Volume 2, No. 4, April 2011

Journal of Global Research in Computer Science

ISSN-2229-371X

RESEARCH PAPER

Available Online at www.jgrcs.info

BRAIN TUMOR SEGMENTATION AND QUANTIFICATION FROM MRI OF BRAIN

*Sudipta Roy[*1],Atanu Saha[*2] and Prof. Samir K. Bandyopadhyay[3], Sr Member IEEE
[*1],[2] B.Tech. 5th Semester Student of Computer Science and Engineering, University of Calcutta

[1]Professor, Department of Computer Science & Engineering,
University of Calcutta, 92 A.P.C. Road,
Kolkata – 700009, India
Email: scse.roy@gmail.com and skb1@vsnl.com

Abstract: Detection of Brain tumour is the most common fatality in the current scenario of health care society. Computational applications are gaining significant importance in the day-to-day life. Specifically, the usage of the computer-aided systems for computational biomedical applications has been explored to a higher extent. Automated brain disorder diagnosis with MR images is one of the specific medical image analysis methodologies. Image segmentation is used to extract the abnormal tumour portion in brain. This paper explores a method to identify tumor in brain disorder diagnosis in MR images.

Keyswords: Tumor Detection, Segmentation, Diagnosis techniques, and Brain MRI

INTRODUCTION

Medical image analysis is an important biomedical application, which is highly computational in nature and requires the aid of the automated systems. These image analysis techniques are often used to detect the abnormalities in the human bodies through scan images.
Automated detection of the abnormalities in medical images is an important andsometimes necessary procedure in medical diagnostics, planning, and treatment.

While detection of abnormalities such as tumor is possible by experts, manual segmentation is usually tedious and time consuming and subject to error. There are many methods that find a tumor in MR images (MRI) semi automatically. In such methods, human intervention is required, which again makes the process timeconsuming and expensive. The critical problem is finding the tumor location automatically and later finding its boundary precisely. An important factor in detecting tumor from healthy tissues is the difference in intensitylevel. However, relying only on the intensity level is usually not enough. Thespatial information available in clusters of pixels that form a tumor should also be used in the detection process.
Segmentation of MR images into different tissue classes, especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), is an important task.

A tumor or tumor is the name for a neoplasm or a solid lesion formed by an abnormal growth of cells which looks like a swelling. Tumor is not synonymous with cancer. A tumor can be benign, pre-malignant or malignant, whereas cancer is by definition malignant. A benign tumor is a tumor that lacks all three of the malignant properties of a cancer. Thus, by definition, a benign tumor does not grow in an unlimited, aggressive manner, does not invade surrounding tissues, and does not spread to non-adjacent tissues (metastasize). Common examples of benign tumors include moles and uterine fibroids.
Malignancy (from the Latin roots mal- = "bad" and -ignis = "fire") is the tendency of a medical condition, especially tumors, to become progressively worse and to potentially result in death. It is characterized by the properties of anaplasia, invasiveness, and metastasis. Malignant is a corresponding adjectival medical term used to describe a severe and progressively worsening disease. The term is most familiar as a description of cancer.

A precancerous condition (or premalignant condition) is a disease, syndrome, or finding that, if left untreated, may lead to cancer. It is a generalized state associated with a significantly increased risk of cancer.
Brain tumor segmentation and quantification from MR images is a challenging task. The boundary of a tumor and its volume are important parameters that can have direct impact on surgical treatment, radiation therapy, or on quantitative measurements of tumor regression rates. The location of tumors in the brain is one of the factors that determine how a brain tumor affects an individual's functioning and what symptoms the tumor causes.
The part of the image that has the tumor has more intensity in that portion and we can make our assumptions about the radius of the tumor in the image, these are the basic things considered in the algorithm.
First of all some image enhancement and noise reduction techniques are used to enhance the image quality, after that

some morphological operations are applied to detect the tumor in the image. The morphological operations are basically applied on some assumptions about the size and shape of the tumor and in the end the tumor is mapped onto the original gray scale image with255 intensity to make visible the tumor in the image. The algorithm has been tried on a number of different images from different angles and has always given the correct desired result.

REVIEW WORKS

There have been significant efforts to develop automated computer algorithms forlocating tumors in brain MRI. A review of pattern recognition methods for MRI segmentationis presented in [1], and methods and applications of MRI segmentation canbe found in [3]. Among supervised methods, the work [6] combines information from a registeredatlas template and user input to train a supervised classifier. The method in [7] detects tumors based on outlier detection and uses affine transformation for the registration. However, this method fails in case of large tumors. The method described in [8] is based on training on healthy brain images instead of training on pathology. Torecognize deviations from normalcy, a multi-layer Markov random field is usedwhich is computationally expensive. In the work reported in [4], the authors employ an atlas based pathological segmentation using affine transformation. They assume tumor growth has a radial expansion from its starting point. All of the above methodsare time consuming, and also need expert input for large set of data. Supervised patternrecognition methods have exhibited problems with reproducibility [2], due tosignificant intra and inter-observer variance introduced over multiple training trials.

The unsupervised method reported in [9] divides the T2 weighted images into fewblocks, and calculates the number of edges, the intensity and the contrast parameter ineach block. It assumes the abnormalities occupy less that 10% of all pixels, and that the blocks containing tumor pixels exhibit fewer edge pixels. However, tumor may fall in different blocks, making parts of the tumor un- detectable. In another method, colour-based clustering is used [10]. The MR image is translated to RGB,and RGB to L*a*b* planes. K-means clustering [12] is used on a* and b* planes tofind thresholds and mark the tumor. The issue with such methods is that they rely onintensity level classification, which is susceptible to misclassification. In this paper, an approach toward tumor detection and segmentation is introduced.

An analysis on filtering techniquessuch as Gabor & QMF filters for noise reductionis performed by [11]. These primitive methodsalong with reducing the noise blur the importantand detailed structures necessary for subsequentsteps. The colour ray casting method todifferentiate the region of interest from thebackground is implemented by [12]. But thistechnique is image dependent and not applicable for gray level images. Expectation maximizationsegmentation (EMS) software package is also usedfor image pre-processing [13]. The main advantage of this technique is that it is a fully automatictechnique. Diffusion filtering combined with simple non-adaptive intensity thresholding is used to enhance the region of interest [14]. The maindrawback of this technique is the non-adaptive nature of the threshold value. Fuzzy connectednessbased intensity non-uniformity correction has beenimplemented by [15]. A sequential approach withfuzzy connectedness, atlas registration and biasfield correction is used in this approach. Theconclusions revealed that the proposed techniquecan be used only if the intensity variationsbetween the images are of a limited range.The effect of inter-slice intensity variationis minimized with the weighted least squareestimation method [16]. The selection of weightsfor the least square method is the majordisadvantage of this approach. The noise removaltechnique using wavelets and curve lets isimplemented in [17]. Hybrid approaches involvingVariance Stabilizing Transform (VST) are alsoused in this work. But this technique is applicablefor images with Poisson noise. Tracking algorithmbased de-noising technique is performed by [18].

Since the seed point for tracking is random innature, this technique is not much efficient. Acontrast agent accumulation model based contrastenhancement is implemented by [19]. Thisimproves only the contrast of the image and the unwanted tissues are not eliminated. The wienerfiltering technique for noise removal in MR brain images is used in [20]. Apart from noise removal,several other pre-processing steps are alsoreported in the literature.

This includes image format conversion, image type conversion etc. Thecombination of three modalities of MR images forfurther processing is proposed in [21]. All theabove mentioned techniques remove only specificartefacts which is not sufficient for highclassification accuracy and segmentationefficiency. Apart from eliminating the noises, for the removal of unwanted tissues such as the skull tissues in MR images are highly essential for accurate identification of the diseases.

Pathology identification is performed by theimage classification technique and then thetreatment is planned based on the nature ofabnormality. After treatment, it is highly essentialto estimate the response of the patient to thetreatment. In case of brain tumor abnormalities the size of the tumor may decrease which indicatesa positive effect and sometimes it may increasewhich shows a negative effect. In any case, it is important to perform a volumetric analysis on MR brain tumor images. Image segmentation covers this objective by extracting the abnormal portionfrom the image which is useful for analysing the size and shape of the abnormal region. Thismethod is also called as “pixel basedclassification” since the individual pixels areclustered unlike the classification techniqueswhich categorizes the whole image. Severalresearch works are reported in the area of medical image segmentation..

PROPOSED WORK

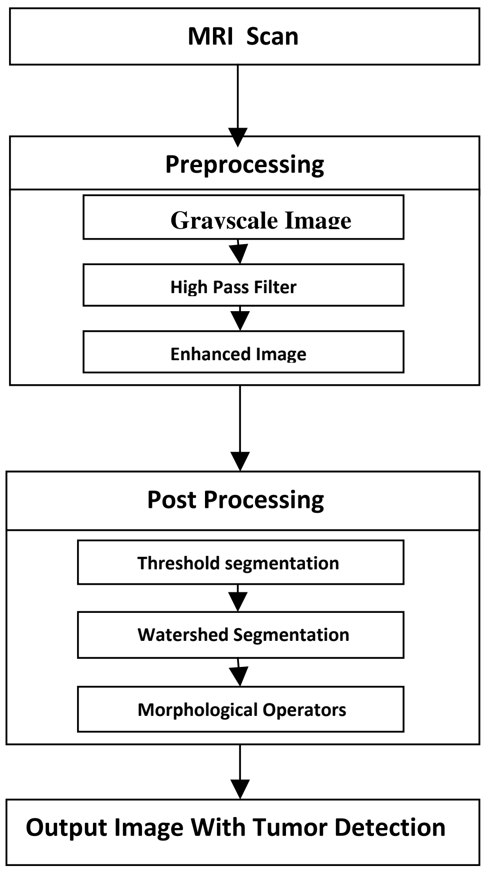
The part of the image containing the tumor normally has more intensity then the other portion and we can assume the area, shape and radius of the tumor in the image. We have used these basic conditions to detect tumor in our code and the code goes through the following steps:

In preprocessing some basic image enhancement and noise reduction techniques are implemented. Apart from that different ways to detect edges and doing segmentations have also been used. The purpose of these steps is basically to improve the image and the image quality to get more surety and ease in detecting the tumor. The basic steps in preprocessing are the following:-Image is converted to gray scale image in first step.Noise is removed if anyThe obtained image is then passed through a high pass filter to detect edgesThen the obtained image is added to original image to enhance it.
In processing the following steps are followed:-

Segmentation is done on basis of a threshold, due to which whole image is converted into binary image. Basic matlab commands for threshold are used for this segmentation.

It is the best method to segment an image to separate a tumor but it suffers from over and under segmentation, due to which we have used it as a check to our output. We have not used watershed segmentation on our input, rather it is only used on our output to check of the result is correct or not and it give the correct answer every time as is shown below.

Morphological operations are applied on the image after converting it into binary form. The basic purpose of the operations is to show only that part of the image, which has the tumor that is the part of the image having more intensity and more area. The algorithm is given below.



Algorithm

Input: MRI Gray Scale Image

Output: Isolation of Tumor

Step1:- Convert MRI scan image into grayscale image.

Step2:- Next the image passed through a high pass filter for removing noise and other spike in the imge.

Step3:- Now filtered image is added to the grayscale image.

Step4:-Convert the enhanced image (image of step3) in to binary image with a threshold value

Step5:- Separate the tumor from segmented image by Watershed - Method

Step6:- Select only that part of the image from step4 which has the tumor with the part of the image having more intensity and more area .

Step7:-Obtained image from step6 are added to the original gray scale image from step1 and the resultant image is output.

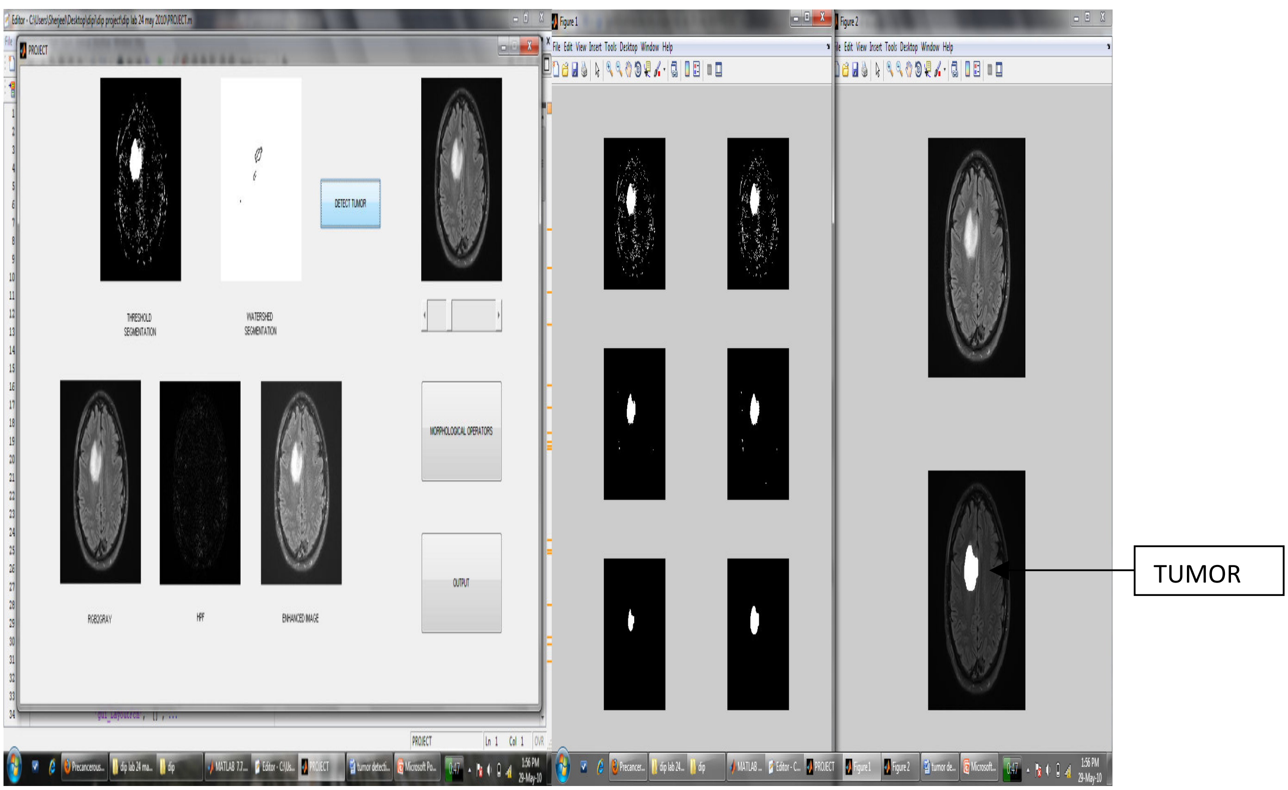
RESULTS

Watershed segmentation uses the intensity as a parameter to segment the whole image data set. Moreover, the additional complexity of estimation imposed to such algorithms causes a tendency towards density dependent approaches.[2]. Three-dimensional-segmentation is a reliable approach to achieve a proper estimation of tumor volume. Among all possible methods for this purpose, watershed can be used as a powerful tool, which implicitly extracts the tumor surface. Watershed segmentation based algorithm has been used for detection of tumor in 2D and in 3D.

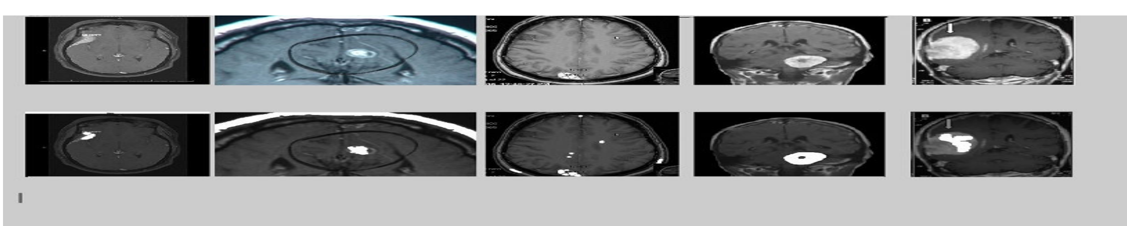
Recent advances in medical image analysis often include processes for an image to be segmented in terms of a few parameters and into smaller sizes or regions, to address the different aspects of analysing images into anatomically and pathologically meaningful regions. Classifying regions using their multi parameter values makes the study of the regions of physiological and pathological interest easier and more definable. Here, multi parameter features refer to the following three specific values for the edges (E), gray values (G), and local contrast (H) of the pixels.

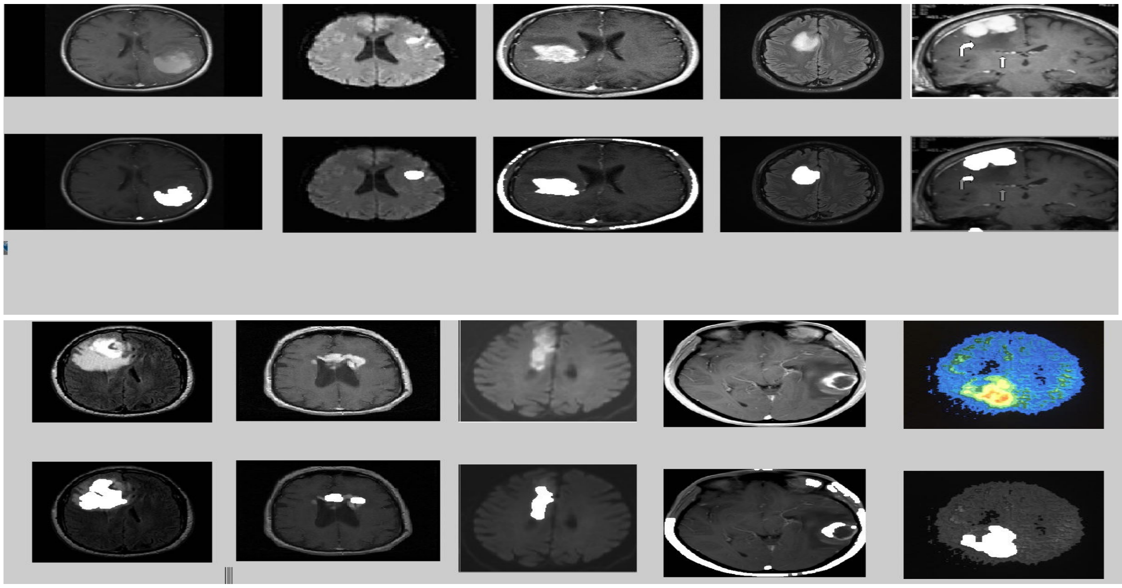
As watershed segmentation technique segregates any image as different intensity portions and also the tumerous cells have high proteinaceous fluid, which has very high density and hence very high intensity, therefore watershed segmentation is the best tool to classify tumors and high intensity tissues of brain. Watershed segmentation can classify the intensities with very small difference also, which is not possible with snake and level set method.

We have mapped the resultant tumor image onto the original grayscale image for presentation purposes. The method presented here is user friendly and doctor can select the brain image from the menu screen and find out enhanced image and portion of the tumor



OTHER RESULTS





CONCLUSIONS

The results show that Watershed Segmentation can successfully segment a tumor provided the parameters are set properly in MATLAB environment. This paper explores a method to identify tumor in brain disorder diagnosis in MR images.

REFERENCES

[1]. Bezdek, J.C., Hall, L.O., Clarke, L.P.: Review of MR image segmentation techniques usingpattern recognition. Medical physics 20(4), 1033–1048 (1993)

[2]. Held, K., Rota, K.E., Krause, B.J., Wells III, W.M., Kikinis, R., Muller-Gartner, H.W.:Markov random field segmentation of brain MR images. IEEE Trans. Med. Imaging, 878–886 (1997)

[3]. Clarke, L., et al.: MRI segmentation: Methods and applications. Magnetic Resonance Imaging13(3), 343–368 (1995)

[4]. Cuadra, M.B., Gomez, J., Hagmann, P., Pollo, C., Villemure, J.G., Dawant, B.M., Thiran,J.: Atlas-based segmentation of pathological brains using a model of tumor growth. In:Medical Image Comp.& Computer-Assisted Intervention MICCAI (2002), pp. 380–387.Springer, Heidelberg (2002)

[5]. Clark, M.C., Hall, L.O., Goldgof, D.B., Velthuizen, R., Murtagh, F.R., Silbiger, M.S.:Automatic tumor-segmentation using knowledge-based techniques. IEEE Trans. on MedicalImaging 17, 187–201 (1998)

[6]. Kaus, M.R., Warfield, S.K., Nabavi, A., Chatzidakis, E., Black, P.M., Jolesz, F.A.,Kikinis, R.: Segmentation of meningiomas and low grade gliomas in MRI. In: Taylor, C.,Colchester, A. (eds.) MICCAI 1999. LNCS, vol. 1679, pp. 1–10. Springer, Heidelberg(1999)

[7]. Prastawa, M., Bullitt, E., Ho, S., Gerig, G.: A Brain Tumor Segmentation FrameworkBased on Outlier Detection. Medical Image Analysis 8, 275–283 (2004)326 M.K. Khandani, R. Bajcsy, and Y.P. Fallah

[8]. Gering, D., Eric, W., Grimson, L., Kikinis, R.: Recognizing Deviations from Normalcy forBrain Tumor Segmentation. Medical Image Computing and Computer-Assisted Intervention,388–395 (September 2002)

[9]. Phooi Yee Lau Voon, F.C.T., Ozawa, S.: The detection and visualization of brain tumorson T2-weighted MRI images using multi parameter feature blocks. In: Engineering inMedicine and Biology Society. IEEE-EMBS, pp. 5104–5107 (2005)

[10]. Wu, M.-N., Lin, C.-C., Chang, C.-C.: Brain Tumor Detection Using Color-Based KMeansClustering Seg. In: IEEE Computer Society, IIH-MSP 2007, pp. 245–250 (2007)

[11]Warburg, O.H. (1969) The prime cause and prevention of cancer. The Second Revised Edition Published by KonradTriltsch, Würzburg, Germany.

[12]Brewer, A.K. (1984) The high PH therapy for cancer, tests on mice and humans. Pharmacology Biochemistry & Behavior, 21, 15. doi:10.1016/0091-3057(84)90152-7

[13]Ralph W.M. (2004) Losing the war on cancer. Townsend Letter for Doctors & Patients.

[14]Kirschner, D. (2009) On the Global Dynamics of a Model for Tumor Immunotherapy. Mathematical Biosciences and Engineering, 6, 573-583.

[15]Ledzewicz, U. (2005) Optimal control for a system modeling tumor anti-angiogenesis. ACSE 05 Conference, CICC, Cairo, 19-21 December 2005, 147-152.

[16]Ghaffari, A. and Nasserifar, N. (2009) Mathematical modeling and lyapunov-based drug administration in cancer chemotherapy. Journal of Electrical & Electronic Engineering, 5, 151-158.

[17]Georgiadis P, Cavouras D, Kalatzis J,Daskalakis A, Kagadis G, Sifaki K, SolomouE. Non-linear least square featuretransformations for improving the performance of probabilistic neural networks in classifying human brain tumors on MRI. Lecture Notes on Computer Science 2007;4707:239-47.

[18]Huang K, Aviyente S. Wavelet feature selection for image classification. IEEE Trans.Imag. Proc. 2008; 17:1709-20.

[19]Jesus C, Noah L, Ebadollahi S, Andrew L,John K. Concept detection in longitudinal brain MR images using multi modal cues.IEEE International Symposium on Biomedical Imaging 2009; 418-21.

[20]Kowaliw T, Banzhaf W, Kharma N, HardingS. Evolving novel image features using Genetic programming based image transforms.IEEE Congress on Evolutionary Computation2009;2502-7.

[21]Pradhan N, Sinha K. Development of a composite feature vector for the detection of pathological and healthy tissues in FLAIR MR images of brain. Bioinformatics and Medical Engineering Journal 2009; 10:1-11.