ANALYSIS OF DISTRIBUTED ESTIMATION AND ARTIFICIAL NEURAL NETWORKS METHODS IN DETECTION OF BRAIN TUMORS FROM MRI IMAGES

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Abstract: Brain is the important part of the body. It is important to detect the abnormalities in brain with accuracy to diagnose it. In this paper two methods to detect brain tumours are analysed. One method is detection of tumours using distributed analysis and the other method is detection using artificial neural networks (ANN).In distributed estimation method pathology free image is used. From this image the objective function of a healthy brain is calculated which is compared with that of the test image. In the ANN method histogram equalization is used for detection of tumour. Additional advantage of this method is that a suitable Neuro Fuzzy classifier can be used to find the type of tumour cells. This method works in two phases namely Learning/Training phase and Recognition/Testing phase.

Index Terms: Artificial Neural networks, Back Propogation, Distributed estimation, Magnetic Resonance Imaging, Magnetic Resonance Tomography, Neuro-Fuzzy classifier, Semi Supervised Learning,

1. INTRODUCTION

A brain tumour, or tumour, is an intracranial solid neoplasm, a tumor (defined as an abnormal growth of cells) within the brain or the central spinal canal. Brain tumours include all tumours inside the 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 blood vessels, in the cranial nerves, in the brain envelopes (meninges), skull, pituitary gland, or pineal gland. Any brain tumour is inherently serious and life-threatening because of its invasive and infiltrative character in the limited space of the intracranial cavity. Its threat level depends on the combination of factors like the type of tumour, its location, its size and its state of development. Usually detection occurs in advanced stages when the presence of the tumour has caused unexplained symptoms.

Magnetic resonance imaging (MRI), magnetic resonance tomography (MRT) is a medical imaging technique used in radiology to visualize internal structures of the body in detail. Brain cancer detection in magnetic resonance images (MRI) is important in medical diagnosis because it provides information associated to anatomical structures as well as potential abnormal tissues necessary to treatment planning and patient follow-up. Here Brain Cancer Detection and Classification System has been designed and developed. The system uses computer based procedures to detect tumour blocks or lesions and classify the type of tumour using Artificial Neural Network in MRI images of different patients. The image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction have been developed for detection of the brain tumour in the MRI images of the cancer affected patients. The extracted features are compared with the stored features in the Knowledge Base. Finally a Neuro Fuzzy Classifier has been developed to recognize different types of brain cancers.

2. RELATED WORK

Evangelia I. Zacharaki and Anastasios Bezerianos introduced a novel semi supervised scheme for abnormality detection and segmentation in medical images. [1]Semi supervised learning does not require pathology modeling and, thus, allows high degree of automation. In abnormality detection, a vector is characterized as anomalous if it does not comply with the probability distribution obtained from normal data[2].

A Brain Cancer Detection and Classification System has been designed and developed by Arati Kothari[3]. The system uses computer based procedures to detect tumor blocks or lesions and classify the type of tumor using Artificial Neural Network in MRI images of different patients with Astrocytoma type of brain tumors. The image processing techniques such as histogram equalization, image segmentation,image enhancement, morphological operations and feature extraction have been developed for detection of the brain tumor in the MRI images of the cancer affected patients.

G. Erus, E. I. Zacharaki, R. N. Bryan, and C. Davatzikos[4] presented a general methodology that aims to learn multi-variate statistics of high dimensional images, in order to capture the inter-individual variability of imaging data from a limited number of training images. The statistical learning procedure is used for identifying abnormalities as deviations from the normal variation.

Indah Soesanti, AdhiSusantooptimized fuzzy logic based segmentation for abnormal MRI brain images analysis is presented [5]. A conventional fuzzy c-means (FCM) technique does not use the spatial information in the image. In this research, we use a FCM algorithm [6]that incorporates spatial information into the membership function for clustering. The FCM algorithm that incorporates spatial information into the membership function is used for clustering, while a conventional FCM algorithm does not fully utilize the spatial information in the image. The advantage of the technique is less sensitive to noise than the others.

3. ABNORMALITY DETECTION USING DISTRIBUTED ESTIMATION ALGORITHM:

Recent information explosion together with technological advances allowing access to electronic content provides an opportunity to collect and process large amount of data, such as medical images. The collection of data of the same kind allows the construction and exploitation of application-specific statistical models that optimally summarize knowledge. Such models can be incorporated into frameworks for anomaly or outlier detection, and model-based segmentation. Most methods, developed for segmenting anomalies, use labeled samples to characterize the abnormal objects. However, since abnormalities are usually rare or there may even be no data that describe specific pathologic conditions, supervised classification methods might be unsuccessful due to highly unbalanced data. Also, outlining and labeling representatives of all types of anomalies in an accurate way requires substantial human effort and is often prohibitively expensive. Semi supervised anomaly detection offers a solution to this problem by modeling normal data and then using a distance measure and thres holding to determine abnormality.

The method is applied for automatically segmenting pathologies in brain images, such as lesions, brain infarction, or dysplasia. From every spatially normalized image, a feature vector x, such as the voxel-wise intensities, is first extracted. A new feature vector ˆx is then synthesized, aiming to be similar to x but having the anomalies removed. A spatial abnormality score map is subsequently created by voxel-wise subtraction, $|x - \hat{x}|$.

Thresholding of such score map gives the segmentation of image anomalies. In contrast to most brain lesion segmentation methods based on outlier detection the proposed method is generic. It does not consider single voxels independently and makes no assumption about shape or intensity profile of the abnormality. Hence, as a stand-alone method, it is expected to have low statistical sensitivity but it can be used as a preprocessing step for locating all possible candidate regions before applying a specialized segmentation algorithm. In order to deal with the large dimensionality, we partition the images into subspaces i.e., locally coherent overlapping blocks. It is assumed that for each location the blocks are generated from a Gaussian distribution and located simplistic for high-dimensional and complex datasets, it seems reasonable for local image partitions. High dimensional data exhibit distributions that are highly sparse and can be represented by lower dimensional manifolds. This study makes two fundamental contributions in discovering abnormality. First, an objective function is defined that evaluates probability of the test data according to a statistical model of normal data in a lower dimensional space, and also exploits similarity with the model representation as well as similarity with the original data. The objective function minimization is formulated as a quadratic optimization problem. Second, the curse of dimensionality is tackled by proposing a scheme where an image is partitioned into a set of overlapping blocks at various locations. The objective function is optimized for each local subspace and then the local subspace estimates are fused into a globally optimal estimate that satisfies coupling constraints. Data fusion is performed by applying a distributed estimation algorithm based on dual decomposition and developed for solving large-scale problems.

3.1 Methodology

The methodology for abnormality segmentation uses 1) a set of pathology-free images in order to calculate an objective function measuring similarity to a healthy brain and 2) a test image (with abnormalities) for which the objective function is maximized. All images are coregistered and the mean image is calculated and subtracted from them. The solution is based on partitioning the spatial domain into overlapping, equally sized blocks in random locations. The algorithmic steps are the following.

First, the test image is scanned and a random block is selected (among the not already scanned locations). By concatenating the image intensities in the block, the test vector $X_0 \in R^d$ is constructed, where d is the number of dimensions (e.g., number of voxels in the block). The same block is then extracted from all pathology-free images forming the training vectors $V_{n \times d}$, where n is the number of subjects. The training set V is used to calculate an objective function.nl(x) the optimization of which gives a new vector $\hat{x} \in R^d$ that is “less abnormal” and also as similar as possible to the original vector x_0. However, since the blocks are overlapping, the solutions cannot be independently calculated for each block. After merging the solutions of all blocks, a spatial abnormality score map is calculated for the whole image by subtracting the reconstructed image from the original one.

3.2 Limitations on Distributed Estimation

This system can only detect the abnormality and location of tumor. But do not provide any knowledge about the type of tumor. Many cancer forms can only be diagnosed after a sample of suspicious tissue has been removed and tested (biopsied).Pathologists view pathologic tissues, typically with brig fieldmicroscopes, to determine the degree of normalcy versus disease. This process is time consuming, and fatiguing. The induced exhaustion created by this process may contribute to diagnostic errors. Also distributed estimation technique is a semi supervised technique. So developed a modified system using feature extraction and artificial neural network, it classifies and identifiespathological tissues in an automated fashion. The designed andimplemented system provides precision detection and real timetracking by classifying the unknown sample image into appropriatetype of cancer, thus do not involve any pathologicaltesting. This supervised technique 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.

4. DETECTION AND CLASSIFICATION OF BRAIN TUMOR USING ANN

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 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. 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 types of brain cancer. 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 designed system is an efficient system for detection and classification of brain cancer from a given MRI image of cancer affected patients. The system also finds sufficient usage under cancer detection in the area of medical sciences such as Computer Aided Diagnosis and Mammography etc. Brain cancer is a complex disease, classified into 120 different types. So called non-malignant (Benign) brain tumors can be just as life-threatening as malignant tumors, as they squeeze out normal brain tissue and disrupt function. The glioma family of tumors comprises 44.4 % of all brain tumors. Glioblastoma type of astrocytoma is the most common glioma which comprises 51.9 %, followed by other types of astrocytoma at 21.6 % of all brain tumors.

4.1 Image Preprocessing

Image preprocessing technique represents essential step of image segmentation which has a great impact on subsequent steps. It involves different techniques to improve image quality before actual segmentation process. Image preprocessing removes irrelevant information like noise and enhances contrast to improve image quality. There are three preprocessing techniques are commonly used. They are: Histogram Equalization, Binarization, and Morphological Operations.

4.2 Image Segmentation

Thresholding has been used for segmentation as it is most suitable for the present application in order to obtain a binarized image with gray level 1 representing the tumor and gray level 0 representing the background. In simple implementations, the segmentation is determined by a single parameter known as the Intensity Threshold. In a single pass, each pixel in the image is compared with this threshold. If the pixel's intensity is higher than the Threshold, the pixel is set to white, in the output. If it is less than the Threshold, it is set to black. The fundamental enhancement needed is to increase the contrast between the whole brain and the tumor. Contrast between the brain and the tumor region may be present but below the threshold of human perception. Thus, to enhance the contrast between the normal brain and tumor region, a sharpening filter is applied to the digitized MRI resulting in noticeable enhancement in image contrast. The dilation operator is used for filling the broken gaps at the edges and to have continuities at the boundaries. Onto the dilated image a filling operator is applied to fill the close contours. After filling operation on an image, centroids are calculated to localize the regions. The final extracted region is then logically operated for extraction of Massive region in given MRI image.

4.3 Feature Extraction

Features are the characteristics of the objects of interest in an image. Feature extraction is the technique of extracting specific features from the pre-processed images of different abnormal categories in such a way that the within- class similarity is maximized and between-class similarity is minimized. Earlier research works report many feature extraction techniques. The work involves extraction of the important features for image recognition. The features extracted give the property of the texture, and are stored in knowledge base. The extracted features are compared with the features of unknown sample image for classification. Texture features are used to distinguish between normal and abnormal brain tumors.The important features are Autocorrelation, Contrast, Correlation, Cluster Prominence, Clustershade, Dissimilarity, Energy, Entropy, Homogeneity, Maximum probability , Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation, Inverse difference normalized.

4.4 Knowledge Base

Knowledge Base is any chunk of information that effectively discriminates one class type from another. In this case, tumor will have certain properties that other brain tissues will not and vice versa. In the domain of MRI volumes, there are two primary sources of knowledge available. The first is pixel intensity in feature space, which describes tissue characteristics within the imaging system. The second is image or anatomical space and includes expected shapes and placements of certain tissues within the image. The nature of tumors limits the use of anatomical knowledge, since they can have any shape and occupy any area within the brain. As a result, knowledge contained in feature space is extracted and utilized.

4.5 Neuro-Fuzzy Classifier

Neuro Fuzzy Classifier has been developed to recognize different types of brain cancers.Fuzzyclassificationis the task of partitioning a feature space into fuzzy classes. Alearn-by-example mechanism is desirable to automate the construction process of a fuzzy classifier. An adaptive network is a multi-layer feed-forward network in which each node performs a particular function (node function) based on incoming signals and a set of parameters pertaining to this node. The type of node function may vary from node to node; and the choice of node function depends on the overall function that the network is designed to carry out. An adaptive classifier partitions the feature space based on labeled training data. In the context of fuzzy classification, classes are overlapping and each training data item is associated with numbers in the unit interval representing degrees of belonging, one value for each class. The overlapping among regions provides the natural smoothness for the input-output mapping. This characteristic makes this model suitable for classification problems, especially for those with overlapping categories. Moreover, the parameters obtained after the learning process can be easily transformed into structure knowledge in the form of fuzzy if-then rules.

4.6 Back Propagation Neural Network

Artificial Neural Networks are networks of interconnected computational units, usually called nodes. The input of a specific node is the weighted sum of the output of all the nodes to which it is connected. The output value of a node is, in general, a non-linear function (referred to as the activation function) of its input value. The multiplicative weighing factor between the input of node j and the output of node i is called the weight wji.With back-propagation, the input data (Extracted Features) is repeatedly presented to the Artificial Neural Network, with each presentation the output of the neural network is compared to the desired output (Grade of Tumor) and an error is computed. This error is then fed back (back-propagated) to the Artificial Neural Network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as Training. 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 weights wji; using a learning algorithm, the most popular of which is the generalized delta rule. After the weights are adjusted on the training set, their value is fixed and the Artificial Neural Networks are used to classify unknown input images.

5. CONCLUSION

Thus distributed estimation algorithm and Artificial Neuro-Fuzzy networks are studied to identify tumours present in human brain. The study ensure that the abnormality can be identified with accuracy.Image partitioning combined with a distributed estimation algorithm has been studied to deal with the high dimensional problem of statistical modeling.Brain cancer detection and classification system are studied using image processing techniques and artificial neural network was successfully completed. The designed brain cancer detection and classification system use conceptually simple classification method using the Neuro-Fuzzy logic. A Neuro-Fuzzy classifier has been developed to recognize different types of brain cancers. Texture features are used in the training of the artificial neural network.

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