Brain MRI Image Segmentation using Grab cut Algorithm

B.Lalitha, T.Ramashri

Abstract; Brain tumor detection is an important task in medical image analysis. Tumor in the brain leads cancer and is to be diagnosed at earlier stage itself. Image processing techniques are applied for MRI images to segment and detect tumor. Detection of tumor in brain is done manually which is complex, tedious task and experience is necessary to detect a simulation results. Hence , many Automatic image segmentation algorithms are developed to detect and segment tumor from MRI images. This image segmentation algorithms uses either texture information or edge information for segmentation of MRI images. Graph-cut optimization approach has been developed recently, which utilizes both texture and edge information. The proposed work extends the graph cut approach in three steps. First a more powerful, iterative version of the optimization is developed. In the second step in order to reduce the user interaction a powerful iterative algorithm is applied for producing the result. Finaly,, a robust algorithm has been developed for border connecting to predict both the alpha-matte around an object boundary and the colours of foreground pixels.

Key words: MRI Image, alpha matte, Graph cut, Interactive image segmentation

I. INTRODUCTION

Brain tumor is an uncontrolled growth of abnormal tissues in brain. Such tumor is the main cause of cancer and is to be diagnosed at earlier stages itself. Tumours in the brain can damage the cells and increases the pressure and swelling within the skull. The abnormalities in the brain can be detected using many image analysis technique like single photon emission tomography(PET), Magnetic resonance imaging(MRI),Computer Tomography(CT),Functional MRI(fMRI).The most common and widely used Imaging technique for brain tumor analysis is MRI.MRI imaging modalities uses a magnetic field and radio waves to obtain fine details of the images of the brain. Most important benefit of MRI Imaging modalities over other imaging techniques is it does not effect any harmful radiation to the human. After MRI process is completed the next task is to separate the tumor area from normal brain cells along with surrounding areas like edema, necrosis etc. The researchers have proposed many algorithms for tumor detection using many methods. Automatic detection of brain tumor using soft computing tools has emerged as important area in tumor detection due to its advantages. These techniques can detect within less time compared to Manual detection.

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II. LITERATURE SURVEY

Over past few years many automated interactive systems are developed to assist physicians in medical imaging analysis [Okuboyejo et al.,2013].With the combination of machine intelligence and human experts an improved efficiency and minimal human intervention can be provided[Lee et al., 2008]. The efficient and interactive segmentation methods facilitate medial image analysis for accurate segmentation of tissue volumes, measurement, anatomical structures and diagnosis of various diseases.

N. A. Al-Azzawi[1] presented a f-Transform based detection using two stage brain tumor . In the preliminary stage presence of tumor is detected by analysing the symmetrical nature of human tissues in the brain. Later edge detection technique using fuzzy set theory is applied to detect tumor edge and finally segmented tumor is obtained using morphological operation. In [3], an implementation of improved cellular neural network is proposed for tumor detection. In CNN the segmentation detectionand location of tumor object is done based on templates given to the simulator. In [4], a graph cut method is applied for segmenting the grey images using energy minimization technique. In this Energy minimization technique energy function are used in terms of logarithm of boundary, region,texture and shape of tumor for prior information. Due to optimal results graph cut method become popular.[5] proposed an automatic brain tumor detection for multi-modality image like T1 ,Blair and T2 MRI Images to calculate Intensity, deformity, shape, region boundary etc.

III. PROPOSED METHOD GRAB CUT ALGORITHM

The Grab Cut technique [8] is related to discrete graph-cut approach, In which the pixels in the image represent graph vertices. The segmentation of image into background and foreground region is Extracted by solving the min cut based problem in graphs. Regions are labelled and assigned either to the sink or source node where segmentation is done by user. The selected regions provide color information that characterize the background and the object which are utilized for segmentation.

Grab cut algorithm is a two step process includes hard segmentation and border matting.

Hard segmentation: it has two parts .In the first part Segmentation is done by placing a rectangle or lasso around the object. Next step is to refine the results by user editing.

Border matting: it is a process in which alpha values are calculated around the object boundary. Matting brush[7] is used to achieve tumor object other than border.

A. *Hard Segmentation (Initial Clustering)*

In hard segmentation rectangle Q is obtained by direct frame selection. the pixel points outside rectangle frame Q is considered as background pixel points Q_B, while all the pixel points Q_U in the Q as tumor region. Assign an initial tag as α =0,to the pixel points with in Q_B as a background pixel points.

The proposed grab cut algorithm is explained in detail using the block level diagram shown below

Input MRI Image → Hard segmentation (Initial Clustering) → EM Algorithm (iterative segmentation) → Border matting → Segmented Tumor object

Fig(1) Block diagram of Proposed Grab cut Algorithm

While all the pixel point P within Q_u in the Q as tumor object with an initial tag α =1. After the above process the image is segmented into two regions with pixel points belonging tumor (α =1) and remaining pixel point as background(α =0).After initial clustering of tumor and background we estimate the GMM of the tumor and background through the pixel points tags into K_T class, that is K Gaussian model in GMM. We need to get 2 K_T Gaussian components This close and well segmented clustering algorithm attributes to improve the efficiency and accuracy of Grab cut iterative segmentation.

B. *EM algorithm for automatic Grab Cut*

This algorithm is a maximum likelihood estimate algorithm, using Jensen inequality and hidden random variable that maximize the probability function. Two sets of clustering parameters to be estimated are two new GMM parameters[13], one for foreground and one for background. Graph cut requires 2 sets thus if we keep k>2 it is difficult to decide the GMM belong to foreground or background. So, fix the value of k=2 k=2 is fixed

C. *Iterative segmentation by energy minimization by using EM algorithm*

In Grab cut the model for MRI Images is replaced by Gaussian mixture model(GMM).Now a new vector k = {k1,..., kn,...,kN}in introduced and assigned to each pixel belonging to GMM's knth component, kn =1,2,…,K

So the energy function is written as

$E(\alpha,k,\theta,z)=U(\alpha,k,\theta,z)+V(\alpha,z)$ (1)

and GMM is defined as[4]

$G(z)=\sum_{i=0}^{k} w_k\, g_k(z;\mu_k,\Sigma_k)$,

$\sum_{i=1}^{k} w_k = 1$ and $0<wk<1$ (2)

Where gk=(z; µk,∑k) is the Gaussian distribution function for each components k,k=1,2-----k;

And wk is the weighting coefficient, vector µk is the means and ∑k is the covariance matrix for kth component and D is the number of dimensions of variable z.

Combine equation 1 and equation 2 term U now become

$U(\alpha,k,\theta,z)=G(\alpha,k,\theta,z)$ (3)

And model θ now become:

$\theta=\{\pi(\alpha,k), \mu(\alpha,k),\Sigma(\alpha,k), \alpha=0,1, k=1.....K\}$ (4)

With Eq. 4, the iterative estimation for GMM parameters is as followed:

1.Initialize GMM θ(t) as θ(0), θ(0)= { µ(k)(0),w(k)(0) } k=1.....K;

2.compute $\Psi(\theta: \theta(t))=\sum_x p(x), z, \underline{\theta}^{(t)}) P(z, x, \underline{\theta}^{(t)})$ for expectation

Where x is the hidden variable

3. Compute θ(t+1)=arg max Ψ(θ; θ(t+1)) and update parameters for maximization.

Repeat step 2 and step 3 until they become same, then go to next step.

Step 4.Based on the best estimation of θ substitute αn to each pixel, thereby clustering MRI Image into two sets.

D. Border Matting

A polyline is drawn for the closed contour c to the segmentation boundary obtained from iterative segmentation algorithm. A new trip map {QU,QB,QF} is computed, in which QU is the set of pixels in a ribbon of width ±w pixels at either side of c. A strong model is assumed for shape of the α profile within QF. Next estimate foreground pixel colours without colours bleeding in from foreground of MRI Images. This can be achieved by stealing pixels from foreground i.e tumor region QU itself. First the Bayes matte algorithm is used to obtain the estimate of foreground colour fn on a pixel n nϵ QF then from neighbourhood ft(n) the pixel colour that is most similar to fn is stolen to form the foreground colour fn.

E. Tumor Detection

The proposed Grab cut based tumor detection Algorithm is described as:

Step 1: separation of object and background:

Input MRI Image is taken and segmented into 2 regions, namely tumor as foreground and all other parts cerebrospinal fluid (CSF),grey matter, white matter as background image.

Step 2: Initialization of label (α) value:

Assign α=1 for tumor region and α=0 for non-tumor region

Step 3:Estimation into GMM Models

Two sets of GMM parameters is estimated using Gaussian components model one for tumor and other for background region.

Step 4: Expectation Maximization algorithm

Apply Expectation Maximization algorithm to get better iterative segmentation by energy minimization function.

Step 4:Border matting

Matting brush is used across the object boundary to achieve tumor object from the background.

Step 5: tumor extraction

Tumor region is extracted from background image stealing the colour of foreground pixel and assigning those pixels around the boundary extraction there by reducing the colour bleeding i.e blurriness in pixel.

IV. SIMULATION RESUTS

In the proposed Grab cut based segmentation method, during initial clustering two regions are considered as background (white matter, grey matter, cerebrospinal fluid) and foreground(tumor) objects based on the rectangle frame selected.Fig.4(a) shows the MRI image and Fig4(b) shows the tumor extracted after grab cut based segmentation algorithm is applied. The proposed Grab cut algorithm detects tumor automatically. Border matting algorithm is applied to extract object boundary from background. The results of images shown in fig4(b) automatically detects tumor compared with graph-cut ,algorithm. In graph cut algorithm tumor is detected along with some parts of white matter with more number of iterations during segmentation. The proposed Grabcut based iterative segmentation uses less number of iteration and tumor is detected within short time.

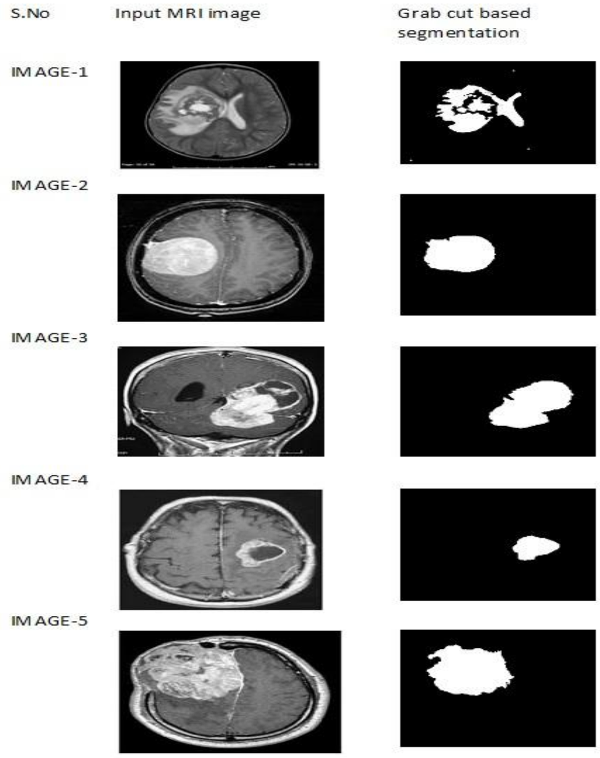

fig 2(a) shows the input MRI Image fig 2(b) segmented image using grab-cut

F. Objective Evaluation and comparison

In this method, we evaluate the performance of the proposed algorithm and also compare the results of existing techniques. Finally performance measure for classifier as tumor or non tumor is obtained based on four events two classifications and two misclassifications which are defined in Table I.

Table I Indicates the definition of performance measure

Measure	Description
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Accuracy	TP+TN/(TP+FN+TN+FP)
Precision	TP/(TP+FP)
Recall	FP/(FP+TP)
F_1Score	$\frac{2}{\frac{1}{Precision}+\frac{1}{Recall}}$

Accuracy: It is the ratio of correctly classified pixels to the total number of pixels in the image.
Sensitivity: it is the ability to detect tumor pixels in image.
Specificity: It is the ability of the algorithm to detect pixels of non-tumor region
Precision: It is the probability of identifying tumor pixels is a true positive.
Recall: It is the probability of identifying non tumor pixels is a false positive rate.
Area of the tumor: This parameter gives the comparison between the area occupied by the tumor after Grab cut algorithm with ground truth data set.
F_1Score:It is the harmonic mean of recall and precision.

F. Objective Evaluation results

The segmentation metric proposed in previous section have been computed for different MRI Image datasets and the results are reported in table 1. The accuracy, precision, recall, sensitivity statistics are reported in table 1 on five MRI Tumor images. The results are compared with graph-cut algorithm the proposed method performs well. The proposed method achieves best average accuracy of 98 .The Precision,F1score,recall are also better compared with other methods reported in literature survey.

Table.1 Objective performance analysis of proposed method

Input image	Accuracy (%)	precision	Recall	F1Score (%)	Area of tumor(%)
Image1	98.48	0.99	0.991	99.432	9.95
Image2	99.63	0.99	0.999	99.566	8.79
Image3	85.51	0.99	0.9067	94.714	14.61
Image4	98.02	0.99	0.985	98.93	3.47
Image5	91.09	0.95	96.848	0.987	13.63

From the above table 1 both qualitatively and quantitative results shows the effectiveness of proposed tool for better segmentation using Grab cut method

V. CONCLUSION

In this method a Grab cut tool is proposed for segmentation of MRI images. The proposed method Segments the whole image into two regions during initial clustering. Two set of Gaussian components estimated for each region using EM algorithm with less minimum energy function are used for iterative segmentation. Finally border matting tool and foreground extraction techniques are applied to get better segmentation with less user interference. The qualitative and subjective results shows the effectiveness of proposed method.

The proposed Grab cut based MRI Image segmentation. uses graph cut algorithm with less user interaction. In future morphological operation along with classifiers can be included for fine refinement of segmented tumor object and classify the MRI Image as tumor or non-tumor region.

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