularly when the clusters are overlapping or fuzzy. However, the fuzzy K-means clustering algorithm cannot be useful when the real-life data include missing values. In several cases, the number of patterns with missing values is so large that if these patterns are removed, then satisfactory number of patterns is not obtainable to distinguish the data set.

In preprocessing the noise is removed by means of diffusion filter (3). Minimum Importance value is set as 0.005. It discards the pixels, when the pixel values lays below 0.005 as noise. The aim of pre-processing is to improve the image data that suppresses undesired distortions or to enhance some image features relevant for further processing and analysis task (4).

RESULTS

Fuzzy clustering and objective function

The objective function (obj_fcn) value is obtained for all clusters for its all iteration. The amount of clusters produced is based on the value that the system gets from the user as the input is defined in Figure 1. The loop is executed continuously up to the maximum iteration value provided by the user that is illustrated in Table 1.

Kernel Based Clustering and Objective Function

It is based on kernel based clustering method. The loop is executed continuously up to the maximum iteration value provided by the user. The objective function (obj_fcn) value is obtained for all clusters for its every iteration which shown in Figure 2. The numbers of clusters produced are based on the value that the system gets from the user as the input. In KFCM, the kernel value should also be provided by the user is indicated in Table 1.

DISCUSSION

This idea proposes a technique to exploit the information provided by the patterns with the missing values so that the clustering results are enhanced. There are a variety of preprocessing techniques to substitute the missing values before clustering the information (5). However, as an alternative of repairing the data set at the opening, the repairing can be carried out incrementally in each of the iteration based on the situation. In that case, it is more likely that less uncertainty is added while incorporating the repair work.

K-Means clustering and Fuzzy-C Means Clustering are very similar in approaches. The major difference is that, in Fuzzy-C Means clustering, each point has a weighting connected with a particular cluster, so a point doesn't sit "in a cluster" as much as has a weak or strong association to the cluster, which is determined by the inverse distance to the center of the cluster. Fuzzy-C means will tend to run slower than K means, since it's actually doing more work. Each point is evaluated with each cluster, and more operations are involved in each evaluation. K-Means just needs to do a distance calculation, whereas fuzzy c means needs to do a full inverse-distance weighting.

FCM Gives greatest outcome for overlapped information set and relatively healthier than k-means algorithm. Dissimilar k-means data point must absolutely belong to one cluster center. Here data point is assigned. Relationship to each cluster center as an outcome of which data point may belong to more than one cluster center.

REFERENCES

1. Elnomery Allam Zanaty, An Adaptive Fuzzy C-Means Algorithm for Improving MRI Segmentation, Open Journal of Medical Imaging, 2013, vol.3, no.4. pp. 125–35.
2. Peter DC, , Kernel-Based Object Tracking, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2003, vol. 25, no. 5, pp. 564–75.
3. Jemila Rose R, Allwin S, Speckle suppressing improved oriented speckle reducing anisotropic diffusion (IOSRAD) filter for medical ultrasound images, Applied Mechanics and Materials journal, 2014; **626:** 106–10.
4. Jemila Rose, R& Allwin, S, Denoising of Ultrasound Cervix Image Using Improved Anisotropic Diffusion Filter (IADF), West Indian Medical Journal, ISSN: 0043-3144 (print), University of West Indies, 2015, DOI: 10.7727/wimj.2014.235.
5. Jemila Rose, R& Allwin, S, Ultrasound Cervical Cancer Based Abnormality Segmentation Using Adaptive Fuzzy C-Mean Clustering, Academic Journal of Cancer Research, vol.6(1),pp.01-07, ISSN 1995-8943, © IDOSI Publications, 2013, DOI: 10.5829/idosi.ajcr.2013.6.1.7324.

Table 1: Fuzzy Clustering Method and Objective Function

Fuzzy Clustering and Objective Function	**Kernel Fuzzy Clustering and Objective Function**
Kernel Value : 150 and Maximum iteration: 100 (user defined)	**Kernel Value : 150 and Maximum iteration: 100 (user defined)**
FCM:Interate count = 1	KFCM:Interate count = 1
obj.fcn = 15797160.205306	obj.fcn = 520.160682
FCM:Interate count = 2	KFCM:Interate count = 2
obj.fcn = 11875960.562010	obj.fcn = 295.287230
FCM:Interate count = 3	KFCM:Interate count = 3
obj.fcn = 11865897.229114	obj.fcn = 155.317386
FCM:Interate count = 4	KFCM:Interate count = 4
obj.fcn = 11745483.520826	obj.fcn = 65.526343
FCM:Interate count = 5	KFCM:Interate count = 5
obj.fcn = 10867011.369465	obj.fcn = 33.595262
FCM:Interate count = 6	KFCM:Interate count = 6
obj.fcn = 8041742.737781	obj.fcn = 28.883550
FCM:Interate count = 7	KFCM:Interate count = 7
obj.fcn = 4525299.902186	obj.fcn = 28.108535
FCM:Interate count = 8	KFCM:Interate count = 8
obj.fcn = 1841134.930424	obj.fcn = 27.788072
FCM:Interate count = 9	KFCM:Interate count = 9
obj.fcn = 988058.173274	obj.fcn = 27.535204
FCM:Interate count = 10	KFCM:Interate count = 10
obj.fcn = 872501.432417	obj.fcn = 27.283703
FCM:Interate count = 11	KFCM:Interate count = 11

obj.fcn = 841492.064459	obj.fcn = 27.034103
FCM:Interate count = 12	KFCM:Interate count = 12
obj.fcn = 826532.186649	obj.fcn = 26.790088
FCM:Interate count = 13	KFCM:Interate count = 13
obj.fcn = 821134.583904	obj.fcn = 26.553215
FCM:Interate count = 14	KFCM:Interate count = 14
obj.fcn = 818922.063918	obj.fcn = 26.323718
FCM:Interate count = 15	KFCM:Interate count = 15
obj.fcn = 817663.775301	obj.fcn = 26.101316
FCM:Interate count = 16	KFCM:Interate count = 16
obj.fcn = 816816.183435	obj.fcn = 25.885476
FCM:Interate count = 17	KFCM:Interate count = 17
obj.fcn = 816203.271130	obj.fcn = 25.675473
FCM:Interate count = 18	KFCM:Interate count = 18
obj.fcn = 815740.933947	obj.fcn = 25.470421
FCM:Interate count = 19	KFCM:Interate count = 19
obj.fcn = 815380.212454	obj.fcn = 25.269324
FCM:Interate count = 20	KFCM:Interate count = 20
obj.fcn = 815090.392422	obj.fcn = 25.071146
FCM:Interate count = 21	KFCM:Interate count = 21
obj.fcn = 814851.495659	obj.fcn = 24.874864
FCM:Interate count = 22	KFCM:Interate count = 22
obj.fcn = 814650.183453	obj.fcn = 24.679515
FCM:Interate count = 23	KFCM:Interate count = 23
obj.fcn = 814477.337035	obj.fcn = 24.484218

FCM:Interate count = 24	KFCM:Interate count = 24
obj.fcn = 814326.576142	obj.fcn = 24.288189
FCM:Interate count = 25	KFCM:Interate count = 25
obj.fcn = 814193.331334	obj.fcn = 24.090738
FCM:Interate count = 26	KFCM:Interate count = 26
obj.fcn = 814074.252765	obj.fcn = 23.891260
FCM:Interate count = 27	KFCM:Interate count = 27
obj.fcn = 813966.827508	obj.fcn = 23.689216
FCM:Interate count = 28	KFCM:Interate count = 28
obj.fcn = 813869.128235	obj.fcn = 23.484119
FCM:Interate count = 29	KFCM:Interate count = 29
obj.fcn = 813779.645762	obj.fcn = 23.275528
FCM:Interate count = 30	KFCM:Interate count = 30
obj.fcn = 813697.175826	obj.fcn = 23.063052
FCM:Interate count = 31	KFCM:Interate count = 31
obj.fcn = 813620.741338	obj.fcn = 22.846379
FCM:Interate count = 32	KFCM:Interate count = 32
obj.fcn = 813549.538105	obj.fcn = 22.625322
FCM:Interate count = 33	KFCM:Interate count = 33
obj.fcn = 813482.896284	obj.fcn = 22.399862
FCM:Interate count = 34	KFCM:Interate count = 34
obj.fcn = 813420.252474	obj.fcn = 22.170186
FCM:Interate count = 35	KFCM:Interate count = 35
obj.fcn = 813361.129126	obj.fcn = 21.936713
FCM:Interate count = 36	KFCM:Interate count = 36

obj.fcn = 813305.119033	obj.fcn = 21.700088
FCM:Interate count = 37	KFCM:Interate count = 37
obj.fcn = 813251.873402	obj.fcn = 21.461162
FCM:Interate count = 38	KFCM:Interate count = 38
obj.fcn = 813201.092502	obj.fcn = 21.220952
FCM:Interate count = 39	KFCM:Interate count = 39
obj.fcn = 813152.518179	obj.fcn = 20.980582
FCM:Interate count = 40	KFCM:Interate count = 40
obj.fcn = 813105.927763	obj.fcn = 20.741238
FCM:Interate count = 41	KFCM:Interate count = 41
obj.fcn = 813061.129018	obj.fcn = 20.504110
FCM:Interate count = 42	KFCM:Interate count = 42
obj.fcn = 813017.955910	obj.fcn = 20.270355
FCM:Interate count = 43	KFCM:Interate count = 43
obj.fcn = 812976.265007	obj.fcn = 20.041071
FCM:Interate count = 44	KFCM:Interate count = 44
obj.fcn = 812935.932391	obj.fcn = 19.817269
FCM:Interate count = 45	KFCM:Interate count = 45
obj.fcn = 812896.850997	obj.fcn = 19.599858
FCM:Interate count = 46	KFCM:Interate count = 46
obj.fcn = 812858.928292	obj.fcn = 19.389633
FCM:Interate count = 47	KFCM:Interate count = 47
obj.fcn = 812822.084260	obj.fcn = 19.187265
FCM:Interate count = 48	KFCM:Interate count = 48
obj.fcn = 812786.249635	obj.fcn = 18.993297

FCM:Interate count = 49	KFCM:Interate count = 49
obj.fcn = 812751.364370	obj.fcn = 18.808150
FCM:Interate count = 50	KFCM:Interate count = 50
obj.fcn = 812717.376281	obj.fcn = 18.632123
FCM:Interate count = 51	KFCM:Interate count = 51
obj.fcn = 812684.239886	obj.fcn = 18.465403
FCM:Interate count = 52	KFCM:Interate count = 52
obj.fcn = 812651.915375	obj.fcn = 18.308072
FCM:Interate count = 53	KFCM:Interate count = 53
obj.fcn = 812620.367736	obj.fcn = 18.160115
FCM:Interate count = 54	KFCM:Interate count = 54
obj.fcn = 812589.565986	obj.fcn = 18.021430
FCM:Interate count = 55	KFCM:Interate count = 55
obj.fcn = 812559.482514	obj.fcn = 17.891836
FCM:Interate count = 56	KFCM:Interate count = 56
obj.fcn = 812530.092525	obj.fcn = 17.771080
FCM:Interate count = 57	KFCM:Interate count = 57
obj.fcn = 812501.373555	obj.fcn = 17.658846
FCM:Interate count = 58	KFCM:Interate count = 58
obj.fcn = 812473.305069	obj.fcn = 17.554769
FCM:Interate count = 59	KFCM:Interate count = 59
obj.fcn = 812445.868124	obj.fcn = 17.458440
FCM:Interate count = 60	KFCM:Interate count = 60
obj.fcn = 812419.045075	obj.fcn = 17.369422
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obj.fcn = 812392.819349	obj.fcn = 17.287261
FCM:Interate count = 62	KFCM:Interate count = 62
obj.fcn = 812367.175244	obj.fcn = 17.211492
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obj.fcn = 812342.097772	obj.fcn = 17.141657
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obj.fcn = 812317.572532	obj.fcn = 17.077303
FCM:Interate count = 65	KFCM:Interate count = 65
obj.fcn = 812293.585606	obj.fcn = 17.017999
FCM:Interate count = 66	KFCM:Interate count = 66
obj.fcn = 812270.123480	obj.fcn = 16.963332
FCM:Interate count = 67	KFCM:Interate count = 67
obj.fcn = 812247.172978	obj.fcn = 16.912914
FCM:Interate count = 68	KFCM:Interate count = 68
obj.fcn = 812224.721219	obj.fcn = 16.866385
FCM:Interate count = 69	KFCM:Interate count = 69
obj.fcn = 812202.755574	obj.fcn = 16.823411
FCM:Interate count = 70	KFCM:Interate count = 70
obj.fcn = 812181.263651	obj.fcn = 16.783685
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obj.fcn = 812160.233264	obj.fcn = 16.746927
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obj.fcn = 812139.652433	obj.fcn = 16.712879
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obj.fcn = 812119.509370	obj.fcn = 16.681311

FCM:Interate count = 74	KFCM:Interate count = 74
obj.fcn = 812099.792476	obj.fcn = 16.652009
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obj.fcn = 812080.490345	obj.fcn = 16.624784
FCM:Interate count = 76	KFCM:Interate count = 76
obj.fcn = 812061.591761	obj.fcn = 16.599462
FCM:Interate count = 77	KFCM:Interate count = 77
obj.fcn = 812043.085703	obj.fcn = 16.575886
FCM:Interate count = 78	KFCM:Interate count = 78
obj.fcn = 812024.961346	obj.fcn = 16.553914
FCM:Interate count = 79	KFCM:Interate count = 79
obj.fcn = 812007.208066	obj.fcn = 16.533418
FCM:Interate count = 80	KFCM:Interate count = 80
obj.fcn = 811989.815447	obj.fcn = 16.514281
FCM:Interate count = 81	KFCM:Interate count = 81
obj.fcn = 811972.773278	obj.fcn = 16.496396
FCM:Interate count = 82	KFCM:Interate count = 82
obj.fcn = 811956.071563	obj.fcn = 16.479669
FCM:Interate count = 83	KFCM:Interate count = 83
obj.fcn = 811939.700518	obj.fcn = 16.464011
FCM:Interate count = 84	KFCM:Interate count = 84
obj.fcn = 811923.650578	obj.fcn = 16.449344
FCM:Interate count = 85	KFCM:Interate count = 85
obj.fcn = 811907.912396	obj.fcn = 16.435593
FCM:Interate count = 86	KFCM:Interate count = 86

obj.fcn = 811892.476844	obj.fcn = 16.422693
FCM:Interate count = 87	KFCM:Interate count = 87
obj.fcn = 811877.335017	obj.fcn = 16.410583
FCM:Interate count = 88	KFCM:Interate count = 88
obj.fcn = 811862.478226	obj.fcn = 16.399208
FCM:Interate count = 89	KFCM:Interate count = 89
obj.fcn = 811847.898005	obj.fcn = 16.388516
FCM:Interate count = 90	KFCM:Interate count = 90
obj.fcn = 811833.586104	obj.fcn = 16.378461
FCM:Interate count = 91	KFCM:Interate count = 91
obj.fcn = 811819.534491	obj.fcn = 16.368999
FCM:Interate count = 92	KFCM:Interate count = 92
obj.fcn = 811805.735345	obj.fcn = 16.360091
FCM:Interate count = 93	KFCM:Interate count = 93
obj.fcn = 811792.181060	obj.fcn = 16.351700
FCM:Interate count = 94	KFCM:Interate count = 94
obj.fcn = 811778.864237	obj.fcn = 16.343792
FCM:Interate count = 95	KFCM:Interate count = 95
obj.fcn = 811765.777681	obj.fcn = 16.336337
FCM:Interate count = 96	KFCM:Interate count = 96
obj.fcn = 811752.914399	obj.fcn = 16.329305
FCM:Interate count = 97	KFCM:Interate count = 97
obj.fcn = 811740.267598	obj.fcn = 16.322669
FCM:Interate count = 98	KFCM:Interate count = 98
obj.fcn = 811727.830676	obj.fcn = 16.316405

FCM:Interate count = 99	KFCM:Interate count = 99
obj.fcn = 811715.597220	obj.fcn = 16.310489
FCM:Interate count = 100	KFCM:Interate count = 100
obj.fcn = 811703.561002	obj.fcn = 16.304900
FCM:Actual iterations= 100	KFCM:Interate count = 100
obj.fcn = 811703.561002	obj.fcn = 16.304900

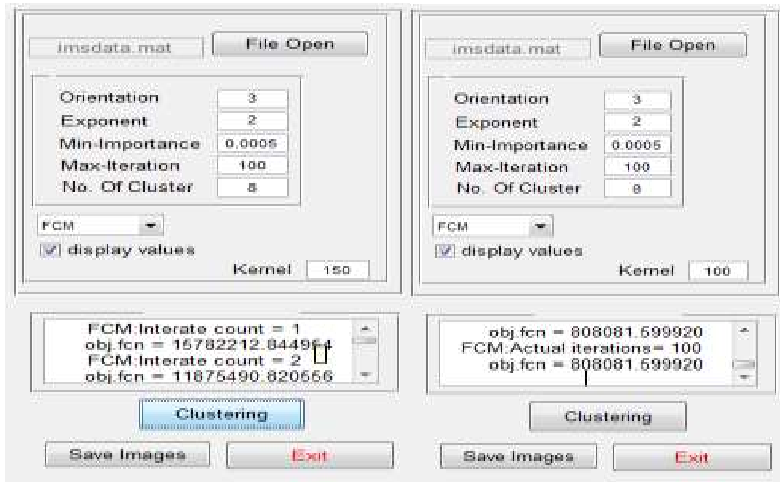

Fig. 1: FCM Clustering

Fig. 2: KFCM Clustering