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NEURAL NETWORK BASED BRAIN TUMOR DETECTION USING MR IMAGES

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ABSTRACT

This is the review of work for Bain tumor detection using MR images. The present paper suggested Neural Network based brain tumor detection. Both hardware and software approach is proposed in this paper. The interdependency of two approaches certainly makes precise detection of maligns cells.

Index Terms: Artificial Neural Network, Brain Tumor, MRI, Neural Network.

1. INTRODUCTION

Brain tumors are composed of cells that exhibit unrestrained growth in the brain. Brain tumor by nature is malignant since it takes up space and invades brain tissue which is required for vital body functions. Because of the invading nature of the brain tumor it affects one of the most important organs in the body. Typical treatment for brain tumors is surgical in nature, although radiation therapy can also be prescribed depending on the particular case.

The Brain Tumors can be classified as follows:

I. Benign Tumor i.e. Non Cancerous Tumor

It is a type of tumor, which is Noncancerous, means they do not spread or invade the surrounding tissue.

II. Malignant Tumor i.e. Cancerous Tumor

It is a type of tumor which is cancerous, means it spreads and invades the surrounding tissue. It is categorized as Primary and Secondary Tumor.

a. Primary Tumor

They start in the brain. Benign tumors represent half of all primary brain tumors Most of them are usually successfully treated with techniques such as surgery.

b. Secondary Tumor (Metastatic)

A secondary (Metastatic) brain tumor occurs when cancer cells spread to the brain from a primary cancer in another part of the body. Secondary tumors are about three times more common than primary tumors of the brain.

One of the principal problems in surgical planning is the precise localization of critical brain structures. It is difficult and time consuming to detect and localize malignant cells using 2D images. 3D views, however, is a difficult task and is traditionally carried out in the clinicians mind. However, with image processing tools, the information in the orthogonal 2D cross-sections can be enhanced and interactively displayed using 3D models.

This image models considerably helps the surgeon in the trajectory optimization process. The spatial information helps in planning of the procedure by allowing him to test and analyze alternative navigational paths through the physical space. Pathological data is in terms of CT, MRI, MR-angiography or functional imaging presenting image information in a way that is more similar to the surgical view of the patient during the operation, thus facilitating the comprehension of the entire anatomy. The images of interest are obtained by the following techniques.

1. X-Ray
2. Computed Tomography-CT Scan
3. Positron Emission Tomography-PET
4. Magneto Encephalography –MEG
5. Biopsy
6. Magnetic Resonance Imaging-MRI

1.1.1 X-rays

X-Rays of the skull were once standard diagnostic tools but are now performed only when more advanced procedures are not available.

1.1.2 Computed Tomography (CT)

Computed tomography (CT) uses a sophisticated X-ray machine and a computer to create a detailed picture of the body’s tissues and structures. It is not as accurate as MRI and does not detect about half of low-grade glimmers. It is useful in certain situations; however a CT scan helps locate the tumor and can sometimes help determine its type .It can also help detect swelling, bleeding, and associated conditions. In addition, computed tomography is used to check the effectiveness of treatments and watch for tumor recurrence.

1.1.3 Positron Emission Tomography

Positron emission tomography (PET) provides a picture of the brain's activity rather than its structure by tracking substances that have been labeled with a radioactive tracer. PET is not routinely used for diagnosis, but it may supplement MRIs to help determine tumor grade after diagnosis. As with magnetic resonance spectroscopy (MRS), PET is also able to distinguish between recurrent tumor cells from dead cells or scar tissues, although MRS is more widely available.

1.1.4 Magneto Encephalography (MEG)

These scans measure the magnetic fields created by nerve cells as they produce electrical currents.

1.1.5 Biopsy

A biopsy is a surgical procedure in which a small sample of tissue is taken from the suspected tumor and examined under a microscope for malignancy. The results of the biopsy also provide information on the cancer cell type.In some cases, such as brain stem gliomas, a biopsy might be too hazardous because removing any healthy tissue from this area can affect vital functions. In such case diagnosis must rely on less invasive and possibly less accurate measures.

1.1.6 Magnetic Resonance Imaging (MRI)

MRI is an imaging technique based on the measurement of magnetic field vectors generated after an appropriate excitation with strong magnetic fields and radio-frequency pulses in the nuclei of hydrogen atoms present in water molecules of a patients tissues. Given that the content of water differs for each tissue, it is possible to quantify the differences of radiated magnetic energy, and have elements to identify each tissue. When specific magnetic vector components are measured under controlled conditions, different images can be acquired and information related to tissue contrast may be obtained, revealing details that can be missed in other measurements.

In MRI, one of the principle regions of interests is the brain. Currently in clinical applications, the boundary of tumor in a head image is usually traced by hand. Thus this manual approach becomes infeasible when used with large data sets. Hence the automatic system for the detection of tumor is necessary. Recently several attempts have also been made to apply neural network architectures to brain tumor analysis.

2. AN OVERVIEW OF RELEVANT LITERATURE SURVEY

In 1997,Yan Zhu* and Hong Yan [2]presented the work on Computerized Tumor Boundary Detection Using a Hopfield Neural Network, which presented a new approach for detection of brain tumor boundaries in medical images using a Hopfield neural network. The boundary detection problem is formulated as an optimization process that seeks the boundary points to minimize an energy functional based on an active contour model. A modified Hopfield network is constructed to solve the optimization problem. Taking advantage of the collective computational ability and energy convergence capability of the Hopfield network, our method produces the results comparable to those of standard "snakes"-based algorithms, but it requires less computing time. With the parallel processing potential of the Hopfield network, the proposed boundary detection can be implemented for real time processing. Experiments on different magnetic resonance imaging (MRI) data sets show the effectiveness of our approach.

In 1997, Wilburn E. Reddick, John O. Glass, Edwin N. Cook,T. David Elkin,[10] and Russell J. Deaton presented the work on Automated Segmentation and Classification of Multispectral Magnetic Resonance Images of Brain Using Artificial Neural Network,which presented a fully automated process for segmentation and classification of multispectral magnetic resonance (MR) images. This hybrid neural network method uses a Kohonen self organizing neural network for segmentation and a multilayer back propagation neural network for classification. To separate different tissue types, this process uses the standard T1-, T2-, and PD-weighted MR images acquired in clinical examinations. Volumetric measurements of brain structures, relative to intracranial volume, were calculated for an index transverse section in 14 normal subjects (median age 25 years; seven male, seven female). This index slice was at the level of the basal ganglia, included both genus and splenium of the corpus callous, and generally, showed the put amen and lateral ventricle. An infraclass correlation of this automated segmentation and classification of tissues with the accepted standard of radiologist identification for the index slice in the 14 volunteers demonstrated coefficients (ri) of 0.91, 0.95, and 0.98 for white matter, gray matter, and ventricular cerebrospinal fluid (CSF), respectively. An analysis of variance for estimates of brain parenchyma volumes in five volunteers imaged five times each demonstrated high intra subject reproducibility with a significance of at least $p<0.05$ for white matter, gray matter, and white/gray partial volumes. The population variation, across 14 volunteers, demonstrated little deviation from the averages for gray and white matter, while partial volume classes exhibited a slightly higher degree of variability. This fully automated technique produces reliable and reproducible MR image segmentation and classification while eliminating intraand interobserver variability.

In 1997,Phooi Yee Lau, Frank C. T. Voon, and Shinji Ozawa[46] presented the work onThe detection and visualization of brain tumors on T2-weighted MRIimages using multiparameter feature block, which presented an analytical method to detect lesions or tumors in digitized medical images for 3D visualization. The authors developed a tumor detection method using three parameters; edge (E), gray(G), and contrast (H) values. The method proposed here studied the EGH parameters in a supervised block of input images. These feature blocks were compared with standardized parameters (derived from normal template block) to detect abnormal occurrences, e.g. image block which contain lesions or tumor cells. The abnormal blocks were transformed into three-dimension space for visualization and studies of robustness. Experiments were performed on different brain disease based on single and multiple slices of the MRI dataset. The experiments results have illustrated that our proposed conceptually simple technique is able to effectively detect tumor blocks while being computationally efficient. In this paper, we present a prototype system to evaluate the performance of the proposed methods, comparing detection accuracy and robustness with 3D visualization.

In 1998, Karsten Held, Elena Rota Kops, Bernd J. Krause, William M. Wells, Ron Kikinis, and Hans-Wilhelm Müller-Gärtner[47] presented work onMarkov Random Field Segmentation of Brain MR Images, which describes a fully-automatic three-dimensional (3-D)-segmentation technique for brain magnetic resonance (MR) images. By means of Markov random fields (MRF's) the segmentation algorithm captures three features that are of special importance for MR images, i.e., nonparametric distributions of tissue intensities, neighborhood correlations, and signal inhomogeneities. Detailed simulations and real MR images demonstrate the performance of the segmentation algorithm. In particular, the impact of noise, in homogeneity, smoothing, and structure thickness are analyzed quantitatively. Even single-echo MR images are well classified into gray matter, white matter, cerebrospinal fluid, scalp-bone, and background. A simulated annealing and an iterated conditional modes implementation are presented.

In 2003, Alan Wee-Chung Liew, and Hong Yan[3] discussed an Adaptive Spatial Fuzzy Clustering Algorithm for 3-D MR Image Segmentation. An adaptive spatial fuzzy c-means clustering algorithm is presented in this paper for the segmentation of three-dimensional (3-D) magnetic resonance (MR) images. The input images may be corrupted by noise and intensity no uniformity (INU) artifact. The proposed algorithm takes into account the spatial continuity constraints by using a dissimilarity index that allows spatial interactions between image voxels. The local spatial continuity constraint reduces the noise effect and the classification ambiguity. The INU artifact is formulated as a multiplicative bias field affecting the true MR imaging signal. By modeling the log bias field as a stack of smoothing -spline surfaces, with continuity enforced across slices, the computation of the 3-D bias field reduces to that of finding the -spline coefficients, which can be obtained using a computationally efficient two-stage algorithm.

In 2005,Dana Cobzas, Neil Birkbeck Mark Schmidt, Martin Jagersand[45] presented their work on 3D Variation Brain Tumor Segmentation using a High Dimensional Feature Set, in which Tumor segmentation from MRI data is an important but time consuming task performed manually by medical experts. Automating this process is challenging due to the high diversity in appearance of tumor tissue, among different patients and, in many cases, similarity between tumor and normal tissue. One other challenge is how to make use of prior information about the appearance of normal brain. In this paper we propose a variational brain tumor segmentation algorithm that extends current approaches from texture segmentation by using a high dimensional feature set calculated from MRI data and registered atlases. Using manually segmented data we learn a statistical model for tumor and normal tissue. We show that using a conditional model to discriminate between normal and abnormal regions significantly improves the segmentation results compared to traditional generative models. Validation is performed by testing the method on several cancer patient MRI scans.

In 2009, Rajeev Ratan, Sanjay Sharma, S. K. Sharma[43] presented their work on Brain Tumor Detection based on multi-parameter MRI Image Analysis. Which presents, Segment of anatomical regions of the brain is the fundamental problem in medical image analysis. While surveying the literature, it has been found out that no work has been done in segmentation method has been developed and validated segmentation 2D & 3D MRI Data. This method can segment a tumor provided that the desired parameters are set properly. This method does not require any initialization while the others require an initialization inside the tumor. The visualization results demonstrate the effectiveness of this approach. In this study, after manual segmentation procedure the tumor identification, the investigations has been made for potential use of MRI data for improving brain tumor shape approximation and 2D and 3D visualization for surgical planning and accessing tumor. Surgical planning now uses both 2D and 3D model that integrate data from multiple imaging modalities, each highlighting one or more aspects of morphology or functions. Firstly the work has carried over calculate the area of tumor of single slice of MRI data set and then it was extended to calculate the volume of the tumor from the multiple image MRI set.

Yan Zhu* and Hong Yan [2] suggested the Hopfield neural network for the detection of brain tumor boundaries which was based on an active contour model. This is more suitable for real time application. The desired detection strongly depends on active contour model. Hence in this work adaptive active contour model was used. The accuracy and speed of detection can further modified by modifying model and neural network training approach. In this similar kind of work Wilburn E. Reddick, John O. Glass implemented hybrid neural network method for segmentation and multilayer back propagation neural network for classification. This was fully automatic detection system. The work can be modified by using neural network approach for all stages. On the other side , Phooi Yee Lau, Frank C. T. Voon, and Shinji Ozawa [46] suggested analytical based approach. This was based on three parameters; Edge(E), Gray(G), an Contrast(H) values. The 3D visualization was also developed for the surgeon. This method is based on analytical computation hence very complex and difficult in the construction. The separate synthesizer and model creator is required for getting the results.

Karsten Held, Elena Rota Kops, have implemented a fully-automatic three-dimensional (3-D)-segmentation technique for brain magnetic resonance (MR) images based on Markov random fields (MRF's). A simulated annealing and an iterated conditional modes implementation were presented. This method itself is not feasible for large numbers of datasets available hence in such kind of work considerable modified algorithm is to be implemented in order to suit for large type of datasets. Alan Wee-Chung Liew, and Hong Yan [03] worked with fuzzy c-means clustering algorithm. In this work the considerable amount of work was carried out for the noisy environment. Rajeev Ratan, Sanjay Sharma, S. K. Sharma [43] pointed out the segmentation problems and in further stage morphological image processing was implemented.

The Brain Tumor Detection is valuable and hence automatic detection is the demand of new era. This is possible by using neural network method for the detection. The neural network can be trained with modified algorithms to give better results. The problem in the acquisition and quality of image will be enhanced by using adaptive filters. The adaptive filters attenuate the noise and hence suitable for noisy environment. In this work neural network based detection with the adaptive filter technique is proposed.

3. THE METHODOLOGY OF THE PROPOSED RESEARCH

A set of eight texture features will be extracted from the tumor and the normal regions.

A gray tone spatial dependence matrix approach, introduced by Haralick which is a well known statistical method for extracting second order texture information from images, is used for this study. This method is based on the estimation of the second order joint conditional probability density function $C(ij\ /\ d,0)$ where 0 = 0, 45, 90 and 135 degrees. Each $C(i, j/\ d,0)$ is the probability of going from gray level i to gray level j, given that the inter-sample spacing is d and the direction is given by the angle 0. This is also referred to as co occurrence matrix. The co occurrence matrix is calculated for the normal and tumor regions (ROI) in the brain images for e =0 degrees and distance d=l. Eight texture features are calculated from the co occurrence matrix.

Let us denote the co occurrence matrix C and N be the number of distinct gray levels in the quantized image.

$$Cx(i) = \sum_{j=1}^{N} C(i,j) \tag{1}$$

$$Cy(i) = \sum_{i=1}^{N} C(i,j) \tag{2}$$

$$Cx+y(k) = \sum_{i=1}^{N} \sum_{j=1}^{N} C(i,j)_{i+j=k} \qquad k = 2,3,\ldots,2N \tag{3}$$

$$Cx-y(k) = \sum_{i=1}^{N} \sum_{j=1}^{N} C(i,j)_{|i-j|=k} \qquad k = 0,1,\ldots,N-1 \tag{4}$$

The following eight texture features are calculated:

1. Angular second moment(ASM)

$$f_1 = \sum_{i=1}^{N} \sum_{j=1}^{N} \{C(i,j)\}^2 \tag{5}$$

2. Contrast(CON)

$$f_2 = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N} \sum_{\substack{j=1 \\ [i-j]=n}}^{N} C(i,j) \right\} \tag{6}$$

3. Inverse Difference Moment (IDM)

$$f_3 = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{1}{1+(i-j)^2} C(i,j) \tag{7}$$

4. Sum Variance (SVAR)

$$f_4 = \sum_{i=2}^{2N} [(i-f)^2]\ c_{x+y}(i) \tag{8}$$

5. Sum Entropy (SENT)

$$f_5 = -\sum_{i=2}^{2N} c_{x+y}(i) \log\left(c_{x+y}(i)\right) \tag{9}$$

6. Entropy (ENT)

$$f_6 = -\sum_{i=1}^{N} \sum_{j=1}^{N} C(i,j) \log\left(C(i,j)\right) \qquad (10)$$

7. Difference Entropy (DENT)

$$f_7 = -\sum_{i=0}^{N-1} c_{x+y}(i) \log\left(c_{x-y}(i)\right) \qquad (11)$$

8. Information Measure of correlation (IMC)

$$f_8 = \frac{HXY - HXY_1}{MAX\{HX.HY\}}$$

Probable methods of Data Analysis: After implementation of the proposed algorithms on MR Brain images,the results will be compared and tallied with the actual results in consultation with the specialist doctors in this field.

4. SCHEME OF PROPOSED RESEARCH WORK

The Process of detection of Brain Tumor using MR image analysis can be broadly divided into following steps (Ref.fig 1)

I. Preprocessing of MR images.

1. Image acquisition
2. Adaptive filter

II. Image Analysis of MR images

1. Segmentation
2. Feature Extraction
3. Enhancement

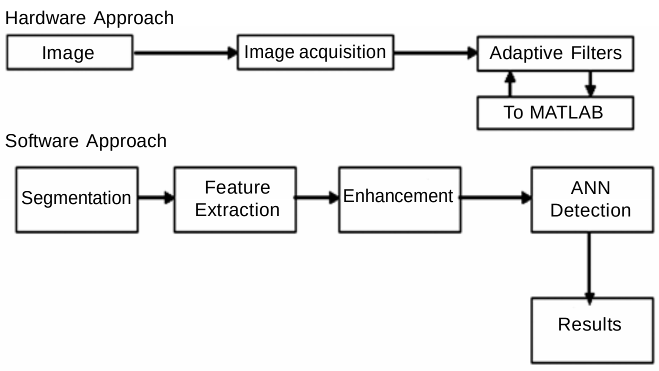

Figure 1: Scheme of Proposed System for Brain Tumor Detection

The resizing of the Image is performed to convenient size so that processing and analyzing can be carried out effectively. The Adaptive Filter is applied to remove the spurious signals present in the image. Then the segmentation and the feature extraction of region of interest(ROI) is obtained so that enhancement of required section can be done through software. The next block of the system is neural network control. The neural network is trained for the detection of tumor present in human brain.

After testing and successful implementation of the proposed scheme with ANN using Mathlab, the real time operation can be performed on the MR Brain Images for the detection of Brain Tumor.

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