International Journal of Engineering, Science and Mathematics
Vol. 6 Issue 6 , October 2017,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

Segmentation of Brain Tumor from MRI Image Blocks using SVM Classifier

Galiyabi. P. S[a]

Abstract

Tumors are one of the most dangerous diseases that are difficult to cure completely when detected after its initial stage. Early detection of this will help to get proper treatment. Tumors cause changes in tissues which can be detected using many imaging techniques like Magnetic Resonance Imaging (MRI). The system is proposed for the autonomous segmentation of tumor tissues from normal tissues in MRI images using Gray Level Co-Occurrence Matrix (GLCM) features extraction and Support Vector Machine (SVM) classifier.

Keywords:

Brain tumor;
MRI image;
GLCM features;
SVM classifier;
Segmentation.

Author correspondence:
First Author,
M.Tech in Embedded Systems,
Vidya Academy Of Science and Technology,
Kerala, India,

1. Introduction

The tumor is an abnormal tissue growth, which is also known as neoplasm or lesion. Brain tumors are classified as primary or secondary according to the cell from which it origins. Primary tumor starts in the brain and usually does not spread to other areas. Secondary (metastatic) tumor spread to the brain from another part of the body and it is always cancerous. Primary tumors are of two types i.e., benign and malignant. The benign tumor grows slowly and rarely spreads. It has a distinct boundary and becomes life threatening only when present in vital areas. The malignant tumor grows quickly and spreads to nearby brain areas so it has irregular boundary [1]. Malignant tumors are cancerous in nature and benign tumor may turn malignant. Studies show that brain tumors are the second leading cause of cancer-related deaths in children under age 20 and in men ages 20-39 and the fifth leading cause of cancer-related deaths in women ages 20-39 so early detection of tumors is critical [2]. Brain tumor treatments are undergone based on the type, size, location of tumor and age and health of the patient.

MRI scanning is a preferred method for evaluating the lesions in the brain [3]. It provides a 3 dimensional view of the brain. The biopsy is prescribed to get more details of the tumor for the treatment only when it is present and much detail about the tumor is not visible in the scanned image. Extracting details from the MRI images manually will be a time consuming task, so there is a necessity for an autonomous way to extract more details from the MRI with less time.

There are many segmentation methods to detect abnormal tissues from brain images, but present technique's lack accuracy. So it needs to be further improved. Brain tumor segmentation methods are generally subdivided as manual, semi-automated and fully-automated based on the human intervention. Manual segmentation requires expert knowledge in the details provided in the MRI image and should mark and label the tumor region using colors manually which is error prone and time-consuming. In a semi-automated method, comments to the software for adjusting the segmentation algorithm are provided from the external. It is better than manual segmentation, but results may vary with the expertise and time

[a] M.tech in Embedded Systems, Vidya Academy of Science and Technology, Kerala, India

for the same user. Fully-automated method does not need any human interaction and it combines artificial neural network and prior knowledge [4]. The current brain tumor segmentation method is categorized to conventional methods, classification and clustering methods and deformable model methods.

Conventional methods work on two-dimensional images and uses standard image processing methods like threshold based methods and region based methods for tumor segmentation. Classification and clustering methods are to automate the diagnosis and analysis of brain images using machine learning. Deformable model methods work on 3-D MRI data, which is very challenging. This method exploits the constraints derived from the image data together with a priori knowledge to segment images of anatomic structures [5]. In spite of many advanced techniques, there is a need for the advancement in current segmentation techniques due to the lack of accuracy and validity, which is to be fulfilled for the adoption of these techniques in the real time clinical application, i.e., the techniques must be trustworthy enough to compete with the result of manual segmentation in terms of accuracy.

The SVM has the ability to learn the nonlinear distribution of the image data without prior knowledge using implicit learning kernel [6]. The proposed method is for the segmentation of brain tumor in MRI by combining the feature extraction and SVM classification method on the image blocks.

The remainder of this paper is organized as follows. Section 2 describes the proposed system. It introduces techniques for segmenting the brain tumor from MRI images. Section 3 describes the experimental result and discussion; it describes the results produced by the proposed method. Final Section 4 concludes the paper.

2. Research Methods

The proposed method is a novel method for the segmentation of brain tumor from MRI images. The method consists of five stages i.e., image preprocessing, image partitioning, feature extraction, training and image reconstruction. Figure 1 shows the block diagram of the proposed method.

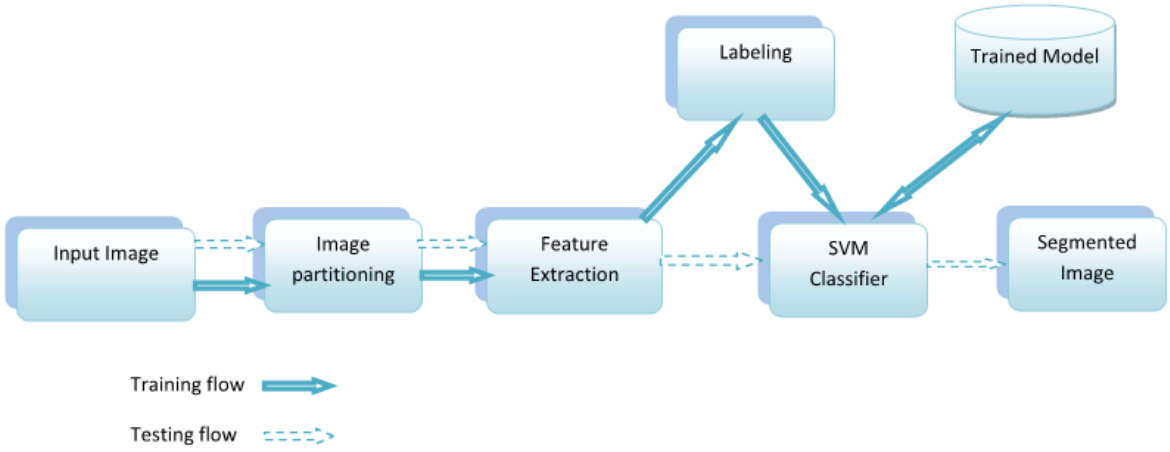

Figure 1. Block diagram of proposed method

A. Image Preprocessing

The experiments are conducted on the T2- weighted MRI images from the BRATS 2015 database which consists four brain MRI sequences, i.e., T1-weighted (T1), T1 with gadolinium enhancing contrast (T1c), T2-weighted (T2) and FLAIR for every patient.

In preprocessing stage, raw MRI (T2-weighted) 3D images are normalized to reduce the intensity variations to make it suitable for further processing. Next step is to remove the exterior area to the brain region in the MRI image to avoid the unnecessary pixel details in the image. Then the training images are converted to 256X256 pixels for converting every image into same dimension.

B. Image Partitioning

Preprocessed MRI images of 256 X 256 pixels are broken down into several smaller blocks of the same size in partitioning stage. Any block size of 4X4 pixels, 8X8 pixels, 16X16 pixels, so on can be selected. In this paper, 4X4 pixels size blocks are selected to improve accuracy of the system after checking 8X8 pixels which lacks accuracy. The resultant number of blocks having tumor will be far less in numbers than other blocks. For better results same numbers of healthy blocks and tumor blocks from the resultant partitioned blocks are selected for training.

C. Feature Extraction

The partitioned blocks data are too large to feed to the classifier directly and it also consists of many unnecessary details which are not required for training. So the desired set of Gray Level Co-Occurrence Matrix (GLCM) features is extracted from the blocks for training classifier. Features are often consists of information about colour, shape, texture or context. Medical images contain more texture information than other data.

GLCM encloses the second-order statistical information of adjacent pixels of an image. It is estimated of a joint probability density function (PDF) of gray level pairs in an image. Only relevant features that improve the accuracy are selected from the set of GLCM features. The training set is developed with the selected features of each block.

The features extracted using Gray Level Cooccurrence Matrix (GLCM) are: Entropy, Energy, inverse difference moment, inverse difference, infinite measure of correlation, difference entropy, difference variance, sum entropy, Contrast, Autocorrelation, cluster prominence, cluster shade, dissimilarity, homogenity, maximum probability, sum of squares, sum average, sum variance.

D. Training

The extracted set of features of each block is labeled as tumor or healthy as per prior knowledge (from ground truth) and fed to the SVM classifier for training. SVM is a binary classification method that takes the input labeled data of two classes and outputs a model file for classifying new data into one of two classes. It is from the training set that the SVM gets its intelligence to classify unknown data. The proposed method uses (Gaussian) radial basis function kernel, or RBF kernel to learn from the training set. RBF kernel on two samples x and x' is:

E. Image Reconstruction

The testing input image is fed to the SVM trained model after the preprocessing and partitioning of the test image, i.e., same as in the training stage. Classification results are generated for each block. These results of each block are used to segment the tumor region in the MRI image.

3. Results andAnalysis

MRI 3D image normalization converts the image into a processable form. Removing the region outside of the brain area improves the performance by reducing the overburden of training unnecessary details which leads to misinterpretation of the classifier. All the training images are converted to 256X256 pixels size images to make uniformity in the image size. MRI brain images are partitioned into blocks of 4X4 pixels blocks and features are extracted from the equal number of tumor and healthy blocks to train the classifier. More satisfactory results were obtained by using 4X4 pixels blocks than 16X16 pixels blocks. Considering every healthy blocks and tumor blocks in the partitioned result for training classifier will lead to over learning of the healthy blocks details, which is much larger in number than tumor blocks and interpret most of the test image blocks as healthy blocks results in a worst classification. Hence, the same number of tumor and healthy blocks from the partitioned blocks are selected to improve the performance of the system.

GLCM features are extracted from the blocks for training. The extracted features decide the performance of the classifier, so only relevant features are selected for better accuracy. Studies show that training the SVM classifier using feature extraction improves the performance much more than training without feature extraction. Tumor blocks in the MRI image are labeled by analyzing the pixel values and its location in the ground truth. Trained model is developed using these selected features of the image blocks and its labels.

Test image is fed to the trained model after preprocessing and partitioning. Each block of the test image is classified as a tumor or healthy by the SVM classifier which is trained using the labeled image blocks. According to the results of the SVM classifier, tumor blocks are identified from the test image and tumor area is segmented using these classified results. The figure 2 (a) shows an input image fed to the SVM trained model and figure 2 (b) shows its segmented output.

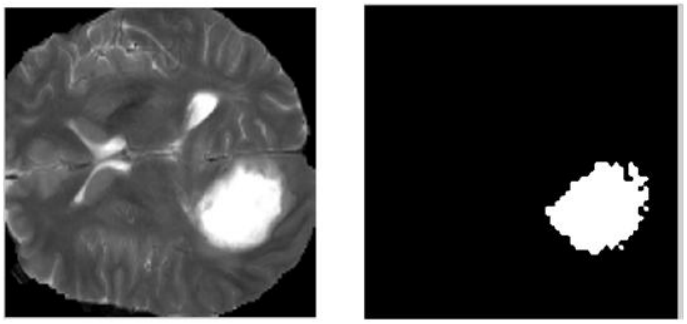

Figure 2. (a) Input image and (b) Output image

The Performance of the proposed system is analyzed by plotting accuracy, sensitivity and specificity of the output images using true positive (TP), true negative(TN), false positive(FP) and false negative(FN) values measured from the segmented output image and ground truth. The table 1 shows the evaluation of segmented results of five images.

Accuracy = (TN+TP)/(TN+TP+FN+FP)

Sensitivity = TP/(TP+FN)

Specificity = TN/(TN+FP)

Table 1Evaluation of segmentation results

Sl. no.	True positive (No. of pixels)	True Negative (No. of pixels)	False Positive (No. of pixels)	False Negative (No. of pixels)	Accuracy	Sensitivity	Specificity
1	13623	48218	3009	686	.94	.95	.94
2	9830	52699	230	2777	.95	.78	.99
3	13904	48208	2862	562	.95	.96	.94
4	4092	59906	10	1528	.98	.72	.99
5	10394	53549	543	1050	.98	.91	.99

4. Conclusion

The proposed system is an autonomous system for the segmentation of the brain tumor in MR images. The system segments the tumor region using SVM classifier which is trained using the features extracted from the healthy and tumor blocks of the MR images. The system performance can be further improved by incorporating deep learning techniques into the system.

References

[1] Ayushi Agarwal, Shradha Gulia, Somal Chaudhary,Malay Kishore Dutta, Carlos M. Travieso, Jess B. Alonso-Hernndez, "Brain Tumors: An Introduction", *Mayfield brain and spine*, 2015.

[2] Jin Liu, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu, and Yi Pan, "A Survey of MRI-Based Brain Tumor Segmentation Methods", *Tsinghua Science and Technology*, Vol. 19, No. 6, pp578-595, December 2014.

[3] Z.-P. Liang and P. C. Lauterbur, Principles of Magnetic Resonance Imaging: A Signal Processing Perspective, *The Institute of Electrical and Electronics Engineers Press*, 2000.

[4] N. Sharma and L. M. Aggarwal, "Automated medical image segmentation techniques", *Journal of Medical Physics/Association of Medical Physicists of India*, vol. 35, no. 1, p. 3, 2010.

[5] H. Suzuki and J.-I. Toriwaki, "Automatic segmentation of head mri images by knowledge guided thresholding", *Computerized Medical Imaging and Graphics*, vol. 15, no. 4, pp. 233-240, 1991.

[6] V. Vapnik, "The Nature of Statistical Learning Theory", *Springer*, 2000.