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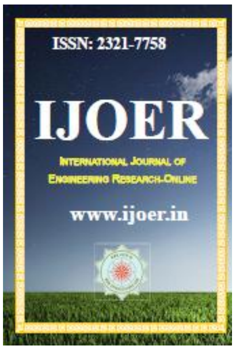
BRAIN TUMOR DETECTION USING IMAGE PROCESSING

SNIGDHA JAIN, SUBHASMIT HALDER, BHUMIKA MEHTA, Dr A.J.PAL



ABSTRACT

Brain tumor may be considered among the most difficult tumors to treat, as it involves the organ which is not only in control of the body. The imaging plays a central role in the diagnosis of brain tumors. Image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. The objective of this paper is to review the past work done on the detection of brain tumors using image processing techniques. The aim of this work is to provide a succinct and concise overview of the work done in this field.

1. INTRODUCTION

1.1. BRAIN TUMOR: A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth (Pal and Pal,1993). Brain tumors are abnormal and uncontrolled proliferations of cells. An inferior or metastatic brain tumor takes place when cancer cells extend to the brain from a primary cancer in a different component of the body.

This paper expresses a well organized technique for automatic brain tumor segmentation for the removal of tumor tissues from images. A brain tumor is an intracranial mass produced by an uncontrolled growth of cells either normally found in the brain such as neurons ,lymphatic tissue, glial cells, blood vessels, pituitary and pineal gland, skull, or spread from cancers primarily located in other organs.

There are more than 120 types of brain and central nervous system (CNS) tumors. Today, most medical institutions use the World Health Organization (WHO) classification system to identify brain tumors. The WHO classifies brain tumors by cell origin and how the cells behave, from the least aggressive (benign) to the most aggressive (malignant).

1.1.1. TYPES OF BRAIN TUMOR:

There are three common types of tumor:

[1]. Benign tumor
[2]. Pre-Malignant tumor
[3]. Malignant tumor

[1] Benign Tumor:-A benign tumor is a tumor is the one that does not expand in an abrupt way; it doesn't affect its neighbouring healthy tissues and also does not expand to non-adjacent tissues. Moles are the common example of benign tumors.

[2] Pre-Malignant Tumor:-Premalignant Tumor is a precancerous stage, considered as a disease, if not properly treated it may lead to cancer.

[3] Malignant Tumor:-Malignancy is the type of tumor that grows worse with the passage of time and ultimately results in the death of a person. Malignant is basically a medical term that describes a severe progressing disease. Malignant tumor is a term which is typically used for the description of cancer.

The tumor cell is present within skull and grows within skull is called primary tumor. Malignant brain tumors are primary brain tumors. The tumor presents outside the skull and enter into the skull region called secondary tumor. Metastatic tumors are examples of secondary tumors . The tumor takes up place in the skull and interferes with the normal functioning of the brain. Tumor shifts the brain towards skull and increases the pressure on the brain. Detection of tumor is the first step in the treatment.

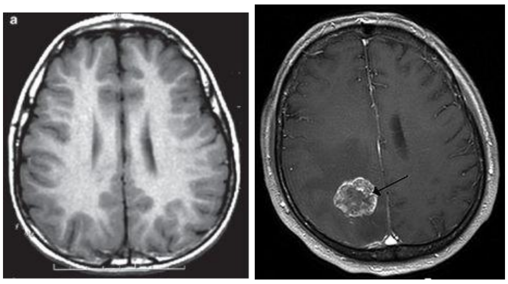


Figure 1 (a) Normal human brain (b) Brain tumor image

Brain contains more number of cells that are interconnected to one another. Different cells control different parts of the body. Some cells control the leg movement. Likewise others cell of the brain controls other parts in the body. Brain tumors may have different types of symptoms ranging from headache to stroke, so symptoms will vary depending on tumor location.

Different location of tumor causes different functioning disorder.

1.1.2. SYMPTOMS OF BRAIN TUMOR:

The general symptoms of brain tumor are:

1) Persistent headache
2) Seizures
3) Nausea and vomiting
4) Eyesight, hearing and/or speech problems
5) Loss of sensation in arm.
6) Walking and/or balance difficulties.
7) Problems with cognition and concentration.

1.1.3. BRAIN TUMOR TREATMENT:

Treatment techniques for the brain tumor are as follows:

[1] Surgery
[2] Radio therapy
[3] Chemotherapy

In the surgery process doctor remove as many as tumor cells from the brain. Radiotherapy is the common treatment used for brain tumors, the beta rays or gamma rays are passed into the brain and applied on the tumor and kill tumor cells. Chemotherapy is one of treatment for brain cancer. In this we are using medicine which controls the tumor cells to reach blood and blood barriers. In chemotherapy the medicine stops the growth of tumor cells and stops the growth normal brain cells.

2. LITERATUE SURVEY: In this paper there are two algorithms: ant colony optimization and genetic algorithm for image segmentation and implementation of artificial neural network for brain tumor detection.

The Ant Colony Optimization (ACO) is a Meta heuristic method of solving complex problem. The ant colony optimization algorithm (ACO) was introduced in the year 1997 as a multi-agent method for solving optimization problems such as the travelling salesman problem by Dorigo and Gambardell.This algorithm was inspired by studying the foraging of the real world ant colony. Ant colony optimization (ACO) is a cooperative search. The basic idea of the Ant colony optimization is to use the counterpart of the pheromone trail used by real ants as a medium for communication. Using these chemical substances the remaining ant finds the optimised solution.

Genetic algorithm (GA) is a search and optimization method which follows the principles of evolution and chromosomal processing of chromosomes. Search begins with a random set of solutions. Three operations reproduction, crossover, and mutation are then carried out. It follows an iterative method till a termination criterion is achieved.

Artificial Neural Network (ANN) is a computational model based on structure and functions of the biological neuron. Information that flows through the network affects the structure of ANN because a neural network changes or learns based on input and output.

The designed and developed system in the following researches works in two phases namely:

- Learning/Training Phase
- Recognition/Testing Phase

2.1. ALGORITHMS FOR IMAGE SEGMENTATION:

2.1.1. ANT COLONY OPTIMIZATION

Lee et al., in [1] have used Segmentation of Brain MR Images using an Ant Colony Optimization. Ant colony Optimization is a meta-heuristic algorithm.This algorithm take inspiration from the foraging behaviour of real ant colonies. This algorithm is mainly based on the way they found the shortest distance between the nest and the food. Firstly, these ants select random routes and leave a volatile chemical substance called a pheromone in their path of movement. Then each ant chooses the path of greatest pheromone trace because the shortest path would have the greater pheromone because it would get lesser time to evaporate. Adopting this method to process image segmentation. In this image segmentation process ants are looking for similar pixels (the pixel over here acts as food source) by using vector features that are not identical. For better performance the whole input image is divided into N × N windows i.e. in matrix form. The windows are kept small because the process gives more efficient result with smaller window than when using larger window sizes such as 5 × 5 or more. All ants are propagated randomly on the whole image space to perform the search activity. In the first case in which the search window falls the processing is done for the background image only after this part this no changes is taken into account from any ant. From next iteration onward all the energy of ants is applied for target segmentation. This process can efficiently segments the target, the background and also provides the distinct clear segmented image. It also segments thin parts more effectively, and it obtains satisfactory effect because of it high iteration. The ACO algorithm runs automatically without any manual help. The segmentation is done effectively but the process is not that fast due to large number of iteration. It produces 66% of accuracy while we are dealing with 2D gel image.

Mostaar et al., in [2] have an improved Ant Colony Optimization Algorithm where Probabilistic Atlas has been used. This improved hybridised ACO-Atlas based segmentation algorithm is used to generate three different pheromone matrices that each of which represents a different tissue class .This hybrid algorithm is also capable to segment the image with no well defined relation between image space or image region and pixels intensities Previously in normal ACO we were getting only one pheromone matrices for the entire image here we are getting three different matrices separately for three different part of a brain image. This new version of ACO is very efficient in segmenting images. It shows feasibility and high accuracy of the algorithm in segmenting the input image. The aim of this procedure is to segment the MR brain image into three separate classes i.e. this improved hybrid segmentation algorithm will generate three different pheromone matrices each of which corresponds to a different brain tissue viz. GM (gray matter), WM (white matter) and CSF (cerebrospinal fluid).This method is slower because the number of iteration is thrice compare to the normal ACO also in this experiment the effect of noise has been neglected.

Logheshwari et al., in [3] have proposed an improved implementation of Brain MRI image Segmentation using Ant Colony System along with FCM. This paper aims to implement ACO hybrid with Fuzzy Algorithm. In this process the segmentation of the Input MR image is done by two consecutive processes firstly ACO and then FCM. After completion of ACO the generated output pheromone matrix (the output matrix with similar pixel) is given to the FCM as an input for further clustering and segmentation.FCM is a clustering technique in which a given dataset is grouped into a number of clusters with maximum similarities. Here the optimal value of ACO through MRI Brain Image is given as an input for FCM. The aim of FCM is to find cluster centers with minimum dissimilarities and give a prominent segmented image. The overall performance and the results show that the ACO with FCM performs better than other existing method since in this technique we are basically segmenting the image twice with two different algorithms. The main reason to use FCM with ACO is that it can assure robustness in case of ambiguity and can store more information because it is a soft segmentation method.

Hasanen et al.,in [4] have proposed Segmentation using Multi ANT Colonies Algorithm (MAC) on a Multi-Core Processor . It is a new concept of parallelization strategy of ACO algorithm for image segmentation on a machine with a multi Core processor. It uses multiple colonies using computer thread programming technique. In this technique multiple ant colonies are used for image segmentation .Each ant colonies are explicitly handled by a thread. To maintain synchronization between the colonies indirect communication between the colonies are proposed. This entire ACO procedure is called MAC. As threads are faster and light weight process it takes less time and also less memory. The given parallelized ACO algorithm enhances the behaviour of the system and reduces the computational time. This algorithm is also efficient compare to the normal sequential ACO.

FOR EXAMPLE-For image 660*396 Normal aco-59.4397 Ms Mac-23.6169 ms .This process is faster and more efficient than other processes.

2.1.2. GENETIC ALGORITHM:

Fan et al., in [5] have used Parallel Genetic Algorithms approach to segment the brain images**.** In this paper, the parallel genetic algorithm has been demonstrated to be a more successful optimizer than the classical genetic algorithm. It has been found that a parallel genetic algorithm makes is more natural where several subpopulations which are isolated are allowed to self-evolve in parallel, and periodically exchange their best individuals by migration with the neighbouring subpopulations. The basic form for the parallel genetic algorithm follows few steps, First, A suitable representation of the genetic operators is defined, and then randomly a population of candidate solution is generated and partitioned into several subpopulations. Second, self-evolution is performed based on the chosen genetic operators: selection, crossover, mutation, and local hill-climbing. Third, the best individuals are sent to the neighbouring subpopulations based on the migration strategy, and the worst ones of the subpopulation are replaced. Fourth, it is determined whether the stopping criteria are satisfied .If satisfied, the iteration is stopped; otherwise step 2 is carried on. This approach has several advantages over the genetic algorithm based method by avoiding the problem of segmentation due to the large biological variation. However, it is Unable to find better quality solutions.

Zhang et al., in [6] proposed a novel segmentation method based on k-means objective function combined with genetic algorithm. This method is known for its global optimum searching ability. The method operates slice by slice via three main steps: 1. the tissues which are not a part of the brain are removed from the original images 2. The problems caused by the in homogeneity in the magnetic field are corrected 3. The tissues are then classified by k-means combined with genetic algorithm. The performance of the segmentation method was evaluated by the comparison with the fuzzy c-means (FCM) algorithm which is commonly used in segmentation of MR brain images. The objective function of k-means algorithm was used here as the Fitness function: From k=1 to k

(Ek)^2= - Σ Σ ||Xm-mk||^2

Where K is the classification number , X is the pixel gray-value of brain tissue and mk is the mean of the values that belong to the sort.

The accuracy of the Proposed method is 3.21% higher than that of FCM algorithm and the time consumed in the proposed method is 0.596 second per image. This method has outstanding advantage in accuracy**,** so the quality of the whole segmentation is higher. However, suboptimal solutions are obtained depending on the choice of the initial cluster centres.

Maulik et al., in [7] proposed a method using active contour in genetic algorithm. Contours are the boundaries in an image. The method uses a small set of manually traced contours of the structure of interest. This framework proves to be effective and also brings considerable flexibility into the segmentation procedure. However**,** Lack robustness due to their sensitivity to noise and data variability.

Gopal et al., in [8] designed a method to diagnose brain tumor through MRI using algorithms such as Fuzzy C Means along with Genetic Algorithm (GA).The detection of tumor is performed in two phases: Pre-processing and then Enhancement in the first phase and segmentation and classification in the second phase. The FCM algorithm attempts to partition a finite collection of n elements into a collection of c fuzzy clusters with respect to some given criterion. Given a finite set of data, the algorithm returns a list of C cluster centres. It helps to obtain the optimum value which is then considered to select the initial cluster point to find the adaptive for tumor detection.

The objective function:

$$\arg\min_{C} \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} \left\| \mathbf{x}_i - \mathbf{c}_j \right\|^2 ,$$

where:

$$w_{ij}^{m} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|\mathbf{x}_i - \mathbf{c}_j\|}{\|\mathbf{x}_i - \mathbf{c}_k\|} \right)^{\frac{2}{m-1}}} .$$

This differs from the *k*-means objective function by the addition of the membership values w_{ij} and the fuzzifier $m \in R$, with $m \geq 1$. The fuzzifier m determines the level of cluster fuzziness. A large m results in smaller memberships w_{ij} and hence, fuzzier clusters. In the limit $m = 1$, the memberships w_{ij} converge to 0 or 1, which implies a crisp partitioning. In the absence of experimentation or domain knowledge, m is commonly set to 2.

However, it produces a less accurate solution.

2.2. ALGORITHM FOR TUMOR DETECTION:

2.2.1. ARTIFICIAL NEURAL NETWORK:

Joshi et al.,in[9]proposed the use of Back Propagation Networks for brain tumor detection. It consists of one input layer, one or two hidden layers and one output layer. The Training of these networks consists in finding a mapping between a set of input values and a set of output values. This mapping is accomplished by adjusting the value of the error is calculated at each step. This error is entered into the ANN. The weights are adjusted such that the error decreases. Hence, with each iteration and the neural model gets closer to the desired output. The error is calculated using the following equation:

$$E_p = \frac{1}{2} \sum_{j} (t_{pj} - o_{pj})^2$$

In this equation, the index p corresponds to one input vector, and the vectors tp and op are the target and observed output vectors corresponding to the input vector p, respectively.

At the end of the iteration we get adjusted weights with fixed values. These are used to classify the input images. Samples of input are taken under different clinical conditions as well as technical conditions. These inputs are successfully classified into different grades of tumor. However, it can only detect location and size of tumor but do not provide any knowledge about the type of tumor.

Othman et al., in [10] proposed a method where decision making is performed using Probabilistic Neural Network.PNN is used here for its advantages over the BP network. It has a higher training speed due to the fact that the weights here are manually assigned but never trained. The proposed algorithm here first converts the image into matrix form and then classification is done by PNN.

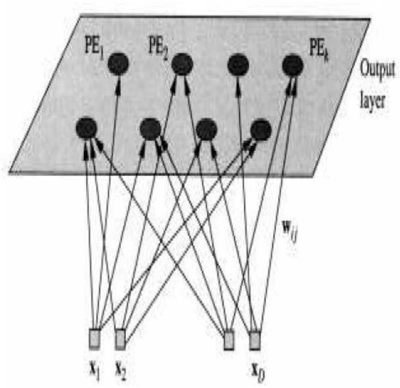
It first takes an input vector p, with a dimension of RX1. Then the vector distance between the input vector and the weight vector is calculated. This is then combined with the bias vector and passed through the radial basis function, which in the paper is defined as:

$$radbas(n) = e^{-n^2}$$

Here n is the output from the previous stage i.e. the distance vector combined with the bias vector.

It gives high accuracy with larger spread value (i.e. the value of the standard deviation).But; a major disadvantage here is that when the spread value is low, the accuracy decreases considerably.

Goswami et al., in[11]put forward a method where detection of brain tumor is done using unsupervised learning algorithms. Unsupervised learning is same as learning without a teacher.In unsupervised learning training data is not available; hence there is no error to yield satisfactory results. It is based on competitive unsupervised learning. Here, Self Organizing Maps (SOM) is used. The output neurons compete to get activated and the winning neurons get ordered with respect to each other. Hence, a mapping from continuous input space to discrete output space is performed by self organizing map.Though suboptimal solutions were generated for some sample input images; still this method has a very high accuracy of 98.6%.



Architecture of a SOM with a 2-D output

Amsaveni et al., in[12] used cascaded correlation networks. These are known as supervised learning techniques. These networks are known as self organizing networks.The proposed algorithm here has some features same as back propagation neural network. Only input and output neurons are present in the network during start, hidden layers are added during the training process one at a time. While training the network different patterns is presented to it .These includes the input pattern and the desired pattern (abnormal or normal). At the output layer, the difference between the actual and target outputs generates an error. This error signal is dependent on the weights of the neurons in each layer. By minimizing the error over the process new values of weights are calculated. The purpose of inserting a new unit is to reduce the total error of the network. The way this algorithm does this is to train the candidate unit so the correlation between the residual error and the output from the candidate is maximized. Hence the algorithm here classifies MRI brain images into normal and abnormal. The performance of the proposed methodology was tested on MRI brain images collected from the diagnostic centers. A total of 50 real images are collected and tested using the proposed algorithm. This process has an accuracy of 91.8%, with a relative error of 8.2%.

3. CONCLUSION: In this paper, various methods and techniques that are being used to detect the brain tumor from scanned MRI images of the brain are evaluated. A comparative study is made of various techniques. Image segmentation is a significant issue in digital image processing and finds extensive application in many fields. After review of well-known traditional techniques it is clearly revealed the various methods which can detect the tumor professionally and provide accurat e results. Brain is scanned, that is, MRI image of the brain is acquired which is noise free. As in literature, many algorithms were employed to segment and detect the brain tumor images. Finally, a detailed comparison was presented and shown the efficiency of various algorithms.

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