An Improved MRI Brain Image Segmentation to Detect Cerebrospinal Fluid Level Using Anisotropic Diffused Fuzzy C Means

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Abstract: - Cerebrospinal Fluid (CSF) is a clear colorless fluid produced in the brain. The changes in CSF protein levels form abnormal brain deposits strongly linked to variety of neurological diseases. Magnetic Resonance Imaging (MRI) of Brain is segmented using Fuzzy C Means (FCM) to detect the CSF level in brain. However, FCM is not suitable to segment the images with noise. This paper presents an algorithm known as Total Variation (TV) Regularization to solve the problems in FCM. Here TV is combined with FCM to eliminate noise but the method results in stair casing effect and takes longer reconstruction time. The proposed hybrid algorithm is the combination of Anisotropic Diffusion (AD) and TVFCM method, which overcomes the problems in traditional TVFCM. AD method first diffuses the image and then is convoluted using convolution filter and is then subjected to TVFCM segmentation. The performance of the proposed method finds the CSF level present in the MRI Brain images with 98% of accuracy, 92% of sensitivity and 97% of specificity. When compared to the traditional FCM and TVFCM, ADTVFCM yields better segmentation accuracy.

Key-Words: - Cerebrospinal Fluid, Segmentation, Magnetic Resonance Image, Fuzzy C Means, Total Variation Regularizer, Anisotropic Diffusion.

1 Introduction

1.1 Background

The task of segmentation is to partition a digital image into multiple segments and to simplify or to change the representation of an image in to more meaningful and easier to analyze. In medical imaging, these segments often correspond to different tissue classes, pathologies, or other biologically relevant structures. The goal of segmentation of MRI images is to find out the level of tissues and lesions present. Cerebro Spinal Fluid protein level changes are found in all stages of human(children, adults and elderly people). CSF level in MRI images may be dark or light based on the different imaging modes. This helps in diagnosing the disease and to plan for the treatment [13].

Clustering techniques are used to segment the MRI images. Clustering can be considered as the most important unsupervised learning problem. Cluster is therefore a collection of objects which are “similar” between them and are “dissimilar” to the objects belonging to other clusters. Fuzzy clustering techniques are best suited to segment the MRI images because the uncertainty of MRI images. Fuzzy C Means (FCM) clustering algorithm [2] is considered as powerful segmentation method because, more information is preserved. But FCM method is sensitive to noise and incomplete data in the image. Therefore the focus of this paper is to improve the FCM approach. The methods to improve FCM are Total Variation (TV) Regularization and Anisotropic Diffusion (AD) where noise from the image is eliminated, and also eliminates the stair casing effect and takes lesser reconstruction time.

1.2 Cerebrospinal Fluid

Cerebrospinal Fluid (CSF) is a watery fluid that is continuously produced and absorbed that flows in the ventricles within the brain and around the surface of the brain and spinal cord. It protects the central nervous system from injury and cushions it from the surrounding bone structure. CSF serves four primary purposes: 1. Buoyancy, 2. Protection, 3. Chemical stability and 4. Prevention of brain ischemia.

CSF can be tested for the diagnosis of a variety of neurological diseases like Alzheimer disease, demyelinating and cognitive disorders [9]. CSF is obtained by a procedure called lumbar puncture.

Removing CSF during lumbar puncture causes severe headache after the fluid is removed, because brain hangs on the vessels and nerve roots, and grip on them stimulates pain fibers. Lumbar puncture is performed to count the cells in the fluid and to detect the levels of protein and glucose. The change in the level of CSF leads to Alzheimer's disease. The earliest stage of Alzheimer causes changes in protein levels such as tau and beta amyloid.
The CSF present in the MRI Brain image is shown in the Fig.1

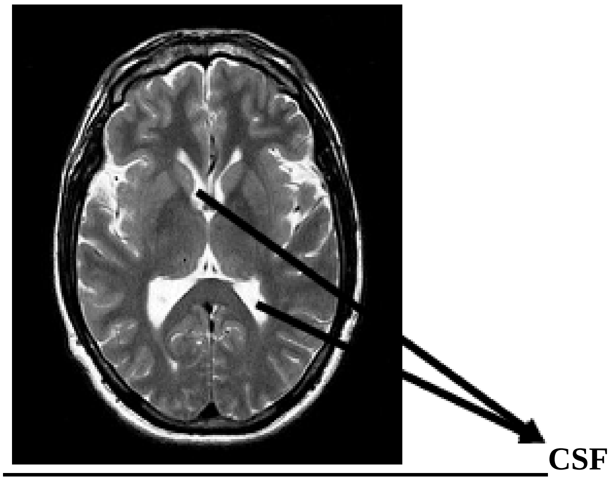

Fig.1 Cerebrospinal Fluid of Brain

1.2 Medical Image Segmentation
Medical imaging is the technique and process used to create images of the human body for clinical purposes. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Although a number of algorithms have been proposed in the field of medical image segmentation, medical image segmentation continues to be a complex and challenging problem. The methods used for medical image segmentation are often application-specific; as such, they can make use of prior knowledge for the particular objects of interest and other expected or possible structures in the image. This has led to the development of a wide range of segmentation methods addressing specific problems in medical applications.

1.3 Magnetic Resonance Imaging
Magnetic resonance imaging (MRI) of the brain is a safe and painless test that uses a magnetic field and radio waves to produce detailed images of the brain and the brain stem. MRI provides detailed information about brain tumor anatomy, cellular structure and vascular supply, making it an important tool for the effective diagnosis, treatment and monitoring of the disease. MRI is done for many reasons. It is used to find problems such as tumors, bleeding, injury, blood vessel diseases, or infection. MRI also may be done to provide more information about a problem seen on an X-ray, ultrasound scan, or CT scan. Contrast material may be used during MRI to show abnormal tissue more clearly. MRI is useful in segmenting the White matter, grey matter and CSF. So segmenting MRI brain images is used to find the lesions present. The three main problem involved in segmenting are noise, intensity inhomogeneity and partial volume averaging.

A number of different imaging modes which can be used with imaging the brain are:

- T_1: Cerebrospinal Fluid is dark and is used for visualizing normal anatomy.
- T_2: CSF is light, but fat is darker when compared to T_1. T_2 is used for visualizing pathology.
- PD (proton density): CSF has a relatively high level of protons, making CSF appear bright. Gray Matter is brighter than white matter.
- Flair: Flair images are used for the evaluation of White Matter plaques near ventricles and is also useful for identifying demyelination.

2 Related Works
Riemenschneider. M et al investigated CSF tau and Abeta42 concentrations in patients with Fronto Temporal Degradation (FTD), Alzheimer Disease and healthy subjects [6]. With the use of these biomarkers, subjects with FTD can be distinguished from control subjects and from patients with Alzheimer Disease with reasonable accuracy. Blennow K et al [9] studied cerebrospinal fluid (CSF) biomarkers for focusing on their role in clinical diagnosis. The two biochemical markers, CSF total tau (t-tau) protein and the 42 amino acid form of beta-amyloid (Abeta42) perform satisfactorily enough to achieve a role in the clinical diagnostic settings of patients with dementia together with the cumulative information from basic clinical work-up, genetic screening, and brain imaging. The very mildest symptomatic stage of Alzheimer Disease exhibits the same CSF biomarker phenotype as more advanced Alzheimer

Disease. In addition, levels of CSF Abeta(42), when combined with amyloid imaging, augment clinical methods for identifying in individuals with brain amyloid deposits whether dementia is present or not. Importantly, CSF tau/Abeta(42) ratios show strong promise as antecedent (preclinical) biomarkers that predict future dementia in cognitively normal older adults [13] given by P. Formichi et al.

The most common clustering algorithm is k means clustering. K-means clustering algorithm uses an iterative refinement technique. It is a method of cluster analysis which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. But K-means method demands the user to specify the number of clusters before the segmentation. Therefore Fuzzy C Means method is used to overcome the disadvantage of k means algorithm. FCM method iterates based on the number of clusters it comes across on the image being considered. Unlike K-means, the fuzzy c-means will return the number of clusters after the segmentation has been done. Therefore the number clusters is approximately the number of iterations.

FCM is robust to blurring and requires no assumption on the probability density functions of the data. However, the original FCM method 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 et al. [3] 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 A. W. C. Liew et al [11]. Zhuang Miao et al [10] performed automatic segmentation of brain tissue based on improved Fuzzy C Means clustering algorithm. To improve the resolution of the image, Joshi Sh et al [14] introduced the Total Variation Regularization. The Total Variation Regularization was improved by optimizing the convex problems using first order primal-dual algorithms given by E. Esser et al [15] and A. Chambolle et al [17]. The Operator Splittings, Bregman methods and frame shrinkage models are used to improve the constrained optimized problems given by S. Setzer et al [20].

The rest of this paper is organized as follows:

- In section 3.1 the pre-processing technique described.
- In Section 3.2 the FCM method is discussed in detail.
- In section 3.3 the TVFCM model is presented.
- In section 3.4 the proposed Anisotropic Diffused TVFCM algorithm has been explained.
- In section 4 the experimental results have been discussed, here we have compared FCM, TVFCM, and ADTVFCM schemes and evaluates the algorithms based on sensitivity, specificity and accuracy

3 Proposed Work

The original MRI of the brain image is pre-processed using pixel Normalization method. The pre-processed image is subjected to segmentation by FCM, TVFCM and ADTVFCM. The result of TVFCM is minimized using ADMM and ADTVFCM is minimized using MM algorithms. The result of segmentation is the detection of CSF level. The overall process of the system is depicted in the Fig.2.

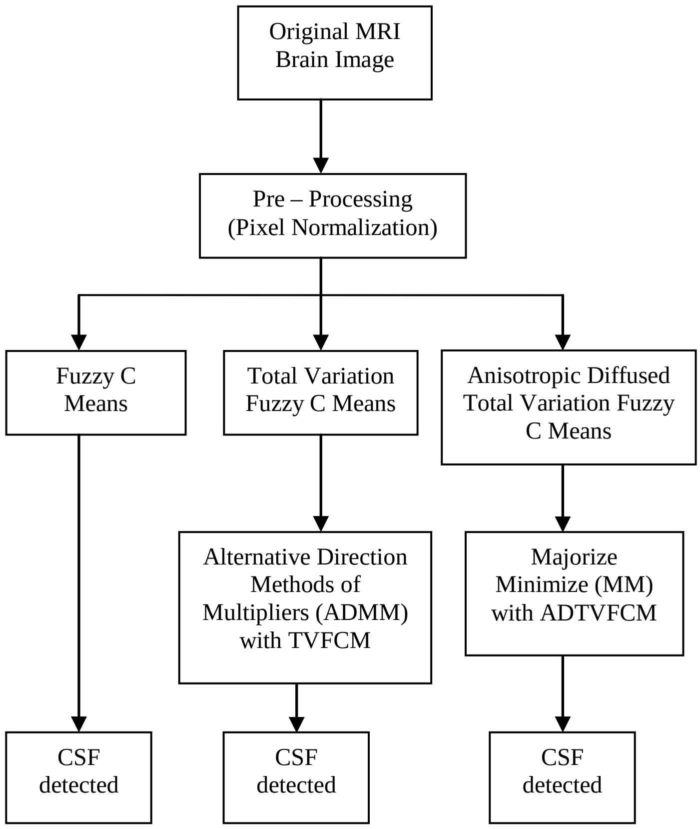

Fig.2 Block Diagram of Proposed Work

3.1 Pre - Processing

The preliminary step in processing the image is Pre-Processing. Pre-Processing, in general, processing of an image in order to prepare it for the primary processing. There are several steps required to prepare data as per the need of the user. There are several pre-processing techniques; some are pixel adjustment, pixel normalization, contrast stretching and so on.

3.1.1 Pixel Normalization

The pre-processing technique used in the proposed system is pixel normalization method. The method is applied to images with poor contrast due to glare. Here the method changes the range of pixel intensity values. The image is normalized before applying clustering methods. The method improves the brightness of the image.

To improve the brightness of the image, normalization performs two steps:

Step 1: The minimum and maximum brightness of the image is computed,

Step 2: The information obtained from the step 1 is used to apply a normalization formula to every pixel.

The input image is taken with noise and has poor contrast. The output is the pre-processed image.

3.2 FCM algorithm

FCM method [21] 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 eqn (1). FCM method is considered as an optimization problem, which is defined for m>1 as,

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

Where,

$$\sum_{k=1}^{c} u_k(j) = 1\ \forall j, \quad u \geq 0 \sum_{j=1}^{n} u_k(j) > 0\ \forall k.$$

The dissimilarity terms in the objective function are the data point (V_k) and the cluster centre (U_k) [11].

Using Lagrange multiplier method we 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 equation (2) and (3). The distance between the jth cluster and kth data point is calculated using $(f(j) - v_k)$.

$$v_k^{(i+1)} = \frac{\sum_{j=1}^{n}(u_k^{(i)}(j))^m f(j)}{\sum_{j=1}^{n}(u_k^{(i)}(j))^m} \quad (2)$$

$$u_k^{(i+1)} = \left(\sum_{l=1}^{c} \frac{\left(f(j) - v_k^{(i+1)}\right)^{\frac{2}{m-1}}}{\left(f(j) - v_l^{(i+1)}\right)^{\frac{2}{m-1}}}\right)^{-1} \quad (3)$$

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 [12] 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.

- **Input:** Pre-Processed brain image.
- **Output:** CSF level Detected Using FCM.

Steps in 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. The 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.

3.3 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 eqn (4) and makes FCM method more robust to noise [1]. The function is given as,

$$j(u,v) = \mu \sum_{j=1}^{n} \sum_{k=1}^{c} (u_k(j))^m (f(j) - v_k)^2 + \sum_{k=1}^{c} TV(u_k) \quad (4)$$

Where,

$$\sum_{k=1}^{c} u_k(j) = 1 \ \forall j,\ u \geq 0$$

Where,
μ - regularizing parameter
TV – Total Variation performs DCT II operations.

The value of the regularizing parameter μ is chosen greater than 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, Discrete Cosine Transform II (DCT II) on the membership function and it is added to the objective function. DCT II can be thought of as the Fast Fourier Transform (FFT) with O(nlogn) arithmetic operation. TVFCM is based on the matrix – matrix operations. 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.

- **Input:** Pre-Processed brain image.
- **Output:** CSF level Detection Using TVFCM.

Steps in 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 to 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.

3.3.2 TVFCM with ADMM

The Alternating Direction Method of Multipliers (ADMM) is a variant of the augmented Lagrangian scheme that uses partial updates for the dual variables. The dual update requires solving a proximity function in *x* and *y* at the same time; the ADMM technique allows this problem to be solved approximately by first solving for *x* with *y* fixed, and then solving for *y* with *x* fixed. Rather than iterate until convergence, the algorithm proceeds directly to updating the dual variable and then repeating the process. This is not equivalent to the exact minimization, but surprisingly, it can still be shown that this method converges to the right answer. The method solves the problems of the form as shown in equation (5),

$$\min_{x,y} f(x) + g(y), \ \text{subject to } x = y \quad (5)$$

The method splits the problem into sub problems that has to be solved. The ADMM method is performed iteratively until the convergence criterion is reached. The objective function of the TVFCM method is written in the general form as of ADMM. To minimize the objective function the x minimization as in equation (4.6), z minimization as in equation (4.7) and the dual variable update as in equation (4.8) are performed.

x minimization= $x^{i+1} = \operatorname{argmin}\left\{f(x) + \frac{1}{2\gamma}||b^i + x - y^i||\right\}$ (6)

z minimization = $z^{i+1} = \operatorname{argmin}\left\{g(x) + \frac{1}{2\gamma}||b^i + x - y^i||\right\}$ (7)

Dual Update = $b^{i+1} = b^i + x^{i+1} - y^{i+1}$ (8)

The process is repeated until the minimized result of the objective function is reached.

3.4 ADTVFCM

Total Variation Regularization for image segmentation results in stair casing effect and takes longer reconstruction time. The diffusion process can be done on the image to remove the disadvantage of TV. The Anisotropic Diffusion algorithm is the ground-breaking work in partial derivatives equations (PDE)-based denoising. AD [5] 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. Anisotropic diffusion is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a non-linear and space-variant transformation of the original image. The directional derivatives at a specific location can be given as shown in the equation (9),

$$f_{\theta,1}(r) = |\nabla f(r)| \cos(\theta - \varphi) \tag{9}$$

Where,

φ denotes the orientation of the gradient,
f denotes the directional derivative,
r denotes the location of each pixel.

∇ denotes the gradient of f

The classical TV is reinterpreted to obtain the new form shown in equation (4.11) as,

$$\mathcal{G}_n(f) = 1/2\pi \int_{\Omega} \int_{0}^{2\pi} |f_{\theta,n}(r)|\, d\theta\, dr \tag{10}$$

$\mathcal{G}_n$ 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 [19]. 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.

- **Input:** Pre-Processed MRI brain image.
- **Output:** CSF Detection Using ADTVFCM.

Steps in 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.

3.4.1 Majorize-Minimize (MM Algorithm)

The Majorize – Minimize (MM) algorithm is an iterative optimization method which exploits the convexity of a function in order to find their maximums or minimums. The MM stands for "Majorize - Minimization" or "Minorize - Maximization", depending on whether Maximization or Minimization is done. MM is a description of how to construct an optimization algorithm. Optimizing the surrogate functions will drive the objective function upward or downward until a local optimum is reached. The Majorize-Minimize algorithm is used to operate by creating a surrogate function that minimizes or majorizes the objective function. Once the function is optimized the function is minimized or majorized. The method is applied to minimize the ADTVFCM.

The majorizing function as shown in eqn (11) is minimized to obtain the expected results. The minimization operation is the iterative step; the iteration is performed until the minimized result is achieved.

$$\mathcal{G}_n(f) \le \mathcal{G}_n\left(f^{(m)}\right) + 1/2\pi \int_{\Omega} \int_{0}^{2\pi} \phi_n^{(m)}(r,\theta)\left|f_{\theta,n} r\right|^2 d\theta\, dr \tag{11}$$

Where,

$\mathcal{G}_n$ is the generalization of directional derivative,

$\phi_n^{(m)}$ is the spatial weights,

- **Input:** Result of ADTVFCM.
- **Output:** Minimized ADTVFCM

Steps in ADTVFCM with MM

1. Result of ADTVFCM is taken as input.
2. The sparse matrix is found from the input image.
3. The difference between sparse matrix and each pixel of original image is found.

4 Experimental Results

The performance of the proposed method for detecting CSF level in brain is calculated using segmentation accuracy (SA). The formula for SA is given as shown in the eqn (12). The proposed system is tested on a database of 150 MRI images with different noise levels. The detection results reveals that ADTVFCM with MM performs better segmentation than TVFCM with ADMM. The MRI Brain images are collected from the database [22] .The FCM, TVFCM and ADTVFCM method are compared and it is found that ADTVFCM outperforms the other methods. The CSF is detected from the brain images under different noise levels.

The original image is shown in the Fig. 5(a) is taken from the database. The original image is pre-processed using Pixel Normalization and the resulting image is shown in Fig. 5(b), here the brightness of the image is improved. The Fig.5(c) to Fig. 5(d) shows the segmentation results of FCM, TVFCM and ADTVFCM. The ADTVFCM method has had clear boundaries and the edges are preserved.

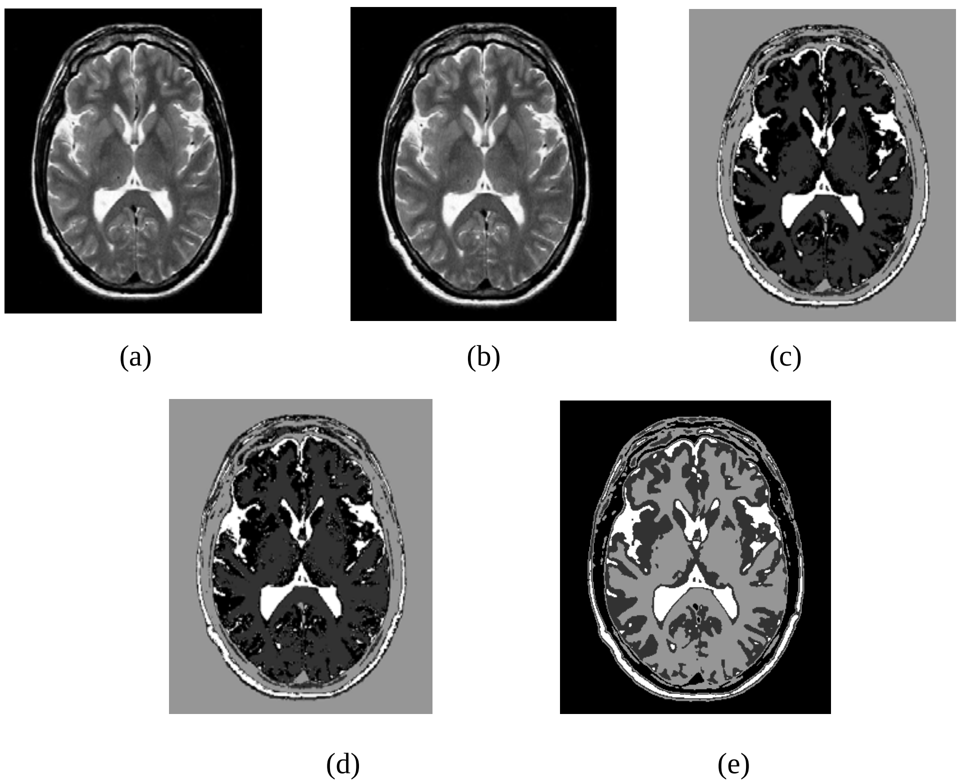

Fig. 5 Segmentation results on MRI image (a) Original MRI image (b) Pre-Processed MRI image (c) CSF detection using FCM (d) CSF detection using TVFCM (e) CSF detection using ADTVFCM

The segmentation accuracy is given as,

$$SA = \frac{\text{No of correctly classified pixels}}{\text{No of pixels}} \quad (12)$$

The segmentation results of FCM, TVFCM and ADTVFCM with different noise levels for the MRI brain image in the database is shown in the Table 1. The result of segmentation accuracy achieved is 98.8%.

Table 1 Performance Analysis for Segmentation Accuracy (SA)

Methods Noise Level (%)	FCM SA (%)	TVFCM SA (%)	ADTVFCM SA (%)
3	97.5	98	98.8
5	95.7	97	98.1
7	88.2	95.8	97

The pictorial representation for the Table 1 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.

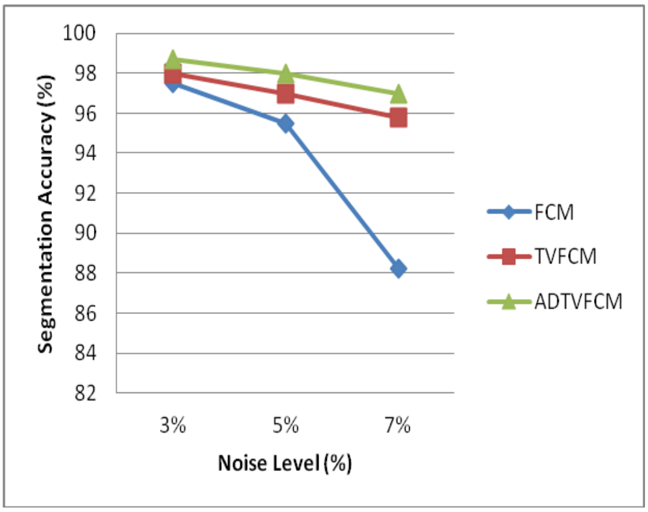

Fig.3 segmentation accuracy comparison with different noise levels

The sensitivity (Se), specificity (Sp) and Accuracy (acc) for the clustering algorithms are evaluated. The Se, Sp, Acc are derived as shown in the equations (13) – (15)

$$Se = \frac{TP}{TP+FP} \quad (13)$$

$$Sp = \frac{TP}{TN+FP} \quad (14)$$

$$Acc = \frac{TP+TN}{TP+FN+TN+FP} \quad (15)$$

Table 2 Performance Results of FCM, TVFCM, and ADTVFCM Methods

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)
FCM	81	93.7	87.6
TVFCM	86.8	95.2	94.7
ADTVFCM	92.6	97.5	98.4

Where, TP-True Positive, FN-False Negative, TN-True Negative, FP-False Positive. The performance results from Table 2 show that ADTVFCM provides sensitivity (Se) of 92.6%, specificity (Sp) of 97.5% and Accuracy (Acc) of 98.4% when compared to FCM and TVFCM, the result of which is shown is the Fig. 4

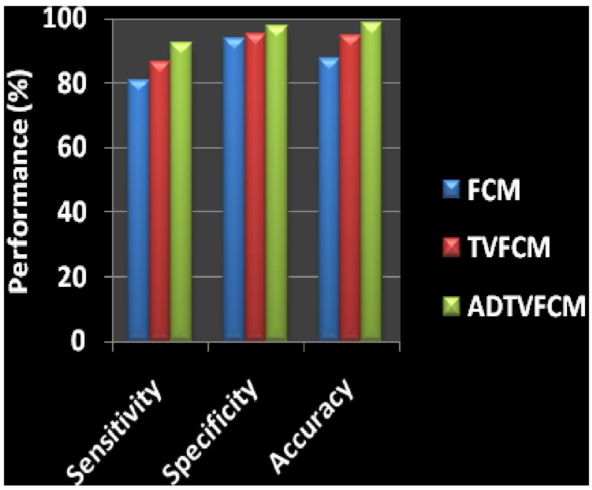

Fig. 4 Se, Sp, Acc of FC, TVFCM, ADTVFCM Method

5 Conclusion and Future Work

In this paper, we have described an Anisotropic Diffused Total Variation Fuzzy C Means segmentation method, based on new objective function, which seems well adapted and efficient for functional MRI data to detect the CSF level. The proposed segmentation method is more robust than the TVFCM and FCM algorithm. ADTVFCM method eliminates the noise in the image and it works properly on gradient-sparse images. The proposed method also minimizes the stair casing effect and ringing artifacts that are common with traditional TV method. The Majorize Minimize algorithm is used for the minimization of ADTVFCM method to obtain the results with better segmentation accuracy. The sensitivity and specificity for ADTVFCM method has less false positives compared to FCM and TVFCM. Experimental results on Brain image datasets of MRI shows that ADTVFCM is efficient and can reveal very encouraging results in terms of quality of the solution found.

Future work includes the optimization of FCM, TVFCM and ADTVFCM using an optimization algorithm like particle Swarm Optimization in an iterative fashion to improve the segmentation accuracy. The method may be used to find other abnormalities like Alzheimer and cognitive diseases.

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