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Brain Tumor Image Segmentation Using Kernel Based Fuzzy C Means Clustering (KFCM) Algorithm

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Abstract: **The kernel based fuzzy c means clustering is proposed in this article for segmentation of MR brain image. To alleviate the problem of drawback of computation cost of segmentation in the Fuzzy C Means is overcome by this kernel based FCM algorithm. The FCM algorithm provides good accuracy in the absence of noise; but in the presence of noise it doesn't give good accuracy. In Kernal Based Fuzzy C Means, First, Enhanced Non Local mean Filter is applied on MR brain image for removal of noise and it replace the gray scale of the denoised image by the average, median filter. The Gaussian Radial basis function is used as a kernel function instead of Euclidean distance.**

***Keywords* — segmentation, Fuzzy clustering, denoised image, Non local means filter, Euclidean distance**

I. INTRODUCTION

The image segmentation can be divided into several categories are thresholding, region growing, clustering, edge detection, and model-based methods (**Pham et al., 2000**). The unsupervised learning algorithm is clustering it groups or cluster the similar patterns and it divided into hard or soft. The function of soft clustering is to arrange every pixel into cluster using various membership values (**Despotovi´c et al., 2015, Ruan et al., 2000**). The most important soft clustering are fuzzy c means clustering algorithm, mixture modeling and hybrid method (**Dunn, 1973 and Bezdek, 1981**) are applied on MR brain image for segmentation purpose.

The FCM algorithm provides good accuracy in the absence of noise; but in the presence of noise it doesn't give good accuracy. So, the segmentation is performed through local spatial and grayscale information (**Ahmed et al., 2002, Szilagyi et al., 2003, Chen &. Zhang, 2004, Cai et al., 2007, Yang &. Tsai, 2008, Krinidis & Chatzis, 2010 and Gong et al., 2013**).

A nonparametric Bayesian model is proposed by (**Ferreira, 2007**) to classify the brain MR image. This method is known as Dirichlet mixture model process. The spatial information is introduced between neighboring pixels into Gaussian Mixture Model for brain MR image segmentation is proposed by (**Nguyen & Wu, 2013**).

II. FCM ALGORITHM

The FCM algorithm is very sensitive to noise and their accuracy of clustering is decreases. To tackle this problem, the objective function of FCM algorithm is modified by addition of spatial information pixel to the neighboring pixel is given by (**Ahmed et al., 2002**). This modification algorithm with objective function is given as:

$$FCM_S = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m}\|x_i - v_i\|^2 + \frac{\alpha}{N_R}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m}\left(\sum_{r\in N_i}\|x_r - v_j\|^2\right)$$

Where the spatial information of the neighbour pixel is controlled by parameter α with $0 < \alpha < 1$, N_i contains set of pixels round pixel i, cordinality of N_i is N_R.

The drawback of FCM_S algorithm is computation expensive because of the calculation of local neighborhood term in each iteration step.

To alleviate this problem, kernel function is used in modification algorithm is presented by (**Chen & Zhang, 2004**). In this algorithm, $\|\bar{x}_i - v_j\|^2$ term is used to replaced the term $\sum_{r\in N_i}\|x_r - v_j\|^2$ in eq. (5.1), where $\bar{x}_i$ represents the gray scale of the filtered image and also used kernel function instead of Euclidean distance.

The enhancement of FCM_S algorithm in two forms is FCM_S1 and FCM_S2. The enhancement of FCM_S1 is done by averaging filter and enhancement of FCM_S2 algorithm is done by median filter. The objective function of this enhancement algorithm is given as follows:

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

This algorithm improves the accuracy, but it is sensitive to high type of noises. Also has to take care about parameter α.

To overcome this problem, Gaussian kernel based FCM method is developed by (**Yang & Tsai, 2008**) where for every iteration the parameter η_j is calculated and it replace

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the parameter α in eq. (5.2) for each cluster. This method also has two forms are GKFCM1 and GKFCM 2 for average and. median filter respectively. The kernel function is estimated using parameter η_j :

$$\eta_j = \frac{min_{j' \neq j}\left(1-K\left(v_{j'}, v_j\right)\right)}{max_k\left(1-K\left(v_k, \bar{x}\right)\right)}$$

In this algorithm, K is the kernel function. The replacement parameter η_j provides better result than FCM_S1 and FCM_S2 algorithm. However the estimation of η_j is not true. The learning scheme of this algorithm require large number of patterns and more number of cluster center is needed to find the optimal value for η_j.

To overcome the problem of parameter adjustment, the combination of fuzzy factor with gray and local information of neighborhood pixel is introduced by (**Krinidis and Chatzis, 2010**). The fuzzy factor $G_{ij} = \sum_{k\in N_i, i\neq k}(1/(1+d_{ik}))(1-u_{ij})^m \|x_i - v_j\|^2$

This equation is embedded into original FCM algorithm is given as follows:

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

The center of the local window is given by pixel i, the pixel j represents the neighborhood, spatial Euclidean distance between pixel i and k is represented by d_{ik}.

The FLICM algorithm is robustness to noise but it is slow because of fuzzy factor is calculated in every iteration. Also fuzzy factor is affected by spatial Euclidean distance due to the details of the image is loosed.

To overcome the problem of FLICM algorithm, the weighted fuzzy factor is used to control the local neighborhood pixel and also used kernel function instead of Euclidean distance. The weighted fuzzy factor G'_{ij} is developed by (Gong et al.,) and is given as:

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

Where ω_{ik} represents the trade off weighted fuzzy factor of pixel k in the local window around the center pixel i and the kernel metric function is given by $1 - K\left(x_i, v_j\right)$. In the algorithm, the computational cost is increases because of the combination of spatial and gray scale information also it didn't preserve the edges of the image.

The proposed framework improves the accuracy and reduces the computational cost by developing denoising algorithm and replaced the Euclidean distance by kernel function in FCM algorithm.

III. PROPOSED FRAMEWORK

The proposed framework is evaluated using denoising method by Enhanced Nonlocal Means Filter (ENMF) and applied the denoising method to kernel based FCM algorithm.

First, the weight is assigned to each pixel is linked with average gray scale of the local window of the denoised image:

$$\varphi_i = \begin{cases} 2+\omega_i & \bar{x}_i < x_i \\ 2-\omega_i & \bar{x}_i > x_i \\ 0 & \bar{x}_i = x_i \end{cases}$$

The importance of eq (5.7) is relevant to the grayscale within a specified neighborhood; the weighting parameter is calculated before the clustering process. Due to this process the computation cost is decease and is varied from FCM_S, FLICM and KWFLICM algorithm. The second important function of weighting parameter is providing the contextual information of original image using distribution of heterogeneity of grayscale within the local neighborhood.

The gray scale of the average and median filter of the denoised MR brain image is replaced by new formation of weighted image.

$$\bar{w}_i = \frac{1}{2+max(\varphi_i)}\left(x_i + \frac{1+max(\varphi_i)}{N_R - 1}\sum_{r\in N_i} x_r\right)$$

Where, the grayscale of the weighted image is represent by x_r, neighborhood of pixel i is denoted by N_i and cardinality of N_i is N_R.

The Euclidean distance in original FCM algorithm is simple and inexpensive, but it is very sensitive to outliers and perturbations. The kernel function is popular method used in machine learning approach. The main function of kernel is to project the data into higher dimensional space; it is used to separate the data easily. The kernel function $\|\emptyset(x_i) - \emptyset(v_j)\|^2$ is used in FCM by replaced the Euclidean distance term $\|x_i - v_j\|^2$ is given as:

$$\|\emptyset(x_i) - \emptyset(v_j)\|^2 = K(x_i, x_i) + K(v_j, v_j) - 2K(x_i, v_j)$$

Where, kernel function is denoted as K.

In this framework, Gaussian Radial basis function kernel is used in kernel fuzzy MR brain image segmentation is given as:

$$K(x_i, v_j) = exp\left(-\frac{\|x_i - v_j\|^2}{2\sigma^2}\right)$$

The kernel width is represented by parameter σ.

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Substitute the Gaussian Radial Basis function kernel function

$$\left\|\emptyset(x_i)-\emptyset(v_j)\right\|^2 = 2\left(1-K\left(x_i,v_j\right)\right)$$

The selection of kernel width is problem and it must be selected carefully. So, the kernel width is selected based on distance variance.

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

The distance between the gray scale of pixel i and average of all gray scale pixels are represent by $d_i = \|x_i - \bar{x}\|$ and $\bar{d}$ denotes the average of all distance.

The objective function of combination of Enhanced non local mean filter with kernel based fuzzy cluster means (ENLMF_KFCM) algorithm is given as:

$$ENLMF\_KFCM = 2\left[\sum_{i=1}^{N}\sum_{j=1}^{c} \begin{matrix} u_{ij}^{m}\left(1-K\left(x_i,v_j\right)\right)+ \\ \sum_{i=1}^{N}\sum_{j=1}^{c}\varphi u_{ij}^{m}\left(1-K\left(\bar{x}_i,v_j\right)\right)\end{matrix}\right]$$

Calculate the center and membership function of proposed framework is given as:

$$u_{ij} = \frac{\left(\left(1-K(x_i,v_j)\right)+\varphi_i\left(1-K(\bar{x}_i,v_j)\right)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(1-K(x_i,v_k)+\varphi_i\left(1-K(\bar{x}_i,v_k)\right)\right)^{-1/(m-1)}}$$

$$v_j = \frac{\sum_{i=1}^{N}u_{ij}^{m}\left(K(x_i,v_j)x_i+\varphi_i K(\bar{x}_i,v_j)\bar{x}_i\right)}{\sum_{i=1}^{N}u_{ij}^{m}\left(K(x_i,v_j)+\varphi_i K(\bar{x}_i,v_j)\right)}$$

In the above equation, the parameter $\bar{x}$ is replaced by the gray scale of the average, median filter and weighted filter is called ENLMF_KFCM1, ENLMF_KFCM2 and ENLMF_KFCMw.

The main steps of the proposed ENLMF_KFCM algorithm are given as follows:

1. Calculate the denoising method of Enhanced local mean filter for brain MR images.

2. Calculate x ̅_i for ENLMF_KFCM1, ENLMF_KFCM2 and calculate w ̅_i for ENLMF_KFCMw

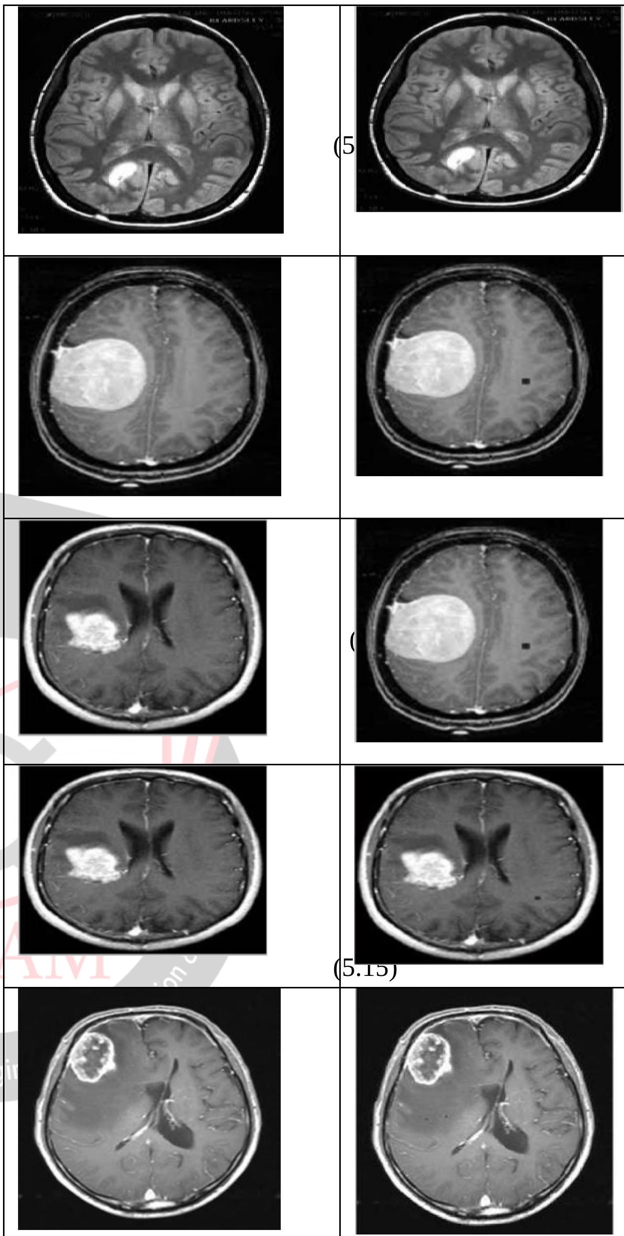
3. Find the cluster center

4. Find the membership function

5. If max‖u^((t+1))-u^((t)) ‖<ε or t>100 then stop or t=t+1 is updated and go to step to step 3.

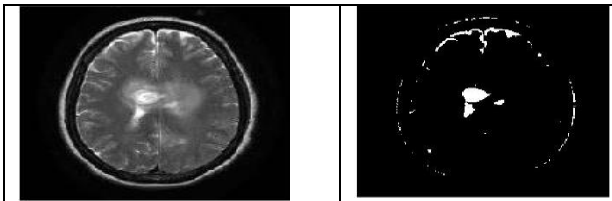
IV. RESULTS AND DISCUSSION

The experiments and performance evaluation are carried on MRI brain images collected from difference modalities. The proposed systems are evaluated using combination of both Enhanced Local mean filter with kernel based fuzzy clustering method. It was implemented with Matlab R2012 in a windows XP system with Pentium 4 CPU 3GHZ and 2GB RAM.



Input Image	Denoised image

Figure 4.1: Denoising Results



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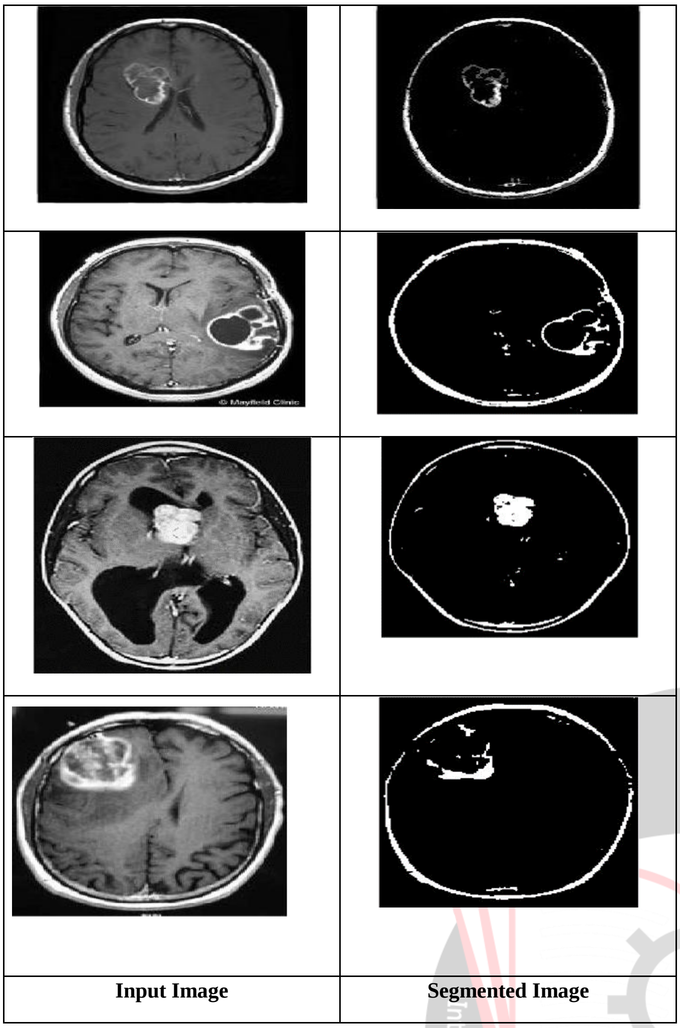

Figure 4.2: Segmentation output using kernel based FCM algorithm

Figure 4.2 illustrates the segmentation output using kernel based FCM framework in where noises in the input images are removed using enhanced local means filter and applied weighted parameter on the local window of the denoised image that control the contextual information of the MR brain images. Then average and median filter of the gray scale image is calculated. Finally, the Gaussian Radial Basis Function kernel is applied on FCM instead of Euclidean distance and find the cluster and membership function. Through all this function the MR Brian images are segmented well and is illustrates in above figure.

Table 4.1 Performance metrics of PSNR

Images	FCM_S1	FCM_S2	ENLMF_KFCMw
Image 1	47.21	47.89	50.015
Image 2	35.46	35.21	38.85
Image 3	41.34	41.56	44.35
Image 4	28.34	29.21	30.91
Image 5	28.79	28.98	31.05
Image 6	34.44	35.56	38.78
Image 7	40.12	41.23	43.34

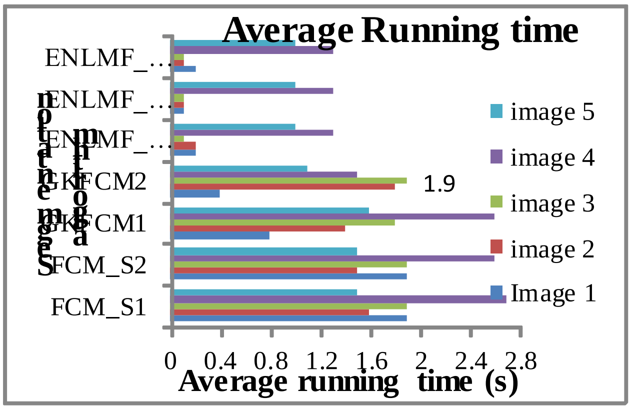

Fig.4.3 Average running time of proposed and existing algorithm

The figure 4.3 illustrate the average running time between proposed and existing algorithm where proposed ELNMF_KFCM algorithm has minimum number of average time in seconds as (1.3-0.2 seconds), (1.3-0.1 seconds), (1.3-0.1 seconds) compared to existing algorithm of FCM_S1 (2.7 -1.9 seconds), FCM_S2 (2.6-1.9 seconds), GKFCM1 has running time of (0.8-2.6 seconds) and GKFCM2 (0.4-1.9 seconds).

The GKFCM1 and GKFCM2 has higher computation cost compared to proposed ENLMF_KFCM1, ENLMF_KFCM2, ENLMF_KFCMw because GKFCM requires number of loops for calculation of each pixel. This calculation is used to update the local contextual information.

The proposed ENLMF_KFCM reduce the computation cost because it measure the gray scale heterogeneity and do not enter the cluster center process.

V. CONCLUSION

The Enhanced non local means filter with kernel based fuzzy c means clustering algorithm is proposed to provides the good segmentation results with low computation cost. The main advantage of this proposed framework is clustering is non dependence due to computational cost is reduced, provide robustness to MR brain images, local context is adaptive.

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