

## Exploring the Role of Big Data Analytics in Enhancing Business Intelligence: A UAE Case Study

Prof. Isabella Müller

Faculty of Computer Science, Technical University of Munich, Munich, Germany

---

### 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( $\rho$ ).

*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:

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

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

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

where  $\sigma$  is an adjustable parameter of GRBF.

The objective function of classical FCM is given by:

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

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

$$d_{ji} = \|x_i - v_j\| \tag{4}$$

$X = \{x_1, x_2 \dots x_n\}$  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:

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

By kernel substitution,

$$\begin{aligned} \|\varphi(x_i) - \varphi(v_j)\|^2 &= (\varphi(x_i) - \varphi(v_j))^T (\varphi(x_i) - \varphi(v_j)) \\ &= \varphi(x_i)^T \varphi(x_i) - \varphi(v_j)^T \varphi(x_i) \\ &\quad - \varphi(x_i)^T \varphi(v_j) + \varphi(v_j)^T \varphi(v_j) \\ &= K(x_i, x_i)K(v_j, v_j) - 2K(x_i, v_j) \end{aligned} \tag{6}$$

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

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

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

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

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

KFCM algorithm is given as follows:

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

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

*Step3:* Compute the fuzzy membership matrix  $\mu_{ji}$  using (8).

*Step4:* Update new cluster centers  $v_j$  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:

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

By incorporation of kernel function, the updated objective function of KFCM\_S is given as below:

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

where  $x_i$  is the grey value of the  $i^{th}$  pixel,  $v_j$  represents the  $j^{th}$  cluster,  $\mu_{ji}$  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:

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

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

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\_S1 and KFCM\_S2. Kernel implication to FCM\_S1 and FCM\_S2 modifies the objective function from (14) to (15) as follows:

$$J_m = \sum_{i=1}^N \sum_{j=1}^c \mu_{ji}^m \|x_i - v_j\|^2 + a \sum_{j=1}^c \sum_{r \in N_i} \mu_{jr}^m \|\bar{x}_r - v_j\|^2 \tag{14}$$

$$J_m = \sum_{i=1}^N \sum_{j=1}^c \mu_{ji}^m (1 - K(x_i, v_j)) + a \sum_{i=1}^N \sum_{j=1}^c \mu_{ji}^m (1 - K(\bar{x}_i, v_j)) \tag{15}$$

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

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

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

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:

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

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

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

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

where  $K(x, y)$ ,  $v_j$  and  $\mu_{ji}$  are defined as same as before,  $N_i$  is the set of neighbors in a window around  $x_i$ ,  $(1 - \mu_{jk})^m$  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:

$$w_{ik} = w_{sc} \cdot w_{gc} \tag{21}$$

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

$$w_{sc} = 1 / (d_{ik} + 1) \tag{22}$$

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:

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

$$\bar{x} = \frac{\sum_{i=1}^N x_i}{N} \tag{24}$$

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

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.

$$\bar{C} = \frac{\sum_{k \in N_i} C_k}{n_i} \tag{26}$$

where  $n_i$  is the local cardinality.

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

$$\eta_{ik} = \frac{\xi_{ik}}{\sum_{j \in N_i} \xi_{ij}} \tag{28}$$

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

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

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

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

### 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 ( $\rho$ ) [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:

$$JS = \frac{I_{gt} \cap I_{seg}}{I_{gt} \cup I_{seg}} \tag{32}$$

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 ( $\rho$ ) 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:

$$\rho = 2 \times \frac{I_{gt} \cap I_{seg}}{I_{gt} + I_{seg}} \tag{33}$$

where,  $I_{gt}$  and  $I_{seg}$  defined as same as in JS. The value of JS and  $\rho$  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  $181 \times 217$ . The image includes four clusters with the corresponding gray values taken as 0, 85, 170 and 255. The 80<sup>th</sup> 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  $\rho$  respectively.

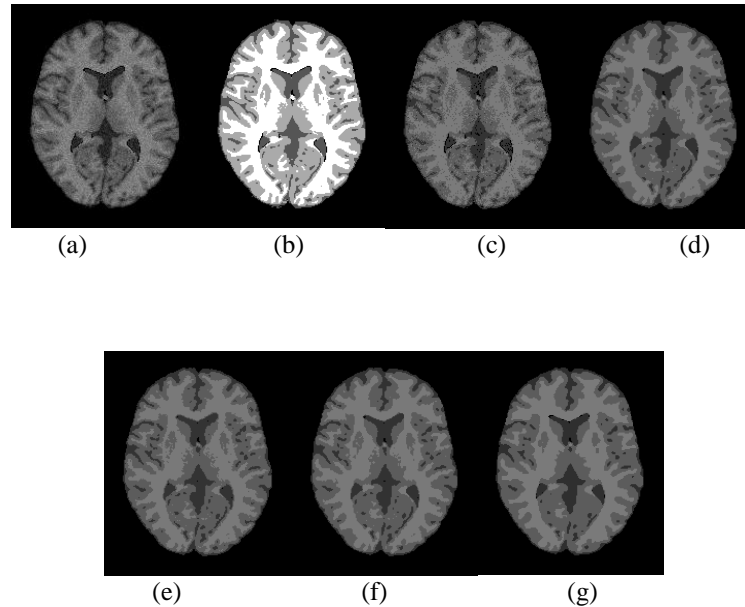


Fig. 1 (a) Input image (b) Ground truth image (c) KFCM result (d) KFCM\_S result (e) KFCM\_S1 result (f) KFCM\_S2 result (g) KWFLICM result.

Table 1. Segmentation evaluation with jaccard similarity.

Brain tissues	KFCM	KFCM_S	KFCM_S		KWFLIC
			1	2	
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_S		KWFLIC
		1	2	M
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 80<sup>th</sup> brain slice with different noise levels 3%, 5%, 7% and 9%. We use  $\alpha = 0.1$  and  $\sigma = 45.0$  in the experiments.

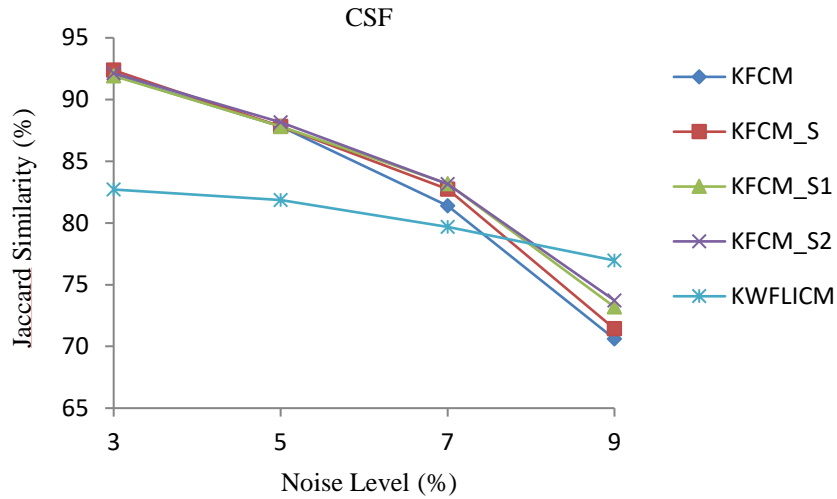


Fig. 2 Segmentation Accuracy (JS) (%) on CSF

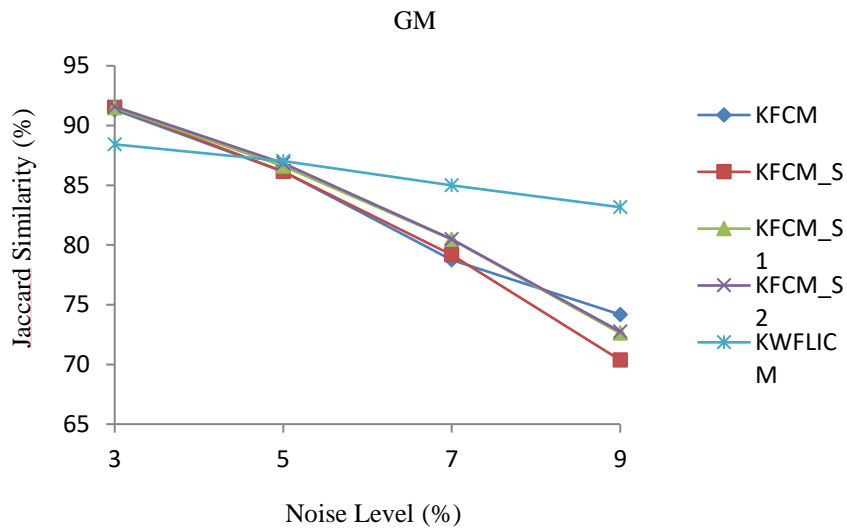


Fig. 3 Segmentation Accuracy (JS) (%) on GM

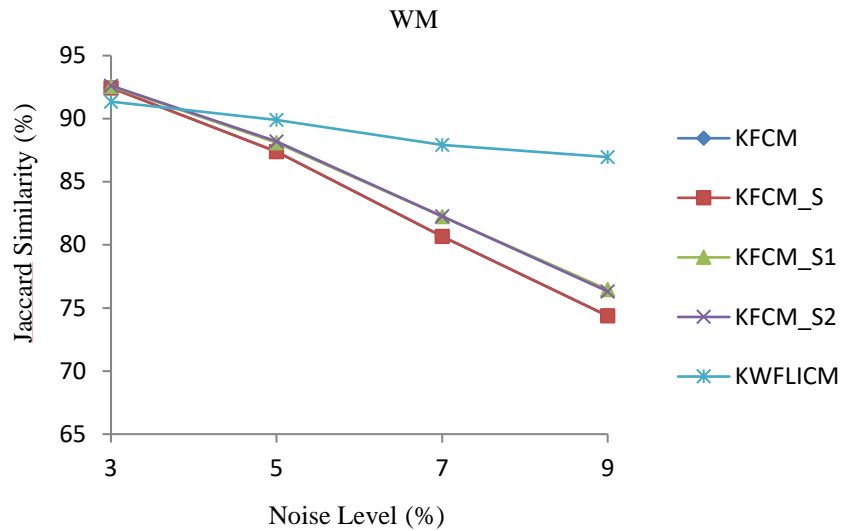


Fig. 4 Segmentation Accuracy (JS) (%) on WM

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

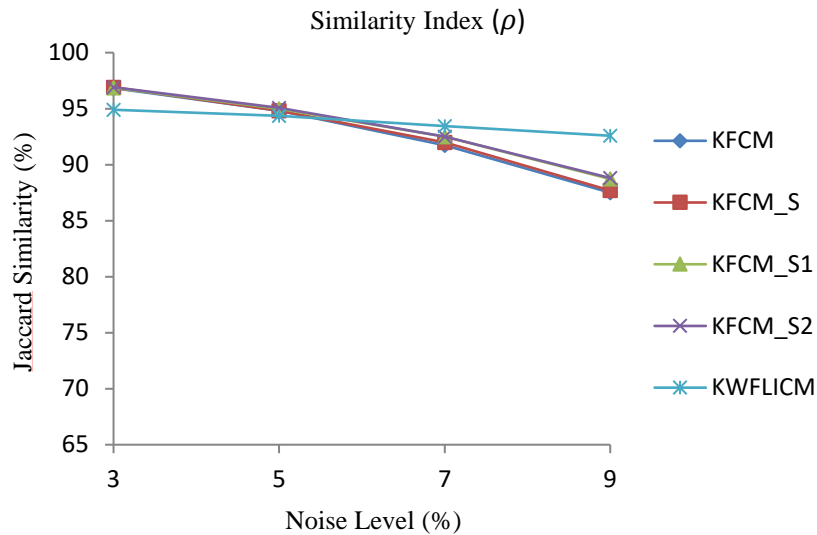


Fig. 4 Similarity Index (ρ) (%)

#### 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  $\rho$ . 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  $\rho$ ).

#### REFERENCES



1. Er. Anjna, Er. Rajandeep Kaur: Review of image segmentation technique. *International journal of advanced research in computer science*, Vol 8, No. 4 (2017).
2. N. Dhanachandra, K. Manglem, Y. J. Chanu: Image segmentation using  $k$ -means clustering algorithm and subtractive clustering algorithm. *Procedia Computer Science*, 54 (2015) 764 – 771.
3. S. Agrawal, R. Panda, L. Dora: A study on fuzzy clustering for magnetic resonance brain image segmentation using soft computing approaches. *Applied soft computing* 24 (2014) 522–533.
4. M. N. Ahmed: A modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI data. *IEEE transactions on medical imaging*, Vol. 21, No. 3 (2002).
5. S. Chen, D. Zhang: Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure. *IEEE transactions on systems, man and cybernetics-Part B: cybernetics*, Vol. 34, No. 4 (2004).
6. DQ Zhang, SC Chen: A novel kernelized fuzzy C-means algorithm with application in medical image segmentation. *Artificial intelligence in medicine* (2004) 32, 37-50.
7. L. Szilagyii, Z. Benyo, S. Szilagyii, H. S. Adam: MR brain image segmentation using an enhanced fuzzy c-means algorithm. *Proceedings of 25th annual international conference of the IEEE engineering in medicine and biology society*, Vol. 1 (2003) 724–726.
8. W. Cai, S. Chen, D. Zhang: Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation. *Pattern recognition* 40 (2007) 825 – 838.
9. S. Krinidis, V. Chatzis: A robust fuzzy local information C-means clustering algorithm. *IEEE transactions on image processing*, Vol. 19, Issue: 5 (2010).
10. M. Gong, Y. Liang, J. Shi, W. Ma, J. Ma: Fuzzy c-means clustering with local information and kernel metric for image segmentation. *IEEE trans. image process*, Vol. 22, No. 2 (2013) 573–584.