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Segmentation of CSF in MRI Brain Images Using Optimized Clustering Methods

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Abstract: Image segmentation is an indispensible part of the visualization of human tissues during the analysis of Magnetic Resonance Imaging (MRI). MRI is an advanced medical imaging technique which provides rich information for detecting Cerebrospinal Fluid (CSF) in brain images. The changes in the CSF protein level forms abnormal brain deposits strongly linked to variety of neurological diseases. The traditional clustering methods yield more false positives. The proposed system encompasses the following steps, Pre-Processing the MRI brain images using Contrast Limited Adaptive Histogram Equalization, Clustering by Fuzzy C Means (FCM), Total Variation FCM (TVFCM), Anisotropic Diffused TVFCM (ADTVFCM), Optimizing the clustering techniques using Particle Swarm Optimization (PSO) (FCM-PSO, TVFCM-PSO and ADTVFCM-PSO). The clustering methods provide only local optimal solution. In order to achieve global optimal solution, the clustering methods are further optimized using PSO. The performance of the optimized clustering methods is measured using defined set of Simulated MS Lesion Brain database. The optimized clustering methods finds the CSF present in MRI brain images with 98% of accuracy, 92% of sensitivity and 97% of specificity.

Key words: Cerebrospinal fluid, segmentation, magnetic resonance image, fuzzy C means, total variation regularizer, anisotropic diffusion, particle swarm optimization

INTRODUCTION

Cerebrospinal Fluid (CSF) is a clear colorless liquid that fills and surrounds the brain and spinal cord. CSF protein level changes are found in all stages of human (children, adults and elderly people). Examination of the CSF may diagnose a number of diseases such as meningitis and encephalitis. The normal flow of CSF is very important to maintain the intracranial pressure to the normal level. The simulation of CSF is helpful to diagnose the disorder and to plan for the treatment. Yet the correctness of the results in these simulations relies on the accuracy of CSF detection. CSF in MRI images may be dark or light based on the different imaging modes. T1 and T2 weighted brain imaging modes are used to extract the CSF from the images and is used for visualizing normal anatomy and pathology. The other imaging modes are Proton Density (PD) and FLAIR. These imaging modes are used to find the grey matter and white matter. These imaging modes help in diagnosing the disease and to plan for the treatment.

One of the efficient method to estimate CSF is clustering the brain images. Clustering is the most fundamental and significant method in pattern recognition and is defined as a form of data compression in which a large number of samples are converted into a small number of representative clusters. It plays a key role in searching for structures in data and involves the task of dividing data points into homogeneous classes or clusters. The goal of segmentation of MRI images is to find out the level of tissues and lesions present. In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster and associated with each element is a set of membership levels. One of the most widely used fuzzy clustering algorithms is the Fuzzy C Means (FCM) Algorithm (Fu and Mui, 2011; Kaur *et al*., 2012). FCM algorithm attempts to partition a finite collection of elements into a collection of fuzzy clusters with respect to some given criterion. Although, FCM algorithm is considered as Efficient Clustering Method, the main factor affecting the performance of FCM is presence of noise in MRI images. The noise in the image is eliminated by modifying the objective function of FCM Method by Total Variation regularizer (TV). TV regularizer (Hu and Jacob, 2012) works efficiently on gradient sparse images for removing spurious oscillations while preserving edges. However, TV regularized methods are not suited to handle the varying in homogeneities as it would introduce the typical staircasing effect. The disadvantage of TV Method is

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eliminated using Anisotropic Diffusion (AD). AD algorithm applies the law of diffusion on pixel intensities to smooth textures in an image. A threshold function is used to prevent diffusion to happen across edges and therefore it preserves edges in the image.

These algorithms are optimized using Particle Swarm Optimization (PSO) in order to find the global optimal solution. PSO is a population-based stochastic approach for solving continuous nonlinear functions. PSO Method optimizes the objective function. PSO is initialized with a group of random particles (solutions) and then searches for optimal solution by updating generations. Particles move through the solution space and are evaluated according to some fitness criterion after each iteration. In every iteration each particle is updated by the two best values, the first one is the fitness value it has achieved so for. This value is called pbest. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This is called the global best value (i.e.) gbest.

LITERATURE REVIEW

FCM Method iterations are based on the number of clusters it comes across on the image being considered. Unlike K-means, the FCM will return the number of clusters after clustering has been done. FCM is robust to blurring but is sensitive to noise and incomplete data. It considers only the intensity of the image and does not take into consideration the spatial context and boundary connections. To overcome this problem, regularization of the image is performed. Cao and Wang (2011) introduced the regularization term for M-FISH images. An adaptive spatial FCM clustering algorithm for MRI images corrupted by noise and intensity non uniformity artifacts based on a dissimilarity index that allows spatial interactions between image pixels was proposed by Liew *et al.* (2000). Miao *et al.* (2011) performed automatic segmentation of brain tissue based on improved Fuzzy C means clustering algorithm. To improve the resolution of the image, Joshi *et al.* (2009) introduced the total variation regularization. The total variation regularization was improved by optimizing the convex problems using first order primal-dual algorithms given by Esser *et al.* (2010). The Operator Splittings, Bregman Methods and Frame Shrinkage Models are used to improve the constrained optimized problems given by Setzer (2011).

Izakian and Abraham (2011) proposed hybrid fuzzy c-means and fuzzy-PSO. FCM algorithm is integrated with FPSO algorithm to form a hybrid clustering algorithm called FCM FPSO which maintains the merits of both FCM and PSO algorithms. FCM-FPSO algorithm applies FCM to the particles in the swarm every number of iterations/generations such that the fitness value of each particle is improved.

Anitha and Selvy (2012) proposed optimized clustering approach for automated detection of white matter lesion in MRI brain images. Clustering algorithms like Fuzzy C-Means Clustering (FCM), Geostatistical Possibilistic Clustering (GPC) and Geostatistical Fuzzy Clustering Model (GFCM) are used to cluster the images. However, clustering techniques are sensitive to initialization and are easily trapped in local optima. In order to obtain an optimized result, the clustered images are undergone optimization. Particle Swarm Optimization (PSO) is a stochastic global optimization tool which is used in many optimization problems.

A probability mixture model and the Bayesian classifier was used by Khayati *et al.* (2008) inorder to extract normal tissue, abnormal tissue and Cerebrospinal Fluid (CSF) which serves primary purpose like buoyancy, protection and chemical stability. Normal tissue refers to white matter and grey matter of brain whereas abnormal tissue refers to lesions of brain in FLAIR-MR images. This method does not focus on the lesions of small size or irregular shape.

PROPOSED RESEARCH

This study mainly focuses on detection of abnormalities in brain images based on the CSF level. MRI brain image is first pre-processed using Contrast Limited Adaptive Histogram Equalization (CLAHE). The algorithm has proven to be successful for enhancement of low-contrast images. The preprocessed image is segmented to extract the CSF in the brain. The extracted CSF from the brain image is then clustered using FCM, TVFCM and ADTVFCM Methods. The clustering methods are then optimized using Particle Swarm Optimization (PSO). PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving. Segmenting the MRI brain image is to extract the CSF in order to find the level for the diagnosis of the disease. The overall process of the system is shown in Fig. 1.

Pre-processing (contrast limited adaptive histogram equalization): Contrast Limited Adaptive Histogram Equalization (CLAHE) was originally developed for medical imaging and has proven to be successful for enhancement of low-contrast images. CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each pixel. This evens out the distribution of used grey values and thus makes

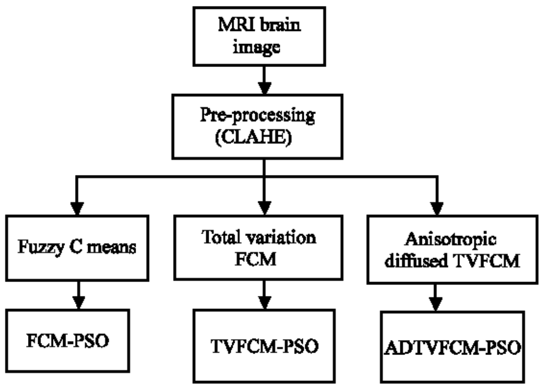

Fig. 1: Block diagram of proposed research

hidden features of the image more visible. The full grey spectrum is used to express the image. CLAHE operates on small regions in the image rather than the entire image. Each small region is contrast enhanced so that the histogram of the output region approximately matches the histogram specified by the distribution parameter. The neighbouring small regions are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas can be limited to avoid amplifying any noise that might be present in the image.

Feature extraction (CSF extraction): MRI brain image is segmented to extract the CSF. The Orthogonal Polynomial Transform is applied to the T1 weighted images. Sin function is applied on each pixel of the image and the matrix is computed for the preprocessed image. Based on the threshold value CSF from the MRI image is extracted. The threshold limit is set to 0.4. The equation for extracting the CSF is given in the Eq. 1:

$$I_{CF} = \sin\left(\frac{I_s(i)^s}{100}\right)^2 + \left(0.05\times \text{rand}\left(\left|I_s\right|\right)\right) \quad (1)$$

FCM algorithm: FCM Method (Szilagyi *et al*., 2007) is used to segment the MRI brain images. To segment the MRI images, the objective function of FCM is obtained using weighted dissimilarity terms as shown in Eq. 2:

$$J(u,v) = \sum_{j=1}^{n}\sum_{k=1}^{c}\left(u_k(j)\right)^m \left(f(j)-v_k\right)^2 \quad (2)$$

The dissimilarity terms in the objective function are the data point (V_k) and the cluster centre (U_k). Using Lagrange Multiplier Method, researchers obtain the minimum saddle point J (i.e.) objective function. Minimum value is achieved by iteratively finding the value of cluster centre and data point as shown in the Eq. 3 and 4. The distance between the jth cluster and kth data point is calculated using ($f(j) - V_k$):

$$v_k^{(i+1)} = \frac{\sum_{j=1}^{n}\left(u_k^{(i)}(j)\right)^m f(j)}{\sum_{j=1}^{n}\left(u_k^{(i)}(j)\right)^m} \quad (3)$$

$$u_k^{(i+1)} = \left(\sum_{l=1}^{c}\frac{\left(f(j)-v_k^{(i+1)}\right)^{\frac{2}{m-1}}}{\left(f(j)-v_l^{(i+1)}\right)^{\frac{2}{m-1}}}\right)^{-1} \quad (4)$$

Where:
J = Objective function
m = Fuzziness membership
u_k = Cluster centre
v_k = Data point

The iteration of the cluster centre and data point continues until the minimum objective value is reached or the iteration continues until difference between last two iterations has minimum value. It has been proved that there exists a subsequence of U and V which converges to a local minimizer or a saddle point of J if f contains at least C different gray values.

Algorithm for FCM:

1. The Pre-processed MRI Brain image is taken as the input
2. Cluster centers have been selected randomly
3. The new membership function ($u_k (j)^m$) is calculated
4. Fuzzy center v_k is computed
5. Steps 3 and 4 are repeated until the minimum objective value is reached

FCM Method is applied on the pre-processed image and the segmentation result obtained is poor because of the noise present in the image. Therefore, FCM Method is not suitable for images with noise and incomplete data.

TVFCM algorithm: TV Method eliminates the noise and makes the segmentation result better. The regularizing parameter along with the objective function of FCM for eliminates the noise which is given in Eq. 5 and makes FCM Method more robust to noise (He *et al*., 2012). The function is given as:

$$J(u,v) = \mu\sum_{j=1}^{n}\sum_{k=1}^{c}\left(u_k(j)\right)^m\left(f(j)-v_k\right)^2 + \sum_{k=1}^{C}TV\left(u_k\right) \quad (5)$$

Where:
μ = Regularizing parameter
TV = Total Variation performs DCT II operations

The value of the regularizing parameter μ is chosen >0 (μ>0). The cluster centre value and the membership value are calculated as in FCM and then the regularizing parameter value is multiplied with the objective function. TV is applied as (Figueiredo *et al*., 2006), Discrete Cosine Transform II (DCT II) on the membership function and it is added to the objective function. The boundaries of the image become smoother with decreasing μ. The value of the regularizing parameter is chosen manually to obtain the best segmentation result and to get the good visual quality of images. As the value of the regularizing parameter is decreased the segmentation result will be better. The algorithm is robust to noise and the segmentation result is better compared to FCM.

Algorithm for TVFCM:

1. The pre-processed MRI brain image is taken as the input
2. Cluster centers have been selected randomly
3. The new membership function ($u_k(j)^m$) is calculated
4. The fuzzy centers v_k is computed
5. The regularizing parameter is multiplied with the objective value
6. Steps 3-5 are repeated until the minimum objective value is achieved
7. Then, DCT II is applied to the membership function

TV Method results in stair casing effect and also it does strongly smooth and may even destroy small scale structures with high curvature edges.

ADTVFCM: The Anisotropic Diffusion algorithm (Osher and Esedoglu, 2004) is the ground-breaking work in Partial Derivatives Equations (PDE) based denoising. AD is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. It applies the law of diffusion on pixel intensities to smooth textures in an image. A threshold function is used to prevent diffusion to happen across edges and therefore it preserves edges in the image. The anisotropic diffusion filter as a diffusion process that encourages intra region smoothing while inhibiting inter region smoothing.

Anisotropic diffusion is the process that creates a scale space where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. The resulting images in this family are given as a convolution between the image and a Gaussian filter where the width of the filter increases with the parameter. This diffusion process is a linear and space-invariant transformation of the original image. The directional derivatives at a specific location can be given as shown in the Eq. 6:

$$f_{\theta,1}(r) = |\nabla f(r)|\cos(\theta-\varphi) \tag{6}$$

Where:

φ = The orientation of the gradient
f = The directional derivative
r = The location of each pixel
∇ = The gradient of f

The classical TV is reinterpreted to obtain the new form shown in Eq. 7 as:

$$g_n(f) = \frac{1}{2\pi\int_{\Omega}\int_{0}^{2\pi}|f_{\theta,n}(r)|d\theta dr} \tag{7}$$

g_n is the generalization of directional derivative. The function will ensure that an edge like discontinuity will not attenuate the smoothing in the direction orthogonal to the edge. This interpretation makes clear the anisotropic smoothing properties exhibited by the standard TV regularizer. The method preserves the discontinuities and also continues to smooth along line like features in the MR images. Once the TV regularizer is reinterpreted, the objective function of the FCM Method is added and the segmentation accuracy is improved than traditional TVFCM.

Algorithm for ADTVFCM:

1. The pre-processed MRI Brain image is taken as input
2. Pixel value is selected
3. The diffusion is performed by diffusion equation
4. The diffused values are filtered using convolution filter
5. The objective function of traditional TVFCM is applied to the filtered image

PARTICLE SWARM OPTIMIZATION

PSO (Osher and Esedoglu, 2004) is a robust stochastic optimization technique based on the movement and intelligence of swarms. It applies the concept of social interaction to problem solving. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in a N-dimensional space which adjusts its flying according to its own flying experience as well as the flying experience of other particles. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best pbest. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called gbest. The basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations with a random weighted acceleration.

After finding the two best values, the particle updates its velocity and positions with following Eq. 8 and 9:

$$v_{id} = w \times v_{id} + c1 \times rand(\ ) \times (p_{id} - x_{id}) + c2 \times rand(\ ) \times (p_{id} - x_{id}) \quad (8)$$

Where:

v_{id} = Velocity of agent i at iteration k
w = Weighting function
c1, c2 = Weighting factor
rand = Uniformly distributed random number between 0 and 1
x_{id} = Current position of agent i at iteration k
P_{id} = pbest of agent i
P_{gd} = gbest of the group

$$x_{id} = x_{id} + v_{id} \quad (9)$$

Fuzzy C Means Particle Swarm Optimization (FCM-PSO): Fuzzy C means algorithm is integrated with PSO algorithm to form a hybrid clustering algorithm called FCM-PSO algorithm where the advantage of both the algorithms are maintained. The local optimal solution obtained by the FCM is removed. The fitness value of each particle is improved by applying FCM to each particle based on the iterations. The algorithm for FCM-PSO is stated as follows:

Algorithm for FCM-PSO:
1 Initialize the PSO and FCM parameters (c1, c2, w)
2 Create the swarm with P particles (x, pbest, gbest, v)
3 Initialize X, V, pbest for each particle and gbest for the swarm
4 Calculate the cluster center using FCM algorithm for each particle
5 Update the membership function for each particle
6 Update the pbest value for each particle
7 Update the gbest value for each swarm
8 Terminate when global optimal solution is reached
9 If global optimal solution is not reached go to step 2

Total Variation Fuzzy C Means Particle Swarm Optimization (TVFCM-PSO): Total Variation Fuzzy C Means algorithm is integrated with PSO algorithm to form a hybrid clustering algorithm called TVFCM-PSO algorithm where the disadvantage of FCM is eliminated and the advantage of the TVFCM and PSO is maintained. The algorithm for the TVFCM-PSO is stated follows:

Algorithm for TVFCM-PSO:
1 Initialize the PSO and FCM parameters (c1, c2, w)
2 Create the swarm with P particles (x, pbest, gbest, v)
3 Initialize X, V, pbest for each particle and gbest for the swarm
4 Cluster centers have been selected randomly
5 The new membership function ($u_k(j)^m$) is calculated
6 The fuzzy centers v_k is computed
7 The regularizing parameter is multiplied with the objective value
8 Then, DCT II is applied to the membership function
9 Update the pbest value for each particle
10 Update the gbest value for each swarm
11 Terminate when global optimal solution is reached
12 If global optimal solution is not reached go to step 2

Anisotropic diffused TVFCM-PSO: Anisotropic diffused TVFCM algorithm is integrated with PSO algorithm to form a hybrid clustering algorithm called ADTVFCM-PSO algorithm where the disadvantage of TVFCM is eliminated and the advantage of the ADTVFCM and PSO is maintained. The algorithm for the ADTVFCM-PSO is stated as follows:

Algorithm for ADTVFCM-PSO:
1 Initialize the PSO and FCM parameters (c1, c2, w)
2 Create the swarm with P particles (x, pbest, gbest, v)
3 Initialize X, V, pbest for each particle and gbest for the swarm
4 Pixel value in a image is selected
5 The diffusion is performed by diffusion equation.
6 The diffused values are filtered using convolution filter
7 Cluster centers have been selected randomly
8 The new membership function ($u_k(j)^m$) is calculated
9 The fuzzy centers v_k is computed
10 Update the pbest value for each particle
11 Update the gbest value for each swarm
12 Terminate when global optimal solution is reached
13 If global optimal solution is not reached go to step 2

EXPERIMENTAL RESULTS

The proposed system is tested on a database of 150 MRI images with different Gaussian noise levels. The MRI Brain images are collected from the Simulated MS Lesion Brain database (18). The performance of the proposed method for detecting CSF level in brain is calculated using Segmentation Accuracy (SA) as shown in Eq. 10. The detection results reveals that ADTVFCM-PSO performs better segmentation than FCM-PSO and TVFCM-PSO. The FCM, TVFCM and ADTVFCM Method are compared with FCM-PSO, TVFCM-PSO and ADTVFCM-PSO and it is found that clustering techniques integrated with PSO outperforms than the general clustering methods. The CSF is detected from the brain images under different Gaussian noise levels. The segmentation accuracy is given as:

$$SA = \frac{\text{No. of correctly classified pixels}}{\text{No. of pixels}} \quad (10)$$

The original MRI brain image is shown in the Fig. 2a. The original MRI brain image is then pre-processed using CLAHE algorithm and the resulting image is shown in Fig. 2b here the brightness of the image is improved. The CSF extracted image is shown in Fig. 2c. Figure 2c and d shows the segmentation results of FCM, TVFCM and ADTVFCM and the Fig. 2e-g shows the segmentation results of FCM-PSO, TVFCM-PSO and ADTVFCM-PSO.

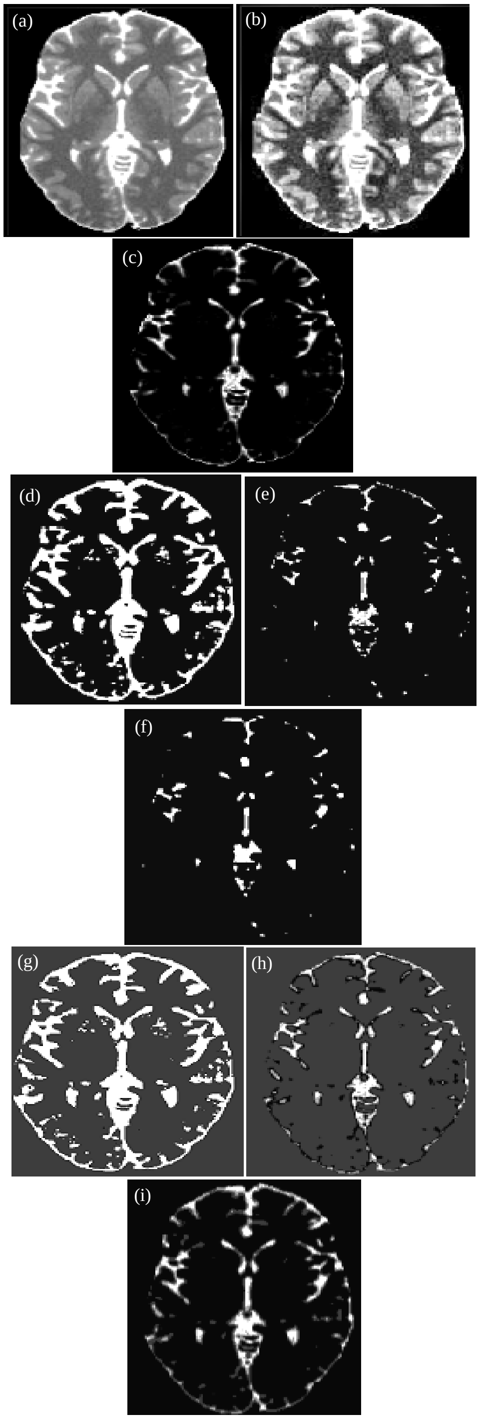

Fig. 2: Segmentation results on MRI image; a) Orignal MRI Brrain; b) CLAHE algorithm; c) CSF extraction; d) CSF detection using FCM; e) CSF detection using TVFCM; f) CSF detection using ADTVFCM; g) CSF detection using FCM-PSO; h) CSF detection using TVFCM-PSO; i) CSF detection using ADTVFCM-PSO

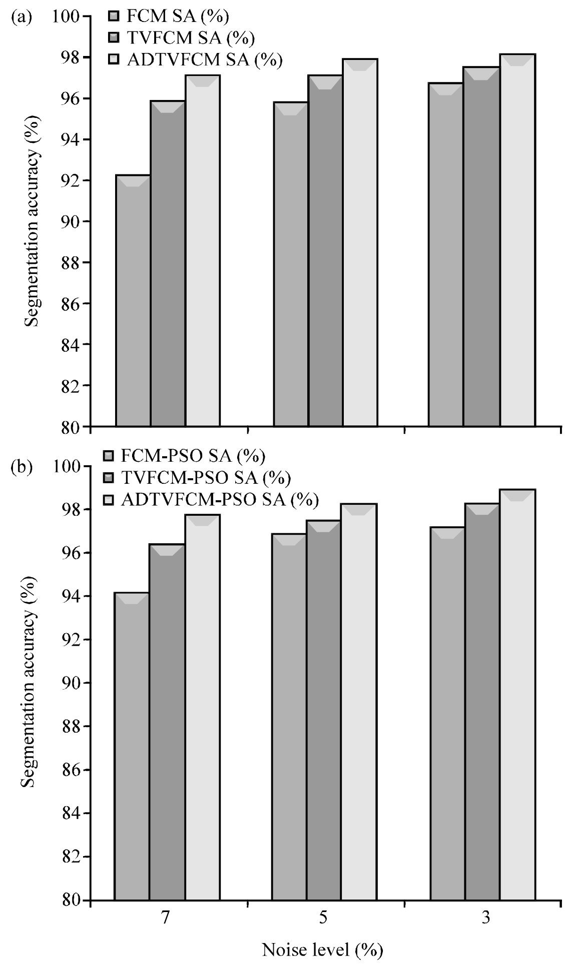

Fig. 3: Segmentation accuracy comparisons with different noise levels using; a) Clustering techniques; b) Optimization techniques

Table 1: Performance analysis for Segmentation Accuracy (SA) using Clustering Methods

Noise level (%)	FCM SA (%)	TVFCM SA (%)	ADTVFCM SA (%)
3	96.7	97.4	98.0
5	95.7	97.0	97.8
7	92.2	95.8	97.0

Table 2: Performance analysis for Segmentation Accuracy (SA) using clustering and PSO Methods

Noise level (%)	FCM-PSO SA (%)	TVFCM-PSO SA (%)	ADTVFCM-PSO SA (%)
3	97.0	98.1	98.7
5	96.7	97.6	98.1
7	94.0	96.2	97.6

The segmentation results of clustering methods and optimized-clustering methods for images with different noise levels are shown in the Table 1 and 2.

The pictorial representation for the Table 1 and 2 is shown in the Fig. 3, the different noise levels are plotted in horizontal coordinates and the segmentation accuracy is plotted in the vertical coordinates.

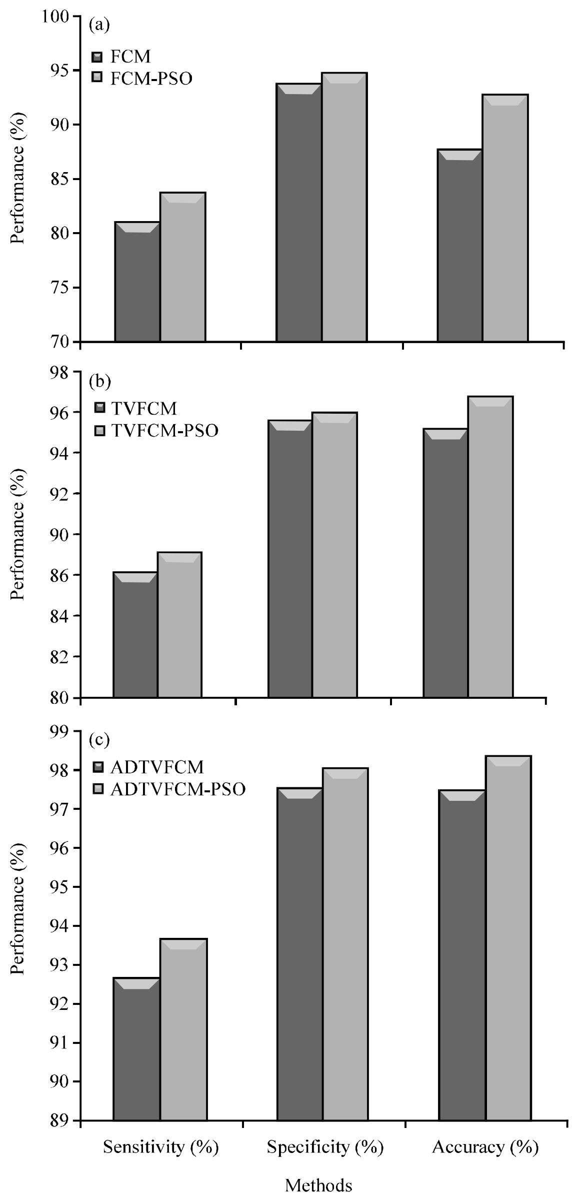

Fig. 4: Se, Sp, Acc of; a) FCM vs. FCM-PSO; b) TVFCM vs. TVFCM-PSO; c) ADTVFCM vs. ADTVFCM-PSO

The Sensitivity (Se), Specificity (Sp) and Accuracy (Acc) for the clustering algorithms and optimized clustering algorithms are evaluated. The Se, Sp, Acc are derived as shown in the Eq. 11-13:

$$Se = \frac{TP}{TP+FN} \tag{11}$$

$$Sp = \frac{TP}{TN+FP} \tag{12}$$

Table 3: Performance results of Clustering Methods and optimization with Clustering Methods

Models	Sensitivity (%)	Specificity (%)	Accuracy (%)
FCM	81.0	93.7	87.6
TVFCM	86.8	95.2	94.7
ADTVFCM	92.6	97.5	97.4
FCM-PSO	83.6	94.6	92.7
TVFCM-PSO	87.9	95.6	96.5
ADTVFCM-PSO	93.6	98.0	98.6

$$Acc = \frac{TP+TN}{TP+FN+TN+FP} \tag{13}$$

Where:

TP = True Positive
FN = False Negative
TN = True Negative
FP = False Positive

The performance results from Table 3 show that ADTVFCM-PSO provides Sensitivity (Se) of 93.6%, Specificity (Sp) of 98% and Accuracy (Acc) of 98.6%. The comparative results of sensitivity, specificity and accuracy for FCM and FCM-PSO, TVFCM and TVFCM-PSO, ADTVFCM and ADTVFCM-PSO are shown is the Fig. 4. When compared to Clustering Methods, Optimized Clustering Methods yields better result.

CONCLUSION

In this study, Particle Swarm Optimization (PSO) technique is combined with best clustering techniques to obtain global optimal solution. The selection of the centriods is done randomly in clustering techniques. In the proposed method, the selection of is based on the pbest and gbest value which yields global optimal solution. The sensitivity and specificity for PSO Method has less false positives compared to clustering techniques. Experimental results on brain image datasets of MRI shows that ADTVFCM with PSO is efficient and can reveal very encouraging results in terms of quality of the solution found.

As the Future research, optimized clustering techniques can be used to find Grey Matter (GM) and White Matter (WM) level for the detection of abnormalities in brain images.

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