Automatic brain tumour MR image segmentation performance analysis using Threshold and Genetic algorithm

B.Balakumar¹, P.Raviraj²

¹Assistant Professor, Centre for Information Technology and Engineering, M.S University, Tirunelveli, India, hellobala2006@yahoo.co.in
²Professor, Department of CSE, Kalaignar Karunanidhi Institute of Technology, Coimbatore, Tamilnadu, India, drpraviraj@gmail.com

ABSTRACT

Brain tumour segmentation is a vital process for early tumour detection and diagnosis. Many brain tumour segmentation methods have been presented, enhancing tumour segmentation methods is still challenging because brain tumour MRI images reveal complex characteristics. In this project we proposed a method for automatic heterogeneous brain tumour MR image segmentation performance analysis using genetic algorithm. The system consists of three stages to detect and segment a brain tumor. In the first stage, MR image of brain is acquired and pre-processing is done to remove the noise and to sharpen the image. In the second stage, edges are detected by using Gabor filter. In the third stage, threshold segmentation is done on the sharpened image to segment the brain tumour and the segmented image is post processed by Genetic algorithm. The proposed algorithms are tested with patients MRI. Results obtained with a brain MRI indicate that this method can improve the sensitivity and reliability of the systems for automated detection of brain tumors.

Keywords: - Median Filter, Gabor filter, Genetic algorithm, Threshold.

1. INTRODUCTION

This project discussed with the concept for automatic brain tumour segmentation. The MRI scanned image is taken for the entire process. The MRI scan is more comfortable than CT scan for diagnosis. It is not affect the human body. Because it doesn't use any radiation. Tumour is defined as the abnormal growth of the tissues. Brain tumour is an abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells. Brain tumours can be primary or metastatic, and either malignant or benign. A metastatic brain tumour is a cancer that has spread from elsewhere in the body to the brain MRI brain tumour segmentation provides useful information for medical diagnosis and surgical planning. However, it is a difficult task due to the large variance and complexity of tumour characteristics in images, such as sizes, shapes, locations and intensities. Tumour is defined as the abnormal growth of the tissues. Brain tumour is an abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells. Brain tumours can be primary or metastatic, and either malignant or benign. A metastatic brain tumour is a cancer that has spread from elsewhere in the body to the brain MRI brain tumour segmentation provides useful information for medical diagnosis and surgical planning [1]. However, it is a difficult task due to the large variance and complexity of tumour characteristics in images, such as sizes, shapes, locations and intensities. If the part of the tumour is spread to another place and grown as its...
own then it is known as secondary. Normally brain tumour affects CSF (Cerebral Spinal Fluid). It causes for strokes. The physician gives the treatment for the strokes rather than the treatment for tumour. So detection of tumour is important for that treatment.

2. EXISTING METHOD

Atlas-based and Asymmetry analysis segmentation methods have been extensively investigated. Brain atlases can provide important data prior to tumour segmentation enhancement by measuring the difference between abnormal and normal brains. However, the deformable registration of the brain atlas to brain images with tumour is an extremely challenging task because of the intensity variations around the tumour caused by edema and the deformations of healthy tissue morphology caused by the tumour mass effect. In a previous study, preprocessing is done by filtering. Segmentation is carried out by advanced K-means and Fuzzy C-means algorithms. Feature extraction is by Thresholding and finally, Approximate reasoning method to recognize the tumour shape and position in MRI image using edge detection method. But they are not good for all types of the MRI images. When a large brain structure deformation appears, the misalignment issues are noted on the aligned atlas, which may significantly decrease segmentation accuracy. Asymmetry analysis may not be useful when a tumour is located across the mid-sagittal plane. We will propose a new paradigm for atlas image construction by computing the atlas as the weighted arithmetic mean of group-wise registered images.

3. PROPOSED METHOD

The proposed method consists of three major steps, i.e., pre-processing, feature extraction and tumour segmentation using the GA method. In the first stage, MR image of brain is acquired and pre-processing is done to remove the noise and to sharpen the image here Brain image enhancement using Median filter with canny edge detection. In the second stage, edges are detected by using Gabor filter. In the third stage, the local independent projection-based classification (GA) method is used to classify each voxel into different classes. To reduce computational costs, we embedded the proposed method in a multi-resolution framework. The proposed algorithm has been extensively evaluated and validated using data, and the experimental results have shown that, with greater preservation of important image features. The method for segmentation proposed here overcomes the drawbacks of the conventional K – means algorithm and gives very satisfactory result both from qualitative and quantitative perspective. The results of segmentation as given above are at par with the recent medical standard. Moreover the success rate of the segmentation in images of brain MRI taken from all the three angles is quite high and satisfactory.

4. METHODOLOGY AND MODULE

List of Modules

1. Brain image enhancement using Median filter with canny edge detection
2. Brain Image Feature extraction with Gabor filter.
4. Computing the image

![Diagram](image.png)
5. PRE-PROCESSING

The idea of the pre-processing is to reduce or eliminate some of the image variations for the illumination of the image. After the image is captured it may be unclear or imprecise.

5.1 Image Detection Pre-processing

In Image detection, Median filter and canny edge detection is used for pre-processing. Median filtering is a nonlinear method used to remove noise from images and very effective at removing noise while preserving edges also salt and pepper type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbours is called the window which slides, pixel by pixel over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value then use Canny Edge Detection Algorithm. The Canny Edge Detection Algorithm processed following steps

(i). **Smoothing**: Blurring of the image to remove noise. To decrease the influence of noise and smooth the image using Gaussian Smooth Mask.(ii). **finding gradients**: The edges should be marked where the gradients of the image has Large magnitudes. Computing derivatives of the image using vertical and horizontal Sobel Operator, so to get the derivatives along both x and y directions, based on which we can get the final gradient magnitude and the norm direction of the edge. Hence two images in this step, one derivative magnitude image and one image recording the gradient directions of corresponding pixels.

\[ |G| = \sqrt{G_x^2 + G_y^2} \] \hspace{2cm} (1)

\[ \Theta = \arctan \left( \frac{G_y}{G_x} \right) \] \hspace{2cm} (2)

\[ K_{GX} = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \] \hspace{2cm} (3)

\[ K_{GY} = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix} \] \hspace{2cm} (4)

\[ |G| = \sqrt{G_x^2 + G_y^2} \] \hspace{2cm} (5)

\[ |G| = |G_x| + |G_y| \] \hspace{2cm} (6)

\[ \Theta = \arctan \left( \frac{|G_y|}{|G_x|} \right) \] \hspace{2cm} (7)

(iii). **Non - maximum suppression**: Only local maxima marked as edges. Round the gradient direction to nearest 45°, corresponding to the use of an 8-connected neighbourhood. Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient direction. I.e. if the gradient direction is north (theta = 90°), compare with the pixels to the north and south. If the edge strength of the current pixel is largest; preserve the value of the edge strength.

(iv). **Double thresholding**: Possible edges are determined by thresholding. The edge-pixels remain after the non-maximum suppression step is marked with their strength pixel-by-pixel. Many of these will probably be true edges in the image, but some may be caused by noise or colour variations for instance due to rough surfaces. This method to differentiate

\[ d_Q ([I_1], [I_2]) = \min_{x \in [I_1], y \in [I_2]} d(x, y) \]

The two related metrics allows us to go between and . In particular, any computation relating to a metric on can be equivalently formulated using its corresponding -invariant metric.
6. FEATURE EXTRACTION WITH GABOR FILTER

Gabor filter is a band pass filters which are used in image processing for feature extraction and texture analysis. Its frequency and orientation are similar to that of the human visual system, and to found appropriate for texture discrimination and representation. Gabor filters are formed by modulating a complex sinusoid by a Gaussian function. Gabor filters have been used widely in pattern analysis application, and it has been proved in extracting more salient features images, which are the two modalities being used in this paper. A set of Gabor filters with different frequencies and orientations was used for extracting salient features from brain images. It is invariant against translation, rotation, and variations due to illumination and scale. Gabor filter also presents desirable characteristics of spatial locality and orientation selectivity. During feature extraction the dimension or size of the image does not change. For instance, in this paper the dimension of brain tumour image, after applying Gabor filter to extract the salient features the dimension still remains the same. Gabor filters at different scales and spatial frequencies.

The Gabor filter based feature extraction is the 2D Gabor filter function is

$$\Psi(x, y) = \frac{f^2}{\pi \gamma^2 \eta} e^{-\frac{x^2}{\gamma^2} - \frac{y^2}{\eta^2}} e^{j2\pi fx'}$$

$$X = x \cos \theta + y \sin \theta$$

$$Y = x \sin \theta + y \cos \theta$$

The equation (24) is spatial domain the Gabor filter is a complex plane wave that is 2D Fourier basis function, multiplied by an origin-centered Gaussian. $f$ is the central frequency of the filter, $\Theta$ the rotation angle, $\gamma$ sharpness (bandwidth) along the Gaussian major axis, and $\eta$ sharpness along the perpendicular to the wave. The phase Ratio of the Gaussian is $\frac{\eta}{\gamma}$. This function has the following analytical form in the frequency domain

$$\Psi(u, v) = e^{-\frac{\pi^2}{f^2}} (\gamma^2 (u' - f)^2 + \eta^2 v^2)$$

$$u' = u \cos \Theta + v \sin \Theta$$

$$v' = -u \sin \Theta + v \cos \Theta$$

The equation (25) is frequency domain the function is a single real-valued Gaussian centered at $f$ at equation (2). The Gabor filter in (1) and (2) is a simplified version of the general 2D form devised. enforces a set of filters self-similar scaled and rotated versions of each other, regardless of the frequency and orientation $\Theta$. Gabor feature, are constructed from responses of Gabor filters by using multiple filters on several frequencies $f_m$ and orientations $\Theta n$. Frequency in this case corresponds to scale information and is thus drawn from [10]

$$f_m = k^m f_{max} , m = \{0, \ldots, m-1\}$$

Where $f_m$ is the $m^{th}$ frequency, $f_0 = f_{max}$ is the highest frequency desired, and $k > 1$ is the frequency scaling factor. The filter orientations are drawn from [10]

$$\Theta_n = \frac{n2\pi}{N}, n = \{0, \ldots, N-1\}$$

Where $N$ is the total number of orientations and $\Theta n$ is the $n^{th}$ orientation. The parameters $f_{max}$, $k$, $M$, $N$, $\gamma$ and $\eta$ are redundant Scales of are selected from exponential spacing and orientations from linear spacing. The most intuitive parameterization is achieved by defining the function envelope cross point at $p = 0.5$, i.e. two filter Gaussians cross on the half magnitude. The cross point parameter $p$ is fixed and the adjustable parameters are now the highest frequency $f_{max}$, number of frequencies $m$ and number of orientations $n$. The bandwidths $\gamma$ and $\eta$ are automatically set using the formula.
7. SEGMENTATION USING GENETIC ALGORITHM (GA)

genetic algorithm (GA) is an optimization technique for obtaining the best possible solution in a vast solution space. Genetic algorithms operate on populations of strings, with the string coded to represent the parameter set. The intensity values of the tumor pixels are considered as initial population for the genetic algorithm. The intensity values of the suspicious regions are then converted as 8 bit binary strings and these values are then converted as population strings and intensity values are considered as fitness value for genetic algorithm. Now the genetic operator’s reproduction, crossover and mutation are applied to get new population of strings. The following steps describe genetic algorithm to find optimal threshold for detect the tumor tissue. Algorithm of Genetic Algorithm

Step 1: Load the image the size is 256x256 (each element corresponds to a gray value Between 0 to 256 and their classes are determined.

Step 2: Divide the image to 3x3 labels (cells). Step 3: Calculate the fitness value for all pixels in the label \( F(x) = \frac{1}{1+x^2} \)

Step 4: Choose two parents randomly for crossover and mutation operation with crossover probability \( PC \) and mutation probability \( PM \). Compute the fitness of parents and child. The fitness function is the normalized histogram function \( F(x) \).

Step 5: Initialize the local optimal value as a 0

Step 6: Initialize the parents for find the cross over function

\( i=x \) position, \( j=y \) position

1. \( Pa= F(i-1,j-1), Pb=F(i+1,j+1) \)
2. \( Pa= F(i,j-1), Pb=F(i,j+1) \)
3. \( Pa= F(i-1,j), Pb=F(i+1,j) \),
4. \( Pa= F(i-1,j+1), Pb=F(i+1,j-1) \)

Step 7: Calculate the child for the parent

\[ C1=Pa - F(x) \]
\[ C2 = F(x)-Pb \]

Step 8: Select a child for local update

\[ \text{Selectchild} = \max (C1, C2) \]

Step 9: Select the local optimal value for find the optimal value for a label

\[ \text{If ( LocalOptimal < SelectChild )then} \]
\[ \text{LocalOptimal} = \text{SelectChild} \]
\[ \text{Else} \]
\[ \text{No change in LocalOptimal After selection of local optimal elements are put in their respective labels.} \]

Step 10: Repeat Step 6, 7, 8 and 9 for all elements until end of the label.

Step 11: Calculate the Mutation for global update

\[ \text{Pm}=\text{oldLocalOptimal} - \text{NewLocalOptimal} \]
\[ \text{Nm}=\text{newOocalOptimal}-\text{oldLocalOptimal} \]
\[ \text{Mutation}= \max (\text{Pm}, \text{Nm}) \]

Step 12: Update optimal value for find Global Optimal

\[ \text{LocalOptimal}=\text{LocalOptimal}+ \text{Mutation} \]

Step 13: Select the Global optimal value for find the optimal value for an image

\[ \text{If (GlobalOptimal < LocalOptimal) then} \]
\[ \text{GlobalOptimal} = \text{LocalOptimal} \]
\[ \text{Else} \]
\[ \text{No change in Global Optimal After selection of Global optimal elements are put in their respective labels.} \]

Step 14: Repeat Step 2 to 12 for all elements until end of the label.

Step 15: Consider Global Optimal value is adaptive threshold for the segmentation
8. RESULT AND SCREENSHOTS

8.1 INPUT IMAGE

PREPROCESSING
SKULL DETECTION: 1

FEATURE EXTRACTION
EDGE DETECTION - Vertical and Horizontal Direction

SEGMENTATION
Segmentation Identification

Segmentation Projected particular region
9. CONCLUSION

An automatic heterogeneous brain tumor MR image segmentation performance analysis using Threshold and Genetic algorithm method is proposed for accurate tumor shape extraction of tumor and calculating tumor shape and position calculation. The method is very fast, robust and reliable for indexing tumor or edema images for both archival and retrieval purposes. An GA-based method was introduced to solve the tumor segmentation problem. The proposed GA used local independent projection into the classical classification model, and a novel classification framework was derived. Compared with other coding approaches, the GA method was more suitable in solving the linear reconstruction weights under the locality constraint.

REFERENCES:

[29] T. Logeswari and M. Karnan, “An enhanced implementation of brain tumor detection using segmentation based on soft computing,” presented...


