ADAPTIVE WEIGHTED-COVARIANCE REGULARIZED KERNEL FUZZY C MEANS ALGORITHM FOR MEDICAL IMAGE SEGMENTATION

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ABSTRACT

Image segmentation is the most common method used to analyze and locate deformities in medical images. Clustering is a technique used in segmentation to group up similar data in a single cluster. FCM is the successful clustering technique employed, which is repeatedly modified by the researcher to make it more robust against noise. In this paper, we present an improved kernel FCM algorithm for image segmentation by introducing a regularization parameter with covariance weighted fuzzy factor and a Gaussian kernel metric. It calculates and uses the heterogeneity of gray scales in the neighborhood location for acquiring local contextual information and replaces the standard Euclidean distance with Gaussian radial basis kernel functions. The main advantages are adaptiveness to local context, preserve image details with enhanced robustness, independence of clustering parameters and decreased computational costs. The experiments are done in Brain Magnetic Resonance Images (MRI) and results are analyzed, show that the proposed algorithm is better segmentation accuracy and efficiency than the other methods.

Keywords: *Fuzzy c-means; Gaussian Kernel; Medical images; Weighted Covariance; Magnetic Resonance Imaging.*

1. INTRODUCTION

Medical imaging is the process of observing the interior parts of the body, which aims at the maintenance of health, the prevention and treatment of disease. Many advanced techniques have been made in modern medicine to improve the collection of information about the human body. It helps in finding the abnormalities in brain, lungs, bones, tissues etc. The goal is to represent a set of meaningful areas from a single image by means of splitting it. It is very important to typically view the details of medical images where both the pre and post-surgery decisions are required in diagnosis because treatments are normally sensitive to particular disease. Many approaches on segmentation have been proposed so far [1], [2]. Clustering technique has a wide and rich history of successful image information among all. The process of converting a dataset by clusters, which are the group of data points that belong together, is known as clustering [3]. It is done by grouping the data in the form of their properties and characteristics. Hard and soft clustering schemes are the two major classifications used, FCM is one of the major techniques used to perform medical image segmentation and it earns satisfactory results in many applications [4]. Although the FCM is good at noise free images, it lags to blend some clear information about the features of the image like location, surface etc. There comes the fuzzy c-means scheme, which gives advanced accuracy of feature description in medical image segmentation [5]. Generally, each pixel of a region in an image will have some properties; those properties are well identified and represented by the use of FCM method.

Fuzzy c-means logic is further stimulated by the use of kernel method [6] which yields better performance. Kernel FCM algorithm is implemented by selecting a best kernel among an extensive set of possibilities [7], [8]. But it provides only limited knowledge about the selection of suitable kernel for a particular task. Although many kernel selection methods have been introduced, the need of producing suitable kernels is still increasing which gives raise to the repeated modification in the kernel FCM [9]. A new method of image segmentation is conducted using Adaptive Weighted-covariance regularized Kernel Fuzzy C Means (AWCKFCM), which is to provide segmentation method with less complexity. The kernel selection and control of contextual information is increased in this technique with the help of weighted [10] covariance image design. The input image is pre-processed and the clusters are formed by the feature extraction technique. FCM's general equation or objective function is found and the spatial contents are added. The kernel metric function is derived by including a regularization parameter and a weighted covariance image calculation, so as to find the distribution of pixels in the local window with respect to its center and neighbor, which helps in producing accurate image details. At last, the new objective function is then acquired by combining the information of regularized parameter with weighted kernel function, which are continuously iterated and the pixels can be classified. The algorithms have been validated in both clinical MRI of brain medical and multimedia images with different types and levels of noises and compared with four recent soft clustering algorithms such as K-Means, FCM, KFCM, PSO-SFCM, and ABC- KFCM respectively. The accuracy of the proposed ARKFCM is calculated by applying the condition noise, i.e the images are tested with and without noise values. The pixel error count and the centroid estimation are the two parameters used in the validation of accuracy. Further, the variance occurred in the pixel generation and their behavior is described as well in the resulting portion.

The proposed adaptive weighted covariance based KFCM algorithm is superior in preserving image details and segmentation accuracy while maintaining a low computational complexity. Also, it provides a solution for various segmentation problems like lack of robustness to outliers, high computational cost, loss of pixel clarity and loss of image details

The remaining of this paper is organized as follows. Section 2 gives some brief background of researches related to the proposed technique. The background of the research is explained in section 3. Section 4 describes the proposed scheme. The experimental results and discussions of the proposed approach are presented in Section 5. Finally, conclusions are summarized in Section 6.

2. LITERATURE REVIEW

Kernel FCM is one of the widely used algorithms which is constantly experimented and modified to give better knowledge about spatial information. Fuhua Zheng et al [11] proposed a fast anti-noise FCM algorithm to reduce the effect of noise by constructing spatial information with the help of pixel value and membership function combination. It gives limited clustering performance, which can be made possible by the use of adaptive choose of optimal parameters. Whereas, proposed FCM approach consumed more time for segmentation and showed complexity to the system.

Weighted fuzzy factor and kernel metric method has been proposed by R.Shalini, V. Muralidharan and M. Varatharaj [12] to identify the tumor cells in brain MR images, which has given improvement in accuracy of segmentation. The details of the pixel distribution can be improved by regularizing the weighted trade-off fuzzy factor. The use of regularization parameter to calculate weight in this paper will result in the selection of best pixel values. The proposed scheme showed comparable outcome in case of more noise, a suitable noise removal factor was to be included.

P.Sivasangareswari, K.Sathish Kumar has made a modification in FCM algorithm [13] based on distance metric to satisfy the problem of intensity in homogeneities and noise. Distance metric has been introduced to reduce the random number of variables from the segmented image of modified FCM. The local neighbor relationship is controlled adaptively with a trade-off fuzzy method, but it leads to misclassification of the kernels associated with the image.

Another method of kernel weighted FCM is proposed earlier by S. Santhosh Kumar, James Albert [14] in which the area of the tumor is calculated and shape is analyzed using edge detection technique. It improves FCM by introducing the weights for pixels within local neighbor windows, but the edge detection is followed by the morphological filtering method which carries more number of iterations. This technique segment only normal brain tissue, the abnormal tissue classification was absent.

Ahmed Elazab et al proposed an adaptive regularized kernel based fuzzy c-means clustering for MRI segmentation purpose [15]. It produced enhanced robustness against loss of pixel details with a regularized parameter inclusion but it requires more number of iterations as it is required to calculate the local coefficient of variance with a square value. The variation of changes between dispersed pixel particles consumes time, thus covariance of weighted image is determined in the proposed algorithm to save time and complexity, which keeps the center pixel as constant and iterates the neighbor pixels. The system was complex when the number of features or iteration was more, thus weight method has been used in our research.

To overcome the above mentioned drawbacks, an effective algorithm is implemented in K-FCM, which enhances the procedure acclimated in our anticipated strategy.

3. PROPOSED SYSTEM

In FCM algorithm, the clusters in the image space are formed by assigning a membership value to each pixel. Fuzzy c-means (FCM) is a clustering method that permits one bit of data to be in the right position to two or more clusters. FCM begins with a starting guess for the cluster centers that are suggested to spot mean location of every cluster. The primary guess for these cluster centers is most like erroneous. Also, FCM allots each data point a membership ranks for every cluster. FCM repeatedly shifts the cluster centers towards the correct place inside a dataset through repeatedly updating the centers of the cluster & the membership grades for every data point. This repetition is based on minimizing an objective function that symbolizes the distance from any given data point to a cluster center weighted by that data point's membership rank.

3.1 Deriving the FCM's general objective function

The initial step of the algorithm is to find the general equation or objective function of the Conventional FCM. The membership function is also achieved after obtaining the objective function of FCM which is denoted as J_{FCM}. Let I be an image that consist of a set of grayscales x_i at pixel $i(i=1,2,.....,N)$, $X=\{x_1,x_2,.....x_N\}\subset R^k$ in k-dimensional space and cluster centers $v=\{v_1,v_2,.....v_c\}$ with c being a positive integer $(2<c<<N)$, and u_{ij} is the membership value for each pixel i in j th cluster $(j=1,2,.....,c)$. The objective function of the FCM algorithm is stated as

$$J_{FCM}=\sum_{i=1}^{N}\sum_{j=1}^{c}u_{ij}^{m}\,\|x_i-v_j\|^2, \tag{1}$$

Here in Eq. 1, m is a weighting exponent to the degree of fuzziness, $m>1$ and $\|x_i-v_j\|^2$ is the grayscale distance between i and v_j. Cost function is reduced when high membership values are allocated to pixels near to the centroid of their respective clusters, then low membership values are allocated to pixels with data far from the centroid. The probability that a pixel belongs to a specific cluster signifies by the membership function. The probability is reliant only on the distance between the pixel & every single cluster centered in the feature domain in the FCM algorithm.

$$\sum_{j=1}^{c}u_{ij}=1,\ u_{ij}\in[0,1],\ 0\le\sum_{i-1}^{N}u_{ij}\le N \tag{2}$$

Using the alternate optimization method membership function and cluster centers are updated iteratively

$$u_{ij}=\frac{1}{\sum_{k=1}^{c}(\|x_i-v_j\|^2/\|x_i-v_k\|^2)^{1/(m-1)}},$$

$$v_j=\frac{\sum_{i-1}^{N}u_{ij}^{m}x_i}{\sum_{i=1}^{N}u_{ij}^{m}}, \tag{3}$$

The presence of noise and image artifacts in FCM can be decreased by adding the external parameter to the fuzziness function J_{FCM}. One of the imperative attributes of an image is that neighboring pixels are exceedingly correlated. It means that, these neighboring pixels have comparative feature values, & the possibility that they have a place with the same cluster is incredible. In clustering this spatial relation is essential, however, in a standard FCM algorithm it is not used. Thus, in this system, spatial information of neighboring pixels are combined with the general equation, this can be denoted as

$$\begin{aligned}J_{FCM\_S}&=\sum_{i=1}^{N}\sum_{j=1}^{c}u_{ij}^{m}\,\|x_i-v_j\|^2\\&+\frac{\alpha}{N_R}\sum_{i=1}^{N}\sum_{j=1}^{c}u_{ij}^{m}\Big(\sum_{r\in N_i}\|x_r-v_j\|^2\Big),\end{aligned} \tag{4}$$

Where α a parameter to manage spatial information of neighbors is N_i is the set of pixel and N_r is the cardinality of N_i. In a homogenous region, the spatial functions just strengthen the original membership, & the clustering outcome

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stays unaltered. For a noisy pixel, on the other hand, this formula decreases a noisy cluster's weighting through the labels of its neighboring pixels. Consequently, misclassified pixels from noisy regions or spurious blobs can effortlessly be revised.

To avoid the neighborhood function to be calculated at every step as it is not so easy to be done frequently, it is decreased by the addition of the term $(1/N_R)\sum_{r\in N_R}\|x_i - v_j\|^2$ with $\|\bar{x}_i - v_j\|^2$, need to calculate once and used in a repetitive manner where $\bar{x}$ is the grayscale of a filtered image.

$$J_{FCM\_S1,2} = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^m \|x_i - v_j\|^2 + \alpha\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^m \|\bar{x}_i - v_j\|^2, \tag{5}$$

In addition, a Gaussian kernel-based FCM is proposed which calculates the parameter η_j at every step of the iterations to replace α for every cluster.

The clustering is consisting of a two-pass procedure at every repetition. The first pass is similar like that in conventional FCM to compute membership function in spectral domain. In second pass, every pixel's membership information is mapped to spatial domain, & spatial function is calculated from that. The FCM repetition continues with the new membership that is combined with the spatial function. The repetition is halted when the maximum dissimilarity between two cluster centers at two continuous repetitions is less than a threshold (=0.02). After the convergence, defuzzification is employed to allocate every pixel to a particular cluster for which the membership is maximal. Membership optimization leads a better clustering average. Here we choose sFCM 1,0 and sFCM 2,0 for testing. But optimization in centroid is highly challengeable. So we are introducing modified centroid weight particle swarm optimization. Then the kernel functions are used here to calculate the parameter value. With the intention to overcome the problem of the standard FCM algorithm, the KFCM algorithm is designed. With the aid of a nonlinear mapping function, the KFCM converts the input data in the image plane into higher dimensional feature space. The complex and nonlinear separable problem in the input plane can be converted with the aid of the mapping function into linearly separable in the future space, which is given by

$$\eta_j = \frac{\min_{j'\neq j}(1-K(v'_j, v_j))}{\max_k(1-K(v_k, \bar{x}))}, \tag{6}$$

Here K is the kernel function. This could give better results than FCM_S1 and FCM_S2. But it requires large number of patterns and many cluster centers to find the optimal value for η_j. To overcome this problem, the spatial context and grayscale information of the neighboring pixels are combined in the later algorithm using a fuzzy factor. The fuzzy factor G_{ij} was included in the objective function of the FCM i.e., (1) as follows

$$J_{FLICM} = \sum_{i=1}^{N}\sum_{j=1}^{c}[u_{ij}^m \|x_i - v_j\|^2 + G_{ij}], \tag{7}$$

A weighted fuzzy factor G'_{ij} has been derived as

$$G'_{ij} = \sum_{k\in N_I, i\neq k} \omega_{ik}(1-u_{ij})^m(1-K(x_i, v_j)), \tag{8}$$

Will control the local neighbor relationship and replace the Euclidean distance with a kernel function, where ω_{ik} denotes the trade-off weighted fuzzy factor around the central pixel i and $1-K(x_i, v_j)$ is the kernel metric function.

3.2 The introduced regularization term

The parameter α used is to estimate the power of noise present in an image. It helps regularizing the pixel information present in the features of the image. The features affected by more noises are able to be corrected in this step with the suitable selection and application of regularization term. If φ_i is too large, the regularized solution is under-smoothed, while if φ_i is too small, the regularized solution does not fit the given data properly. A good recovered image can be obtained by choosing a suitable φ_i. In general, the strength of the regularization relates to the noise level: the more severe the noise, the larger the regularization. Thus, regularization term used in this system denotes the variation of the features according to the noise. If the evaluated regularization parameter is higher, then it denotes the image containing more noise. The setting up of the regularization parameter needs a prior knowledge about noise data which is not easily possible. Hence, adaptive calculation of α is necessary according to the pixel being processed.

The adaptive technique is carried away by defining the covariance information of the pixels. The distribution of pixels and their relationship is estimated by adding a regulating factor of covariance matrix to each pixel value. It is based on the inverse of the covariance between all neighborhood pixels and the center pixel.

Consider the covariance equation of pixels x_i and v_i as follows,

$$\mathrm{cov}(x_i, v_i) = \frac{\sum_{k<N_i}\sum_{i=1}^{N_i}(x_k - \overline{x_i})(v_k - \overline{v_i})}{N_i - 1} \quad (9)$$

Where x_k is the grayscale of any pixel falling in the local window is set N_i around the pixel i and $\overline{x_i}$ is its mean gray scale value. Then the covariance equation $\mathrm{cov}(x_i, v_i)$ is applied to derive the corresponding weights within the local window and it is denoted as ω_i.

$$\omega_i = \frac{1}{|\mathrm{cov}(x_i, v_i)|}$$

This can also be determined as

$$\omega_i = |\mathrm{cov}(x_i, v_i)|^{-1} \quad (10)$$

The regularization parameter is calculated with the ultimate weight assigned to every pixel in the local window

$$\varphi_i = \begin{cases} 2+\omega_i & \overline{x_i} < x_i \\ 2-\omega_i & \overline{x_i} > x_i \\ 0 & \overline{x_i} = x_i \end{cases} \quad (11)$$

The parameter φ_i assigns higher values for those pixels with high covariance (for pixel i being brighter than the average grayscale of its neighbors, φ_i will be $2+\omega_i$, and ω_i will be large when the sum of covariance within its neighborhood is large) and lower values otherwise. The proposed parameter φ_i is embedded into the eq (5). The φ_i will get into a homogenous clustering according to the pixel distribution (11) while the other existing algorithms tend to make the clustering.

That yields more homogeneous labels by incorporating the contextual information.

3.3 Devising a Weighted Image

The grayscale value of the median filter from the original image $\overline{x}$ can also be replaced by the newly formed weighted image, shown in (12). It is formed by utilizing φ_i obviously for making the weighted image free from parameters that are difficult to adjust.

$$\overline{\xi_i} = \frac{1}{2+\max(\varphi_i)}\left(x_i + \frac{1+\max(\varphi_i)}{N_R - 1}\sum_{r\in N_i} x_r\right) \quad (12)$$

In which x_r and N_i are the grayscale and neighborhood of pixel i and N_r is the cardinality of N_i.

3.4 Measuring distance using kernel function

The Euclidean distance metric is converted into a kernel metric as it is robust against outliers and noise. The kernel functions are able to project the data into higher dimensional space where the data could be more easily separated. Thus the Euclidean distance term $\| x_i - v_j \|^2$ is replaced by $\| \varphi(x_i) - \varphi(v_j) \|^2$.

$$\| \varphi(x_i) - \varphi(v_j) \|^2 = K(x_i, x_i) + K(v_j, v_j) - 2K(x_i, v_j) \quad (13)$$

Where K is the kernel function. This paper also uses Gaussian Radial Basis Function (GRBF), which is a popular kernel function used in various Kernalized learning algorithms to modify the derived kernel function as

$$\| \varphi(x_i) - \varphi(v_j) \|^2 = 2(1 - K(x_i, v_j)) \quad (14)$$

The adaptive regularization parameter and kernel metric distance (14) are now replaced into the objective function of FCM as

$$J_{AWCFCM} = 2\left[\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}{}^{m}(1 - K(x_i, v_j)) + \sum_{i=1}^{N}\sum_{j=1}^{c}\varphi_i u_{ij}{}^{m}(1 - K(\overline{x_i}, v_j))\right] \quad (15)$$

This equation will goes into an alternate optimization to produce $J_{AWCKFCM}(u, v)$ as follows

$$u_{ij} = \frac{((1 - K(x_i, v_j)) + \varphi_i(1 - K(\overline{x_i}, v_j)))^{-1/(m-1)}}{\sum_{i=1}^{N}(1 - K(x_i, v_k) + \varphi_i(1 - K(\overline{x_i}, v_j)))^{-1/(m-1)}} \quad (16)$$

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}{}^{m}(K(x_i, v_j)) + \varphi_i K(\overline{x_i}, v_j)\overline{x_i})}{\sum_{i=1}^{N} u_{ij}{}^{m}(K(x_i, v_j) + \varphi_i K(\overline{x_i}, v_j))} \quad (17)$$

When $\overline{x_i}$ is replaced with the weighted image $\overline{\xi_i}$ that is applied in eq (12), to get the objective function algorithm as $AWCKFCM_w$ (15) and the membership function and cluster centres for newly formed AWCKFCM is denoted as (16), (17).

The proposed algorithm AWCKFCM produce a new challenge of bringing the clear contextual information about the picture based on the local heterogeneity of local grayscale distribution. It is generalized by the effective use of regularizing weighted covariance parameter which safeguards the image quality. Each component present in the pixel is examined and elaborated by the design of weighted coefficient parameters in the kernels. This designed algorithm will differentiate noise from meaningful data, where meaningful data contains the spatial characteristics of the picture. Noises present in the image are further removed by the estimation of weights.

4. EXPERIMENTAL RESULT

The AWCKFCM algorithm is implemented using MATLAB software packages. Every experiments are conducted with window size of 3 × 3 pixels, maximum number of iterations t = 100, and ε = 0.001. The accuracy of segmentation is measured using the Jaccard Similarity (JS) metric [18] which is defined as the ratio between the intersection and union of segmented volume $S1$ and ground truth volume $S2$.

$$JS(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \qquad (18)$$

The proposed Adaptive Weighted-covariance KFCM result in producing strong robustness and better performance over other existing algorithms. The weighting factor with the combination of covariance is a measure of the collinearity between the center pixel and the pixels in local window and takes into account the compactness of pixels in the clusters. The result improves the representation of pixel details, as well as good at noisy images. The proposed methodology is evaluated by comparing it with the existing algorithms and a series of segmented images and their information are collected. The k-means, FCM [17], Kernel FCM [9], Particle Swarm Optimization-SFCM (PSO-SFCM), and Artificial Bee Colony KFCM are taken into consideration. Estimation of covariance weight leads to better kernel selection and clustering formation that is done based on AWCKFCM algorithm. It show good balance between smooth borders and preserving image details due to the introduction of adaptive local contextual information measure φ_i to replace the fixed value of α. The covariance measure introduced in the local contextual information classifies the pixels affected by noise and gradually makes it efficient by comparing dispersion of the pixel with its centre and neighbour. This section begins with the comparison of the traditional K-Means, FCM and KFCM by means of its merits and demerits.

K-Means algorithm is a fast, robust and provides tighter clusters normally easy to understand. But it contains problems such as presence of noise and outliers in the image and also it fails to solve non-linear type of datasets. The other problem is that the two highly overlapping data cannot resolve into two clusters. FCM gives best result for overlapped data set and comparatively better then k-means algorithm. Data point is assigned membership to each cluster center as a result of which data point may belong to more than one cluster center. But it is expense for more number of iterations and Euclidean distance measures can unequally weight underlying factors.

The kernel based combination of the FCM i.e, KFCM algorithm suits well for all types of medical images. It has high efficiency, low time requirement, and successive clusters distribution. Thus, it is used in this paper. The multiple KFCM and their combination with the hybrid classifiers are evaluated by performing experiments on the medical data sets and the results are tabulated for verification that is shown in the following part. SFCM-MPSO is a novel method that has a global searching ability in the feature segmentation naturally. However, the maximum and minimum velocity of particles has obvious impact on the convergence rate and it affects the efficiency [18]. ABC-KFCM is also a new method introduced to solve the segmentation problems found in the traditional methods. It is providing comparatively high efficiency than the other methods mentioned above. Thus, by considering these algorithm methods, the proposed algorithm is designed and experiments are done to demonstrate their performance over the other technique.

Many investigations have been carried out so far on using contextual information and grayscale values to enhance the quality of segmentation. But how the contextual information shall be used effectively is still a challenge. The below mentioned figure analysis fig 1, 2, 3, 4, 5, 6 clearly shows that the proposed AWCKFCM algorithm performs well in medical image representation. A normal input image fig 1. is taken from Digital Imaging and Communications in Medicine (DICOM) studies and experiments are conducted with the above mentioned algorithms. The application of regularized parameter containing weighted covariance retains the picture details and displays a clear view of balance between smooth borders and edges, which can be visible from fig 6.

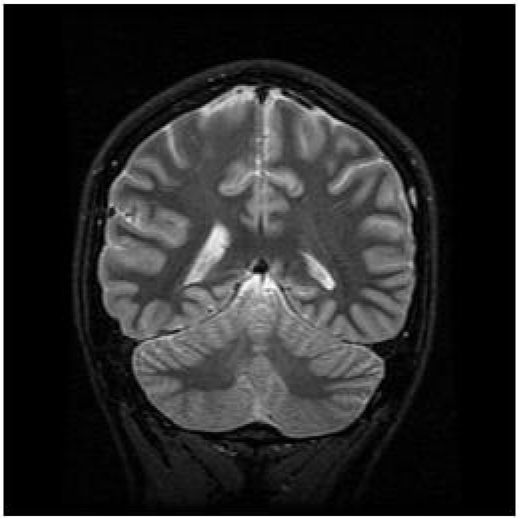

Figure 1: Input DICOM Image

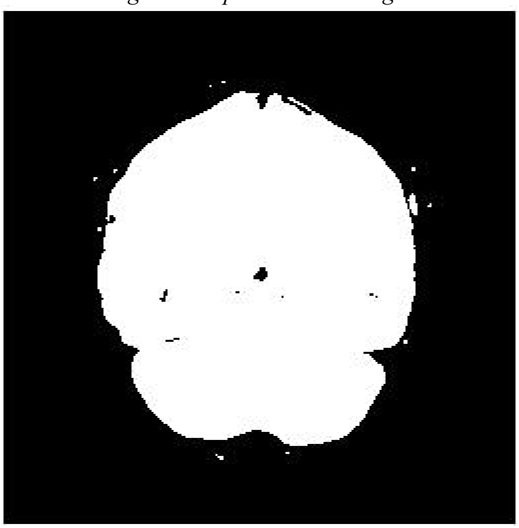

Figure 2: K Means Clustering

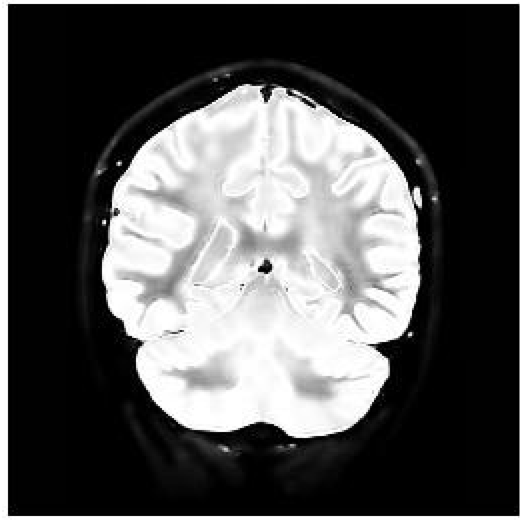

Figure 3: FCM Clustering

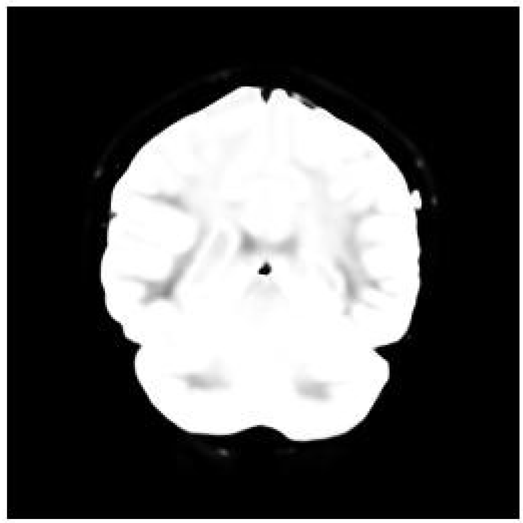

Figure 4: SFCM-MPSO Clustering

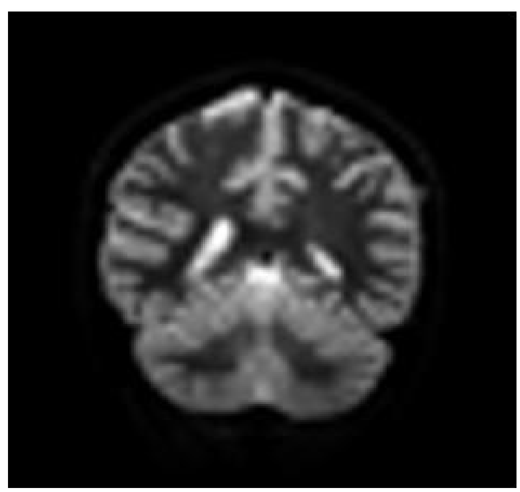

Figure 5: ABC-KFCM

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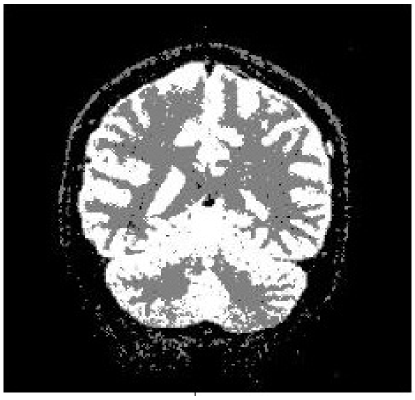

Figure 6: Proposed AWCKFCM

The table 1 and table 2 denotes the ranges of the k-means, FCM, KFCM, PSO-SFCM, ABC-KFCM and the proposed AWCKFCM by means of accuracy of segmentation. The centroid value represents the average accuracy of segmentation. It also calculates the pixel error value with the centroid, which is given in table 2.

Table 1: Comparison analysis of segmentation accuracy and pixel error for medical images

Method	Pixel Error Count and Cluster Centers				Segmentation Accuracy	Time
	Centroids	Error Pixel	Centroids	Error Pixel	Average Accuracy	In (secs)
K-Means	6.6254, 98.6115	1195	6.4421, 77.6890, 125.2745	1201	91.68	50.73
FCM	6.7935, 101.1125	976	6.154, 76.2868, 123.0570	987	93.18	72.22
KFCM	6.2517, 99.9285	522	121.5948, 70.2040, 4.3013	548	96.28	75.56
PSO-SFCM	6.7106, 99.1261	437	76.2868, 6.1541, 123.0570	440	96.95	99.45
ABC-KFCM	6.2476, 99.9264	424	121.5908, 70.1984, 4.2976	429	97.03	98.37
Proposed AWCKFCM Without Noise	6.2474, 99.1042	420	121.5818, 70.1978, 4.2865	425	97.61	89.70
Proposed AWCKFCM With Noise 30%	6.2517, 99.9342	654	122.6012, 70.2531, 4.3013	673	96.88	88.55

Table 2: Comparison analysis of segmentation accuracy and pixel error for multimedia images

Method	Pixel Error Count and Cluster Centers				Segmentation Accuracy	Time
	Centroids	Error Pixel	Centroids	Error Pixel	Average Accuracy	(in sec)
K-Means	151.4870, 25.5933	63655	121.0076, 167.7719, 22.3747	63667	75.73	124.59
FCM	153.6055, 25.0161	59223	122.3355, 168.4849, 20.4672	59238	77.40	133.45
KFCM	23.5953, 154.3047	51236	18.3111, 168.1686, 121.3009	52656	80.18	135.21

PSO-SFCM	153.6055, 25.0161	48744	118.1560, 167.5352, 21.7026	48751	81.40	145.87
ABC- KFCM	23.5943, 154.2998	40589	18.3012, 168.1643, 121.2986	40899	84.45	144.44
Proposed AWCKFCM Without Noise	23.5936, 154.2094	40322	18.3012, 168.1566, 121.2984	40573	85.67	139.78
Proposed AWCKFCM With Noise 30%	23.5953, 154.4471	52387	18.3210, 168.1684, 121.2988	53664	81.02	138.88

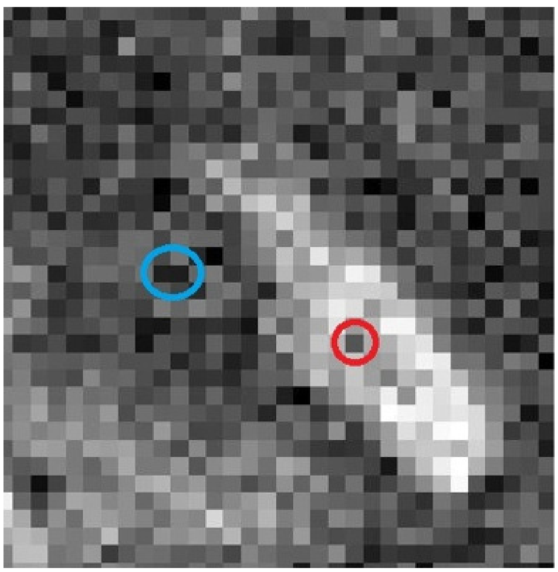

Figure 7: Input image

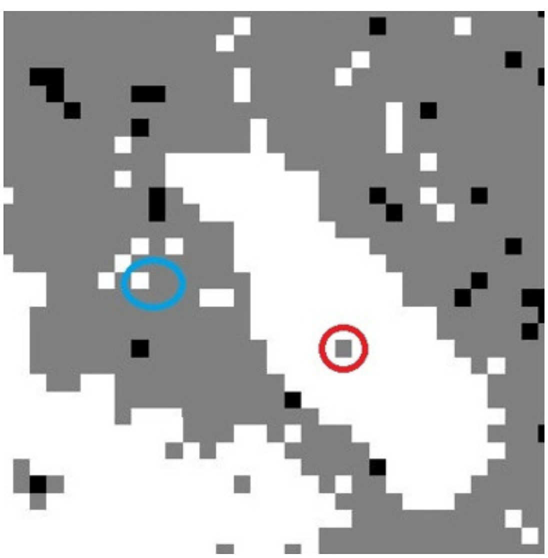

Figure 8: KFCM using variance method

4.2 Variance method

The above given figures indicate the change of pixels with respect to other pixels instead of center.

In figure 7 and Figure 8, the blue marked pixel tends to behave as the neighboring pixel because of the rapid change occurred. Whereas the red marked pixel retains its originality in local window as there is low noise surrounded by it. It will not deviate with the consideration of central pixel which makes a contradiction of variation in pixels. Thus it is necessary to replace variance with covariance factor which performs deviation by focusing the central pixels.

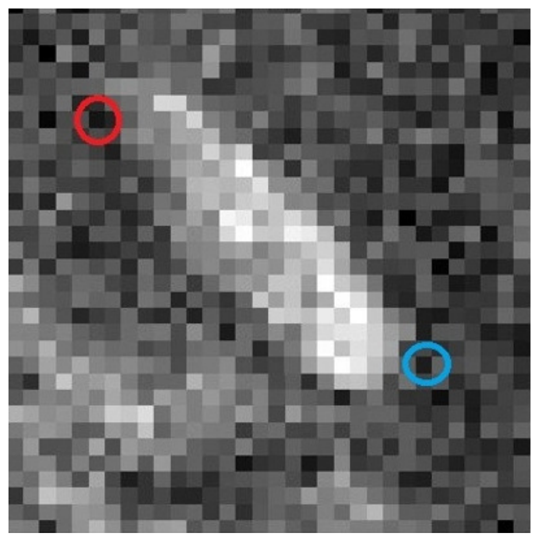

Figure 9: Input image

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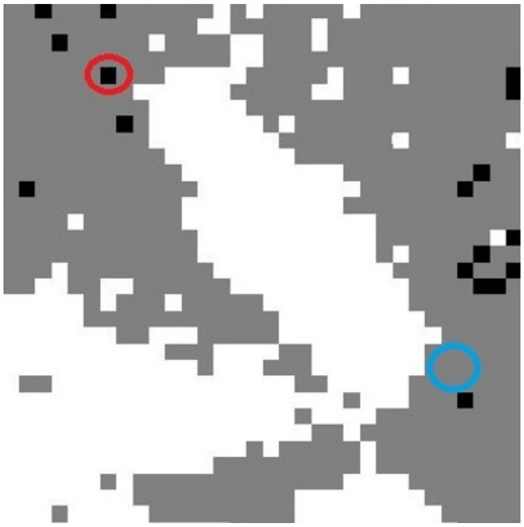

Figure 10: KFCM using covariance method

4.3 Determination of covariance factor

The figure 9 and figure 10 shows the difference of pixel formation due to its center and neighbor. In figure1, the red color circle denotes the condition that central pixel is free from noise and some pixels within its local window may be corrupted by noise. The central pixel tends to suppress the outlier or neighbor pixel and retain its originality shown in fig8. Whereas the blue circle denotes the case that the central pixel is corrupted by noise, while the other pixels within its local window are homogenous, not corrupted by noise, the distribution of the neighboring pixel alters the center and forms a cluster as shown in fig 9 & 10.

4.4 Comparison of the proposed system with other system.

The proposed algorithm and its application are compared with an early literature given by Ramani *et al.* [19] shows that combination of FCM with the Association Rule mining concept. The algorithm is developed by the researchers to remove the cyclic repeated patterns in sequential pattern mining (SPM) application, which comes under data mining category. The performance is measured by calculating the execution time, memory and database difference ratio. Whereas, our research is used for the application of medical sciences that deals with clinical MRI scan images that implements the pixel based classification technique. In both the methods, the clusters are formed with the help of FCM clustering algorithm and each features are added are added separately to provide various applications. The threshold value determination is added in [19] helps in identifying the sequential patterns found hidden in the data mining applications, whereas the spatial kernel metrics based weighted covariance added in this system helps in identification of pixels found in the diseased part of the medical images. The difference of characteristics between the two algorithms has been explained in the below table.

Table 3: Comparison of application in SPM-FCM and the proposed ARKFCM

Algorithms	Process	Data used	Evaluation parameter
Ramani et al [19] (The support of the sequential pattern for the real life data mining application)	Clustering FCM, clusters formation, rule generation , fixing of threshold values,	Ming data- Set mining data repository	Execution time, memory and database difference ratio
ARKFCM (Pixel based classification technique in solving segmentation problems faced by medical applications)	Clustering FCM, Spatial addition, Kernel function, Regularization, devising a weighted covariance	Clinical data-MRI brain image data	Pixel error count, centroids, variance among pixels

5. CONCLUSION

Kernel based segmentation method is being frequently used by many researchers in recent days. Modifications and improvements are continually arriving to provide more and more better results in medical image segmentation. The proposed Adaptive Weighted covariance KFCM is has also been designed in such a way to increases the accuracy of segmentation in KFCM with its significant way of pixel details representation. The evaluation based on weights and covariance vector is a new combination of segmentation method employed in this, involve in improving the accuracy by the centroid value and its location. The noise, outliers and bounded pixels are separated carefully and the image features are clustered to locate the diseased part. The experimental verification of the method with Brain MR Images has been done with two cases such as MR image with 30% noise and without noise. In both the cases the proposed AWCKFCM method performs well, represented in the table values. The pixel error count and the centroid or cluster centers are

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calculated to get the accuracy of the compared systems. It shows that AWCKFCM is efficient among the other algorithms and it provides good segmentation accuracy even in the presence of noise. Further, new techniques can be developed in with the knowledge of the system and by combining the AWCKFCM with some hybrid classifiers, which can be taken as a future research.

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