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A COMPARATIVE STUDY AND PERFORMANCE ANALYSIS OF KERNELIZED FUZZY C- MEANS BASED METHODS FOR SEGMENTATION OF BRAIN MAGNETIC RESONANCE IMAGES

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ABSTRACT

In spite of being an effective image segmentation algorithm, the standard fuzzy c-means (FCM) is very sensitive to Rician noise and outliers in images. Thus, segmentation with FCM becomes problematic for brain magnetic resonance (MR) images where we need to segment tissues such as cerebrospinal fluid (CSF), gray matter (GM) and white matter (WM) from these images. Various FCM algorithms have been extended to their kernelized versions to make them enough robust to noise, outliers and other imaging artifacts and to reveal non-Euclidean structure of input data. This paper presents a comparative performance analysis of brain MRI segmentation methods based on kernelized FCM using performance measures such as jaccard similarity (JS) and similarity index(ρ).

Keywords: *image segmentation; fuzzy c-means; magnetic resonance (MR) images; imaging artifacts.*

I. INTRODUCTION

Image segmentation is the foremost and very challenging task in image analysis. It partitions an image into several non-overlapping groups or regions having similar features or homogeneous characteristics. It is a very helpful tool in many fields including image processing, traffic analysis, health care, pattern recognition etc.

The segmentation of magnetic resonance (MR) images has a significant application in the field of biomedical image processing. It facilitates the description of anatomical structures and other regions of interest. In bio-medical analysis, the structure of the brain is closely observed through MR images and the focus is on the identification of tumors, classification of tissues and blood cells, etc. In brain tumor, segmentation consists of segmenting the abnormal tissues from normal tissues such as cerebrospinal fluid (CSF), gray matter (GM) and white matter (WM). Manual description of these tissues is very tedious task and requires involvement of expert(s) to draw the boundaries of the tissues. So, there is a need of a computer based system for effective segmentation of brain MR images is to detect the abnormalities in the brain of a patient being examined and ultimately leading to treatment of disease.

There are various brain imaging techniques like computed tomography (CT), position emission tomography (PET) and MR imaging (MRI). Although all these imaging techniques provide valuable information about anatomical structure of the brain but MRI is the best technique for the diagnosis of diseases. This imaging technique does not cause any radiation damage to the internal tissues of the patient's body as it does not use harmful rays such as X-rays or radioactive material.

Post processing of Brain MR Images needs few algorithms to extract the particular information from these MRI. Several automated segmentation techniques have been developed such as threshold based, region growing, cluster based etc. In General, image segmentation is a clustering of the pixels in the image according to some predefined criteria. Hence the clustering techniques can be easily applied to MR images for their segmentation and these algorithms are very efficient in their work. In the case of clustering, the similar data samples or pixels in the image are grouped into one cluster. Generally, clustering can be partitioned into two categories [1], hard clustering and soft clustering. In hard clustering, each data object is assigned to exactly one cluster, but in soft clustering (also is called fuzzy clustering) each data object belongs to each cluster to a certain degree. k-means [2] and fuzzy c-means (FCM) [3] algorithms are the most popular clustering algorithms. In k-means (which is based on hard clustering), the partitions are optimized by minimizing the total distance within the clusters and every data point either belongs to a certain cluster or not. Relying on the basic idea of k-means, FCM also designs an objective function to perform a fuzzy partitioning such that the given data point can belong to several partitions or groups with varying degree of membership. However, both k-means and FCM are sensitive to noise, outliers and other imaging artifacts due to not considering any spatial information in the image. To overcome this sensitivity, the spatial information is introduced in the algorithm which is derived from the neighborhood of the pixels in the image [4]. The objective function of FCM is modified by incorporating a spatial neighborhood term and FCM algorithm with spatial information (FCM_S) is proposed. Additionally, two variants of FCM_S [5] called FCM_S1 and FCM_S2 are presented to reduce the computational complexity of FCM_S. Furthermore, a kernel-induced distance [5,6] is utilized to replace the Euclidean distance of FCM based algorithms and then kernel versions of FCM_S, FCM_S1 and FCM_S2 called KFCM_S, KFCM_S1 and KFCM_S2 respectively, are presented. To speed up the image segmentation process of FCM with spatial information, an enhanced fuzzy c-means (EnFCM) [7] clustering algorithm is produced in which a linearly-weighted sum image is introduced. Like EnFCM, a fast-generalized fuzzy c-means (FGFCM) [8] clustering algorithm is proposed in which a non-linearly-weighted sum image is defined. These two weighted sum images in EnFCM and FGFCM are computed by using the neighborhood of the pixel. Aiming at the problems in FGFCM, one parameter-free algorithm fuzzy local information C-means **(**FLICM) [9] is introduced in which a novel fuzzy factor is defined to replace the parameter in FGFCM. Furthermore, kernelized weighted fuzzy local information C-means algorithm (KWFLICM) [10] introduced a trade-off weighted fuzzy factor and kernel distance measure to further enhance the performance of FLICM.

The rest of this paper is organised as follows:In Section 2, Kernelized fuzzy c-means clustering algorithms (KFCM, KFCM_S, KFCM_S1 and KFCM_S2) are introduced, followed by the KWFLICM algorithm. The experimental comparisons are presented in Section 3. Finally, Section 4 gives our conclusions and future work.

II. ANALYSIS OF EXISTING WORK

2.1 Kernelized Fuzzy C-Means (KFCM)

Classical fuzzy c-means (FCM) [3] clustering has been proven effective for clusters with spherical shape only. So, kernelized fuzzy c-means algorithm (KFCM) [6] was introduced to deal with other non-spherical shaped clusters. KFCM performs a nonlinear input space mapping to a high dimensional feature space. The mapping consumes very much time so; Mercer kernel functions are used that generate kernel induced distance to replace Euclidean distance in FCM algorithm.

A kernel in a high dimensional feature space is represented by a function K as:

$$K(x,y) = \langle \varphi(x), \varphi(y) \rangle \quad \textbf{(1)}$$

where $\varphi(.)$ is an implicit nonlinear map. The most commonly used kernel function is gaussian radial basis function (GRBF) which is given below:

$$K(x,y) = exp\left(\frac{-\|x-y\|^2}{\sigma^2}\right) \quad \textbf{(2)}$$

where σ is an adjustable parameter of GRBF.
The objective function of classical FCM is given by:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} \mu_{ji}^{m} d_{ji}^{2}(x_i, v_j) \quad \textbf{(3)}$$

where, $d_{ji}$is the Euclidean distance measure between object x_i and cluster center v_j.

$$d_{ji} = \|x_i - v_j\| \quad \textbf{(4)}$$

$X = \{x_1, x_2 \dots . x_n\}$ is a data set in the m-dimensional vector space,$\mu_{ji}$is the fuzzy membership matrix of x_i with j^{th}cluster, m is the fuzzification parameter, v_j is the prototype of the center of cluster j.
Using (1), objective function of FCM is modified as follows:

$$J_m^{\varphi} = \sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^{m}\left\|\varphi(x_i)-\varphi(v_j)\right\|^2 \qquad (5) \qquad \mathbf{(5)}$$

By kernel substitution,

$$\left\|\varphi(x_i)-\varphi(v_j)\right\|^2 = \left(\varphi(x_i)-\varphi(v_j)\right)^T\left(\varphi(x_i)-\varphi(v_j)\right)$$
$$= \varphi(x_i)^T\varphi(x_i) - \varphi(v_j)^T\varphi(x_i)$$
$$-\varphi(x_i)^T\varphi(v_j) + \varphi(v_j)^T\varphi(v_j)$$
$$= K(x_i,x_i)K(v_j,v_j) - 2K(x_i,v_j) \qquad \mathbf{(6)}$$

Using GRBF, (5) can be rewritten as follows:

$$J_m^{\varphi} = 2\sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^{m}\left(1-K(x_i,v_j)\right) \qquad \mathbf{(7)}$$

The necessary conditions for minimizing (7) are the following equations:

$$\mu_{ji} = \frac{\left(1-K(x_i,v_j)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(1-K(x_i,v_k)\right)^{-1/(m-1)}} \qquad \mathbf{(8)}$$

$$v_j = \frac{\sum_{j=1}^{N}\mu_{ji}^{m}K(x_i,v_j)x_i}{\sum_{j=1}^{N}\mu_{ji}^{m}K(x_i,v_j)} \qquad \mathbf{(9)}$$

KFCM algorithmis given as follows:

Step1: Set the values of various parameters such as number c of the cluster prototypes, fuzzification parameter $m > 1$, termination condition ε and the total number of iterations n.

Step2: Initialize the set of random cluster centres $V = [v_1, v_2, \ldots., v_c]$and set $\varepsilon > 0$ to a very small value.

Step3: Compute the fuzzy membership matrix μ_{ji} using (8).

Step4: Update new cluster centersv_j using (9).

Repeat Steps 3 and 4 until the following termination criterion is satisfied:

$$V_{new} - V_{old} < \varepsilon$$

2.2 Kernelized Fuzzy C-Means with Spatial Constraints (KFCM_S) and its Variants

Aiming at simplicity of computations and improvement in clustering results, FCM_S [5] is extended to its kernelized version KFCM_S [5,6]. The objective function of FCM_S is given as below:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^{m}\left\|x_i - v_j\right\|^2 + \frac{a}{N_R}\sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^{m}\sum_{r\in N_i}\left\|x_r - v_j\right\|^2 \qquad \mathbf{(10)}$$

By incorporation of kernel function, the updated objective function of KFCM_S is given as below:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^{m}\left(1-K(x_i,v_j)\right)$$
$$+\frac{a}{N_R}\sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^{m}\sum_{r\in N_i}\left(1-K(x_r,v_j)\right) \qquad \mathbf{(11)}$$

where x_i is the grey value of the i^{th} pixel, v_j represents the j^{th} cluster, μ_{ji} represents the fuzzy membership value of i^{th}pixel with j^{th} cluster, $x_r$are the neighbors of x_i, parameter $a$is the regularization parameter which controls the effect of the penalty term,N_i stands for the set of neighbour pixels that exist in a window around x_i (excluding x_i) and N_R is the cardinality of N_i.

For minimizing (11), this iterative algorithm computes the membership matrix $\mu_{ji}$and the cluster center v_j as follows:

$$\mu_{ji} = \frac{\left(\left(1 - K(x_i, v_j)\right) + \frac{\alpha}{N_R}\sum_{r\in N_i}\left(1 - K(x_r, v_j)\right)^m\right)^{\frac{-1}{m-1}}}{\sum_{k=1}^{c}\left(\left(1 - K(x_i, v_k)\right) + \frac{\alpha}{N_R}\sum_{r\in N_i}\left(1 - K(x_r, v_k)\right)^m\right)^{\frac{-1}{m-1}}} \quad (12)$$

$$v_j = \frac{\sum_{i=1}^{N}\mu_{ji}^m\left(K(x_i, v_j)x_i + \frac{\alpha}{N_R}\sum_{r\in N_i}K(x_r, v_j)x_r\right)}{\sum_{i=1}^{N}\mu_{ji}^m\left(K(x_i, v_j) + \frac{\alpha}{N_R}\sum_{r\in N_i}K(x_r, v_j)\right)} \quad (13)$$

The neighbourhood information has to be computed at each iteration which is very time consuming process. To reduce the computation time of KFCM_S, Chen and Zhang proposed its two variants [6], named KFCM_S1andKFCM_S2. Kernel implication to FCM_S1 and FCM_S2 modifies the objective function from (14) to (15) as follows:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^m\left\|x_i - v_j\right\|^2 + \alpha\sum_{j=1}^{c}\sum_{r\epsilon N_i}\mu_{jr}^m\left\|\bar{x}_r - v_j\right\|^2 \quad (14)$$

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^m\left(1 - K(x_i, v_j)\right) + \alpha\sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^m\left(1 - K(\bar{x}_r, v_j)\right) \quad (15)$$

The membership matrix μ_{ji} and cluster center v_j are calculated by equations given as follows:

$$\mu_{ji} = \frac{\left(\left(1 - K(x_i, v_j)\right) + \alpha\left(1 - K(\bar{x}_i, v_j)\right)\right)^{\frac{-1}{m-1}}}{\sum_{k=1}^{c}\left(\left(1 - K(x_i, v_k)\right) + \alpha\left(1 - K(\bar{x}_i, v_k)\right)\right)^{\frac{-1}{m-1}}} \quad (16)$$

$$v_j = \frac{\sum_{i=1}^{N}\mu_{ji}^m\left(K(x_i, v_j)x_i + \alpha K(\bar{x}_i, v_j)\bar{x}_i\right)}{\sum_{i=1}^{N}\mu_{ji}^m\left(K(x_i, v_j) + \alpha K(\bar{x}_i, v_j)\right)} \quad (17)$$

For KFCM_S1, $\bar{x}_i$ represents the mean-filtered image and for KFCM_S2, $\bar{x}_i$ represents the median-filtered image. To speed up the clustering process, $\bar{x}_i$ is computed in advance.

2.3 Kernelized Weighted Fuzzy Local Information C-means (KWFLICM)

Gong et al. presented the KWFLICM algorithm [10] by combining the kernel metrics and weighting factor on FLICM [9] to provide better and effective segmentation results and noise immunity. The objective function of FLICM is given below:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c}\left[\mu_{ji}^m\left\|x_i - v_j\right\|^2 + G_{ji}\right] \quad (18)$$

Addition of kernel metric to FLICM, updated the objective function in the following manner.

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c}\mu_{ji}^m\left(1 - K(x_i, v_j)\right) + G'_{ji} \quad (19)$$

$$G'_{ji} = \sum_{\substack{k \in N_i \\ i \neq k}} w_{ik} \left(1 - \mu_{jk}\right)^m \left(1 - K(x_k, v_j)\right) \quad \textbf{(20)}$$

where $K(x, y)$, v_j and μ_{ji} are defined as same as before, N_i is the set of neighbors in a window around x_i, $\left(1 - \mu_{jk}\right)^m$ is a penalty which can accelerate the iterative convergence to some extent. w_{ik} is the trade-off weighted fuzzy factor of k^{th} in a local window around x_i defined below:

$$w_{ik} = w_{sc}.w_{gc} \quad \textbf{(21)}$$

where w_{sc} is the damping extent of the neighbor pixels from the central pixel and it is defined as

$$w_{sc} = {}^{1}\!/_{(d_{ik} + 1)} \quad \textbf{(22)}$$

where d_{ik} is the spatial Euclidean distance between the k^{th} pixel in neighbors and the central pixel. And for w_{gc}, we need to follow some computations given below:

$$C_k = \frac{var(x)}{(\bar{x})^2} \quad \textbf{(23)}$$

$$\bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} \quad \textbf{(24)}$$

$$var(x) = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N} \quad \textbf{(25)}$$

where $var(x)$ and $\bar{x}$ are the intensity variance and mean in a local window of the image, respectively and C_k itself is the local coefficient of variation. Next we project C_k into kernel space and calculate $\bar{C}$ i.e. mean of C_k in local window.

$$\bar{C} = \frac{\sum_{k \in N_i} C_k}{n_i} \quad \textbf{(26)}$$

where n_i is the local cardinality.

$$\xi_{ik} = exp[-(C_k - \bar{C})], \qquad k \in N_i \quad \textbf{(27)}$$

$$\eta_{ik} = \frac{\xi_{ik}}{\sum_{j \in N_i} \xi_{ij}} \quad \textbf{(28)}$$

$$w_{gc} = \begin{cases} 2 + \eta_{ik}, & C_k < \bar{C} \\ 2 - \eta_{ik}, & C_k \geq \bar{C} \end{cases} \quad \textbf{(29)}$$

where constant 2 guarantees the weight w_{gc} is non-negative. The two updated formulas for minimizing objective function, with respect to μ_{ji} and v_j is obtained as follows:

$$\mu_{ji} = \frac{\left(\left(1 - K(x_i, v_j)\right) + G_{ji}\right)^{-1/(m-1)}}{\sum_{k=1}^{c} \left(\left(1 - K(x_i, v_k)\right) + G_{ki}\right)^{-1/(m-1)}} \quad \textbf{(30)}$$

$$v_j = \frac{\sum_{i=1}^{N} \mu_{ji}^m K(x_i, v_j) x_i}{\sum_{i=1}^{N} \mu_{ji}^m K(x_i, v_j)} \quad \textbf{(31)}$$

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III. EXPERIMENTAL RESULTS

This section portrays some experimental results on brain MRI images to show the segmentation performance of various kernelized FCM algorithms. We try to have experimental results for KFCM, KFCM_S, KFCM_S1, KFCM_S2 and KWFLICM. Furthermore, we compare the performance efficiency of all these segmentation methods. The segmentation performance is evaluated quantitatively by using two measures i.e. jaccard similarity (JS) and similarity index (ρ) [3].

JS is the ratio between intersection (number of common pixels) and union (number of identical pixels) of the segmented class and ground truth class. It is the indication of similarity between $I_{gt}$and I_{seg}, and defined as:

$$JS = \frac{I_{gt} \cap I_{seg}}{I_{gt} \cup I_{seg}} \quad \textbf{(32)}$$

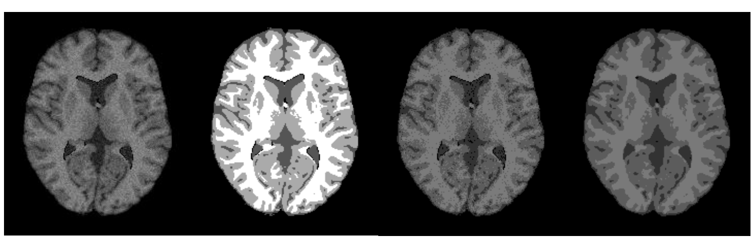
where,I_{gt} represents the set of pixels in ground truth image and I_{seg} represents the set of pixels in segmented image.The segmented output image is compared with its corresponding ground truth image and the similarity within each cluster is calculated.

Similarity index (ρ)is another important measure which not only considers similar pixels, but also the contribution of the dissimilar pixels towards its value. It provides the overall segmentation accuracy for all the classes. It is defined as:

$$\rho = 2 \times \frac{I_{gt} \cap I_{seg}}{I_{gt} + I_{seg}} \quad \textbf{(33)}$$

where, I_{gt} and I_{seg} defined as same as in JS. The value of JS and ρ ranges from 0 to 1, with a value near to one indicates more accurate segmentation. If the values of these parameters are near to zero, it means there are a lesser number of common pixels between the segmented output image and the corresponding segmented ground truth image. The value near to one indicates more accurate segmentation.

In our experiments, we apply these segmentation methods to a medical image i.e. brain MR image of size 181 × 217. The image includes four clusters with the corresponding gray values taken as 0, 85, 170 and 255. The 80th slice of simulated brain MR image with 9% Rician noise, ground truth image and segmentation results using various segmentation methods are shown in Fig. 1. Table 1 and Table 2 provide the comparison of different algorithms quantitatively in terms of JS and ρ respectively.



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

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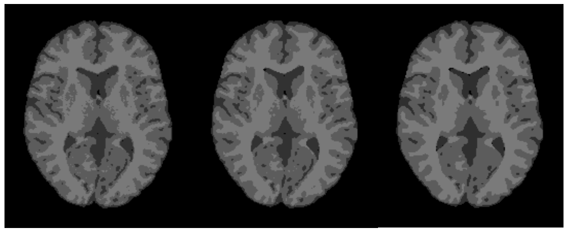

(e) (f) (g)

Fig. 1 (a) Input image (b) Ground truth image (c) KFCM result (d) KFCM_S result (e) KFCM_S1 result (f) KFCM_S2 result (g) KWFLICM result.

Table 1. Segmentation evaluation with jaccard similarity.

Brain tissues	KFCM	KFCM_S	KFCM_S1	KFCM_S2	KWFLICM
CSF	70.61	71.43	73.20	73.73	76.90
GM	74.17	70.36	72.60	72.75	83.16
WM	74.37	74.37	76.46	76.31	86.96

Table 2. Segmentation evaluation with similarity index.

KFCM	KFCM_S	KFCM_S1	KFCM_S2	KWFLICM
87.50	87.69	88.72	88.81	92.58

Table1 illustrates the superior segmentation results of KWFLICM for CSF, GM and WM. In general, MR images are contaminated with Rician noise. So, to further test the performance of segmentation algorithms we apply these algorithms on simulated 80th brain slice with different noise levels 3%, 5%, 7% and 9%. We use $\alpha = 0.1$ and $\sigma = 45.0$ in the experiments.

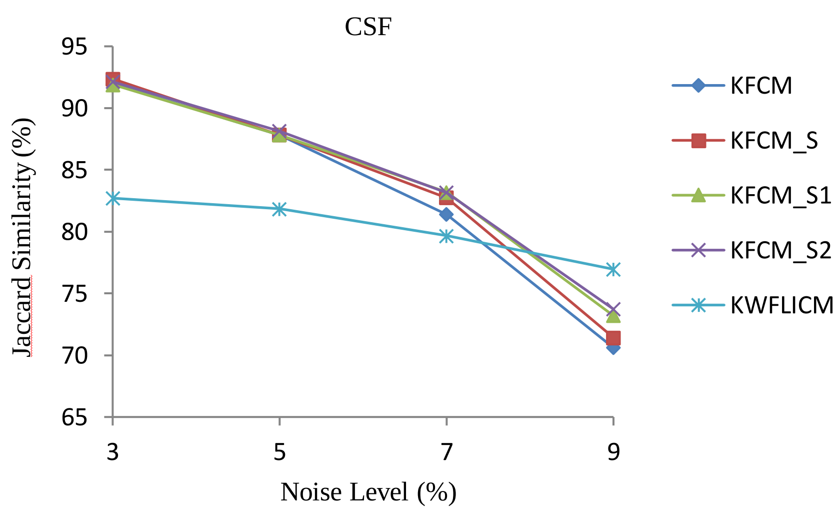

Fig. 2 Segmentation Accuracy (JS) (%) on CSF

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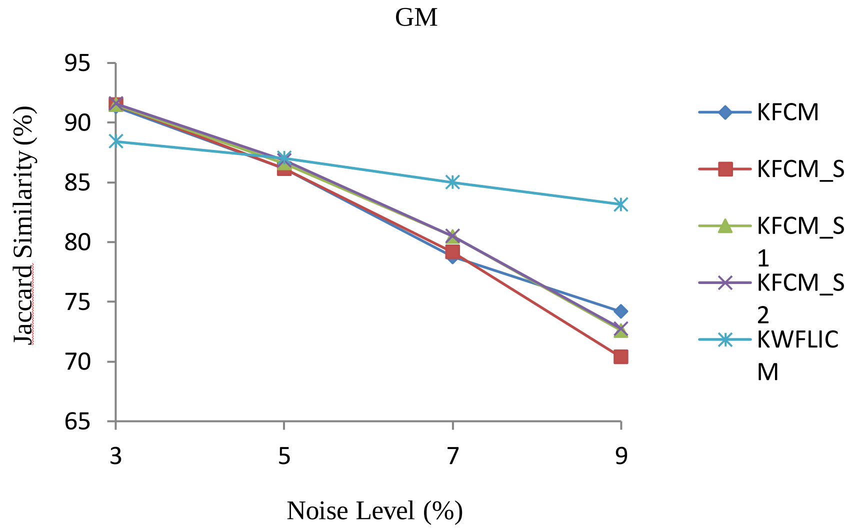

Fig. 3 Segmentation Accuracy (JS) (%) on GM

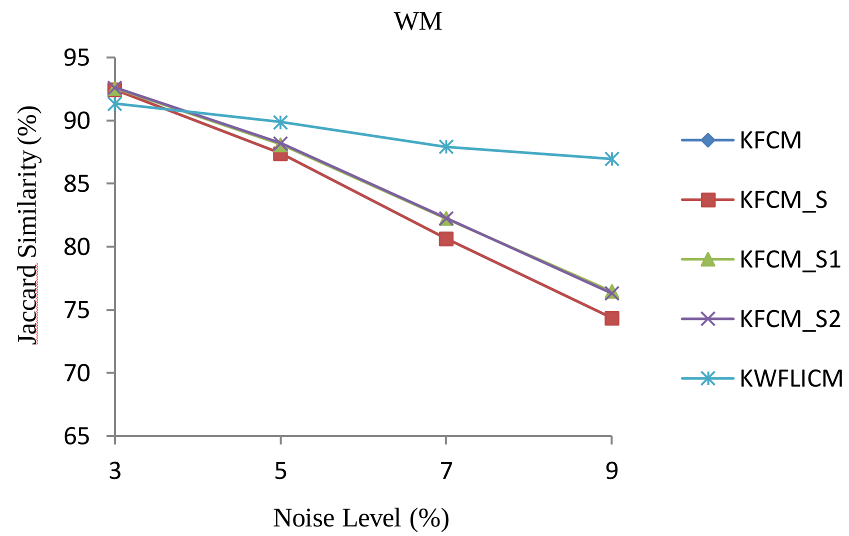

Fig. 4 Segmentation Accuracy (JS) (%) on WM

Fig. 2, 3 and 4 show the segmentation results for MR image having different noise levels on CSF, GM and WM regions respectively.

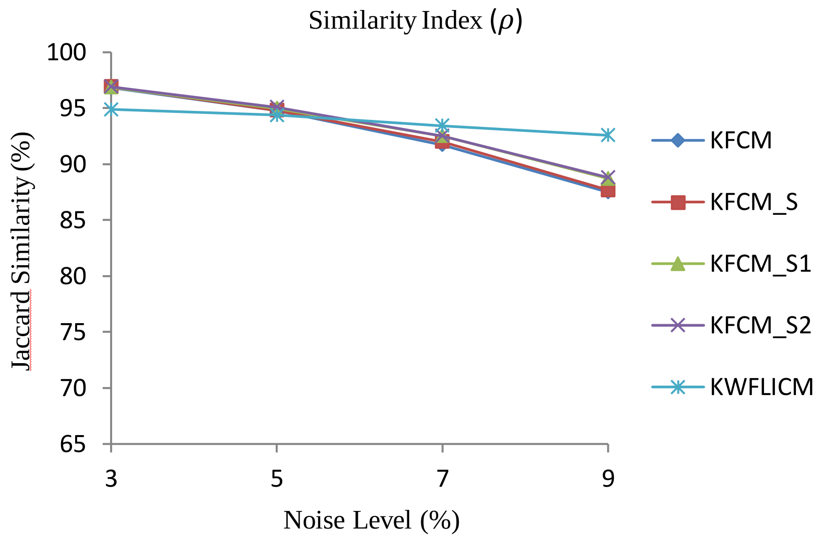

Fig. 4 Similarity Index (ρ) (%)

IV. CONCLUSION

We present a comparative study and performance analysis of kernelized fuzzy c- means based segmentation methods for brain MR images. The performance evaluation parameters are JS and ρ. Unlike KFCM, KFCM_S, KFCM_S1 and KFCM_S2, KWFLICM can overpower the effect of noise. Although, as the noise increased in the image, segmentation results get worse but in comparison with several state-of-the-art methods, KWFLICM gives better results for high noisy images. For example for noise level 9%, KWFLICM gives highest segmentation performance for both the performance metrics (JS and ρ).

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