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Quick Detection of Brain Tumor using a Combination of E-M and Levelset Method

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Abstract

In medical image processing, Brain tumor segmentation from MRI scan slice without human intervention has become one of the most challenging area in research.MR image slices usually contain a significant amount of noise caused by operator interactions, environmental or external factors, machines used etc, which in turn may cause serious segmentation inaccuracy. Our main aim is to recognize a tumour and its quantification from a specific MRI scan of a brain image to obtain the best segmentation in minimum time. In this paper, we are trying to develop a robust segmentation technique, by combining two segmentation algorithms, expectation maximization and level set. This algorithm framework composed of three stages. 1. Pre-processing is used for background separation of brain; it can be also called as pre-segmentation method 2. Abnormal regions in brain is detected by using Expectation Maximization (EM) algorithm and in 3. A level set method to sharpen the segmented EM output to get sharp and accurate boundaries. At the end of the process, the tumour region is extracted from the MR images and its exact position and shape is determined with minimum time. The Experimental results clearly define the effectiveness of our approach in its accuracy and computation time when compared with other EM based method.

Keywords: Expectation-Maximization, Feature Extraction, Image Segmentation, Level Set, Pre-processing

1. Introduction

Analysis of medical image plays an important role to detect the degenerated and abnormal tissue. There are many existing medical imaging techniques available for diagnosis, they are MRI, CT, PET etc. For a completely automated system MRI plays an important role than any other imaging system. Magnetic resonance image provide a better contrast between the tissue regions, which helps in easy identification of the abnormal region in brain. Hence MR image is the most widely and effectively use medical imaging technique in the diagnostic of various cancerous diseases.

Brain tumor is considered as one of the most incurable disease affecting the human body in the present scenario. The tumor is normally found on the different regions of brain, which may affect the body's vital function. There may present one or more tumour which may be very small to detect even by using any conventional imaging techniques or by manual segmentation. Detecting the tumour location and its ability to spread from one region to another quickly makes treatment more complicated. In advanced studies the occurrence of brain tumour has increased to a great extent. But unfortunately these tumors are detected very lately, after which the symptoms appear, which inturn a real threat to human life. Disorder

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in brain may cause hearing/speech problem, memory lapse, talking and eye sight problem, understanding, personality changes etc.

Segmentation of brain from MRI image slice is very complicated and challenging task that researchers are facing recently. Precise and accurate segmentation technique is necessary for tumor detection and their classifications. In medical image segmentation boundary detection and volume estimation plays an important role on surgical treatment and radiation therapy .The tumor location in brain helps to determine the factors affecting an individual's normal functioning.

In this paper, we are trying to adopt a new method for a fully automatic method, for brain image segmentation` based on a combination of Expectation Maximization (EM) and level set methods. The main advantage is that, it does not require any extra supervision or training of data sets. The combination of these two methods takes the advantage of both methods while cancelling their drawbacks of each other.

This paper is sectioned as follows: Section 2) deals with basic concepts of pre-processing. Section 3) gives a clear cut idea about expectation-maximization (EM) algorithm, section 4) deals with level set method and implementation. Some experimental comparison is done in section 5), and section 6) Conclusion.

2. Related Works

In Medical image processing, segmentation is considered as one of the hottest research topic. Researchers have suggested various methodologies and algorithms for successful segmentation of images. There are many existing approaches for the successful segmentation of brain image, such an automatic and semi- automatic method. In practical, manual segmentation is very difficult and tedious process, it require human interaction and in some cases it fails to produce accurate result, hence automated brain tumour segmentation method is most preferred now a days. Different types of automatic segmentation method include FCM (Fuzzy C-Means), level set methods, snake method, k-nearest neighbour (KNN), fuzzy connectedness, region growing and Markov random field methods[1–8].

Lee, et al.[9] in his paper, gave an idea about how to make use of Support Vector Machine (SVM) classifier in brain tumour segmentation and he also suggest that SVM based classifier is having high performance output compared with the other existing classifiers. Corso, et al.[11] in his paper gave us a new idea for segmentation based on extended graph-shifts method. In our paper we are combining level set and EM algorithm is used for successful segmentation. Level set method takes the advantage of shrink and grow (wrap around) to take the shape of any type of object as in snake algorithm but it solves the problem of splitting and merging too. Level set method provides an easy way to solve the parameterization problem. The main advantage of using level set method is, it solves the curves and cone by taking it as a function with higher dimensions that produces the curve to move under some forces, this method was first developed by Osher in his paper[11]. This method provides an efficient and accurate numerical tool for analysing and tracking the curve evolution problems. There are many existing level set segmentation approaches for MR image segmentation. Latter Geodesic active contour, method was used for medical image segmentation[13] and[14]. In level set method the user can tune and change the parameters according to his desire to get the desired result that is why this method is suggested as a very useful one. Oliver, et al. in[13,14] in his paper, he tries to develop a completely automatic method using expectation maximization(EM) algorithm for image segmentation. This algorithm completely depends on probability density function (pdf) estimation, for each tissue region class identification.

Brain tumors, can't be simply classified based on intensity variation or their existing size, which may be due to overlapping intensities with normal tissue. In this paper we are trying to propose a fully automatic and rapid method for surface quantification of edema on brain MRI. For this, here we are considering EM algorithm (Expectation Maximization) for primary segmentation of brain image. which help us to automate the seed selection point in level set method. Our next aim is to obtain sharp and accurate boundary, which can be done with the help of level set method, which help us to segment brain image more correctly. This method was developed, purely based on the previously published work done by[9,10].

3. Proposed Works

Our proposed method is builds on an existing algorithm. Here a combination of expectation maximization (EM), and level set method has been taken in to consideration.

This algorithm make use of Gaussian distribution estimation for each tissue class and the level set method will help to provide sharp boundaries for accurate volumetric segmentation .

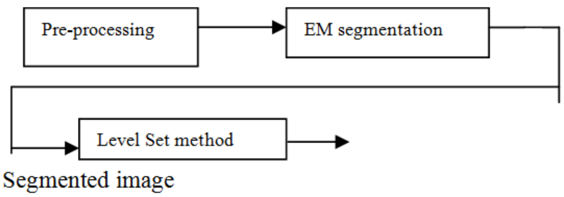

Figure 1. Basic block diagram for segmentation.

Our proposed system mainly consists of three main parts 1) Pre-processing 2) EM algorithm and 3) Level set. Here background is assumed to have a lower mean intensity value than the tumor region and hence there is no loss of generality. In pre-processing background separation is done ie we are extracting the region of interest for segmentation. Threshold value is calculated between voxels of tumour and non tumor region. In our proposed system, a new algorithm is developed to find out a threshold value after each iteration and a way to update the threshold value based on each iterations. After that a speed function is also performed with the help of level set there by bringing the contour close to the selected region so as to get a sharp boundary. Speed function fails to work properly for noisy image or when the desire object's boundary is not distinct. So in order to improve the level set performance, regions information is first integrated. This region information is obtained from the EM based segmentation method that we are doing first. The image intensities in level set method are be described by Gaussian distribution function, using means and variances as its parameter. The combination of these two algorithms helps us to get highly accurate image segmentation. Moreover, this paper solves the problem of initial seed selection in the level set by using EM algorithm in pre segmentation process, thereby providing a fully automatic method for the segmentation of brain tumor.

3.1 Pre-processing

Pre-processing is mainly done to enhance the visual appearance of images. Pre-processing helps to improve the manipulation in the datasets. Normally image enhancement technique may lead to image artefacts or information loss. In this paper, in pre-processing we are giving importance to back ground separation so as to get the desired region of interest. The main operations in pre-processing are thresholding, region filling and morphological operations.

Pre-Processing-Algorithm

- Step 1: calculate the Mean
- Step 2: Thres holding- It solate object by converting grey scale image in to binary image
- Step 3: Region Filling-Used to remove holes in the binary image.
- Step 4: Morphological Opening-Remove noise &small objects from the background
- Step 5: Region Filling-this is again done to fill the outer circle that remain un filled
- Step 6: Masking-to encapsulate the block by hiding the underlying logic & create a user interface for the block.

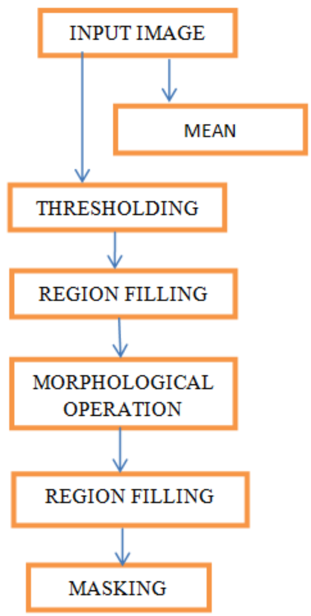

Figure 2. Flow chart of pre-processing.

3.2 Expectation Maximization Segmentation

EM algorithm is used for finding estimated parameters of maximum-likelihood or maximum a posteriori in a statistical model when the data are "incomplete" or missing. The parameter is estimated iteratively in two step. It has two steps, first is E step, whicqsazsh Calculate the expected value of the log likelihood function and in M step which computes parameters for maximizing the M value based on the value found on E step. These estimated parameters are then used to find the distribution of the latent variables in the next E step.

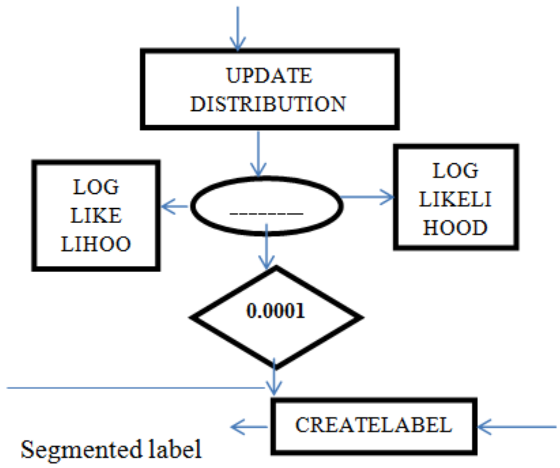

Figure 3. Flow chart of EM algorithm.

The equation for EM is as follows

$$p(Ti - j \mid yi,\theta) = \frac{p(yi \mid \Gamma i = 1, \theta j)\, p(\Gamma i = j)}{\sum_k [p(yi \mid \Gamma i = k,]\theta k)\, p(\Gamma i = k)} \qquad (1)$$

Where yi gives the intensity value at voxel i, Γi represents the class of voxel i, and estimated distribution parameter is given by θ. This distribution parameter estimates are then updated based on maximum likelihood estimates on the image intensities, and the intensities are updated according to the current bias estimate.

The EM Algorithm

- Step 1: For image I, the system consisting of K number of classes.
- Step 2: Φ (0) is initially estimated, based on the number of classes and image histogram.
- Step 3: E-step is first computed and based on its estimated parameter M-step is executed until it convergence .The E-step compute the class probability of each pixel at each iteration based on the current estimation of Φ(t). The new expectation value of Φ(t+1) is determined in M-step, based on values of E-step. The maximum estimator of Φ is produced after convergence
- Step 4: Classification matrix C is generated.
- Step5: Colour and label is assigned to the segmented image based on the classification matrix C.

After segmentation of brain MR image, boundaries are detected by using level set method. After that, we find out labelling of the image and finally exact location of the tumor.

3.3 Level Set Method

It is a numerical tool for the analysis of shape and surface. This method helps to perform the numerical computations including curves, shapes and surfaces on a fixed Cartesian grid without parameterization of objects. It can follow the shapes change topology. This segmentation method has many advantages compared with other method; it has a greater ability to tackle complex geometry shape and topology changes. The level set method work is mainly based on a shape and speed driven function. Its flexibility in modelling any shape and structure is very high .By providing the initial zero level set or seed point, the whole segmentation process becomes automatic then. Moreover, this Level set method does not require any additional machinery to execute the process. With the help of Gaussian distribution local image intensities are described with different means and variances. Local gaussian distributions fitting energy is defined by level set function as mean and variance as variables. It solves the problem of image segmentation which has minimum energy distribution by the evolution of an interleaved level set and by calculating mean and variance the local intensities can be estimate through an iterative process.

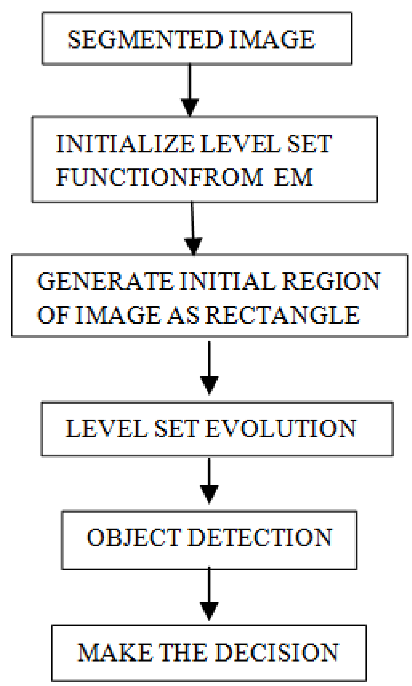

Figure 4. Flow chart of level set method.

Image gradient is useful for the formulation of speed function which helps in converging the boundary value. But the speed function fails to work on noisy image or when the boundary of the desire object's is not distinct[25,11]. To improve the level set performance, regions information is integrated so as to minimize the energy; here it is done by expectation maximization (EM) algorithm. We see that when tumor likelihood regions are at higher level, the tumour growing speed increases considerably. In this paper, we assume that the image is partitioned into two regions: fore ground and back ground.

Algorithm for level set

- Step 1: Initializing the level set function Φ ,from the output obtained by EM algorithm
- Step 2: Update local means using.
-

$$Ui(x) = \int [\omega(y-x)Mi\varepsilon(\varphi((y))dy] \tag{2}$$

- Step 3: Update local variances using.
-

$$\int [\omega(y-x)Mi\varepsilon(\varphi((y))dy]) \tag{3}$$

- Step 4: Update the level set function Φ.

$$(\partial\phi)/\partial t = -\delta\varepsilon(\phi)(e1-e2) + v\delta\varepsilon(\phi)div(\nabla\phi/\nabla\varnothing)) + \left(\nabla^2\varnothing\right) - div((\nabla\phi/\nabla\varnothing)) \tag{4}$$

- Step 5: Till the convergence criteria is met, its repeated from step 2

4. Experimental Evaluation and Results

In this section, the segmentation result obtained is based on expectation maximization and level set method is discussed. This three dimensional segmentation method, gives importance to the segmentation of tumour region based on tumour volume. Of different existing methods level set based method can be said as most accurate numerical tool for the tumor volume and its boundaries extraction. In Level set segmentation, tumour detection can be done in both 2D and 3D images. The results obtained in this by the combination of two algorithms is relatively good due to the combination of local and global information's.

This work was implemented using MATLAB version 7.12.0. We run our experiments on a core i4/2.4 GHZ computer with 6 GB RAM and an NVEDIA (2 GB VRAM) VGA card. To extract the tumor, first step of our medical system starts from the original MRI image, First pre-processing is done, to remove skull, next process is to segment the brain image. This is done with the help of EM algorithm. The intensity value of tumor region is different than background or other part of a tumor image. The pixel value is different in the tumor part as compared with other part of an image. Extracting tumor with level set method, first we have to perform a task to find out speed function and after that a value for threshold is provided. Then, the value above the threshold is chosen. This value is quite important for extracting tumor.

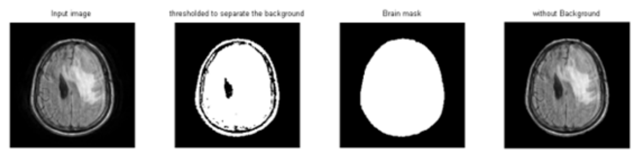

Figure 5. Segmented images after EM algorithm.

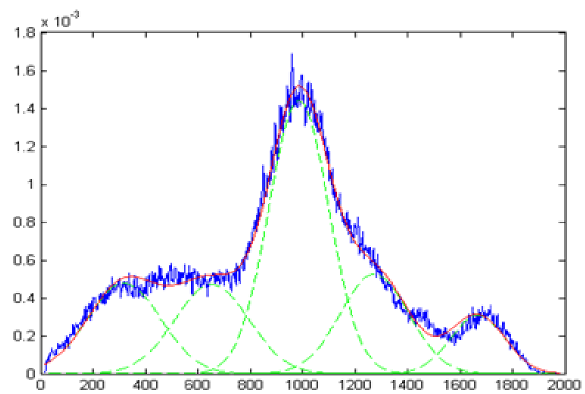

Figure 6. Histogram of the segmented image after EM segmentation.

A combination of EM algorithm and level set segmentation technique can work well in any image having intensity in homogenity and if the image is noisey, therefore level set method can be said as one of the best existing tool to classify tumors having high intensity variation. Moreover it can also classify the images having small intensities variation, which is not possible with snake based segmentation method and atlas based method. In this work we are mapping the resultant tumor image onto gray scale image. The proposed method is user friendly and simple to understand. Currently, accuracy of our method is calculated by comparing our result with the existing results of various segmentation method and also from the segmentation results obtained from the human experts.

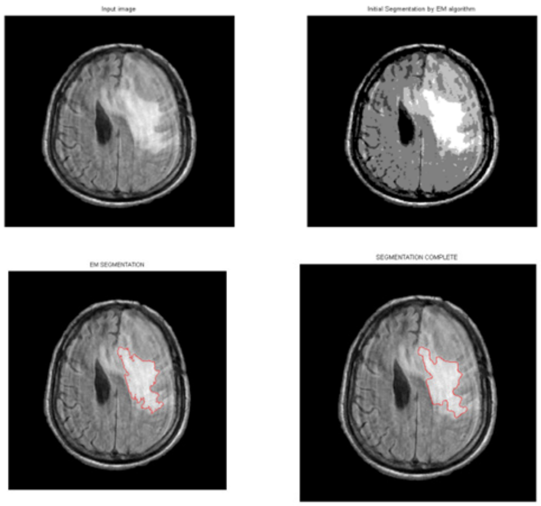

Figure 7. Final segmented image after level set method.

5. Conclusion

In this paper, we proposed a new combination of image segmentation method based on region-based active contour model in a variational level set framework and expectation maximum algorithm. Our model effectively makes use of the local image intensities described by Gaussian distribution. This local intensity are introduced as two variables mean and variance by the energy function which are a spatially varying functions. Our proposed method works well in noisy image and images having intensity in homogeneity. By comparing our model with the other models, we can clearly demonstrate the working efficiency and its capability of our method in handling intensity in homogeneity.

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