ISSN 2348-375X

Unique Journal of Engineering and Advanced Sciences

Available online: www.ujconline.net

Research Article

HESSIAN ANALYSIS IN MULTISCALE BRAIN TUMOR SEGMENTATION

Jamcey VP[1*], Manikandaprabu N[2]

PG Scholar, Department of Electronics and Communication Engineering, Hindusthan College of Engineering and Technology, Anna University Chennai, India

[2]Assistant Professor, Nandha Engineering College, Erode, India

Received: 09-03-2014; Revised: 07-04-2014; Accepted: 06-05-2014

*Corresponding Author: **Jamcey V P**

PG Scholar, Department of Electronics and Communication Engineering, Hindusthan College of Engineering and Technology, Anna University Chennai, India E-mail: vpjamcey@gmail.com

ABSTRACT

This paper deals with the automatic segmentation of tumor in brain MRI. Tumors are uncontrolled growth of tissues in any part of the body. Tumors may be of different types and they have different Characteristics and different treatment. Being in brain, tumor is inherently serious and life-threatening because of its limited space of the intracranial cavity (space formed inside the skull). Most Researches show that the number of people who have brain tumors were died due to the fact of inaccurate detection. Generally, CT scan or MRI are directed into intracranial cavity produces a complete image of brain, which is visually examined by the physician for detection & diagnosis of brain tumor. To avoid inaccurate determination, this paper uses a method in the detection (segmentation) of brain tumor based on Hessian analysis. Hessian analysis is used for Multi-scale blob detection, that corresponds to detection of tumors. This method detects every tumor, in addition some non tumors also were detected. The tumor likelihoods for the remaining tumor candidates were estimated using a logistic regression model based on blobness, and morphology features. It also reduces the time for analysis in addition. At the end of the process the tumor is extracted from the MRI and classified as normal and abnormal.

Keywords: Segmentation, Medical imaging, Hessian analysis, Logistic regression model.

INTRODUCTION

Image segmentation is a challenging and important problem, which is a necessary step in image analysis for high-level image interpretation and understanding of object recognition, robot vision, and medical imaging. The aim of image segmentation is to partition an image into a set of disjoint regions with uniform and homogeneous attribute such as colour, intensity, tone or texture etc.

Detection and segmentation of brain tumors in MRIs (Magnetic Resonance Images) is an important and very time-consuming task to be completed manually by medical experts. Normally the anatomy of the Brain can be viewed by the CT scan or MRI scan. In this paper the MRI scanned images are taken for the entire process. The MRI scan is comfortable than CT scan for diagnosis as it does not affect the human body. Because this doesn't use any radiation. It is based on the radio waves and magnetic field. For early detection of abnormalities in brain parts, MRI imaging is the most efficient in imaging technique. Unlike computerized Tomography (CT), MRI image acquisition parameters are adjusted for generating high contrast image with different gray level for various cases of neuropathology. There are different types of algorithm that were developed for brain tumor detection. But they may also have some drawback in detection and extraction.

The tumor may be of primary or secondary. If it is an origin, then it is primary. If the part of the tumor is spread to another place and grown as its own then it is known as secondary. Normally brain tumor affects Cerebral Spinal Fluid (CSF). It might cause strokes. The physician would give treatment for the strokes rather than the treatment for tumors. So detection of tumor is important for treatment. The lifetime of the person who is affected by the brain tumor will increase if it is detected at current stage. That will increase the lifetime about 1 or 2 years. For the accurate detection of the malignant tumor it needs a 3-D representation of brain and 3-D analyzer tool. In this paper we focused on detection of mass tumor detection. The developing platform for detection is MATLAB. Because it would be easy to develop and execute. At the end, we are providing systems that detect the tumor and thereby segmentation.

RELATED WORKS

Detection and segmentation of Brain tumor accurately is a challenging task in MR images. One of the benefits of an MRI scan is that it is safe to the patients. It applied by strong magnetic fields and non-ionizing emission in the radio frequency range, unlike CT scans and traditional X-rays, which both use ionizing radiation. Conventional methods for computing tumor volumes are not dependable and are error susceptible.

In[1] paper presents a segmentation method which com-pares between K means clustering and Fuzzy c means clustering method where by segmentation using Fuzzy c means proved to be better by segmenting the tumors which goes undetected by k means clustering. A novel method for segmentation was used in the breast tumor detection in[2] which is based on hessian analysis. Using this method multiscale tumor has been detected and computation time required is less when compared with Fuzzy c means algorithm. Hessian analysis has been used to detect several common geometrical structures, such as vessels, blobs, and plates[4-9]. Frangi[4] proposed a vessel enhancement filter based on Hessian analysis that calculated the second order local derivatives of an image and measured the vesselness according to the basis of all eigen values of these local derivatives. Hessian-based blob detection was also applied to detect prostate lesions in MRI images and showed high sensitivity with a reasonable number of FPs[7]. To the best of our knowledge, however, blob detection algorithms have not been applied to brain lesions.

Our hypothesis is that blob detection based on Hessian analysis can improve segmentation of brain lesions with low contrast boundaries or nearby shadows and faster method compared to others.

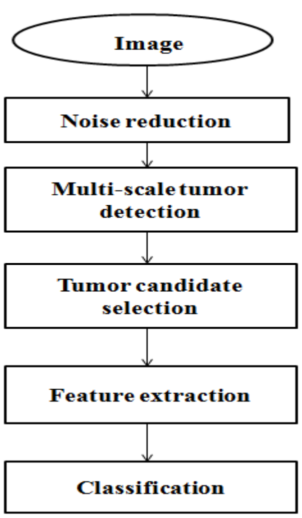


Figure 1: Flow chart of proposed system

METHODS

A flowchart of the proposed system is shown in Fig. 1.Rician noise reduction was applied to reduce the rician noise and improve the quality of the MRI images before tumor detection. Rician noise degrades the quality of the images. For the detection of tumor candidates, multi-scale blob detection was used to segment the blob-like structures in the MRI images. Single-scale blob detection can only detect blob-like structures of a specific size. Because the sizes of lesions are variable, multi-scale blob detection was used to detect blob-like structures of different sizes. To remove redundant non tumors from the tumor candidates, tumor candidate selection was applied. The tumor likelihoods of the remaining tumor candidates were estimated using logistic regression models with blobness, and morphology features. Finally, the performance of the proposed system was evaluated by applying different thresholds for tumor likelihood.

Rician Noise Reduction

A wavelet-based multiscale products thresholding scheme is presented here for noise suppression of magnetic resonance images[3]. A Canny edge detector-like dyadic wavelet transform has been employed. This results in the significant features in images evolving with high magnitude across wavelet scales, while noise decays rapidly. To exploit wavelet interscale dependencies we multiply the adjacent wavelet subbands to enhance edge structures while weakening noise. In the multiscale products, edges are effectively distinguished from noise. Thereafter, an adaptive threshold is calculated and imposed on the products, instead of on the wavelet coefficients, to identify important features.

The possibilities of arrival of noise in modern MRI scan are very less. The main aim of this paper is to detect and segment the tumor cells. But for the complete system it needs the process of noise removal. For better understanding in the function of this noise removal method, we added the rician noise artificially as in figure 2(b) and removed it using the above method[3]. Figure 2(c) shows the de-noised image.

Tumor Candidate Detection Based on Multi-Scale Blob Detection

Hessian analysis was adopted to enhance several geometrical structures, including tube-like, blob-like, and plate like structures[4-7]. The principle of this analysis is to compute the second derivatives along the three dimensional directions by convoluting the MRI image with derivatives of the Gaussian kernel. The Hessian matrix is defined by the following formula:

$$H_\sigma(x,y,z) = \begin{pmatrix} I_{xx} & I_{xy} & I_{xz} \\ I_{yx} & I_{yy} & I_{yz} \\ I_{zx} & I_{zy} & I_{zz} \end{pmatrix} \tag{1}$$

Where the scale σ indicates the standard deviation of the Gaussian distribution and indicates the second deviation along the direction ith and jth. The scale σ could be used to control the radius of the enhanced blob-like structures. Large blob-like structures are enhanced when a high-scale value is used. The eigenvectors and Eigen values ($|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$) can be computed by solving the Hessian matrix at each pixel. The computed eigenvectors indicate three orthogonal directions of the detected object, and the Eigen values indicate the degrees of curvatures along the corresponding directions. To enhance blob-like structures in the MRI images, the likelihood of blob-like structures and the magnitude of the Eigen values of a pixel can be formulated as follows:

$$R_B = \frac{|\lambda_1|}{\sqrt{|\lambda_2||\lambda_3|}} \tag{2}$$

$$M = \sqrt{\sum_{n=1}^{3} \lambda_n^2} \tag{3}$$

Where R_B represents the likelihood of the blob-like structure and M represents the magnitude of the eigen values of a pixel. In the blob-like structures, the curvatures along three orthogonal directions should be high and similar. Therefore R_B, can achieve its maximum when the object is similar to the blob-like structure.

In general, the magnitudes of the eigen values of objects are usually larger than the magnitude of the background. Therefore M, can be used to distinguish between the objects and the background. The blob-like structures can be enhanced using the following formula:

$$B_\sigma(\boldsymbol{\lambda}_\mathbf{p}) = \begin{cases} \left(1-e^{-\frac{R_B}{2\alpha^2}}\right)\left(1-e^{-\frac{M}{2\beta^2}}\right), & \text{if } \lambda_1>0, \lambda_2>0, \text{and } \lambda_3>0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Where λ_p indicates the Eigen values at the position p = (x,y,z) and α and β represent the sensitivity parameters of the terms R_B and M , respectively. The sensitivity parameter can control the weight of the corresponding term. In our study, the sensitivity parameters α and β were set at 0.5. This condition (λ_1 >0,λ_2 >0and λ_3 >0) only enhances dark objects. Because lesions usually have different sizes, one single scale cannot detect all lesions. To detect lesions with different sizes, multi-scale blobness measurements can be used. The formula is as follows:

$$\text{Blobness}(\boldsymbol{\lambda}_\mathbf{p}) = \max_{\sigma_{\min}\leq\sigma\leq\sigma_{\max}} B_\sigma(\boldsymbol{\lambda}_\mathbf{p}) \tag{5}$$

Where σ_{min} and σ_{max} are the minimum and the maximum scales, respectively.

Tumor Candidate Selection

After tumor candidate detection, many redundant non tumors were included with the tumor candidates due to the high sensitivity of the blobness measurement. If all tumor candidates were used to extract the features and estimate the tumor likelihoods, the processing might take a long time and the performance of the system might be poor due to the high frequency of FPs. Therefore, tumor candidate selection was adopted to eliminate the FPs from the tumor candidates. High blobness values indicate that the candidate is similar to a blob-like structure[11]. The non tumors might have lower blobness values than that of suspicious lesions. Therefore, the mean and the maximum blobness values of a tumor candidate were used to eliminate FPs using the following formulas:

$$\text{Blobness}_{\text{mean}}(T) = \frac{\sum_{\mathbf{p}\in T}\text{Blobness}(\boldsymbol{\lambda}_\mathbf{p})}{N_T} \tag{6}$$

$$\text{Blobness}_{\max}(T) = \max_{\mathbf{p}\in T}\text{Blobness}(\boldsymbol{\lambda}_\mathbf{p}) \tag{7}$$

where T represents a tumor candidate with total N_T voxels and p indicates a voxel belong to the tumor T candidate. Another feature used in the tumor selection was the size (Size) of the tumor candidate. Because the tumor detection based on Hessian analysis is sensitive to intensity variation, many small regions were also detected as tumor candidates. These regions are usually smaller than true lesions, and their size can be used to eliminate many FPs from among the tumor candidates. For tumor candidate selection, a linear regression model[10] was applied to eliminate the FPs from among the tumor candidates. The tumor selection function $L_S(T)$ is as follows:

$$Z(T) = \beta_0 + \sum_{i=1}^{N_f}\beta_i x_i \tag{8}$$

$$L_S(T) = \frac{1}{1+e^{-Z(T)}} \tag{9}$$

Where N_f is the number of features, x_i is the feature value and the constant coefficient β_0 and the corresponding coefficient β_i are estimated by the linear regression model. Finally, the tumor selection criterion can be represented as follows:

$$L_S(T) \geq \text{TH} \tag{10}$$

Where TH is a threshold to determine the remaining tumor candidates from FPs. The detected regions remained as tumor candidates when the values estimated by the tumor selection model were equal to or greater than TH. The detected region was removed from the tumor candidates when the values estimated by the tumor selection model were less than TH. In our experiments, the tumor criteria threshold was set at 0.5.

Feature Extraction

After the tumor candidate selection, most of FPs was eliminated from the tumor candidates. To further improve the performance of the system, two feature groups (blobness, and morphology) were extracted to estimate the tumor likelihoods of the remaining tumor candidates.

Blobness Features: The blobness value could be used to discriminate the tumors from the non tumors in the remaining tumor candidates. Tumors are indicated by the high blobnes value. In our study, the max, the mean, and the standard deviation of the blobness values were used as the blobness features. In addition, the blobness value of a voxel of a real tumor might be higher when the voxel position is closer to the center of a tumor candidate. Therefore, a real tumor might have a smaller distance between the center of the tumor candidate and the blobness centroid relative to other tissues. The distance between the center of a tumor candidate and the blobness centroid was used as a feature in this study. The center of the tumor candidate (x_c , y_c , z_c) can be represented as follows:

$$x_c = \frac{1}{N_T}\sum_{i=1}^{N_T} x_i, \quad y_c = \frac{1}{N_T}\sum_{i=1}^{N_T} y_i, \text{ and } \quad z_c = \frac{1}{N_T}\sum_{i=1}^{N_T} z_i \tag{11}$$

Where (x_i , y_i , z_i) indicates the position of a voxel in a tumor candidate. The blobness centroid (x_{cd} , y_{cd} , z_{cd}) can be formulated as follows:

$$x_{cd} = \frac{1}{\text{Sum}_{\text{Blob}}}\sum_{i=1}^{N_T} x_i \times \text{Blobness}(\boldsymbol{\lambda}_\mathbf{p})$$

$$y_{cd} = \frac{1}{\text{Sum}_{\text{Blob}}}\sum_{i=1}^{N_T} y_i \times \text{Blobness}(\boldsymbol{\lambda}_\mathbf{p})$$

$$z_{cd} = \frac{1}{\text{Sum}_{\text{Blob}}}\sum_{i=1}^{N_T} z_i \times \text{Blobness}(\boldsymbol{\lambda}_\mathbf{p}) \tag{12}$$

Where Sum_{Blob} indicates the summation of the blobness values in a tumor candidate and λ_p represents the Eigen values of the voxel p. Finally, the distance between the center of the tumor candidate and the blobness centroid, can be defined as follows:

$$\text{Dis} = \sqrt{(x_c - x_{cd})^2 + (y_c - y_{cd})^2 + (y_c - y_{cd})^2}. \quad (13)$$

Morphology Features: Morphology and shape features can provide useful information for tumor diagnosis. The morphology features of our study included two categories: shape and ellipse fitting[8]. For the shape features, the volume, radius, spiculation[11], and two 3-D compactness features[11] were included. The radius and spiculation were used to describe the margin property of a lesion, and the two 3-D compactness features were used to characterize the relation between the surface and the volume of a lesion. The ellipse fitting features are used to describe the degree of regularity of a tumor candidate.

Other Features: Other Features include correlation, energy, and homogeneity.

Classification

Classification is done using a SVM classifier. SVMs are discriminative classifiers, originating from machine learning. They require a training step to find a separating hyperplane for the data in the feature space. A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one target value" (i.e. the class labels) and several attributes" (i.e. the features or observed variables). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

The extracted features include tumor blobness features, morphological features and in addition contrast, energy, and correlation. Features subset selection is performed using support vector machines (SVMs). The binary SVM classification accuracy, sensitivity, and specificity, assessed by leave-one-out cross-validation on 50 brain tumors, are respectively 81%, 85%, and 80%.

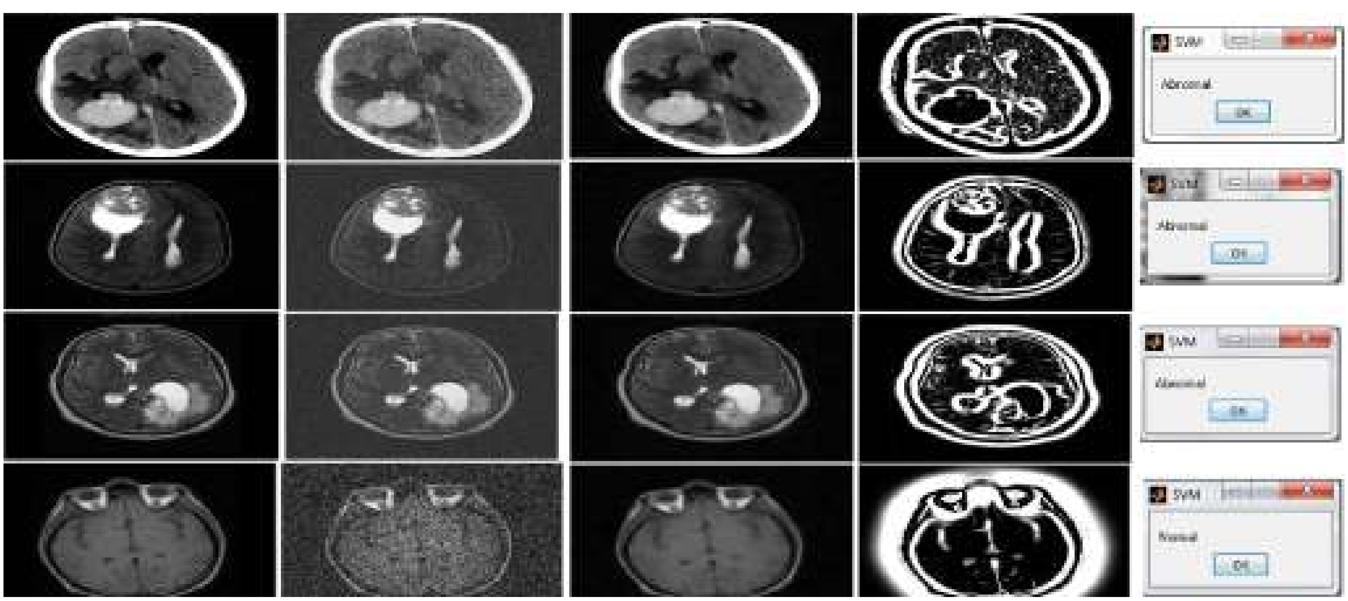
RESULTS AND COMPARISON

The method has been applied to 5 different MRI. These images contain tumors with different sizes, intense ties, shapes and locations. This allows us to illustrate the large field of application of our method. To the best of our knowledge, however, blob detection algorithms have not been applied to breast lesions and in this paper, a system based on a multi-scale blob detection algorithm was first proposed for detection of brain lesions/tumor in MR images.

Moreover time for analysis is reduced while comparing two other algorithms. Two algorithms have been used for comparison of time for analysis, which is k means segmentation and Fuzzy c-means segmentation. Table below shows the time computed for these three and algorithms.

Table.1. Computed time for different algorithms

Image/ Algorithm	1 (s)	2 (s)	3 (s)	4 (s)	5 (s)
Hessian	14.12	6.34	7.17	8.65	7.22
K-means	15.38	9.42	8.31	11.67	9.45
Fuzzy c-means	87.23	36.34	17.50	98.33	37.47



From the above observation, time required for Hessian analysis seems to be less when compared to other two methods. In addition Hessian analysis is highly sensitive to detect intensity variation. So none of the lesion/ tumors goes undetected where as Fuzzy c-means and k-means are not able to respond to small intensity variation. Hence Hessian proves to be a better method than K means or fuzzy c-means. After Segmentation, classifier is used to classify tumors and accuracy, sensitivity and specificity, assessed by leave-one-out cross-validation on 50 brain tumors, are respectively 81%, 85%, and 80%.

CONCLUSION

In this study, we proposed a system based on multi-scale blob detection for analyzing MRI images. After rician noise reduction, Hessian analysis with multi-scale blob detection was adopted to detect the lesions by using blobness measurements of MRI images. Tumor candidate selection was then applied to remove the redundant non tumors from the tumor candidates. Finally, the tumor candidates with tumor likelihoods higher than a specific threshold were considered to be tumors. Segmentation could be done, although being a novel technique in brain tumor segmentation and also could prove that time for analysis is less compared to k-means and Fuzzy c-means. Finally a classification technique was used to classify as normal and abnormal.

REFERENCES

1. Selvakumar J, Lakshmi A, Arivoli T, Brain tumor segmentation and its area calculation in brain MR images using K-mean clustering and fuzzy C-Mean algorithm", 2012
2. Moon WK, Shen YW, Bae MS, Huang CS, Chen JH, and Chang RF et.al, Computer aided tumor detection based on multi scale blob detection algorithm in automated breast ultrasound images, Ieee transactions on medical imaging, 2013; 32(7).
3. Bao P, Zhang L, Noise reduction for magnetic resonance images via adaptive multiscale products thresholding, IEEE transactions on medical imaging, 2003; 22(9).
4. Frangi A, Niessen W, Vincken K, and Viergever M, Multiscale vessel enhancement filtering, in Medical Image Computing and Computer-Assisted Intervention—MICCAI'98,Kikinis.
5. Perona P and Malik J, Scalespace and edge detection using anisotropic diffusion, IEEE Trans. Pattern Anal. Mach. Intell.,1990; 12(7):629–639.
6. Sato Y, Nakajima S, Shiraga N, Atsumi H, Yoshida S, Koller T, Gerig G, and Kikinis R et.al Three dimensional multiscale line filter for segmentation and visualization of curvilinear structures in medical images, Med. Image Anal.,1998; 2:143–168.
7. Vos PC, Barentsz JO, Karssemeijer N, and Huisman HJ, Automatic computer aided detection of prostate cancer based on multiparametric magnetic resonance image analysis, Phys. Med. Biol., 2012; 57: 1527-1542.
8. Ye X, Lin X, Dehmeshki J, Slabaugh G, and Beddoe G, Shapebased computeraided detection of lung nodules in thoracic CT images,IEEE Trans. Biomed. Eng., 2009; 56(7): 1810–1820.
9. Chang JM, Moon WK, Cho N, Park JS, and Kim SJ, Radiologists performance in the detection of benign and malignant masses with 3D automated breast ultrasound (ABUS), Eur. J. Radiol., 2011; 78: 99–103, Apr. 2011
10. Hosmer D and Lemeshow S, Applied Logistic Regression. New York: Wiley Interscience, 2000.
11. Bribiesca E, An easy measure of compactness for 2D and 3D shapes, Pattern Recognit., 2008; 41:543–554.

Source of support: Nil, Conflict of interest: None Declared