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Performance Analysis of Fuzzy C-Means Clustering Methods for MRI Image Segmentation

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Abstract

MRI is one of the most eminent medical imaging techniques and segmentation is a critical stage in investigation of MRI images. FCM is most usually used techniques for image segmentation of medical image applications because of its fuzzy nature, where one pixel can belong to multiple clusters and which lead to better performance than crisp methods. Conventional FCM fail to perform well enough in the presence of noise and intensity inhomogeneity in MRI images. Various FCM variations like BCFCM, PFCM, SFCM, FLICM, MDFCM, FCM−S1, FCM−S2, TEFCM, RFCMK, WIPFCM and KWFLICM, have been proposed to overcome these predicament by using the spatial statistics available in the images. In this paper all these techniques, used for segmentation, are implemented and compared in terms of two classes of cluster validity functions, fuzzy partition and feature structure, on the basis of their performance for the noisy MRI images. All these FCM variants are analyzed in terms of Partition Coefficient, Partition Entropy, Time Complexity and Segmentation Accuracy.

Keywords: Fuzzy C-Means (FCM); Image Segmentation; Magnetic Resonance Imaging (MRI); Medical Imaging.

1. Introduction

Medical images characteristically comprise complex configurations and their accurate segmentation is crucial for quantifiable diagnosis[1]. Image segmentation and contour extraction are the utmost instinctive techniques for medical image visualization[21]. Image segmentation is a thought provoking assignment in medical image investigation as the images contain complex boundaries and often affected by noise. FCM is most frequently used technique in medical image applications[1]. Most of the times, MRI images, contains noise and intensity inhomogeneity. Conventional FCM couldn't dealt with these effects[4] so many FCM variations like BCFCM, PFCM, SFCM, FLICM, MDFCM, FCM−S1, FCM_S2, TEFCM, RFCMK, WIPFCM and KWFLICM are proposed in the recent years to overcome limitations of conventional FCM by using the spatial information or by estimating the bias field for inhomogeneity or by making changes to the cost function. These methods are validated by their performance on real MRI images as well as synthetic images. Validation of these methods is done by using cluster validity functions for real MR images. Two types of cluster validity functions, fuzzy partition and feature structure, are used to evaluate the efficiency of clustering[19, 20].

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Effectiveness of the discussed methods is evaluated in terms of Segmentation Accuracy (SA)[6] for synthetic image tainted by Gaussian noise (For noise density, $\sigma = 0$ to 0.1).

The main contributions of the paper are as follows:

- FCM and 09 latest variants are validated by implementation of real MRI images as well as synthetic images.
- Performance comparison of FCM and variants is done in terms of Partition Coefficient Partition Entropy and Time Complexity for real MRI images.
- Performance comparison of FCM and variants is done in terms of Segmentation Accuracy for synthetic image corrupted by Gaussian noise.

Section-2 of the research paper deals with literature survey in this field. This includes background and latest related work. FCM and variants are explained in terms of mathematical and system model with their strength and limitations in section-3. Section-4 includes results/performance analysis with algorithm and implementation issues. Conclusion, which is follow by references, is explained in section-5.

2. Literature Survey

FCM finds its applications in variety of problems varying from data analysis to segmentation of images. K. Xiao *et al.*,[11] performed Gaussian smoothing on input image and proposed a method to find the weightage for each feature using bootstrapping technique when dealing with multiple features. To deal with intensity in homogenities, Pham *et al.*[12] proposed Adaptive FCM. In this case, the centroids are multiplied by unknown multiplier filed, which represents the inhomogeneity. First and second order regularization terms are included in the cost function to make the multiplier field varying slowly and smoothly.

Jude *et al.*[13] used multidimensional features formed by GLCM feature generation model to include spatial information into FCM. Extra dimensions make the process time consuming so to overcome this, distance metric based compression is proposed to selects the representative pixels of the groups and perform clustering on them, which resulted in fast and effective clustering. Enhanced FCM is proposed by Szilagyi *et al.*,[14] to fasten the segmentation process as well as to reduce the noise effect. For achieving this, a new factor which includes the pixel intensity along with mean of neighborhood pixels is calculated in advance of the segmentation process and computational complexity is condensed by considering the histogram count of the voxels into the cost function.

Noise inhomogeneity effect is reduced in a faster way by GCFFCM proposed by Jingjing Song *et al.*,[15]. GCFFCM algorithm uses a gain field to deal with inhomogeneity and uses the histogram of the image to reduce the computational time. Abbas Biniaz *et al.*,[16] proposed Gaussian spatial FCM, in which the membership function is updated twice in the algorithm to reduce the noise effect. First update is similar to the conventional FCM but in the second update, a spatial factor is included which contains the Gaussian average of neighborhood membership values. Another method to deal with noise affect is proposed by Shan Shen *et al.*,[17] called as Improved FCM (IFCM). In IFCM the distance term of FCM is modified by including two terms, feature attraction and distance attraction, which are calculated by considering weighted average of neighborhood intensity differences and weighted average of spatial difference respectively. The parameters that are giving weightage to these terms are optimized at every step by using a simple artificial neural network model.

A prior probability and fuzzy spatial information are used in ISFCM, proposed by Zulaikha Bevi *et al.*,[18] to minimized the noise affect in MRI images. In this method, cluster centers are initialized using histogram based FCM in the first step to achieve faster convergence and the membership updating equation is modified in a way to use probability obtained by the proportion of amount of pixels belongs to the cluster with pixels in the neighborhood and spatial information.

3. FCM and Various FCM Based Techniques

In FCM, it is possible for a data sample to belong to multiple clusters at the same time. The similarity is indicated by the membership value. In FCM a data sample is assigned with a membership value based on its similarity with the cluster center. The membership values are between 0 to 1 and more the similarity, higher the membership value.

Defuzzification is applied at the end of the clustering process to decide the clustering. FCM is a repetitive algorithm and the solution is achieved by repetitively updating the cluster center and membership value. These updating equations are obtained by solving the cost function. Let $X = \{x_1, x_2, x_3, \ldots, x_N\}$ denotes the data with N data samples. It has to be partitioned into c-clusters by minimizing the subsequent cost function

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^m \|x_j - v_i\|^2 \tag{1}$$

where, u_{ij} represents the membership of x_j with the ith cluster, v_i is the ith cluster center, $\| \cdot \|$ is a norm metric and 'm' is a constant. The parameter m decides the fuzziness of the consequential partition. By taking the derivative of the equation and make it equal to zero by using Lagrange method, the following equations are achieved

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m} \tag{2}$$

$$u_{ij} = \sum_{k=1}^{c} \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|} \right)^2 \tag{3}$$

Many variations to the FCM have been proposed because conventional FCM couldn't perform well in the presence of noise and intensity inhomogeneity. These FCM variants are discussed as

3.1 Bias-Corrected Fuzzy C-Means (BCFCM)

Ahmed et al.,[2] proposed a bias field estimation based FCM, known as BCFCM. In BCFCM, voxel is modal as the sum of observed intensity and a bias field term to deal with intensity inhomogeneity intensity of MRI. The objective function of FCM is modified by including neighborhood information. It acts as regularization term and helps to reduce the effect of salt and pepper noise. The modified objective function used in BCFCM is given by

$$J = \sum_{j=1}^{N} \sum_{i=}^{c} u_{ij}^m \|y_j - \beta_j - v_i\|^2 + \frac{\alpha}{N_R} \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^m \left(\sum_{k \in N(x_j)} \|y_k - \beta_k - v_i\|^2 \right) \tag{4}$$

Here, β_i is the bias field value at the jth voxel, N_R represents size of neighborhood to be considered. β_i helps in removing the inhomogeneity effect in segmentation. The neighborhood effect on objective function is controlled by the parameter α. Selection of the parameter α heavily affects the accuracy of results, for example small value of α for low Signal to Noise Ratio (SNR) resulted in leakage of boundaries in the segmented image. This method cannot be applied when multiple features have to be considered as input.

3.2 Possibilistic Fuzzy C-Means (PFCM)

Yang et al.,[3] introduced a penalty term to the FCM objective function which is inspired by Neighborhood Expectation-Maximization (NEM) algorithm to decrease the effect of noise in the segmentation process. The penalty is formed by using the neighborhood information and few changes are made to it to satisfy the criterion of FCM. The modified objective function used in PFCM is given by

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} (u_{ij})^m d^2(x_j, v_i) + \gamma \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ij})^m (1 - u_{ik})^m w_{jk} \tag{5}$$

where, w_{jk} represents the neighborhood region, γ is the controlling parameter similar to α in BFCM. If x_k is neighbor of x_j then $w_{jk} = 1$ else $w_{jk} = 0$. In PFCM cluster center updating equation hasn't affected by the changes made to objective function, only membership updating will change. This will result in less computational complexity. Like BFCM, PFCM also gives satisfactory results for low SNR data and it can be applied even for multidimensional input feature data also. But it deals only with noise and it can't reduce the effect of intensity inhomogeneity.

3.3 Spatial Fuzzy C-Means (SFCM)

To overcome the noise effect on the segmentation phase, Chuang *et al.*,[4] used spatial information while updating the membership function in the repetitive FCM algorithm because the neighborhood pixels possess same properties as the centre pixel. In contrast to BCFCM and PFCM, the objective function is not changed in the Spatial FCM (SFCM) instead the membership function is updated twice. The first updation is similar to the conventional FCM but in the second step, a spatial function is defined as sum of the membership values in spatial domain in the entire neighborhood around the pixel under consideration. It is define as

$$h_{ij} = \sum_{k \in N(x_j)} u_{ik} \tag{6}$$

where, $N(x_j)$ is the neighborhood under consideration around x_j. The spatial function is used in updating membership function again given by the equation

$$u_{ij} = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^c u_{kj}^p h_{kj}^q} \tag{7}$$

when surrounding pixels belongs to the same cluster as the centre pixel, the membership function will gain larger values. In smooth regions clustering remains unchanged because spatial function will just strengthens the membership function. The correction of misclassified pixels from noisy regions will happen when spatial function decreases the weight of a noisy pixel by considering its neighborhood pixels. The Spatial FCM works well for high as well as low density noise. It can be applied for single and multiple feature data. Compared to other methods; it gives superior results without any boundary leakage even at high density noise, when *q* value is carefully selected. Parameter (p, q) selection is very crucial in SFCM. High value of *q* may results in blurring of fine details.

3.4 FCM_S1 & FCM_S2

Chen and Zhang *et al.*,[7] suggested a novelsystem to reduce the computational complexity taken by BCFCM. The noise reduction is taken care by taking the neighborhood information but in contrast to BCFCM, it computes the spatial term prior to the repetitive FCM algorithm. The variations of FCM proposed here are FCM_S1, FCM_S2. The modified cost function is specified as

$$J = \sum_{i=1}^{C} \sum_{k=1}^{N} u_{ik}^m \|x_k - v_i\|^2 + \alpha \sum_{i=1}^{C} \sum_{k=1}^{N} u_{ik}^m \|\bar{x}_k - v_i\|^2 \tag{8}$$

where, $\bar{x}_k$ is mean or median of neighborhood pixels for FCM_S1, FCM_S2, respectively. This algorithm work well in the presence of noise also since it used spatial information also in the cost function. It can be used for multidimensional data. The computational complexity will be less as the spatial term is computed only once.

3.5 Fuzzy Local Information C- Means (FLICM)

The limitations faced by most of the variations of FCM techniques, which are trying to use the spatial information, are due to their dependence on noise density. FLICM algorithm is suggested by Krinidis and Chatzis[5] to overcome the usage of the parameter selection when dealing with segmentation of noisy images. A fuzzy factor G is introduced into the objective function of conventional FCM. *G* is defined as

$$G_{ki} = \sum_{j=N_i \& i \neq j} \frac{1}{d_{ij} + 1} (1 - u_{kj})^m \|x_j - v_k\|^2$$

The objective function of FLICM is given as

$$J = \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ki}^m \|x_i - v_k\|^2 + G_{ki} \tag{9}$$

where, d_{ij} is the spatial Euclidean distance from pixel i to j so pixels near to the center pixel will affect the fuzzy factor most. The objective function looks like a small change to BCFCM but it resulted in better approach. When a centre pixel is a noisy pixel, it will belong to a noisy cluster but the neighborhood forces the noisy pixel to their cluster in order to minimize the objective function. FLICM can be used when the prior knowledge of noise is not available. It is independent of any parameter selection. It can be used for multidimensional data but can't deal with intensity inhomogeneity.

3.6 Multi-dimensional Fuzzy C-Means (MDFCM)

Jamal *et al.*,[6] introduced a new method to reduce the noise effect by using spatial information. The segmentation is carried by considering the multiple features like mean, standard deviation, singular value and intensity of the pixel hence called multi-dimensional FCM. The features used in FLICM are pixel intensity mean, largest singular value of local window with standard deviation. Before the segmentation, instead of using all the features, different combination of features can be formed. The feature set selection depends on the requirement. If accuracy is the constraint, considering all the features gives better results. If computational cost is the criteria, then selection of few important features like, Eigen value, pixel intensity is recommended. In MDFCM by considering the spatial information, in terms of different features, result in improved efficiency compared to most of the variations of FCM. Even with the images, despoiled by high density noise, MDFCM resulted in clear boundaries and noise free clustering. The main disadvantage of this method is computational complexity because of multidimensional data.

3.7 Weighted Image Patch Based FCM (WIPFCM)

A new approach to use the spatial information in FCM process was introduced by ZexuanJi *et al.*,[9]. In this method, image patches are considered instead of just pixels, which add additional information to the data. Weight vectors are assigned to every image patch based on their variance with respect to their neighboring pixels. The expression to carry out this weight assignment is given by

$$\xi_{kr} = \exp\left[-\left(\sigma_{kr} - \frac{\sum_{r \in N_k} \sigma_{kr}}{n_k}\right)\right] \tag{10}$$

where, $\xi_{kr}c$ and σ_{kr} represent the weight and variance of rth pixel in k^{th} patch respectively, later it is normalized to make the sum of the weights equal to one. The weight vector assigned here results in removing effect of edges and noisy pixel on clustering process by assigning less weight to them. The objective function for WIPFCM is given by

$$J = \sum_{i=1}^{C} \sum_{k=1}^{N} u_{ik}^m \sum_{r \in N_k} w_{kr} \|I_{kr} - v_{ri}\|^2 \tag{11}$$

where, I_k represents the image patch of size $q \times q$ around the pixel, x_k, v_i represents the cluster center of size $q \times q$. In this method noise is handled effectively by utilizing the spatial information. There is no external parameter to be selected like in other methods. This method increase computational burden because each pixel need to be represented by a patch and additional step of calculation of their weights is required.

3.8 Kernel Weighted Fuzzy Local Information C- Means (KWFLICM)

Maoguo Gong *et al.*,[10] proposed kernel weighted variation of FLICM. In this approach they have introduced trade off weights to the pixels and replaced the Euclidean distance with kernel metric based distance. In FLICM a factor is introduced which utilizes spatial distance and Euclidian distance of neighboring pixels from the centre pixels but it fails to analyze the neighboring pixels when the centre pixel itself is noisy. To overcome this disadvantage of FLICM, KWFLICM utilizes more local information by utilizing spatial variance instead of Euclidian distance. The weight

assigning technique is similar to the one used in WIPFCM, here in addition to that, it utilizes spatial distance also and it can be explained by these equations

$$w_{ij} = w_{gc} \cdot w_{sc} \tag{12}$$

$$w_{gc} = \begin{cases} 2 + \beta_{ij}\sigma_j \; < \bar{\sigma} \\ 2 - \beta_{ij}\sigma_j \; \geq \bar{\sigma} \end{cases} \tag{13}$$

$$w_{sc} = 1/(d_{ij} + 1) \tag{14}$$

where, β_{ij} is the weight obtained using the formula given in WIPFCM after normalization, w_{gc} is made positive by keeping these conditional statements, $\bar{\sigma}$ is the average variance in the local window. The objective function is given by

$$J = \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^m (1 - K(x_i, v_k)) + G_{ki}' \tag{15}$$

and the fuzzy factor G_{ki}' is given by

$$G_{ki}' = \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^m \sum_{i \neq j \& j \in N_i} w_{ij}(1 - u_{ki})^m [1 - K(x_i, v_k)] \tag{16}$$

where, N represents the local window around the pixel, $K(x_i, v_k)$ is the kernel based distance measure. The kernel used in this method is Gaussian radial basis function (GRBF). For this Gaussian kernel, the bandwidth parameter is estimated using the variance of the zero-mean input data. It can be expressed by the following relations

$$\sigma = \left(\frac{1}{N-1} \sum_{i=1}^{N} (d_i - \bar{d})^2 \right)^{\frac{1}{2}} \tag{17}$$

$$d_i = \|x_i - \bar{x}\| \tag{18}$$

The kernel distance is obtained by bulging the input data into a high dimensional space by using the kernel. KFLICM is independent of any external parameter selection and it utilizes local information in an effective way by using the spatial variance and spatial positioning. Kernel metric distance used here leads better clustering performance in the presence of image artifacts, noise and outliers.

3.9 Strong FCM

The data given to FCM is projected into a high dimensional space using kernels and distance between the cluster centre and data points is calculated in that domain. It leads to better clustering of complex noised data. This technique is proposed by S. R. Kannan et al.,[8]. In this he has proposed two techniques based on this approach and also a new method to initialize the cluster centres to improve the performance of FCM. First FCM technique proposed is **Robust Fuzzy C-means Based Kernel Function (RFCMK)** algorithm. In proposed technique the modified cost function is given by

$$J = 2 \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^m (\beta - K(x_i, v_k)) \tag{19}$$

and kernel function is expressed as

$$K(x_i, v_k) = -\frac{\|x_i - v_k\|^2}{\alpha} + \beta, \quad \beta > 0 \tag{20}$$

Cost function here is obtained by projecting the data into higher dimensional space by non-linear transformation and it is minimized using the properties of kernel functions. The updating expressions for membership function and cluster centres can be obtained by differentiating the cost function and making it equal to zero using Lagrange multiplier technique as done in the conventional FCM. Second FCM technique proposed is **Tsallis Entropy Based Fuzzzy C-Means (TEFCM)** algorithm. This is an extension to the previous technique, because previous technique cannot distinguish similar intensity objects of different clusters. To overcome this problem an extra term is introduced into the cost function and modified cost function is

$$J = 2 \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^m \beta K(x_i, v_k) + \frac{\alpha_i}{\gamma - 1} \left(\sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^m - 1 \right) \qquad (21)$$

where, $\alpha_i = \frac{n}{\zeta}(x_i + ((n/c)/N_R) \sum_{j \in N_i} x_j)$ is a term which will include data from neighborhood and ζ is a factor which regulates the outcome of neighborhood terms. By including this extra term, spatial information is also included in the objective function, which leads to improved performance. Time consumption is less because neighborhood term is calculated only once and it is utilized in the clustering process.

4. Results

FCM and variants are validated by their performance on real MRI images as well as synthetic images by using cluster validity functions. Two forms of cluster validity functions, fuzzy partition and feature structure, are commonly applied to estimate the efficiency of clustering. The characteristics terms for the fuzzy partition are Partition Coefficient, Vpc[19] and Partition Entropy, Vpe[2]. They are defined as

$$V_{pc} = \frac{\sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^2}{N} \qquad (22)$$

$$V_{pe} = \frac{-\sum_{j=1}^{N} \sum_{i=1}^{C} [u_{ij} \log u_{ij}]}{N} \qquad (23)$$

The fuzzy partition validity functions are indication of fuzziness means and partition, with less fuzziness means better performance. As a result, the best clustering is achieved when the value **Vpc is maximal** or **Vpe is minimal**. V_{pc} and V_{pe} measure only the fuzzy partition and lack a direct connection to the featuring property so another validity function, **Vxb**, is also used. It is based on the feature structure and defined as

$$V_{xb} = \frac{-\sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij} \|x_j - v_i\|^2}{N * (\min_{i \neq k} \{\|v_k - v_i\|^2\})} (24) \qquad (24)$$

A worthy clustering outcome produces samples that are compressed within one cluster and disconnected between diverse clusters. **Minimizing Vxb** is desired for good clustering. Figure 1 shows the resultant images after applying the various FCM based techniques for MRI image.

By Fig. 1, it is observed that BCFCM successfully removed the noise but it lost some of the edge information giving very smooth edges. PFCM shows good clustering irrespective of noise and contains edge details. FLICM also gave good clustering, which is independent of noise and also doesn't lost edge details. RFCMK is successful in removing noise but mixed two clusters into one cluster. Results of SFCM, FCM_S1 & S2, MDFCM, KWFLICM, TEFCM and WIPFCM contain a little noise in the clustered image but remains edge information. The performance of the discussed methods is evaluated in terms of the parameters Vpc, Vpe, Vpx and time complexity (time taken by these methods). The values of these parameters for real MRI image are shown in Fig. 2 to 5. In these Figs, X-axis represents performance in the presence of different noise densities.

The performance of FCM and variants is evaluated in terms of Segmentation Accuracy (SA) for synthetic image corrupted by Gaussian noise (For noise density, $\sigma = 0$ to 0.1). The values of SA are shown in Table 1 and SA is defined as[2]

$$SA = \frac{\text{Number of Correctly Classified Pixels}}{\text{Total Number of Pixels}}$$
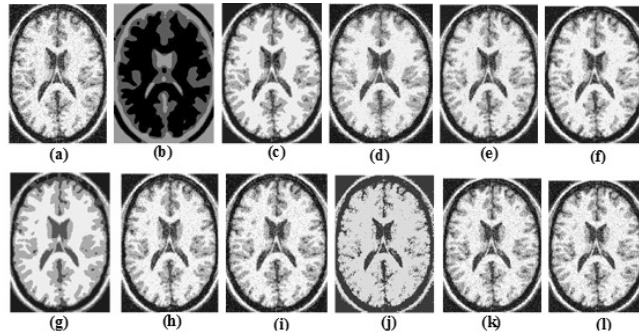
Fig. 1. (a) MRI Image with Gaussian Noise Density $\sigma = 0.03$ and K Value (no of clusters) = 4, De-Noised Images using; (b) BCFCM; (c) PFCM; (d) SFCM; (e) FCM$_-$S1; (f) FCM$_-$S2; (g) FLICM; (h) MDFCM; (i) KWFLICM; (j) RFCMK; (k) TEFCM and (l) WIPCM.
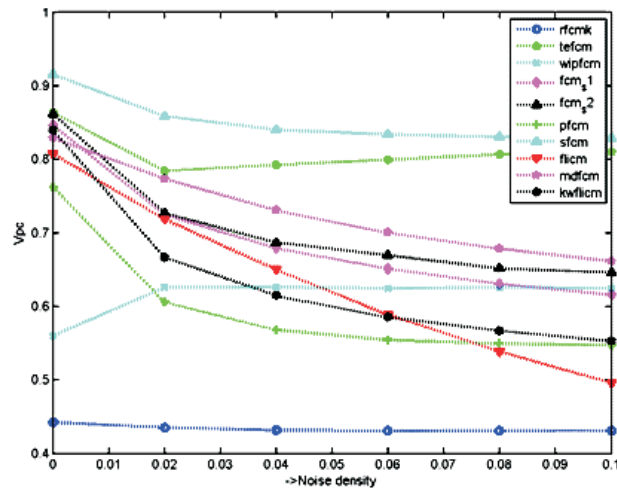

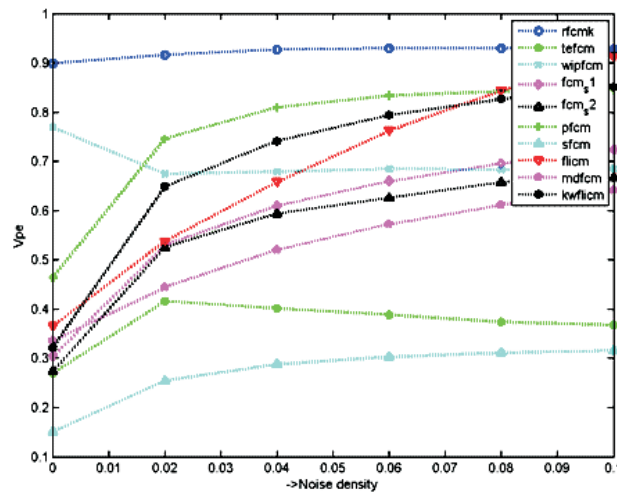Fig. 2. Comparison of Various FCM based Techniques based on V_{pc}.

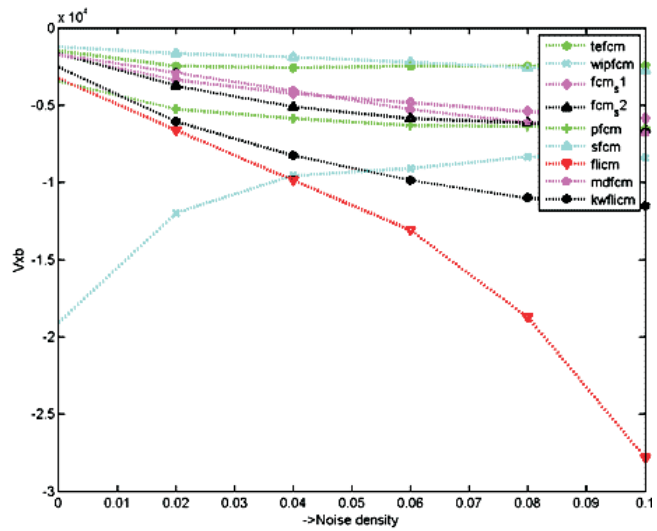Fig. 3. Comparison of Various FCM based Techniques based on V_{pe}.

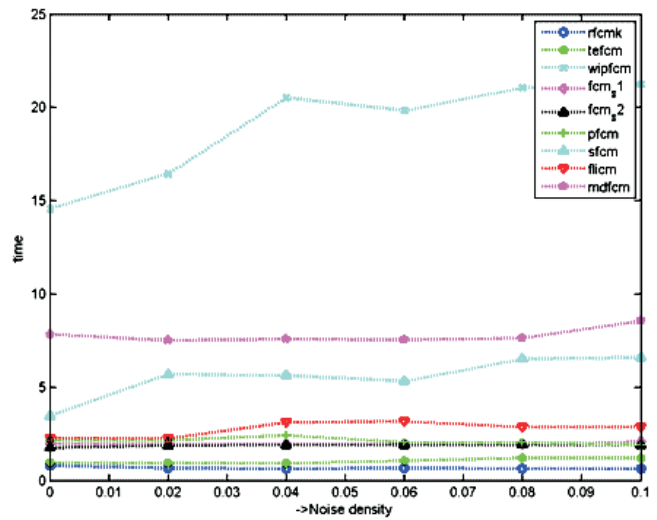Fig. 4. Comparison of Various FCM based Techniques based on V_{xb}.

Fig. 5. Time Complexity (in seconds) of Various FCM based Techniques.

Table 1. 1SA for Synthetic Image Corrupted by Gaussian Noise.

	Noise density					
Method	0	0.02	0.04	0.06	0.08	0.10
RFCMK	100	92.90	84.12	78.06	73.93	70.53
TEFCM	100	92.84	84.26	78.27	73.91	70.43
WIPFCM	100	99.65	99.37	98.47	97.43	95.91
FCM	100	92.83	84.17	78.15	74.02	70.49
FCM−S1	100	98.73	94.31	89.76	85.72	82.27
FCM_S2	99.99	99.01	95.36	90.94	87.33	84.04
PFCM	100	100	99.95	99.72	98.88	97.62
SFCM	100	99.78	99.41	99.41	98.38	91.11
FLICM	99.55	99.54	99.52	99.50	99.42	99.28
MDFCM	99.77	99.74	99.18	97.91	96.43	95.05
KWFLICM	100	96.70	89.90	83.98	79.51	75.78

5. Conclusions

High value of Partition Coefficient (Vpc) implies better performance since it is calculated on the basis of membership values and high membership value for a single cluster implies better clustering. Similarly low value of Partition Entropy (Vpe) implies better clustering. SFCM, TEFCM and MDFCM resulted in high Vpc and low Vpe values. Low value of Vxb represents better clustering since it is computed by taking the difference between data and cluster prototypes and more number of good clustered samples implies that sum of their difference will be less so it will results in lesser value of Vxb. When considering Vxb, RFCMK gives best result and WIPFCM, MDFCM, KWFLICM give good results. When it comes to time complexity, RFCMK, TEFCM, FCM_S1 & S2 gain advantage. All the methods leading to good SA, when applied on image without noise but when the image is corrupted by noise, FLICM gives results with consistent accuracy, followed by PFCM, WIPFCM and MDFCM.

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