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Holder Exponent Technique for Multi Resolution Medical Image Segmentation

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***Abstract*---**Image segmentation is a technique to locate certainobjects 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 Holder Exponent 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.

***Keywords*---**Image Segmentation, Holder Exponent, Clustering, Gabor Filter, Morphological Operation

I. INTRODUCTION

WITH the increasing size and number of medical images, the use of computers in facilitating their processing and analyses has become necessary. In particular, as a task of delineating anatomical structures and other regions of interest, image segmentation algorithms play a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes, diagnosis, study of anatomical structure, and computer-integrated surgery. Classically, image segmentation is defined as the partitioning of an image into non-overlapping, constituent regions which are homogeneous with respect to some characteristics such as intensity or texture[11]. Very high spatial resolution images provide a hugeamount of details and information. Thus, it is possible to extract new thematic classes and to detect smaller objects. But all those advantages are strongly tied to a major drawback from an image processing point of view. The processing of such images becomes very tricky; the local variability of the grey level values and the large number of data is a limiting factor for most of the classical analysis tools [7].

Image segmentation is the process of division of the image into regions with similar attributes [1]. It is an important step in the image analysis chain with applications to pattern recognition, object detection, etc. Until now, most approaches in this domain use the statistical model for the underlying image but in a parametric form [9]. Image segmentation is usually performed as a preprocessing step for many image understanding applications, for example in some land-cover and land-use classification systems. A segmentation algorithm is used with the expectation that it will divide the image into semantically significant regions, or objects, to be recognized by further processing steps. Most image segmentation methods take a parameter (usually a threshold for the dissimilitude between adjacent regions) and output a partition of the image. This usually translates into a single-scale analysis of the image: small thresholds give segmentations with small regions and much detail, large thresholds give segmentations preserving only the most salient regions. For a high-resolution aerial image, for example, at coarse scales we may find fields, while at finer scales we may find individual trees or plants [3].

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II. A SURVEY ON RECENT RESEARCHES

Image segmentation is widely used in a variety of applications such as robot vision, object recognition, geographical imaging and medical imaging. Classically, image segmentation is defined as the partitioning of an image into non-overlapped, consistent regions which are homogeneous with respect to some characteristics such as gray value or texture. Previously, some researchers have analyzed some methods to segment the high resolution image. Here some of the recent researches depend upon the image segmentationtechniques are specified.

Fuzzy c-means (FCM) algorithms with spatial constraints (FCM_S) have been proven effective for image segmentation. However, they still have the following disadvantages: 1) Although the introduction of local spatial information to the corresponding objective functions enhances their insensitiveness to noise to some extent, they still lack enough robustness to noise and outliers, especially in absence of prior knowledge of the noise; 2) In their objective functions, there exists a crucial parameter α used to balance between robustness to noise and effectiveness of preserving the details of the image, it was selected generally through experience; 3) The time of segmenting an image is dependent on the image size, and hence the larger the size of the image, the more the segmentation time. Weiling Cai *et al*. [10] proposed a work byincorporating local spatial and gray information together, a novel fast and robust FCM framework for image segmentation, i.e. Fast Generalized Fuzzy c-means clustering algorithms (FGFCM), was proposed in their work. FGFCM can mitigate the disadvantages of FCM_S and at the same time enhances the clustering performance. Furthermore, FGFCM not only includes many existing algorithms, such as fast FCM and Enhanced FCM as its special cases. The experiments on the synthetic and real-world images show that FGFCM algorithm was effective and efficient.

Christoph Rhemann *et al*. [2] presented a new approach to the matting problem which splits the task into two steps: interactive trimap extraction followed by trimap-based alpha matting. That paper has three 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; (iii) a database of 27 ground truth alpha mattes of still objects, which was considerably larger than previous databases and also of higher quality.

Image segmentation can be performed on raw radiometric data, but also on transformed colour spaces, or, for high-resolution images, on textural features. Roger Trias-Sanz *et al*. [3] 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 method to quantitatively evaluate the quality of hierarchical image segmentation was presented, and the behaviour of the segmentation algorithm for various parameter sets was also explored.

A.E. Dorr *et al*. [6] described a three-dimensional atlas of the mouse brain, 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.

T. Esch *et al*. [5] proposed an optimization approach that enhances the quality of image segmentation using the software Definiens Developer. The procedure aims at the minimization of over- and under segmentations in order to attain more accurate segmentation results. 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.

Frederic Galland *et al*. [4] proposed a new and fast unsupervised technique for segmentation of high-resolution synthetic aperture radar (SAR) images 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. The segmentation was obtained by minimizing the stochastic complexity of the image. Different strategies for the pdf parameter estimation were analyzed, and a fast and robust technique was proposed. Finally, the relevance of that approach was demonstrated on high-resolution SAR images.

Texture in high-resolution satellite images requires substantial amendment in the conventional segmentation algorithms. Debasish Chakraborty *et al*. [8] proposed a measure to compute the Holder exponent (HE) to assess the roughness or smoothness around each pixel of the image. The localized singularity information was incorporated in computing the HE. An optimum window size was evaluated so that HE reacts to localized singularity. A two-step iterative procedure for clustering the transformed HE image was adapted to identify the range of HE, densely occupied in the kernel and to partition Holder exponents into a cluster that matches with the range. Holder exponent values (noise or not associated with the other cluster) were clubbed to a nearest possible cluster using the local maximum likelihood analysis.

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 Holder Exponent. The basic flow diagram of the proposed method as shown in the Fig. 1.

Fig. 1 Basic Flow of the Proposed System

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

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

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

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

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

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

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 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 using HE

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

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

Eqn. 8 means that cluster Q contains that range of HE 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 HE values. Then we select the HE 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 HE 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 HE values where the density is 'locally' higher.

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

Cluster weight is computed with the formula

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

Where, k is the number of cluster resides in the kernel. $freq$ is the total number of HE falling in the range of k^{th} cluster residing in the kernel. $W(Cluster_k)$ is the possibility (or weighting factor) to assign the HE 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

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

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

IV. RESULTS AND DISCUSSION

In this section, 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. 2 shows the query image and also the image output of Gabor filter.

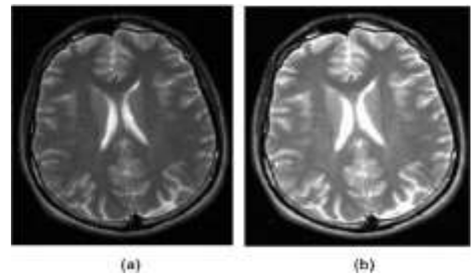

Fig. 2 (a) Input image and (b) Gabor filter output

After applying Gabor filter, the output image is subjected to morphological operations like dilation and erosion. Fig. 3 shows the output image after morphological operations.

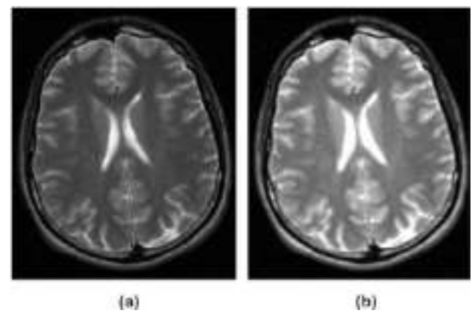

Fig. 3 (a) Input image and (b) Image after Morphological operations

Then the image is transformed using Holder exponent.

Holder Exponent is used to assess the roughness or smoothness around each pixel of the image. The measure of dispersion is used to compute the Holder Exponent. 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 we get the segmented output of the given medical image. Fig. 4 shows the segmented output of the medical image.

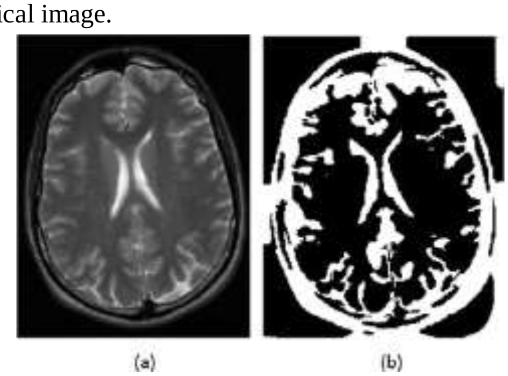

Fig. 4 (a) Input image and (b) Segmented image

A. Comparative Analysis

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. The existing segmentation method is Image segmentation using Fuzzy C-Means (FCM) algorithm [14].

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

TABLE: I
OVERLAP MEASURES (GM, WM) OBTAINED FOR DIFFERENT SEGMENTATION METHODS

Segmentation Method	White Matter (%)	Grey Matter (%)
Fuzzy C-Means algorithm	85.60	83.21
Robust Fuzzy C-Means Algorithm	86.09	84.08
Proposed Method	89.32	87.60

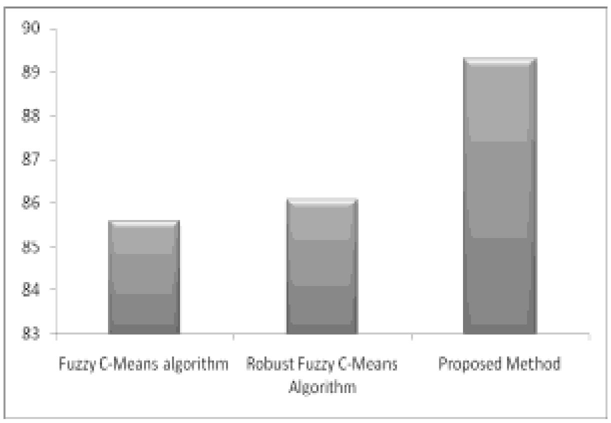

Fig. 5 White Matter comparission

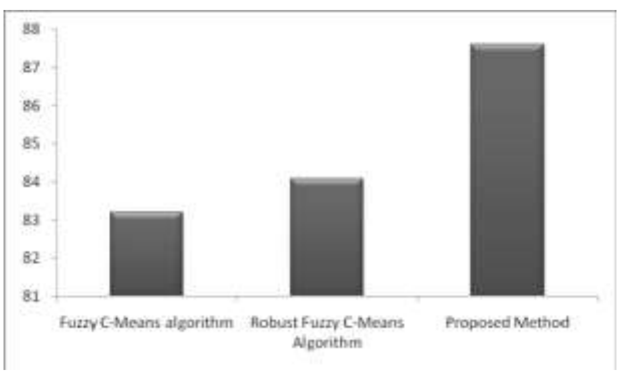

Fig. 6 Gray Matter comparission

Fig. 5 gives the graphical representation about the percentage of white matter in the MRI image and Fig. 6 gives the graphical representation about the percentage of grey matter in the MRI image. Fig. 5 and Fig. 6 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 we proposed a medical image segmentation algorithm based on Holder Exponent. Since, HE can be used as a tool to measure the roughness or smoothness around each pixel in the image, and also HE 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 Holder Exponent based strategy globally leads to better results than the other state of the art methods existing now.

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