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Research Article

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IDENTIFY BRAIN TUMORS IN 2 D MRI IMAGES USING FAST BOUNDING BOX METHOD

Anjana Tiwari* and Shipra Rathore

Abstract

Image segmentation is a problem in computer vision and is of more important than anything else for medical imaging. For most subsequent image analysis task, medical image segmentation is an important step. In neuro imaging analysis, the segmentation of an atomic structure for brain plays a crucial role. It involves accurate tissue segmentation of brain magnetic resonance (MR) images by the study of many brain disorders. It is lacking variety by an human expert for studies of involving larger databases in manual segmentation of the brain tissues like white matter, gray matter and cerebrospinal fluid in MR images. By the overlapping of MR intensities of many different tissue classes and by the presence of a spatially and smoothly varying intensity makes the segmentation much complicated. The main objective of this study is to develop strategies and methodologies for identifying the brain tumors in 2 d MRI images using automated approaches. It is a challenging task in MRI for accurately detection and segmentation of brain tumor. The MRI image is a type of image that produces a high contrast images which indicates regular and irregular tissues which also helps to distinguish the overlapping of each limb in margin. Fast bounding box methodis used for better detection of cancer. MATLAB Simulink, is used for the simulation.

Key Words: Magnetic Resonance (MR) Images Segmentation Of Brain Tumor, Identifying The Brain Tumors, Detection Of Brain Tumor, Fast Bounding Box Method.

INTRODUCTION

Segmentation is a type of process of which helps in splitting an observed image into itssimilar, comparableand componentregions. To change and make easier to do the representation of an image into a thing which make it more meaningful, simple to examine and analyze is the main aim of segmentation. The process of dividinga digital image into parts and multiple regions is segmentation which is referred in computer vision. For image segmentation, there are three different approaches which are used. Region based is a first approach, which depends onthe consistencyof spatially localized features and other pixel statistics. The second method used is based on of boundary finding relying on the gradient features at a subset of the spatial positions of an image whereas the third one is approach used for classification of pixel. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. It provides additional information about the contents of an image by identifying edges and regions of similar color, intensity and texture, while simplifying the image from thousands of pixels to less than a few hundred segments. Also by image segmentation, is frequently used to help and support in isolating, seperating or removing the precise detail of portions of an image. So to locate objects and boundaries in images, image segmentation is typically been used. The result of image segmentation gives a set of regions which collectively viewed as a cover of an entire image, or a set of contours which is used to extract from the image. It is also used to provide additional information about the contents of an image by identifying edges and regions of similar color, intensity and texture, while it is also used to simplify the image from thousands and many hundreds of pixels to less than a few hundred segments. With reference to some characteristic or calculated property of an image, each of the pixels in a region is similar to other. The segmentation of 2D and 3D images is anvaluable step for a heterogeneity of image analysis and visualization tasks. Hence, image segmentation is one of the early problems and has a broad and extensive application domain.

The segmentation problem can be divided into two parts, supervised approach and unsupervised approach.

- In supervised segmentation approach, the model parameters are supposed to be known *a priori*. In segmentation framework, the model

Department of Computer Science Kalinga University, Naya Raipur, (C.G), India
Correpondence and Reprint Requests: Anjana Tiwari
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parameter priori is used for judging the pixel labels. The MRF model has been formulated using Maximum a Posteriori (MAP) criterion and Bayesian framework [1,2], to minimize the pixel labelling problems. Noisy images alsocontaining textured images can be segmented using MRF model could be formulated in observed manner can be achieved. Noisy images also containing textured images can be segmented using MRF model could be formulated in observed manner can be achieved. A supervised image segmentation method have been proposed by Nanda *et al*. [8].

Figure 1 *NC Landsat map 2002*

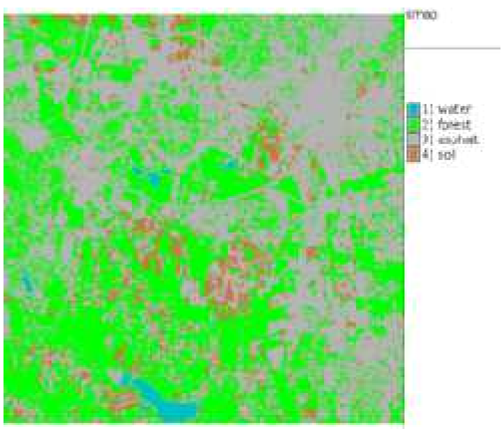

Figure 2 *Supervised Segmentation of Map*

- In unsupervised segmentation approach, the number of labels of class and the number of model parameters are not known. It is indeed required simultaneously, the calculation and judgement of image labels and model parameters. Since the estimation of image label rely upon the optimal set of parameters, the unsupervised image segmentation approach hence it is regarded as an incomplete data problem. For handling this type of problem, an iterative method namely expectation maximization (EM) algorithm has been put forward for consideration [11,16]. For restoration, the rough calculation for parametersusing iterated conditional mode (ICM) algorithm is introduced by Besag *et al* [2].

Figure 3 *NC Landsat map 2002*

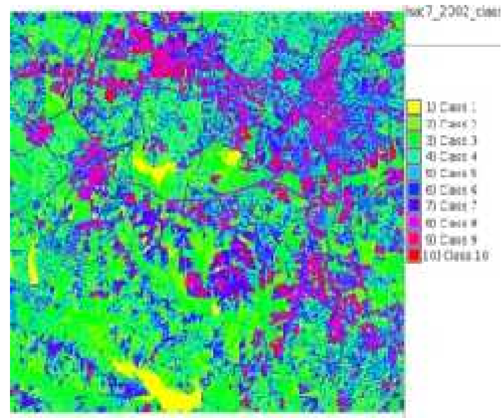

Figure 4 *Unsupervised Segmentation of Map*

The applications or field where segmentation are used are in medical imaging i.e. in locating tumors, for measuring tissue volumes, for computer-guided surgery, for diagnostic treatment planning, for study of anatomical structure. It is also used in locating objects in satellite images, in face recognition, in automatic traffic controlling systems, in machine vision etc.

Magnetic Resonance Imaging (Mri)

The safe and painless test of the brain is done using magnetic resonance imaging. To obtain the detailed images of the brain and the brain stem the MRI uses the magnetic field and the radio waves. Alarge doughnut-shaped magnet which consist of a tunnel in the center has been used to develop the MRI scanner. The tunnel consist of the slides where the patients are been placed. In hospitals and in radiology centers, the MRI machines are located.

During the examination of the patient, the magnetic position of the atoms of the body of the patient is easily manipulated by the radio waves, which are sent to a computer by picking up the images of patient using a powerful antenna. Millions of calculations, cross-sectional black and white images of the body is performed in the computer. The scanned area of this images obtained by MRI is then converted into the three-dimensional pictures. A variety of conditions and the problems associated with the brain such as cysts, tumors, infections, bleeding and swelling of brain parts, or problems with the blood vessels can be detected using MRI. In some cases, the X-ray, CAT scan, or ultra sound cannot provide clear images of parts of the brain but the MRI can be used to provide clear images of parts of the brain that can't be seen as in other scanners.

MRI is atechnique which isproviding strong and abundant information about the soft tissue of human is technically is an advanced medical imaging technique. As compared to other imaging techniques, it has several advantages which is used to obtain 3-dimensional data with high contrast between soft tissues. For analysis of computer-aided image, the automatic or semi-automatic techniques are used. It is an important and essential task for segmentation of MR images into different tissue classes.

The contrast of an MR image rely on how the way the image of the brain has been developed. To highlight the different component being imaged and to obtain the high contrast images the alteration of radio frequencies and gradient pulses is done.

Figure 5 *Arrow shows the brain tumor*

There are two features which make segmentation easy, first is weighting and the second is artifacts. Using different techniques, the MR images can be easily obtained. The different properties of the depicted or represented materials of the resulting images are highlighted. T1weighted images and T2 weighted imagesare the most common weightings, which helps to highlight the properties T1-relaxation and T2-relaxation respectively. For a successful segmentation selection of the most appropriate weighting is important.

According to Pham *et al*. the properties of the tissues that are to be segmented have to be known to make a well-founded decision [42]. T1-weighted images gives us high contrast between different tissues which have different T1-relaxation times. T1- weighted images gives us high contrast between white matter and gray matter. Also in T1- weighted images air, bone and CSF have low intensity, whereas gray matter is dark gray and the white matter is light gray. But in T2-weighted images, the intensities of white matter and gray matter are similar and are gray. As contrast to T1-images, T2-images have high contrast between CSF and bone, but the contrast between white matter and gray matteris not as good as compared to T1-images.

In MR images there the various types of artifacts are present. The performance of a segmentation algorithm is affected by the change in presence and appearance of the images which is made by artifacts. For image segmentation the most important and commonly used artifacts are intensity in-homogeneities and the partial volume effect. Intensity in-homogeneities cannot be always seen by the human eye, but have negative influence on automatic segmentation process.

This may obvious and apparent itself by making one part of the image intensities brighter or darker than another part. The radio frequency (RF) coils are the reasons for its cause. To compensate the in-homogeneities, there exist many different methods. In in-homogeneity field, the true pixel intensity is multiplied by the value of the field in that pixel because of which it can often thought to be a multiplicative field. There are many methods which are used to extracts the in-homogeneities during segmentation.

The partial volume effect obtained when a pixel cannot be accurately placed to one tissue type. This is caused because the intensity in the pixel is formed by more than one tissue. It is present because one pixel contains many body cells and the signal emitted or obtained from these cells make up the detected intensity in this pixel. This effect is most apparent at edges between different tissues. In brain segmentation, the partial volume effect will make a significant problem since the brain has a complex folded surface [13].

METHODOLOGY

The method used for identifying brain tumor in 2D MRI image is fast boundinng box algorithm (FBB). FBB operates in two steps. Firstly, the input set of 2D MR slices are processed in bounding box and then it is used find axis-parallel rectangles. Next, these bounding boxes are positioned close together to identify the tumor/edema.

The method can be explained using this flow chart-

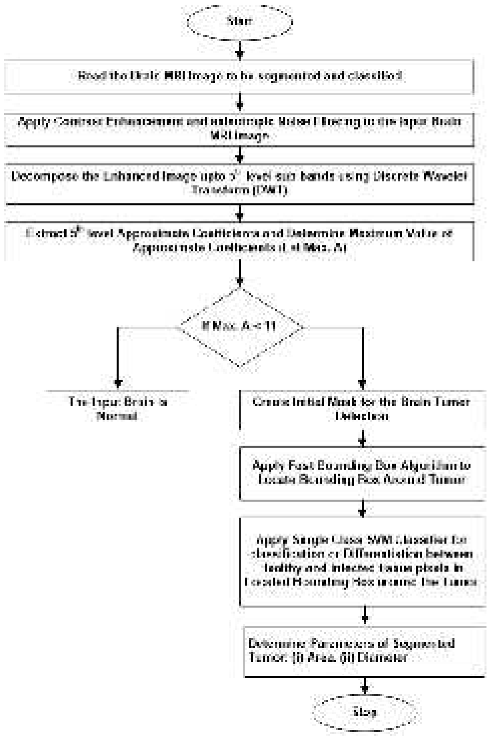

Figure 6 Step showing algorithm

- ➢ Firstly read the brain MRI image which is to be segmented and classified and enhanced image is obtain.
- ➢ Now the enhanced image is decomposed upto fifth level sub band using discrete wavelet transform (DWT).
- ➢ Now extract fifth level approximate co efficient and determine the maximum value of approximate co efficient. Let the maximum coefficient be A.
- ➢ Now by using if then rule
- ➢ If A <11 Then the input brain is normal
- ➢ And if not hen it has brain tumor.
- ➢ If A is greater than 11 then algorithm used is described below:
- ✓ Create initial mask for brain tumor detection.
- ✓ Now fast bounding box algorithm is applied to locate bonding box around tumor present in the brain.
- ✓ For classification and differentiation between healthy and infected tissue pixels present in bonding box around tumor, apply single class support vector machine (SVM) classifier is used.
- ✓ Then the area and diameter of segmented tumor is determined.

RESULT ANALYSIS

The result is seen by using two different examples.

- ✓ Taking first example which is having one tumor

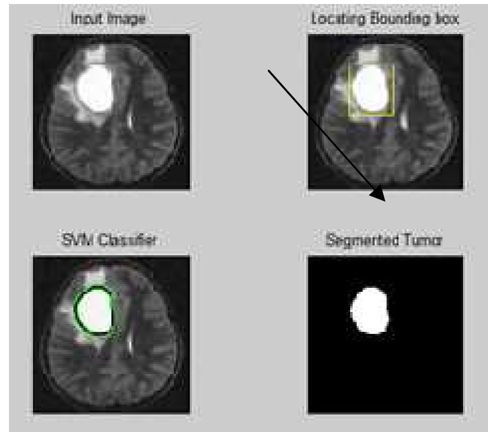

Figure 7 Figure showing all the output of all the steps

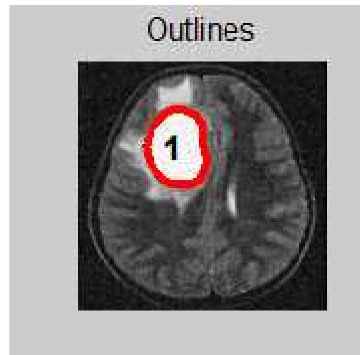

Figure 8 Bounding Box around tumor present

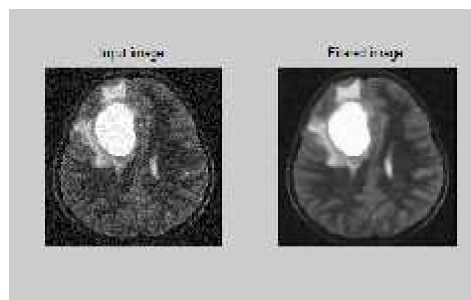

Figure 9 Comparison between input image and processed image

- ✓ Taking second example which is having two tumors

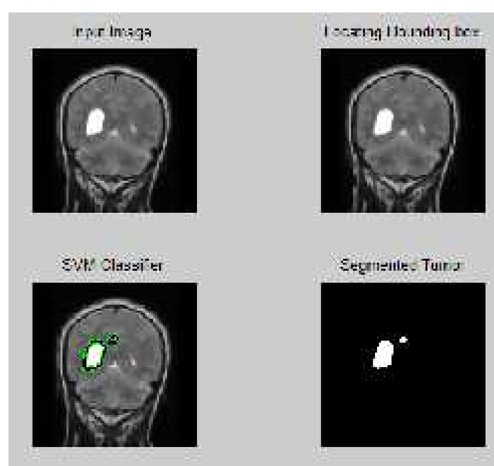

Figure 10 showing all the output of all the steps

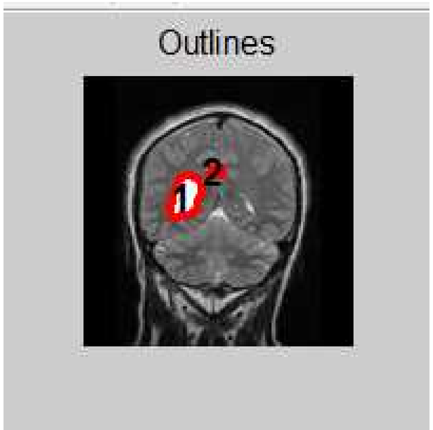

Figure 11 *Bounding Box around tumor present*

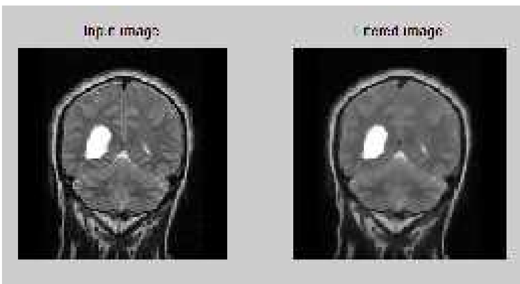

Figure 12 *Comparison between input image and processed image*

CONCLUSION

It can be seen that the fast bonding box algorithm provides the better output then texture based algorithm and single thresholding technique. Multiple area selection can be done using this method. Complexicity is decreased. Percentage of the false recognition is less.

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