

# Detecting Brain Tumor in Magnetic Resonance Images Using Hidden Markov Random Fields and Threshold Techniques

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**Abstract**— Brain tumors are created by abnormal and uncontrolled cell division inside the brain. The segmentation of brain tumors which is carried out manually from MRI is a crucial and time consuming task. The accuracy of detecting brain tumor location and size takes the most important role in the successful diagnosis and treatment of tumors. So the detection of brain tumor needs to be fast and accurate. Brain tumor detection is considered a challenging mission in medical image processing. This paper concerns presenting an approach which will be useful for improved detection of brain tumor using Hidden Markov Random Fields (HMRF) and Threshold methods. The proposed method has been developed in this research in order to construct hybrid method. The aim of this paper is to introduce a scheme for tumor detection in Magnetic Resonance Imaging (MRI) images using (HMRF) and Threshold techniques. These methods have been applied on 3 different patient data sets. They have the property of organizing their soothing effect on the final segment of brain tumor homogeneous tissue regions, while the edges between different tissues constituents are better kept.

**Keywords**— Brain Tumor; Detection; Magnetic Resonance Images; Hidden Markov random fields ; Threshold.

## I. INTRODUCTION

A brain tumor is the evolution of abnormal cells in the brain. Most brain tumors are called primary brain tumors, that is to say they are constructed in the brain and are not expanded from other areas [1]. Tumors may constitute and remain in one location, or may be invasive and spread into adjacent tissues. Tumors are classified either into benign (non-cancerous) or malignant (cancerous). Thus, it is difficult to call any brain tumor "benign", because both kinds can cause serious problems [2]. MRI is a developed medical imaging technique wealthy with information about the human soft tissue anatomy. Its advantages that outweigh than other imaging techniques make

it capable of supplying 3-dimensional data with high contrast between soft tissues [1]. One of these advantages is that for diagnosing diseases related to internal brain lesion and to study brain diseases. Thus, the doctor needs to analyze medical images. Therefore, to study the growth of a tumor; it is necessary to know accurately the changes in the images[2]. The segmentation of brain MR image is used for extracting meaningful objects from an image. MR image can be segmented into different tissue classes which are white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF)[3]. Image segmentation makes divisions to the image that transform it into regions with boundaries each with similar attributed pixels. The regions have to be strongly related to the depicted object and features in interest, this is very important in order to achieve a useful image analysis and interpretation. In this context, where gray level and label images are modeled using random fields and dedicated probabilistic models; image segmentation then consists in recovering hidden data, the labels, from noisy and blurred observed data, the gray levels[4]. The expectation maximization (EM) algorithm is widely used to estimate the parameters of the relevant probabilistic models. To detect brain tumor Hidden Markov random field (HMRF) models have been largely proposed [4]. These models give interesting results to segment homogeneously noisy regions. One of the widely used methods in image segmentation is Threshold. It is useful in discriminating foreground from the background. By selecting an accurate threshold value  $T$ , the gray level image can be converted into binary image[7, 8]. It is important that the binary image has to include all of the necessary information about the position and the shape of objects in interest. Obviously, the most common way to convert a gray level image to a binary image is to select a single threshold value ( $T$ ). Then, all the gray level values below this  $T$  will be classified as black (0), and those above  $T$  will be

white (1). Since thresholding is the simplest method of image segmentation, it can be used to create binary images from a gray scale images[9]. The morphological operations are basically based on some assumptions about the size and shape of the tumor. These operations are applied on the image obtained after threshold segmentation [10]. The final technique of image subtraction is applied to obtain the exact tumor region. In the present study a new method of brain tumor detection has been introduced using hybrid methods which is a combination between HMRF and threshold methods.

## II. HIDDEN MARKOV RANDOM FIELD MODEL

The concept of a Hidden Markov Random Field (HMRF) model is derived from Hidden Markov Model (HMM) [3], which is defined as processes generated by a Markov chain whose state sequence cannot be observed directly, only through a sequence of observations. Hidden Markov random field model which is applied into brain MR image segmentation has particularly proved its efficiency for the problems in medical imaging[11]. HMRF is a graphical probability model in which the true states are not observed but are estimated indirectly through an observation field. In a HMRF model, there's an observable random field  $y = (y_1, \dots, y_N)$  where each  $y_i$  is the feature value of a voxel. The goal is to infer a hidden random field  $x = (x_1, \dots, x_N)$  where  $x_i \in L$ . In the image segmentation context,  $x_i$  is a configuration of labels and  $L$  is the set of all possible labels [12]. HMRF also holds conditional independencies between  $x$  and  $y$ :

$$P(y|x) = \prod_{i \in S} P(y_i|x_i) \quad (1)$$

The sites  $S$  is related to one another via a neighborhood system  $N = \{N_i, i \in S\}$ , where  $N_i$  denotes the sites adjacent to voxel  $i$ . A stochastic field  $X$  is said to be a Markov random field if for all  $i \in S$  is independent from the neighboring voxels given its neighborhoods. Thus, the joint probability is given  $x_i$ 's neighborhood configuration  $x_{N_i}$ , according to the local conditional independencies of MRFs, (2) can be rewritten as:

$$P(y, x) = P(y|x)P(x) = P(x) \prod_{i \in S} P(y_i|x_i) \quad (2)$$

Given  $x_i$ 's neighborhood configuration  $x_{N_i}$ , according to the local conditional independencies of MRFs, (2) can be rewritten as:

$$P(y_i, x_i|x_{N_i}) = P(y_i|x_i)P(x_i|x_{N_i}) \quad (3)$$

This way the joint distribution of  $(y, x)$  has been highly decoupled. If it is assumed that  $y$  is drawn from a probability function  $f(y_i; l, \theta)$ , with parameter set  $\theta$  and  $l \in L$ , the marginal distribution of  $y_i$  can be obtained:

$$P(y_i|x_{N_i}, \theta) = \sum_{l \in L} P(y_i, l|x_{N_i}, \theta) = \sum_{l \in L} f(y_i; \theta_l) P(l|x_{N_i}) \quad (4)$$

### Estimating HMRF Using The EM Algorithm

According to the MAP criterion, the seek is to the labeling  $x^*$  which satisfies

$$x^* = \arg \max_x \{P(y|x, \Theta)P(x)\} \quad (5)$$

An MRF can equivalently be characterized by a Gibbs distribution:

$$P(x) = Z^{-1} \exp(-U(x)) \quad (6)$$

Where  $Z$  is a normalization constant and  $U(x)$  is a potential function.

The prior probability  $P(x)$  is a Gibbs distribution (6), and the joint likelihood probability is:

$$P(y|x, \Theta) = \prod_i P(y_i|x, \Theta) = \prod_i P(y_i|x_i, \theta_{x_i}) \quad (7)$$

Where  $P(y_i|x_i, \theta_{x_i})$  is a Gaussian distribution with parameters  $\theta_{x_i} = \left( \mu_{x_i}, \sum_{x_i} \right)$ .

Where  $P(y_i|x_i, \theta_{x_i})$  is a Gaussian distribution with parameters. Similar to the inference of the Gaussian mixture models, one can also estimate the MAP parameters of HMRF using an EM algorithm. Following the procedures of EM, the estimates are iteratively updated as below [16]:

1. Start with the initial parameter set  $\Theta^{(0)}$ .
2. Calculate the likelihood distribution  $P(y_i|x_i, \theta_{x_i})$  given by (7).
3. Using the current parameter set  $\Theta^{(t)}$  to estimate the labels by MAP estimation:

$$\begin{aligned} x^{(t)} &= \arg \max_{x \in X} \{P(y|x, \Theta^{(t)})P(x)\} \\ &= \arg \min_{x \in X} \{U(y|x, \Theta^{(t)}) + U(x)\} \end{aligned} \quad (8)$$

The implementation of the MAP estimation is discussed in the next section.

4. The posterior distribution has been computed for all possible  $l \in L$  and all voxels  $y_i$ :

$$p^{(t)}(l|y_i) = \frac{N(y_i; \theta_l) P(l|x_{N_i}^{(t)})}{P^{(t)}(y_i)} \quad (9)$$

Where  $N(y_i; \theta_l)$  is the Gaussian distribution of  $y_i$  with parameter  $\theta_l = \left( \mu_l, \sum_l \right)$ .

The marginal probability:

$$p^{(t)}(y_i) = \sum_{l \in L} N(y_i; \theta_l) P(l|x_{N_i}^{(t)}) \quad (10)$$

Here it has been resulted that:

$$P(l|x_{N_i}^{(t)}) = \frac{1}{Z} \exp \left( - \sum_{j \in N_i} V_c(l, x_j^{(t)}) \right) \quad (11)$$

$V_c(l, x)$  is called the clique potential of field  $x$ .

5.  $P(l|x_{N_i}^{(t)})$  is used to update the parameters of Gaussian.

#### MAP Estimation

In (8) the total posterior energy has been introduced in order to find  $x$ 's MAP estimate:

$$x = \arg \min_{x \in X} \{U(y|x, \Theta) + U(x)\} \quad (12)$$

The total posterior energy has two compositions: the likelihood energy and the prior energy. The likelihood energy is defined by:

$$U(y|x, \Theta) = \sum_i U(y_i|x_i, \Theta) = \sum_i \left[ \frac{1}{2} (y_i - \mu_{x_i})^T \Sigma_{x_i}^{-1} (y_i - \mu_{x_i}) + \ln \sum_{x_i} y_i \right] \quad (13)$$

It's easy to see that the likelihood energy is proportional to the minus log-likelihood of the  $P(x|y)$ :

$$\log P(x|y) \propto -U(x|y) \quad (14)$$

Note that  $U(x|y) = U(y|x) + U(x) + c$  is the posterior energy, where  $c$  is a constant and the prior energy function  $U(x)$  has the form:

$$U(x) = \sum_{c \in C} V_c(x) \quad (15)$$

Which is the sum of clique potentials  $V_c(x)$  over all the cliques  $C$ . A clique is defined as a subset of sites in which every pair of distinct sites are neighbors. The value of clique potential depends on the local configuration and physical properties of the clique. In the context of image segmentation, a clique potential is usually used to characterize the influence from adjacent voxels on voxel  $i$ . For this project, the clique potential of voxel  $i$  is defined as the number of its adjacent voxels who have different labels:[16]:

$$V_c(x_i) = \frac{1}{2} (1 - I_{x_i, x_j}) \quad (16)$$

Where  $x_j \in N_i$ , and

$$I_{x_i, x_j} = \begin{cases} 0, & x_i \neq x_j \\ 1, & x_i = x_j \end{cases} \quad (17)$$

#### III. THRESHOLD TECHNIQUES

Threshold technique is one of the important techniques in image segmentation; it is considered the most useful and the simplest way to distinguish objects from the background in classes. For instance, an image involves an object, made up of pixels, which has homogeneous grey level and a background with a different grey level. The image can be segmented into two different regions using simple thresholding, that classifies all pixels with grey level values greater than  $T$  as object pixels and pixels with grey level values smaller than  $T$  as background pixels. It is necessary to mention that the shape information of an image histogram can be employed indirectly by most of thresholding techniques. The exemplary case is a bimodal shape of histogram because of grey level at the decline curve

can be selected as the value of threshold segmentation. The  $T$  value can be defined by the following:

$$T = T[x, y, p(x, y), f(x, y)] \quad (18)$$

Where:  $T$  is the threshold value.

$x, y$  are the coordinates of the threshold value point.  $P(x, y), f(x, y)$  are points the gray level image pixels.

Threshold image  $g(x, y)$  can be defined[7, 11]:

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \leq T \end{cases} \quad (19)$$

The process is completed by ending the segmentation is with scanning the image pixel by pixel and labeling each pixel as object or background. This scan depends on whether the gray level of that pixel is greater or less than the value of  $T$ . Applying threshold presents a clear and simple segmentation because it removes the shadows leaving only the objects in the image [18]. The objects in subject are darker than the background, so any pixel with a gray level  $< T$  is labeled black (0) and any pixel with gray level  $> T$  is labeled white (255)[17].

#### IV. PROPOSED APPROACH

The proposed approach of estimation and segmentation has been applied on three MRI images. These images belong to cases of different ages and gender. They are chosen from Tikrit Hospital after they have been diagnosed by a doctor who is specialist in brain tumors and the result was including three cases of brain cancer of the type of Glioma.

##### A. Read MRI Images

In the first series the first step has to be taken is to upload the MRI images raw into a program where it is converted into a formula can be processed using MATLAB.

##### B. Apply EM Algorithm

To use HMRF-EM algorithm framework for image segmentation, first an initial segmentation has to be generated using k-means clustering on the gray-level intensities of pixels. The initial segmentation provides the initial labels  $x^{(0)}$  for the MAP algorithm, and the initial parameters  $\Theta^{(0)}$  for the EM algorithm[12]. Then the EM algorithm has been run, and the resulted label configuration  $x$  will be a refined segmentation result. After that for preserving the edges obtained by some edge detection algorithm such as Canny edge detection can be applied [15]. The binary edge map  $z$  is obtained by performing Canny edge detection on the original image, and the observation  $y$  is obtained by performing Gaussian blur on the original image. Some results are shown in Figure (1). It is obvious that the initial labels obtained by the k-means algorithm are not smooth enough, have morphological holes, and do not preserve the Canny edges. Thus, the HMRF refines labels overcome all these disadvantages[15,16,18]. The last consequence of this process is represented by the production of final labels with 7 EM iterations and 10 MAP iterations.

##### C. Apply Threshold

The final experiment the threshold segmentation is implemented using MATLAB and the segmentation techniques in the three cases of MRI images illustrated in the Figure (1,2,3).

## V. RESULTS AND DISCUSSIONS

The current study presents a hybrid method includes two methods one of them is HMRF-EM which employs good initial classification of the image and the other is threshold which gives the final segmentation. Therefore, HMRF-EM segmentation algorithm for brain MR images gives a good image segmentation and well estimated parameters for each tissue type.

Analysis by Markov field described by HMRF-EM algorithm has been used for the segmentation of MRI images. K-means is used to initialize labels gray scale pixel. The initial segmentation gives label by MAP and the initial parameters by EM. Thus, as a segmentation parameter, the maximum iteration of MAP = 10, maximum iteration EM = 7 and a number labels ( $k = 2$ ) for initialization K-means. The HMRF-EM algorithm was applied on a T1 weighted MRI image. Figure (1,2,3) shows the result obtained after segmentation with time 17.5 seconds. The significance of the detected changes has been assessed by applying thresholding on final labels that obtained by HMRF-EM algorithm and produced with 7 EM iterations and 10 MAP iterations. This application has been carried out when the value of T is 235 of the image as it is shown in figures (1,2,3). The final result clearly shows the form of the brain tumor and that gives the possibility of calculating the size of the brain tumor in the future.

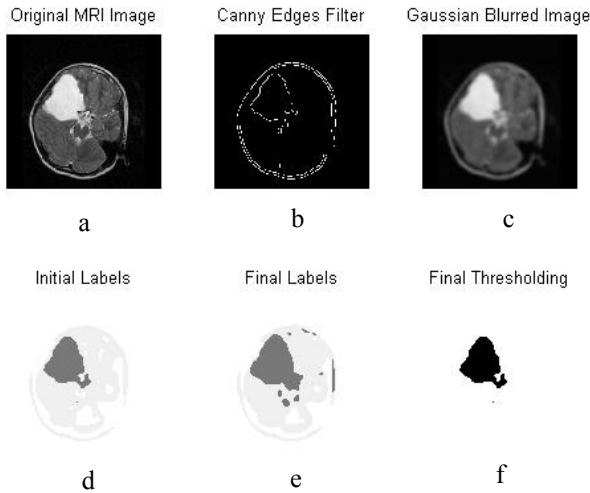


Fig. 1. Edge-prior-preserving image segmentation results for Case number One: show final labels Edge-prior-preserving image segmentation results. (a) Original image. (b) Canny edges. (c) Gaussian blurred image. (d) Initial labels obtained by k-means, where  $k = 2$ . (e) Final labels obtained from the HMRF-EM algorithm. (f) Final tumor region using threshold technique.

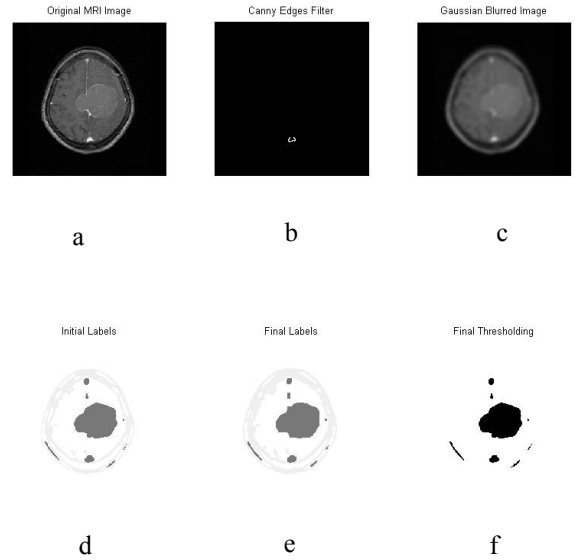


Fig. 2. Edge-prior-preserving image segmentation results for Case number One: show final labels Edge-prior-preserving image segmentation results. (a) Original image. (b) Canny edges. (c) Gaussian blurred image. (d) Initial labels obtained by k-means, where  $k = 2$ . (e) Final labels obtained by the HMRF - EM algorithm (f) Final tumor region using threshold technique.

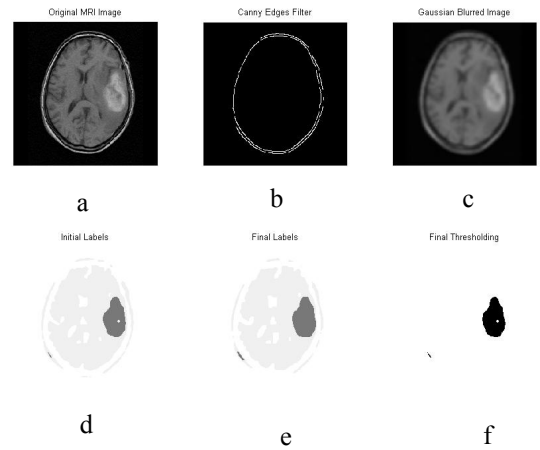


Fig. 3. Edge-prior-preserving image segmentation results for Case number One: show final labels Edge-prior-preserving image segmentation results. (a) Original image. (b) Canny edges. (c) Gaussian blurred image. (d) Initial labels obtained by k-means, where  $k = 2$ . (e) Final labels obtained from the HMRF - EM Algorithm (f) Final tumor region using threshold technique.

## VI. CONCLUSION

The proposed method has been developed in this research in order to present a hybrid method that facilitate diagnosing the brain tumor from brain MRI images using a HMRF - EM algorithm which in turns produces final labels. Threshold has been applied on the result obtained from the HMRF - EM algorithm. As a final consequence of the whole process the result obtained shows a segmentation with high accuracy of MRI brain tumor images and that gives the possibility of calculating the size of the brain tumor in the future.

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