Brain Tumor – Computer Based Diagnosis, Categorization and Sectionalization

Kshama Dwivedi, Anup Maurya, Mayur Shishupal

***Abstract*— Brain tumors are insidious experts of invasion. They begin innocuously, just a single cell that has become chemically off-balanced. The system uses computer based procedures to detect tumor blocks or lesions and classify the type of tumor using Artificial Neural Network in MRI (Magnetic Resonance Imaging) images of different patients with brain tumor. The histogram equalization, image adjustment, thresholding functions are used for detection of tumor. Brain tumor segmentation consists of separating the different tumor tissues (solid / active tumor, edema, a necrosis) from normal brain tissues: gray matter (GM), White matter (WM), and cerebrospinal fluid (CSF). The multi-scale is applied to the traditional gradient vector flow (GVF) algorithm for segmentation of brain tumors in MRI images.**

***Index Terms*— Brain tumor segmentation, Multi Scale GVF, Artificial Neural Network, MRI Images**

I. INTRODUCTION

A brain tumor is an intracranial solid neoplasm, a tumor (defined as an abnormal growth of cells) within the brain or the central spinal canal. Some tumors are brain cancers. Brain tumors include all tumors inside the human skull (cranium) or in the central spinal canal. They are created by an abnormal and uncontrolled cell division, usually in the brain itself, but also in lymphatic tissue, in the blood vessels, in the cranial nerves, in the brain envelopes (meninges), skull pituitary gland, or pineal gland. Within the brain itself, the involved cells may be neurons or glial cells (which include astrocytes, oligodendrocytes, and ependymal cells). Brain tumors may also spread from cancers primarily located in other organs (metastics tumors).

One particular application area where neural networks show some promise is the field of Magnetic Resonance (MR) image segmentation. Most previous studies of neural network based MR image segmentation have employed the back propagation (BP) algorithm. M. Ozkan and B. M. Dawant presented a BP neural network approach to the automatic characterization of brain tissues from multimodal MR images. In their papers, the ability of a three layer BP neural network to perform segmentation based on a set of images acquired from a pathological human subject were studied. The results were compared with those obtained using a traditional Maximum Likelihood

Classifier (MLC). Neural networks-based segmented images appear less noisy than MLC segmented images.Brain Cancer Detection and Classification System are implemented using Artificial Neural Network. The design based on Image processing Techniques,Artificial Neural Network and Graphical User Interface was successfully completed and used in the system to Detect and Classify the Tumor. The designed Brain Cancer Detection and Classification System use conceptually simple Classification method using the Neuro- Fuzzy logic. Texture features are used in the Training of the Artificial Neural Network. Co-occurrence matrices at different directions are calculated and Grey Level Co-occurrence Matrix (GLCM) features are extracted from the matrices. The above procedure effectively classifies the tumor types in brain images taken under different clinical circumstances and technical conditions, which were able to show high deviations that clearly indicated as abnormalities in area with brain disease.

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The proposed system is an efficient system for detection of tumor and classification for given MRI images .The method of detection and classification work is carried out during the process is explained in the coming section. This method is developed in Matlab simulation environment in order to check for applicability of proposed method.

Several modifications have been made in designing the active contours, in order to make them appropriate in specific applications. One of such modifications was proposed by Xu and Prince [6], which is called "gradient vector flow (GVF) snake". In the GVF method, a dense vector field is generated from the image by using vector diffusion, which guides the snake to fit a specific boundary. The GVF snake has several advantages over the original snakes. For instance, the GVF snake is independent from the initial point. Also, it does not require prior knowledge about whether to inflate or deflate. Furthermore, in contrast to the original snake, in GVF method, the external force is not entirely irrotational. Thus, it can capture image concavities. Therefore, GVF has become a popular method in medical image segmentation.

However, since the gradients are highly prone to noise, small scale details and tumor intensity inhomogeneity, the GVF external force is difficult to be handled in segmentation of tumors in brain MRI images. Moreover, the evolution of the GVF snake is greatly dependent on the edge map created for it. For assuring the convergence of GVF snake, the edge map should be in such a way that while including all important edge information present in the image, it excludes the false edges created by lower intensity changes. In addition, the traditional GVF method requires selection of several parameters, which increases the time required for convergence.

In this work, the idea of multi-scale based GVF (MSGVF) snake is proposed to overcome the above problems with GVF

snake. In this algorithm edge maps are updated in a multi-scale based approach which helps the gradient operator to deal with noise more efficiently. Along with this multi-scale GVF, two modifications have also been made in order to improve the noise performance of the original GVF method, in detecting tumor boundaries. At first, the well known canny edge operator is applied in
combination with upper and lower thresholds producing a threshold-based edge detector, by which false edges are eliminated and most of the prominent edges around the tumor area are detected. Secondly, a B-spline snake (or Bsnake) is used in this paper to represent the active contour. The B-snake has significant advantages over the traditional snake, for example, it exhibits local control, it can capture corners by allowing multiple knots, and its representation is compact.

II. METHODOLOGY

A. *DETECTION*

The work carried out involves processing of MRI images that are affected by brain cancer for detection and Classification on different types of brain tumors. The image processing techniques like histogram equalization, image segmentation, image enhancement and then extracting the features using Gray Level Co-occurrence Matrix are used for Detection of tumor. Extracted feature are stored in the knowledge base. A suitable Neuro Fuzzy Classifier is developed to recognize the different types of brain cancers. Images used are MRI images. The system is designed to be user friendly by creating Graphical User Interface (GUI).

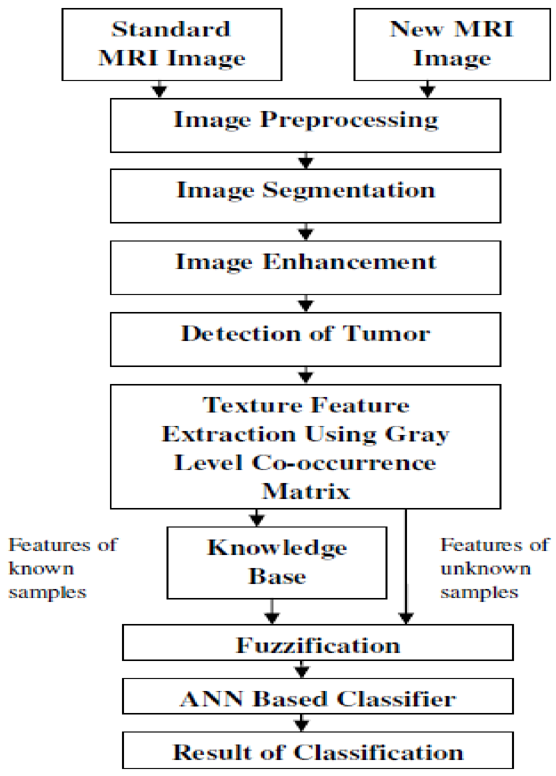


Figure 1. Block Diagram of the System

The designed and developed system works in two phases namely Learning/Training Phase and Recognition/Testing Phase. In Learning/Training Phase the ANN is trained for recognition of different Astrocytoma types of brain cancer. The known MRI images are first processed through various image processing steps such as Histogram Equalization, Thresholding, and Sharpening Filter etc. and then textural features are extracted using Gray Level Co-occurrence Matrix. The features extracted are used in the Knowledge Base which helps in successful classification of unknown Images. These features are normalized in the range -1 to 1 and given as an input to Artificial Neural Network Based Classifier. The unknown MRI images affected by cancer of type Astrocytoma are used for testing in Recognition/Testing Phase.

B. *CLASSIFICATION*

A suitable artificial neural network classifier is designed in this paper to identify the different grades of brain tumors. Artificial neural networks are composed of simple elements operated in parallel. These elements are inspired from biological nervous system. Each element in a network called neuron. The sum of multiplication of weights and inputs plus bias at the node is positive then only output elements fires. Fire means it discharges energy to next element. Otherwise it doesn't fire. The artificial neural network is an adaptive system. Adaptive means system parameters are changed during the operation. The system parameter is nothing but weights. Two layer feed forward neural network is taken in this paper .The two layer feed forward neural network consists of one input layer and one output layer and one hidden layer and one output. In the hidden layer 10 nodes are taken .In the two layer feed forward network two log sigmoid transfer function are used.
The two layer feed forward network with two log sigmoid functions are more widely used in classification, pattern recognition .It gives better results in these classification. If the sum of multiplication of weights and input values are greater than log sigmoid function then output value becomes '1' ,
otherwise the output value become '0' shown in Fig.2.

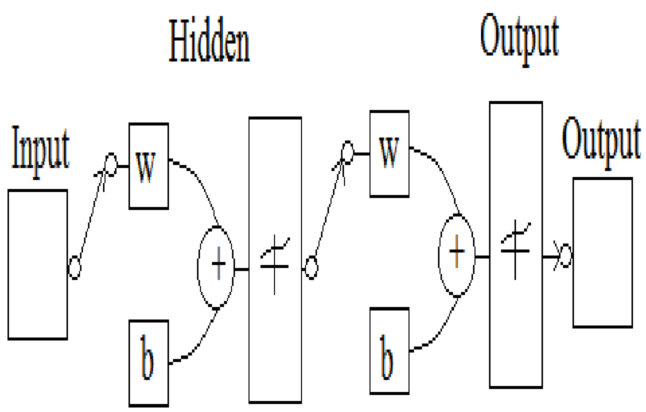


Fig.2 Two layer feed forward network with log sigmoid transfer function
The two layer feed forward neural network is trained with back propagation learning method .Standard back propagation method is gradient descent method.
As is windrow, hoof learning rule, in which the weights are moved along the negative gradient of performance function.

Properly trained back propagated networks gives reasonable results. The neural network system is designed in two phases.
1) Learning/Training
2) Recognize/Testing
There are four steps in training process
1) Assemble the training data
2) Create the two layer feed forward network
3) Training the network
4) Simulate the network

The known samples are applied to the two layer feed forward neural network is trained with back propagation algorithm .Training/Learning means changing the weights of the network. Change the weights until it gives the proper output. After training the neural network the network parameters are fixed. In this paper we trained the neural network with 36 MRI brain tumor samples. Total four classifications are in the brain tumors .Each of 9 samples for four different classes. Total 36 input MRI brain tumor samples are trained to neural network through back propagation learning/training.

Train the neural network until it gives proper output. In the second stage i.e. in recognize/testing the unknown samples are applied to the trained network. The trained network compares the unknown sample with the all trained input samples and classifies the unknown sample based on trained input samples. In this paper totally four brain tumor grades exist. Take different known MRI samples for different grades and apply to trained neural network and check whether it is working properly or not. The proposed method gives correct output for the known samples and then it is tested for the unknown samples. The proposed method has given better performance in this paper.

C. SEGMENTATION

Multi scale Gradient Vector Flow (MSGVF)

The GVF snake can become more robust to noise, small scale details and intensity inhomogeneity, by using the GVF in multi-scale stages. This algorithm is based on scale space theory. The basic concept of scale space theory is generating a sequence of images $I\sigma(x,y)$ from the initial image $I0(x,y)$. As σ (scale) increases, $I\sigma(x,y)$ becomes a coarser version of the image obtained in the previous stage. In each scale, the resulting smoothed image from the previous stage is lowpass filtered and the threshold-based edge map of this image is computed. The threshold is applied due to the generation of various edges around the tumor, among which false edges are also present due to inhomogeneity in image intensities and noise. The value of the upper threshold was chosen for dealing with the edges caused by noise and large image gradients. However, the lowpass filtering and using the upper threshold causes the edges to become blurred, thus, their detection and localization becomes difficult. Therefore, the lower threshold is selected considering the intensities on tumor boundary, in order to preserve the important edges. Here, the edge map is computed using Gaussian smoothing filters and threshold-based canny edge detector.
The Gaussian filter used for the scale generation is defined as:

$$h\sigma(x,y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

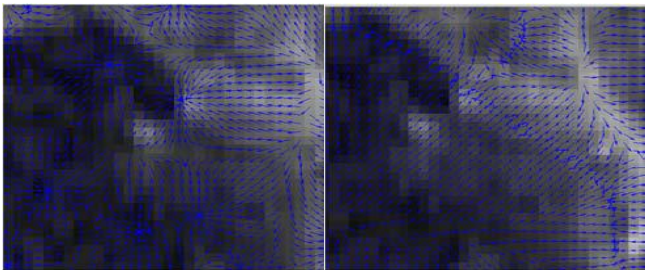
where σ (the standard deviation of the Gaussian filter) denotes the scale. The smoothed image in each scale can be acquired by the convolution of the smoothing filter with the image obtained in previous scale:

$$I_{\sigma_i}(x,y) = h_{\sigma_i}(x,y) * I_{\sigma_{i-1}}(x,y)$$

The multiscale edge map is computed by taking the laplacian of the smoothed image:

$$f_{\sigma_i}(x,y) = |\nabla I_{\sigma_i}(x,y)$$

The number of scales is selected to be 5. The Gaussian filter is applied in each scale with standard deviations equal to σ = 3, 15, 31, 63, and 127. In fact, the ability of changing the smoothing window size in multi-scale approach has led to precisely aligning the gradient map according to the true edges appeared in tumor boundaries. As it can be observed from Fig.3, the gradient vectors become in alignment with tumor boundaries by increasing the scale.



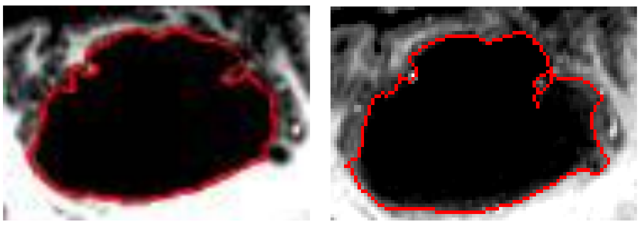
(a) (b)

Fig. 3. The GVF of a part of tumor boundary in different scales: (a) scale 1 (σ=3), and (b) scale 5 (σ=127). The figure shows the alignment of gradient
vectors (in blue) with tumor borders over scale.

The initial contour for the GVF snake is selected manually, which is updated in each of the proceeding scales. The GVF B-snake deformation initializes from the position of control points reached in the previous scale. The segmentation is completed after 40 iterations.

III. RESULT

The MSGVF B-Spline was successfully applied on the datasets and compared to the manual segmentation performed by an expert rater. The algorithm was run on individual slices containing tumor. The result of applying the MSGVF Bspline snake in comparison with the MSGVF with traditional snake is shown in Fig.4.

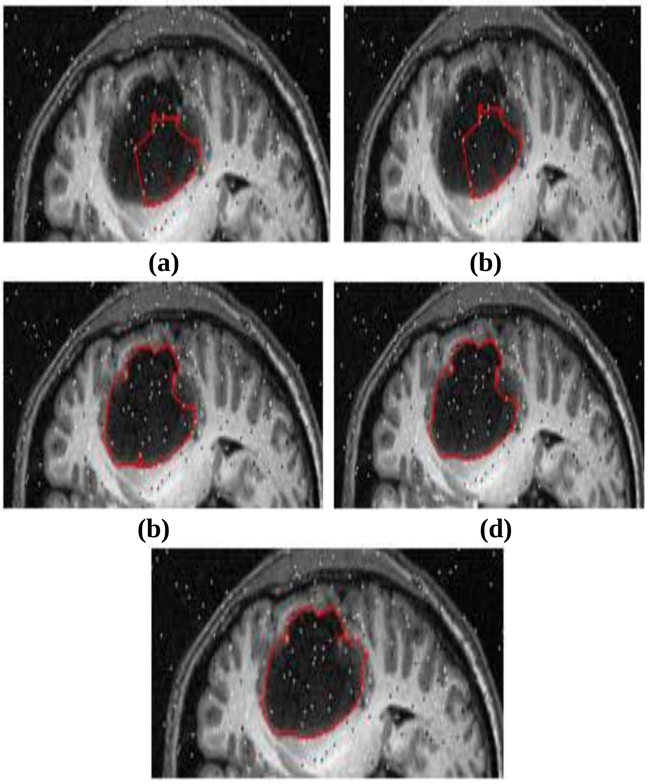


(a) (b)

Fig. 4. The result of applying (a) MSGVF Bspline algorithm, and (b) MSGVF with traditional snake on one of the slices of case 1. As it can be observed the B-spline snake performs superior to the traditional snake in capturing the corners.

This figure illustrates the ability of B-snake in capturing the corners, which is due to the local control of B-snakes and the feasibility of selecting knots. Therefore, here the results of MSGVF with B-snake are considered for further analysis on the performance of multi scale method.

As mentioned previously, the MSGVF is meant to be more robust against noise and intensity inhomogeneity in contrast to traditional GVF. Therefore, salt and pepper type of noise with intensity in the range of 0.01- 0.03 was added to the images in order to examine the performance of the MSGVF Bspline algorithm. This type of noise was chosen because it produces high variations in the gradients of the image. As GVF s segmentation method is highly dependent on gradients of the image, the gradients can be trapped by the edges created by this type of noise. Thus, it can best examine the performance of gradient operator in edge detection during the curve evolution. The effects of applying the MSGVF Bspline with Gaussian kernel in various scales in the presence of noise are shown in Fig. 4.



(a) **(b)** **(b)** **(d)** **(e)**

Fig. 5. The performance of the MSGVF algorithm with Gaussian filter in presence of noise (with intensity= 0.01). The segmented part is shown in red. The result in (a) scale 1 (σ=3) , (b) scale 2 (σ=15) (c) scale 3(σ=31), (d) scale 4 (σ=63), and (e) scale 5 (σ=127).

As it is apparent from Fig.4, the performance of MSGVF with Gaussian smoothing filter in the presence of noise is highly improved over the subsequent scales. The visual inspection of the result of Fig. 5(d) shows the ability of the proposed method in tumor segmentation. These results were evaluated qualitatively by comparing manual segmentation carried out by an expert radiologist with the outcome of the algorithm in each scale. Then, the resulting sensitivity and accuracy for one of the datasets were calculated to represent the evaluation, which are summarized in Table I.

TABLE I
THE VALIDATION RESULTS FOR COMPARING THE PERFORMANCE OF THE ALGORITHM OVER SCALE

Scale No.	Accuracy (%)	Sensitivity (%)
Scale 1	63.54	24.26
Scale 2	69.89	49.23
Scale 3	77.26	59.12
Scale 4	79.99	72.18
Scale 5	88.12	93.45

IV. CONCLUSION

The brain tumor diagnosis, categorization and sectionalization is successfully implemented by using Artificial Neural Network, and Multi Scale Gradient Vector Flow.

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