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An Efficient Segmentation Technique for Mri Medical Images

M. Ganesh, V. Palanisamy

Abstract: ***Image segmentation is a technique to locate certain objects or boundaries within an image. Image segmentation plays a crucial role in many medical imaging applications. There are many algorithms and techniques have been developed to solve image segmentation problems. Spectral pattern is not sufficient in high resolution image for image segmentation due to variability of spectral and structural information. Thus the spatial pattern or texture techniques are used. Thus we proposed an efficient image segmentation technique, in which we have used the concept of Adaptive Fuzzy C-Means Algorithm for segmentation of high resolution medical image. The proposed method is implemented in Matlab and verified using various kinds of high resolution medical images. The experimental results shows that the proposed image segmentation system is efficient than the existing segmentation systems.***

Index Terms: ***Image Segmentation, Adaptive Fuzzy C-Means Algorithm, Clustering, Gabor Filter, Morphological Operation.***

I. INTRODUCTION

Neurological conditions are the most common cause of serious disabilities and have a major, but often unrecognized, impact on health and social services. It can change the shape, volume and distribution of brain tissue. The advantages of magnetic resonance imaging (MRI) over other diagnostic image modes are its high spatial resolution and excellent discrimination of soft tissues. MRI is the preferred imaging techniques for examining neurological conditions which requires segmentation into different classes which are regarded as the best available representations for biological tissues and it can be performed by using image segmentation [1].

Spectral pattern is not sufficient in high resolution image for image segmentation due to variability of spectral and structural information. Thus the spatial pattern or texture techniques are used. Thus the concepts of Adaptive Fuzzy C-Means Algorithm for segmentation in high resolution image are used. Adaptive Fuzzy C-Means Algorithm is basically used to measure the local regularity of image.

Local Binary Patterns is a technique that describes the texture in terms of both statistical and structural characteristics. Adaptive Fuzzy C-Means Algorithm is used to assess the roughness or smoothness around each pixel of the image. The measure of dispersion is used to compute the Adaptive Fuzzy C-Means Algorithm [2].

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*****Correspondence Author(s)
M. Ganesh*, Department of ECE, Info Institute of Engineering, Coimbatore, India.
V. Palanisamy, Principal, Info Institute of Engineering, Coimbatore, India.

The window size is assessed to detect the localized singularities. Larger window size is insensitive to noise that leads to loss of information of singularity, while the smaller window size represent the singularity well but sensitive to noise. So it is preferable to determine the window from two respects.

- Additional singularity should not be contained in the same window
- The size of the window should be enlarged on the location without obvious singularity.

An iterative clustering procedure is adapted to detect the range of cluster contained in the kernel, localize the cluster center (this approach moves the range of Adaptive Fuzzy C-Means Algorithm values in the direction where the density is higher), and identify the cluster contained in the kernel (background, range). A clustering procedure including maximum likelihood analysis is used to classify the Adaptive Fuzzy C-Means Algorithm image.

II. RECENT RESEARCHES

Incorporating local spatial and gray information together [3], a novel fast and robust FCM framework for image segmentation, i.e. Fast Generalized Fuzzy c-means clustering algorithms (FGFCM). FGFCM can mitigate the disadvantages of FCM_S and at the same time enhances the clustering performance.

A new approach regarding matting problem [4] which splits the task into two steps: interactive trimap extraction followed by trimap-based alpha matting. That paper has two contributions: (i) a new trimap segmentation method using parametric max-flow; (ii) an alpha matting technique for high resolution images with a new gradient preserving prior on alpha.

Image segmentation can be performed on raw radiometric data, but also on transformed colour spaces, or, for high-resolution images, on textural features [5] have reviewed several existing colour space transformations and textural features, and investigate which combination of inputs gives best results for the task of segmenting high-resolution multispectral aerial images of rural areas into its constituent cartographic objects such as fields, orchards, forests, or lakes, with a hierarchical segmentation algorithm.

A three-dimensional atlas of the mouse brain [6] manually segmented into 62 structures, based on an average of 32 µm isotropic resolution T2-weighted, within skull images of forty 12 week old C57Bl/6J mice, scanned on a 7 T-scanner. Individual scans were normalized, registered, and averaged into one volume. Structures within the cerebrum, cerebellum, and brainstem were painted on each slice of the average MR image while using simultaneous viewing of the coronal, sagittal and horizontal orientations.

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An optimization approach that enhances the quality of image segmentation using the software Definiens Developer. [7] The optimization iteratively combines a sequence of multiscale segmentation, feature-based classification, and classification-based object refinement. The developed method has been applied to various remotely sensed data and was compared to the results achieved with the established segmentation procedures provided by the Definiens Developer software.

A new and fast unsupervised technique for segmentation of high-resolution synthetic aperture radar (SAR) images [8] into homogeneous regions. That technique was based on Fisher probability density functions of the intensity fluctuations and on an image model that consists of a patchwork of homogeneous regions with polygonal boundaries.

A method for detecting the high resolution locations of membranes from low depth-resolution images [9]. They have approached that problem using both a method that learns a discriminative; over-complete dictionary and a kernel SVM.

III. PROPOSED WORK

Here, we proposed an efficient image segmentation technique to segment the high resolution medical images. Initially, the filtering technique is applied to the query image to remove the noise content in the medical image. Then morphological operations like dilation and erosion are done over the filtered image. Finally, the image is segmented using Adaptive Fuzzy C-Means Algorithm.

A. Gabor Filtering

Gabor Filter, a kind of frequency filter, which has been applied to texture analysis, moving object tracking and face recognition, are also shown to be good fits in character recognition field. The primary step for high resolution image segmentation is, removing the noise from the query image using Gabor filter. This filter removes the noise content from the image and makes the image ready for the recognition.

The complex term of the image $g(x,y)$ can be represented as

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp\left(-\frac{x'^2+\gamma 2y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\psi\right)\right) \quad (1)$$

The real component of the image $g(x,y)$ can be represented as

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp\left(-\frac{x'^2+\gamma 2y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad (2)$$

The imaginary component of the image $g(x,y)$ can be represented as

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp\left(-\frac{x'^2+\gamma 2y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad (3)$$

Where,

$$x' = x\cos\theta + y\sin\theta \quad (4)$$

$$y' = -x\sin\theta + y\cos\theta \quad (5)$$

In this equation, λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the sigma of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function.

B. Morphological Operations

Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image. The most basic morphological operations are dilation and erosion. For Dilation, the value of the output pixel is the maximum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1, and for erosion, the value of the output pixel is the minimum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to 0, the output pixel is set to 0.

C. Image Transformation

The Adaptive Fuzzy C-Means Algorithm analysis is used here to transform the image for the identification of the texture. It does not require any prior information about the pixel intensity. The predefined measure is used to estimate the degree of texture around each pixel. The pre-defined measure is one of the most important characteristics to compute the Adaptive Fuzzy C-Means Algorithm. The roughness or smoothness around each pixel can be assessed by the appropriate estimation of the mea-sure. In this paper we determine the measure of dispersion of pixel values using linear regression analysis.

Let the subset Ω^* of the region Ω contains only those pixels which intersect the perimeter of the circle of radius r. Hence for t number of increasing radius (i.e., $r=1$ to t) there will be t number of subsets Ω^*. Subsequently the radius r versus the intensity values $I(i)$ of that subset Ω^* is plotted and from the least square fit of regression line calculate the intensity value J for each radius r. As a result, a new measure $K(i)=|I(i)-J|$, for each $i\in\Omega^*$ is obtained. In turn this provides the dispersion of pixels from the line of regression. The above measure can be represented as:

$$\mu disp(\Omega*)=\{K(i)=|I(i)-J|; Min(I(i))\le J\le Max(I(i))\} \quad (6)$$

where J is the derived intensity value for radius r using the regression equation. $\mu disp(\Omega*)$ is the measure of dispersion of pixels contained in the subset Ω^*.

Logarithmic plots of computed measure K versus radius R values are drawn and got the Adaptive Fuzzy C-Means Algorithm α as follows:

$$A=\frac{1}{n}\sum_{r=1}^{t}\sum_{i=1}^{m}\log\frac{K(i)}{R(r)} \quad (7)$$

where t is the total number of identified balls,

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m is the number of intersected pixel on the perimeter of the circle of radius $R(r)$ and N is the total number of pixels under each ball of radius $R(r)$.

D. Clustering

The range RQ of a cluster in the Adaptive Fuzzy C-Means Algorithm image is defined as follows Let us consider the below equation $G = \{gkl, AdaptiveFuzzy\ value\ \ in\ G(k,l)\}$, where $k = 1,\ldots,m$ and $l = 1,\ldots,m$ is a kernel with m^2 Adaptive Fuzzy C-Means Algorithm Q is a cluster in G with center $CQ(mean)$. Then the range RQ of the cluster Q contains only those values satisfying the following properties:

$$Abs(gkl - CQ) < RQ \qquad (8)$$

Eqn. 8 means that cluster Q contains that range of AFCM value, which have a minimum degree of association (represented by RQ).

Localization of cluster is to find a center in the dataset where the 'density' (or number) of range of pixel values in G within a range, i.e., RQ is locally maximal. Primarily the cluster center is initialized with the mean AFCM values. Then we select the AFCM values within the RQ from the center of G (i.e., mean of G).

This is implemented iteratively by decreasing RQ with a constant value until absolute difference between the initial center (CQ) and present center (ME) reaches the desired value (minimum difference). In the first iterations (when RQ is still large) this technique moves the range of AFCM values to regions of the data where the 'global' density is higher (these regions often contain the large number of pixels). After some iteration (when RQ is equal to constant value) the kernel center moves towards an actual range of AFCM values where the density is 'locally' higher.

The Cluster identification consists of two parts, Background and Range. Backgrounds are the AFCM values in the AFCM image not included between $(CQ - RQ)$ and $(CQ + RQ)$ values. Such AFCM values, either belongs to another cluster or do not belong to any cluster (noise; are not significantly associated with other AFCM values). AFCM values belonging to other clusters are not considered at the time of threshold calculation for the current cluster. Ranges are the AFCM values represented as $(CQ - RQ) \le AFCM \le (CQ + RQ)$. AFCM values belonging to the cluster are significantly correlated.

Cluster weight is computed with the formula

$$W(Cluster_k) = \frac{freq}{n * m} \qquad (9)$$

Where, k is the number of cluster resides in the kernel. $freq$ is the total number of AFCM falling in the range of k^{th} cluster residing in the kernel. $W(Cluster_k)$ is the possibility (or weighting factor) to assign the AFCM value in the k^{th} cluster. n and m represent the number of row and column of the kernel respectively. Maximum weighted cluster is identified with the equation

$$MaxW(Cluster_k) = (\sup\{W(cluster_k)\}, k = 1,\ldots,L) \qquad (10)$$

Where, L is the number of cluster contained in the kernel.

IV. RESULTS AND DISCUSSION

The results obtained during the process of proposed medical image segmentation are discussed. Initially, Gabor filter has to be applied to the input query image to reduce the noise content in the image. Since, the segmentation has to be done in a clear image to get accurate segmented output. Fig. 1 shows the query image and also the image output of Gabor filter.

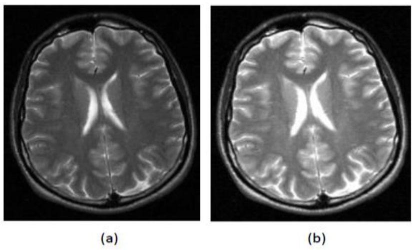

Fig. 1 (a) Input image and (b) Gabor filter output

After applying Gabor filter, the output image is subjected to morphological operations like dilation and erosion. Fig. 2 shows the output image after morphological operations.

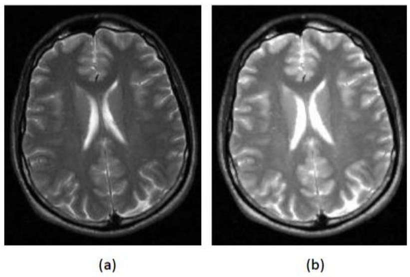

Fig. 2 (a) Input image and (b) Image after Morphological operations

Then the image is transformed using Adaptive Fuzzy C-Means Algorithm. Adaptive Fuzzy C-Means Algorithm is used to assess the roughness or smoothness around each pixel of the image. The measure of dispersion is used to compute the Adaptive Fuzzy C-Means Algorithm. After image transformation, clustering is applied to cluster the image contents to form the segmented image. This noise can be removed by applying the mean value for each pixel from the neighbor pixels. Thus the segmentation output of the given medical image as shown in the Fig. 3.

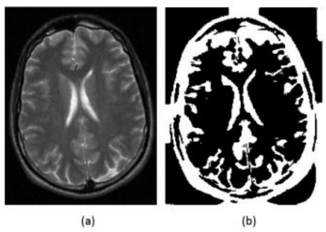

Fig. 3 (a) Input image and (b) Segmented image

A. Comparative Analysis

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Magnetic Resonance Imaging (MRI) is one of the most common ways to visualize brain structures. Based on this imaging technique, the study of the main cerebral tissues (namely, white matter (WM) and grey matter (GM)) is in particular a key point in the context of computer-aided diagnosis and patient follow-up. Our proposed image segmentation technique is compared with the existing technique depend upon the white matter and grey matter of the segmented brain MRI image.

Table: I show the percentage of white matter and grey matters in the proposed image segmentation as well as the existing segmentation technique.

Table: I Overlap measures (GM, WM) obtained for different segmentation methods

Segmentation Method	White Matter (%)	Grey Matter (%)
Active contours model	79.32	76.56
Graph cut	81.45	79.74
Fuzzy C-Means algorithm	85.60	83.21
Kernel-based fuzzy C-means algorithm	82.78	80.94
Multiple kernel fuzzy C-means algorithm	86.24	82.56
Robust Fuzzy C-Means Algorithm	86.09	84.08
Adaptive Fuzzy C-Means Algorithm	88.24	86.39

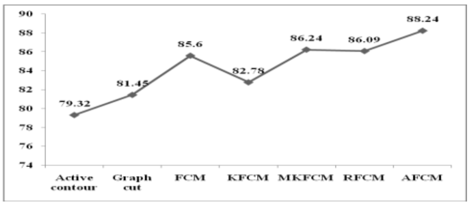

Fig.4 White Matter comparission

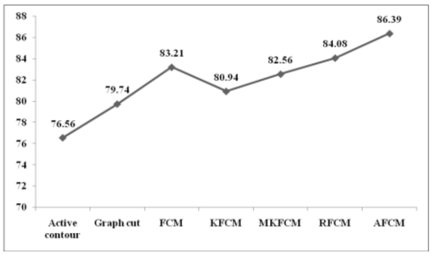

Fig.5 Grey Matter comparission

Fig. 4 gives the graphical representation about the percentage of white matter in the MRI image and Fig. 5 gives the graphical representation about the percentage of grey matter in the MRI image. Fig. 4 and Fig. 5 shows that the proposed medical image segmentation technique is more efficient than the existing Fuzzy based segmentation since the percentage of overlap measures (WM and GM) is high as compared with the existing technique.

V. CONCLUSION

Image segmentation is the most challenging and active research area in the field of image processing for the last decade. In spite of the availability of a large variety of state-of art methods for brain MRI segmentation, but still, brain MRI segmentation is a challenging task and there is a need and huge scope for future research to improve the accuracy, precision and speed of segmentation methods. Here the medical image segmentation algorithms based on Adaptive Fuzzy C-Means Algorithm are proposed. Since, AFCM can be used as a tool to measure the roughness or smoothness around each pixel in the image, and also AFCM does not require any prior information about the pixel intensity. Our work gives more overlap measures as compared to the existing technique, thus our medical image segmentation technique is more efficient. The proposed segmentation results shows that, the use of Adaptive Fuzzy C-Means Algorithm based strategy globally leads to better results than the other state of the art methods existing now.

REFERENCES

1. Birgani P. M, Ashtiyani M, Asadi S, “MRI Segmentation Using Fuzzy C-means Clustering Algorithm Basis Neural Network,” ICTTA, 2008.
2. Pietikainen M, Hadid A, Zhao G, Ahonen T ,2011,” Computer Vision Using Local Binary Patterns,” Computational Imaging and Vision 40- Springer-Verlag London Limited 2011.
3. Weiling Cai, Songcan Chen, and Daoqiang Zhang, 2007, "Fast and Robust Fuzzy C-Means Clustering Algorithms Incorporating Local Information for Image Segmentation," Journal of Pattern Recognition, Vol. 40, No. 3, pp. 825-838.
4. Christoph Rhemann, Carsten Rother, Alex Rav-Acha, and Toby Sharp, 2008, "High Resolution Matting via Interactive Trimap Segmentation," In Proc. of the CVPR’08.
5. Roger Trias-Sanz, Georges Stamon, and Jean Louchet, 2008, "Using colour, texture, and hierarchial segmentation for high-resolution remote sensing," ISPRS Journal of Photogrammetry & Remote Sensing, Vol. 63, pp. 156-168.
6. Dorr A.E, J.P. Lerch, S. Spring. Kabani, and R.M. Henkelmanb,2008, "High resolution three-dimensional brain atlas using an average, magnetic resonance image of 40 adult C57Bl/6J mice,” Journal of Neuro Image, Vol. 42, pp. 60-69.
7. Esch T, M. Thiel, M. Bock, A. Roth, and S. Dech, 2008, "Improvement of Image Segmentation Accuracy Based on Multiscale Optimization Procedure," IEEE Geoscience and Remote Sensing Letters, Vol. 5, No. 3, pp. 463-467.
8. Frederic Galland, Jean-Marie Nicolas, Helene Sportouche, Muriel Roche, Florence Tupin, and Philippe Refregier,2009, "Unsupervised Synthetic Aperture Radar Image Segmentation Using Fisher Distributions," IEEE Tractions on Geoscience and Remote Sensing, Vol. 47, No. 8, pp. 2966-2972
9. Daniel Glasner, Tao Hu, Juan Nunez-Iglesias, Lou Scheer, Shan Xu, Harald Hess, Richard Fetter, Dmitri Chklovskii, and Ronen Basri,2011. "High Resolution Segmentation of Neuronal Tissues from Low Depth-Resolution EM Imagery," In Proc. of the 8th international conference on Energy minimization methods in computer vision and pattern recognition, pp. 261-272.

AUTHOR PROFILE

Ganesh M obtained his Bachelor’s degree in Electronics and Communication Engineering from Arunai Engineering College, Thiruvannamalai. Then he obtained his Master’s degree in Applied Electronics from Sathyabamma University, Chennai and doing Ph.D degree in Digital Image Processing from Anna University, Coimbatore. Currently, he is a Assistant professor at the department of Electronics and Communication Enginering, INFO Institute of Engineering, Coimbatore. His specializations include Image segmentation and Enhancement for Different Images.

Dr. Palanisamy V was born nearby Village at Namakkal in July 1949 and had his schooling at Namakkal. He completed his B.E. – Electronics & Communication Engineering in the year 1972 at P.S.G. College of Technology. He completed his M.Sc. (Engg) in the field of Communication Systems at College of Engineering, Guindy, (presently Anna University, Chennai) in the year 1974. He was sponsored by Government of Tamilnadu to do his Ph.D in Communication-Antenna theory. at Indian Institute of Technology, Kharapur, West Bengal in the year 1981 and successfully completed the same. He retired as Principal, Government College of Technology, Coimbatore and presently working as Principal in Info Institute of Engineering, Coimbatore. He is a member in number of Academic boards, AICTE & University inspection committee.

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