ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 1, Issue 5, November 2012

A New Fuzzy C Means for Brain Image Segmentation Using Anisotropic Diffused Regularization

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ABSTRACT

Medical Imaging is the technique and a process used to create images of the human body for clinical or medical science. Magnetic Resonance (MR) Brain image segmentation plays an important role in neurosurgical planning and clinical diagnosis. MR image is segmented using Fuzzy C means (FCM) method, the objective function of FCM is modified by a regularizing function called Total Variation (TV)FCM. The proposed robust image regularization Anisotropic Diffusion Total Variation (ADTV) regularization method focuses on smoothing the images and reducing the steps by reinterpreting the traditional TV regularization. The method preserves the discontinuities and also continues to smooth along line like features in the MR images and the comparison of proposed scheme with classical TV demonstrates the performance improvement. The method shows the consistent improvement in the reconstruction of images. The method is combined with the FCM and the results of segmentation are improved.

1 Introduction

The task of segmentation is to partition a digital image into multiple segments and to simplify and / or change the representation of an image to be more meaningful and easier to analyze more precisely. Image segmentation is the process of assigning a label to each pixel in an image such that pixels with the same label share certain visual characteristics. The vital role of image analysis is to distinguish different objects in an image that are of interest and rest of the object. The primary role is to extract object boundaries to understand the content of an image for searching and mining in medical image records. The goal of segmentation of MRI images is to find out the level of tissues and lesions present. This helps in diagnosing the disease and to plan for the treatment. Fuzzy clustering techniques [1,2] are best suited to segment the MRI images because the uncertainty of MRI image is widely presented in data. In particular, the transitional regions between tissues are not clearly defined and their memberships are intrinsically vague. In hard image segmentation the information is not preserved, while in fuzzy clustering, more information is preserved. The most and powerful segmentation is the Fuzzy c-means (FCM) [3] clustering algorithm. The focus in this paper is to improvement of the FCM approach and applies it to MRI brain image segmentation.

FCM allows pixels to belong to multiple clusters with varying degrees of membership. One of the major disadvantages of FCM is that it is sensitive to noise; therefore, traditional FCM algorithm has proven to be problematic because medical images always include considerable uncertainty and unknown noise. To overcome this problem regularization parameter is added to the objective function of the original FCM method called Total Variation regularization. This method eliminates the noise in the image. In the present work, the TV regularizer is modified by the introducing the novel image regularization penalties to overcome the practical problems. The method inherits the properties of the Classical TV and preservers the discontinuities. Our motivation is to make the segmentation regions and boundaries well connected.

2 Related Works

FCM is robust to blurring, applicable to multispectral data and requires no assumption so the probability density functions of the data. However, the original FCM method is sensitive to noise and incomplete data because it considers only the intensity of the image and does not take the spatial context and boundary connections into consideration. To overcome this problem regularization of the image is done. Li and Mukaidono [4] apply regularization by the entropy of the membership function, while Miyamoto and Umayahara [5] regularized the FCM by a quadratic term. Both of these regularizers restrict the admissible membership function within the space of smooth functionals. In Pham et al. [6], the unknown grain field was incorporated within the minimizing FCM functional and appropriate grain field regularizing terms were added to correct the smooth non uniformity within the segmentation process. This method was further improved by Cao et al. [7] for M-FISH images by using another regularization term. 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. [8]

The gradient sparsity-promoting norm was recently also explored for multi-class image partitioning and labeling, e.g., in the convex relaxation approaches of the Potts model [9]. Genetic Approach on Medical Image Segmentation proposed by R Venkateswaran [10], the computational complexity is more in this method. A sparsity promoting method called total variation (TV) regularized FCM (TVFCM) has proposed as the previous work, The TV regularizer works effectively on gradient-sparse images for removing spurious oscillations while preserving sharp edges.

Images often have edge and ridge like features, the anisotropic image smoothing is often more desirable. The anisotropic second-degree functional introduced in [15] and [16] is variant to image rotations. The main goal of this paper is to introduce Anisotropic Diffusion, which inherits the desirable properties of the classical TV penalty (e.g., feature-preserving smoothing, invariance to rotation and translation, convexity, and simplicity). The directional derivatives along different directions are preserved. The Majorization–Minimization (MM) algorithms [17,18] are introduced to solve the anisotropic regularized recovery problems. The algorithm successively minimizes the sequence of quadratic surrogate penalties. The surrogate functionals majorize the image and are dependent on the current image iterate. The use of desirable properties is to develop computationally efficient algorithms to determine the better results.

The rest of this paper is organized as follows: the preprocessing technique in section 3.1 and 3.1.1. The original FCM method is reviewed in Section 3.2. The new TVFCM model is presented in section 3.3. TVFCM with ADMM method is reviewed in section 3.3.1. The Anisotropic Diffused TVTFCM in section 3.4 and ADTVFCM with MM in section 3.4.1 we compare the FCM, TVFCM, and ADTVFCM schemes and observe that ADTVFCM method works effectively on gradient-sparse images for removing spurious oscillations while preserving sharp edges.

3.1 Proposed System

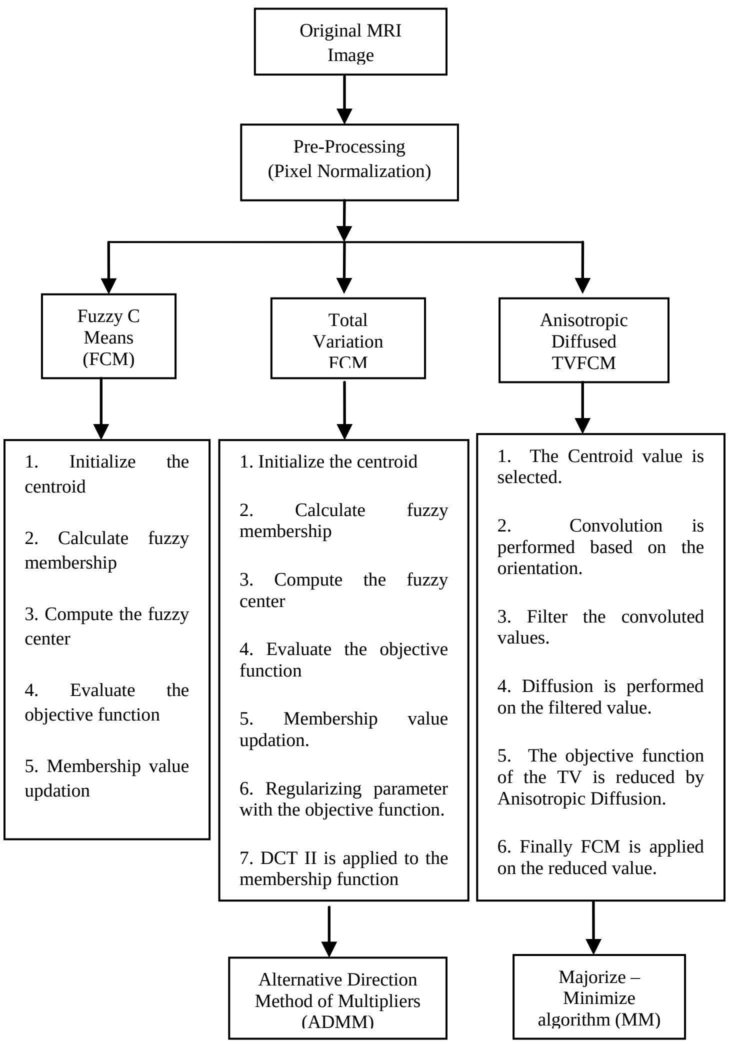


Fig.1.1 Block Diagram of Proposed Work

3.1 Pre - Processing

In general, processing of an image in order to prepare it for the primary processing. The preliminary step in processing the image is Pre-Processing. In this stage there are several steps required to prepare data as per the needs of the user. There are several preprocessing techniques; some are pixel adjustment, pixel normalization.

3.1.1 Pixel Normalization

The preprocessing technique used in this paper is pixel normalization method. The method changes the range of pixel intensity values. The technique is applied to images with poor contrast due to glare. Normalize the image before applying clustering methods. The method improves the brightness of the image.

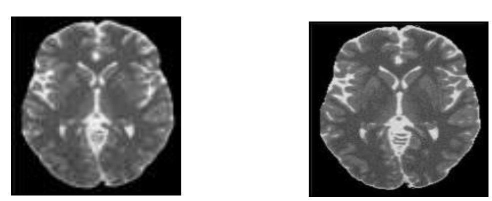
To improve the brightness of the image, normalization performs two steps:

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 as shown in Fig. 1.2 (a). The output of the pre-processing by normalization is shown in Fig. 1.2 (b)

$$v = (\text{image} - \min) / (\max - \min)$$



(a) (b)

Fig. 1.2 (a) Original image (b) Pre-Processed image

ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
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3.2 FCM algorithm

FCM is used to segment the images. To segment the MRI images, the objective function is obtained by weighted dissimilarity terms as shown in eqn (1). FCM method is considered as an optimization problem, which is defined for m>1 as,

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

Where,

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

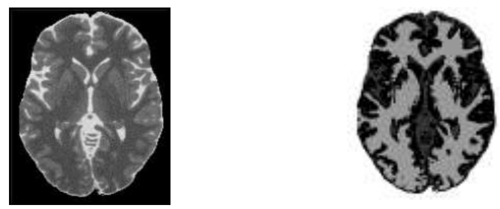
The dissimilarity terms such as data point and the cluster center [11] is defined to find the objective function. Using Lagrange multiplier method we obtain the minimum saddle point J (i.e.) objective function. This is achieved by iteratively finding the value for U and V. The cluster center and the membership function is calculated form eqn (2) and (3) as follows,

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

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

The cluster center and the new membership function are calculated iteratively. The iteration continues until the minimum objective value is found or the iteration continues until difference between two iterations has minimum value. It was 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.

The input image is chosen with 7% noise and is pre-processed image as shown in Fig. 1.2. FCM method is applied on the pre-processed image and the segmentation result obtained is very poor. Therefore, FCM method cannot be applied to images with noise. The result of the FCM segmentation with noise is shown.



(a) (b)

Fig. 1.3(a) Preprocessed image (b) Result of FCM

3.3 TVFCM algorithm

TV method is used to make segmentation result better by eliminating the noise and missing data in the image. This method uses regularizing parameter with the objective function of the FCM for eliminating the noise, as shown in eqn (4) and makes FCM method more robust to noise. The function is given as

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

Where,

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

The value of the parameter μ will be chosen greater than 0 (μ>0). The cluster center value and the membership value are calculated as in FCM then the regularizing parameter value is multiplied

ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 1, Issue 5, November 2012

with the objective function. The Discrete Cosine Transform II (DCT) [13,14] operation is applied 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 segments in the results become smoother with decreasing µ. The value of the parameter is chosen by hand to obtain the best segmentation result and to get the good visual quality of images. As the value of the parameter is decreased the segmentation result will be better. The result of TVFCM with noisy image is shown in Fig. 1.4(b). the algorithm is very robust to noise and the segmentation result is better compared to FCM.

3.3.1 TVFCM with ADMM

The ADMM method is used to solve the optimization problems that use partial updates for the dual variables. The method solves the problems such as,

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

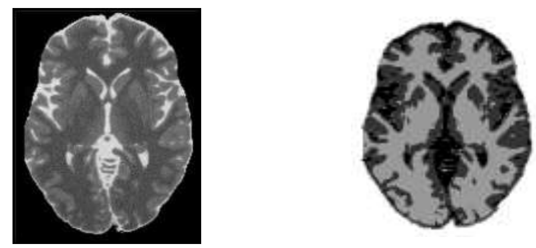
The method splits the problem into sub problems that has to be solved. The ADMM method is performed iteratively until the convergence criterion is reached. The objective function of the TVFCM method is written in the general form as of ADMM. To minimize the objective function the x minimization in eqn (6), z minimization in eqn (7) and the dual variable update in eqn (8) is 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.



(a) (b)

Fig. 1.4 (a) Preprocessed image (b) Result of TVFCM

3.4 ADTVFCM

Anisotropic diffusion aims 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. The total variation is reinterpreted in the form of directional derivatives as given in eqn (10). The directional derivatives at a specific location can be given as,

$$f_{\theta,1}(r) = |\nabla f(r)| \cos(\theta - \varphi) \tag{10}$$

Where φ denotes the orientation of the gradient. The classical TV is reinterpreted to obtain the new form shown in eqn (11) as,

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

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

ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
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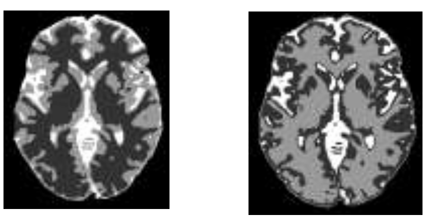
of the FCM method is added and the segmentation accuracy is improved than traditional TVFCM.

3.4.1 Majorize-Minimize (MM Algorithm)

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 (12) is minimized to obtain the expected results. The minimization operation is the iterative step; the iteration is performed until the minimized result is achieved.

$$G_n(f) \le G_n\left(f^{(m)}\right) + 1/2\pi \int_\Omega \int_0^{2\pi} \varphi_n^{(m)}(r,\theta) \left|f_{\theta,n} r\right|^2 d\theta\, dr \qquad (12)$$



(a) (b)

Fig.1.5 (a) Pre-Processed image (b) Result of ADTVFCM

4 Results

4.1 Experimental Results

The segmentation accuracy (SA) is given calculated as in the eqn (13). The FCM, TVFCM and ADTVFCM method are compared and found that ADTVFCM outperforms the other methods. The segmentation accuracy is given as,

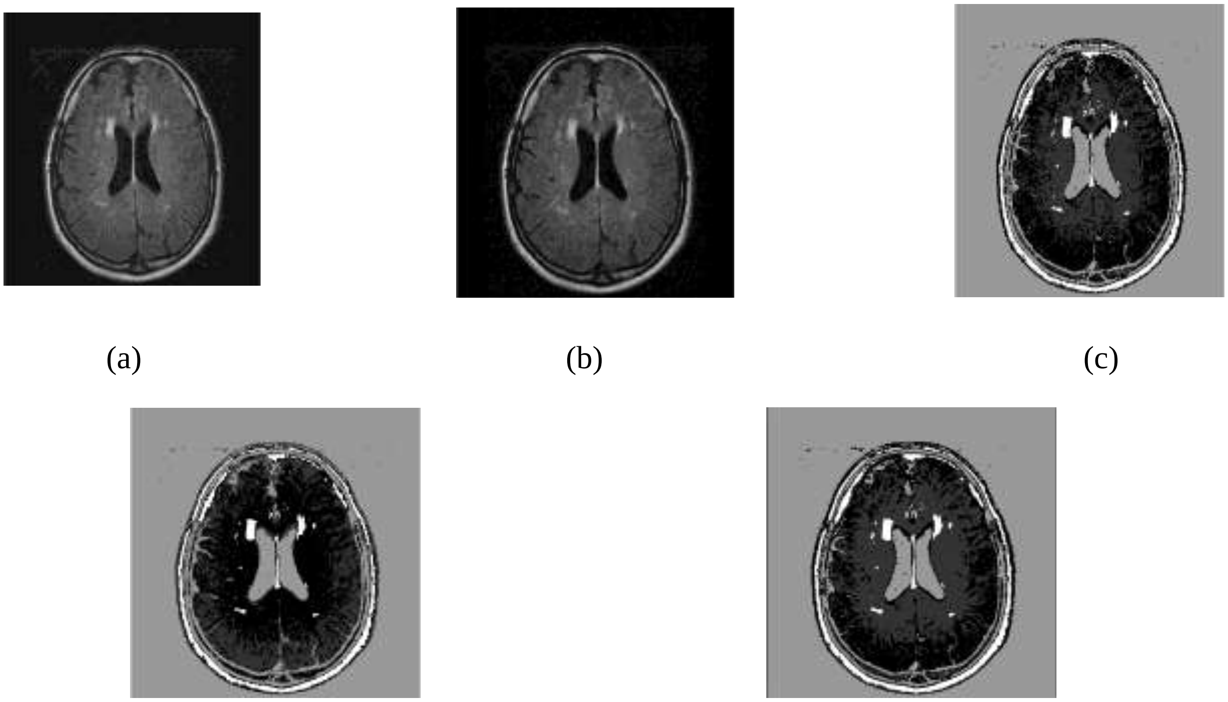
$$SA = \frac{correctly\ classified\ pixels}{all\ pixels} \qquad (13)$$

The segmentation results of FCM and TVFCM with different noise levels for the brain image in the database is shown in the Table 1. The original image is shown in the Fig. 2.2 (a) is taken from the database. The preprocessed image is shown in Fig. 2.2 (b) where the brightness of the image is improved. The Fig. 2.2 (c) and Fig. 2.2 (d) shows the segmentation results of FCM and TVFCM. The results of TVFCM have segments with smoother boundaries and the edges are preserved.

Table.1

Noise Level (%)	**FCM SA**	**TVFCM SA**	**ADTVFCM SA**
3	0.9749	0.9803	0.9895
5	0.955	0.9701	0.9812
7	0.8826	0.9584	0.9756
11	0.7740	0.9315	0.9586
19	0.7505	0.9206	0.9454
23	0.7270	0.8996	0.9267
27	0.7158	0.8823	0.9051
31	0.6989	0.8547	0.8868
39	0.6872	0.8519	0.8653

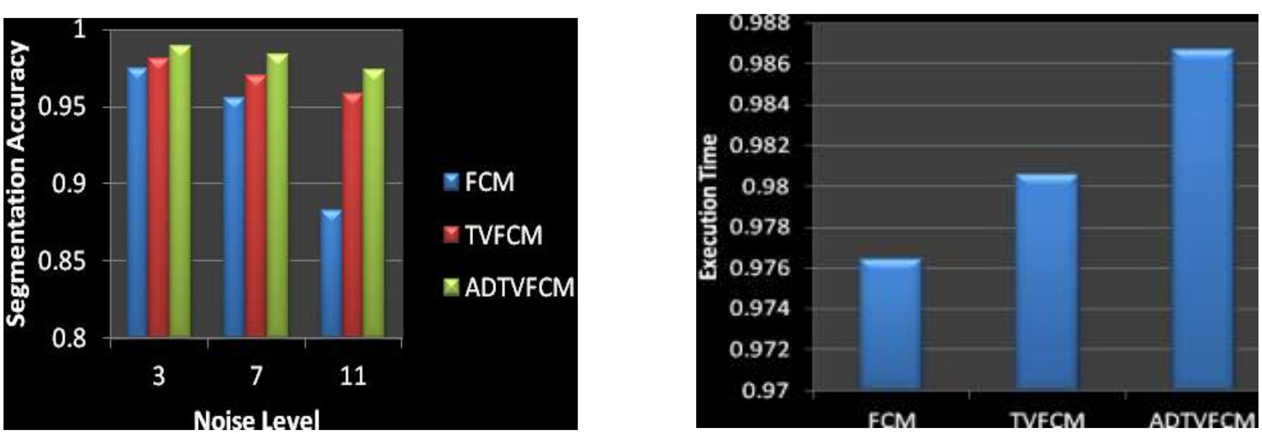
The performance analysis is shown in the Fig. 2.2(a), the different noise levels are plotted in horizontal coordinates and the segmentation accuracy is plotted in the vertical coordinates. The analysis based on the execution time is shown in Fig.2.2(b). The segmentation results of TVFCM method are better when compared to traditional FCM method.



(a) (b) (c)

(d) (e)

Fig 2.1 Segmentation results on real MRI image (a) Real MRI image (b) Pre-Processed image (c) using FCM method (d) using TVFCM method (e) using ADTVFCM method.



(a) (b)

Fig. 2.2 (a) Comparison of segmentation accuracy with images having different noise levels. (b) Result by execution time.

5 Conclusions 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 segmentation. The proposed segmentation method is more robust than the TVFCM algorithm. This method eliminates the noise in the image and it works properly on gradient-sparse images. The method minimizes the staircase and ringing artifacts that are common with traditional TV. The Majorize Minimize algorithm is used for the minimization the ADTVFCM method to obtain the results with good segmentation accuracy. As the future work the results obtained using FCM, TVFCM, ADTVFCM can be optimized using optimization algorithm like particle Swarm Optimization in an iterative fashion to improve the segmentation accuracy.

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