Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 12 (22): 2332-2337, 2012
ISSN 1812-5654 / DOI: 10.3923/jas.2012.2332.2337

An Efficient High Resolution Medical Image Segmentation Technique Using Holder Exponent

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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. Brain image segmentation is one of the most important parts of clinical diagnostic tools. Brain images mostly contain noise, inhomogeneity and sometimes deviation. Therefore, accurate segmentation of brain images is a very difficult task. However, the process of accurate segmentation of these images is very important and crucial for a correct diagnosis by clinical tools. 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, the concept of holder exponent for segmentation of high resolution medical image is an efficient image segmentation technique. 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.

Key words: Image segmentation, holder exponent, clustering, Gabor filter, morphological operation

INTRODUCTION

For some applications, such as image recognition or compression, we cannot process the whole image directly for the reason that it is inefficient and unpractical. Therefore, several image segmentation algorithms were proposed to segment an image before recognition or compression. Image segmentation is to classify or cluster an image into several parts (regions) according to the feature of image, for example, the pixel value or the frequency response (Huang and Wu, 2006).

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 (Birgani *et al*., 2008).

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 Holder Exponent for segmentation in high resolution image are used. Holder Exponent is basically used to measure the local regularity of image (Trujillo *et al*., 2012).

Local binary patterns is a technique that describes the texture in terms of both statistical and structural characteristics. 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 (Pietikainen *et al*., 2011).

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 holder

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exponent 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 Holder Exponent image.

RECENT STATUS OF IMAGE SEGMENTATION

Incorporating local spatial and gray information together (Cai *et al.*, 2007), 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 (Rhemann *et al.*, 2008) which splits the task into two steps: Interactive trimap extraction followed by trimap-based alpha matting. That paper has two contributions: (1) A new trimap segmentation method using parametric max-flow and (2) 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. Trias-Sanz *et al.* (2008) 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 (Dorr *et al.*, 2008) 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.

An optimization approach is proposed to minimize over-and under segmentations in order to attain more accurate segmentation results using Definiens Developer software (Esch *et al.*, 2008). 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.

A new and fast unsupervised technique for segmentation of high-resolution Synthetic Aperture Radar (SAR) images (Galland *et al.*, 2009) 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.

Texture in high-resolution satellite images requires substantial amendment in the conventional segmentation algorithms. Chakraborty *et al.* (2009) 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.

A method for detecting the high resolution locations of membranes from low depth-resolution images (Glasner *et al.*, 2011). They have approached that problem using both a method that learns a discriminative; over-complete dictionary and a kernel SVM.

PROPOSED WORK

Here, an efficient image segmentation technique to segment the high resolution medical images are proposed. 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.

Gabor filtering: Gabor filters can serve as excellent band-pass filters for one-dimensional signals. A Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Gabor filters is having various transforms, image properties, operators, frequencies and various features which are used in detecting image segmentation. 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:

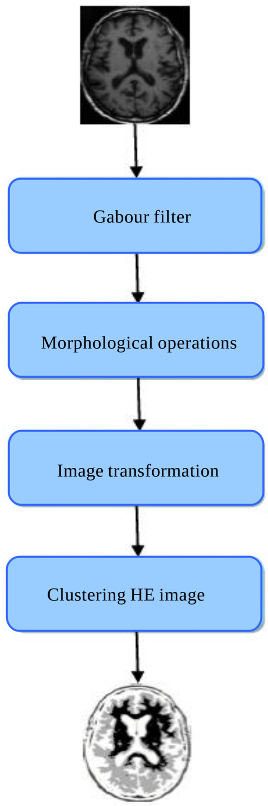

Fig. 1: Basic flow of the proposed system

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

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 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 γ is the spatial aspect ratio and specifies the ellipticity of the support of the Gabor function.

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.

Morphological operations are affecting the form, structure or shape of an object. Applied on binary images (black and white images-Images with only 2 colors: Black and white). They are used in pre or post processing (filtering, thinning and pruning) or for getting a representation or description of the shape of objects/regions (boundaries, skeletons convex hulls). 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 two principal morphological operations are dilation and erosion. Dilation allows objects to expand, thus potentially filling in small holes and connecting disjoint objects. Erosion shrinks objects by etching away (eroding) their boundaries. These operations can be customized for an application by the proper selection of the structuring element, which determines exactly how the objects will be dilated or eroded. The dilation process is performed by laying the structuring element B on the image A and sliding it across the image in a manner similar to convolution (will be presented in a next laboratory). The difference is in the operation performed. It is best described in a sequence of steps:

Step 1: If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel

Step 2: If the origin of the structuring element coincides with a 'black' in image, make black all pixels from the image covered by the structuring element

The erosion process is similar to dilation, but we turn pixels to 'white', not 'black'. As before, slide the structuring element across the image and then follow these steps:

Step 1: If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel

Step 2: If the origin of the structuring element coincides with a 'black' pixel in the image and at least one of the 'black' pixels in the structuring element falls over a white pixel in the image, then change the 'black' pixel in the image (corresponding to the position on which the center of the structuring element falls) from 'black' to a 'white'

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 the measure of dispersion of pixel values using linear regression analysis are determined.

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. From the least square fit of regression line, the intensity value J is calculated for each radius (r). As a result, a new measure K (I) = |I(i)-J|, for each I∈Ω* is obtained. In turn this provides the dispersion of pixels from the line of regression. The above measure can be represented as:

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

where, J is the derived intensity value for radius r using the regression equation and μdisp (Ω*) 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 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, 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).

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 exponent value in G (k, l)}

where, k = 1, ..., m and l = 1, ..., m is a kernel with m^2 Holder Exponent (HE). Q is a cluster in G with center GQ (mean). Then, the range RQ of the cluster Q contains only those HE values satisfying the following properties:

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

Equation 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, the selection of 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)≤HE≤(CQ+RQ). HE values belonging to the cluster are significantly correlated.

Cluster weight is computed with the formula:

$$W(\text{Cluster}_k) = \frac{F_{req}}{n \times m} \quad (9)$$

where, k is the number of cluster resides in the kernel. F_{req} is the total number of HE falling in the range of kth cluster residing in the kernel. W (cluster_k) is the possibility (or weighting factor) to assign the HE value in the kth cluster. n and m represent the number of row and column of the kernel, respectively. Maximum weighted cluster is identified with the equation:

$$\text{MaxW}(\text{Cluster}_k) = \left(\sup\{W(\text{cluster}_k)\}, k = 1, \ldots, L\right) \quad (10)$$

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

RESULTS AND DISCUSSION

To show the robustness of the proposed HE analysis is used in this study. This is done by applying the K-mean separately on the transformed images obtained from the Holder exponent analysis and comparing the results with other algorithms. Simultaneously the results of the proposed segmentation method, compared with other results to show the robustness of the proposed segmentation method.

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. Figure 2 shows the query image and also the image output of Gabor filter.

After applying Gabor filter, the output image is subjected to morphological operations like dilation and erosion. Figure 3 shows the output 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 the segmentation output of the given medical image as shown in the Fig. 4.

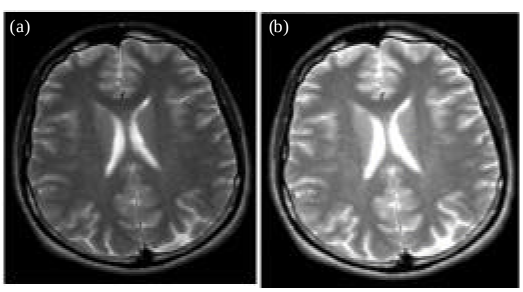

Fig. 2(a-b): (a) Input image and (b) Gabor filter output

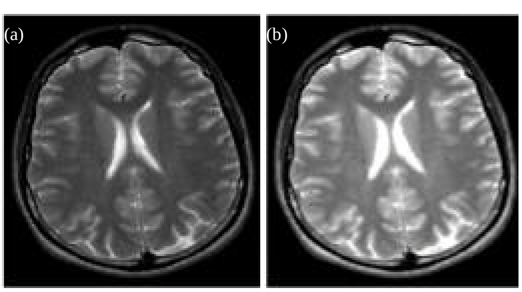

Fig. 3(a-b): (a) Input image and (b) Image after morphological operations

The other algorithms needs number of class as an input to segment the image whereas proposed technique need not require any input for segmentation. They only considers the information of pixel value for segmentation. The proposed segmentation technique also considers association of HE values to increase the classification accuracy.

In other methods, an iteration procedure is carried out until all pixels get classified in the image whereas in the proposed technique, iteration is done to identify the range of HE densely occupied in the kernel, and to partition those Holder exponent into a cluster which matches with that range. Holder exponent values (noise or not associated with the other cluster) are clubbed into a nearest possible cluster using the local maximum likelihood analysis. Proposed segmentation method is simple and takes very less computation time while other algorithms is time consuming.

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.

Table 1 show the percentage of white matter and grey matters in the proposed image segmentation as well as the existing segmentation technique.

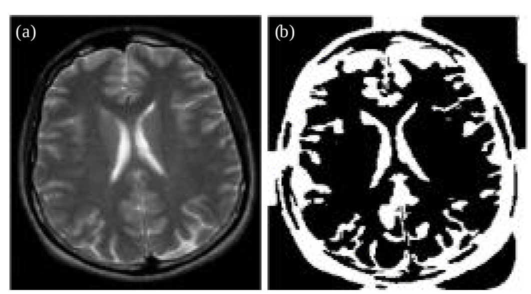

Fig. 4(a-b): (a) Input image and (b) Segmented image

Table 1: 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
Proposed method	89.32	87.60

CONCLUSION AND FUTURE SCOPE

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 Holder exponent are proposed. 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. Present 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 methods existing now.

The availability of very high spatial resolution images in remote sensing brings the texture segmentation of images to a higher level of complexity. Such images have so many details that the classical segmentation algorithms fail to achieve good results. In the case of BRAIN images, a texture can be so different within a same class that it becomes very difficult even for a human to segment or interpret those images. The study of the high frequency content of the data seems to be a good way to study those images. A new method which uses the singularity information to achieve the segmentation. It is based on the computation of the Holder regularity exponent at each point in the image.

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