I J C T A, 9(24), 2016, pp. 299-306
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ISSN: 0974-5572

Detection and Classification of Brain Tumourusing Back Propagation Algorithm

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ABSTRACT

Automated abnormal brain tumor detection is important for clinical diagnosis. Over the last decades several methods had been presented. MRI brain images demonstrate superior soft tissue contrast than CT scans and plain films making it the ideal examination of the brain, spine, joints and other soft tissue body parts. Due to this reason MRI brain tumor images used for this research paper. Wavelets are widely used for data compression, signal analysis, signal reconstruction, de-noising, etc. Wavelet transform is an effective tool for feature extraction from MRI brain images, because they allow analysis of images at various levels of resolution due to its multiresolution analytic property. However, this technique requires large storage and is computationally expensive. In order to reduce the feature vector dimensions and increase the discriminative power, the Back propagation algorithm (BPA) has been used. BPA is appealing since it effectively reduces the dimensionality of the data. In this research paper we proposed a novel hybrid system to classify a image is normal or abnormal . The proposed system employed a digital wavelet transform to extract features then used by aBack propagation algorithm to classify the image normal or abnormal. Classificationefficiency is 93.28%. has been obtained for brain image.

Keywords: MRI Brain tumor, Wavelet transform, Back propagation algorithm.

1. INTRODUCTION

Brain tumor is any mass that results from an abnormal and an uncontrolled growth of cells in the brain. Brain tumors can be cancerous (malignant) or non-cancerous (benign). Benign brain tumors are low grade, non-cancerous brain tumors, which, grow slowly and do not affect the surrounding normal tissue. They are homogeneous, demarcated, well defined and are known as non- metastatic tumors, because they do not form any secondary tumor. Whereas, malignant brain tumors are cancerous brain tumors, which grow rapidly and the surrounding normal tissue. They are heterogeneous, not well defined, grow in a disorganized manner and are known as metastatic tumors, because they initiate growth of similar tumors in distant organs. Malignant brain tumors (or) cancerous brain tumors can be counted among the most deadly diseases.

Many diagnostic imaging techniques can be performed for the early detection of brain tumors such as Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). Compared to all other imaging techniques, MRI is efficient in the application of brain tumor detection and identification, due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation, and is a noninvasive technique. MRI is rapidly growing medical imaging technique and capture high resolution images of soft tissues. In the soft tissues of the human body MRI provides thorough detail about abnormalities that may not be identified by X-rays and CT scan. Several methods have been developed for feature extraction from MRI but wavelet transform is the best method for feature extraction.

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The proposed hybrid system for brain tumordetection in MRI brain images and categorize them using artificial neural network.The proposed system uses discretewavelets transform for feature extraction .These extracted features were given as ainput to classify the MRI brain images are normal or abnormal. The main objective of the research work is to develop a system as a diagnostic tool for detection of tumour in brain. This work involves various features from the given images using discrete wavelet transform and morphological operations followed by a neuro classifier. The MRI brain images were collected from various hospitals, and the collected image's involves various operations likeenhancement, segmentation, feature extraction and classification.

2. LITERATURE SURVEY

Gholam-Ali Hossein-Zadeh and Hamid Soltanian-Zadeh [1] proposed a new method for the analysis of the fMRI data with improved activation-detection sensitivity. The performance of the new method (at a false alarm rate of) is significantly better than the cross-correlation method at the signal contrast level of 1%. This superiority is less pronounced at the signal contrast levels of 2%, 3%, and 4%. This is an advantage of the proposed method. Clearly, among different detection methods, the more powerful method is the one with superior performance in the low SNR situations where either the signal is weak or the noise is high.

Ays¸ eDemirhan [3] developed an algorithm that combines threshold and morphological operations. Segmentation operation is performed by an unsupervised SOM network. They developed an algorithm, based on the hit histograms of the BMUs of the output neurons for clustering the SOM instead of using an additional NN. The statistical analysis of the experimental results has indicated that the developed algorithm can segment brain MR images with good accuracy.

Pauline John, [4] presents an efficient method of classifying MR brain images into normal, benign and malignant tumor, using a probabilistic neural network. This approach gives very promising results in classifying MR images. Most of the existing methods can detect and classify MR brain images only into normal and abnormal [2]. Whereas, with the help of the texture statistics obtained from LH and HL sub bands, is able to classify brain tumor into benign and malignant.

AndacHamamci*, Nadir Kucuk, KutlayKaraman [7] suggested a segmentation algorithm for the problem of tumor delineation which exhibit varying tissue characteristics. As the change in necrotic and enhancing part of the tumor after radiation therapy becomes important, they also applied the Tumor-cut segmentation to partition the tumor tissue further into its necrotic and enhancing parts.

YAO-TIEN CHEN [11] proposes an approach integrating 3DBayesian level set method with volume rendering for brain tumor and tissue segmentation and rendering. A prior probability estimation of the tumor and tissue is incorporated into 3D Bayesian level set method for 3D segmentation. The 3D Bayesian level set method is then used to continuously segment the 3D targets (e.g., tumor, tissue, and whole brain) from a series of brain images.

3. METHODOLOGY

The collection MRI brain images undergone for feature extraction using discrete wavelet transform. Discrete Wavelet Transform represents the data into a set of high pass (detail) and low pass (approximate) coefficients. Image is first divided into blocks of 32×32. Then each block is passed through two filters: in this the first level, decomposition is explained to breakdown the input data into an approximation and detail coefficients [4], detail coefficients and approximate coefficients are separated as LL, HL, LH and HH coefficients. After that all the coefficients are discarded, except the LL coefficients. LL coefficient transformed into the second level. In MR imaging process the existence noise due to magnetic field, patient motion and other effects, must be eliminated using pre-processing methods.

The preprocessing is used to eliminate any interfere in the image to identify the tumor. It is significantly increasing the reliability, robustness of the image. It is used to remove the noise and enhance the image using Gaussian filter. To reduce the work area only to the relevant region that exactly contains the brain. It acquisition the image from the database as the input image.

Next weuse, Back Propagation algorithm [Rumelhard and Mcclelland (1986), Jain (1996))] is used in layered feedforward ANN. This algorithm works for feed-forward networks with continuous output. In this network, the neurons are organized in layers and send their signals in the forward direction. The errors generated are propag14ated in the backward direction. The network receives the input by neurons in the input layer and the output of the network is given by the neurons on an output layer. The network consists of one or more intermediate hidden layers. Supervised learning is used in Back Propagation algorithm i.e., Examples of both the input and the output to be computed is given to the algorithm. The error between the input and the computed output is calculated.

The network is trained with random weights and later the weights are adjusted to get the minimal error. The network will be perfect if the error is minimal. In back propagation, the weights and thresholds are changed each time an example is presented, such that the error gradually reduces. This is repeated until there is no change in the error.BPN classifier gives fast and accurate classification that can be effectively used for segmenting MRI brain images with high level of accuracy.

The basic block diagram for brain tumour detection shown in fig(1).

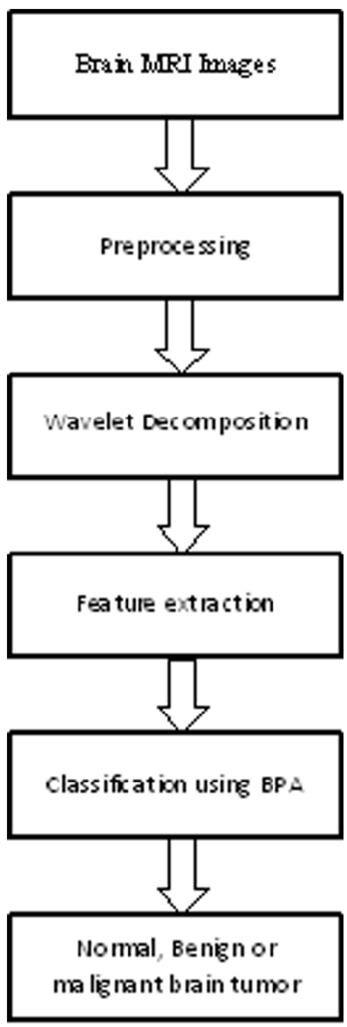


Figure 1: Steps in brain tumor classification

4. PREPROCESSING

In signal processing, it is necessary to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

5. WAVELET DECOMPOSITION

Wavelets one of the most exciting research areas in signal processing today. Wavelet analysis is similar to Fourier analysis in the sense that it breaks a signal down into its constituent parts for analysis. Whereas the Fourier transform breaks the signal into a series of sine waves of different frequencies, the wavelet transform breaks the signal into its “wavelets”, scaled and shifted versions of the “mother wavelet”.

When analyzing signals of a non-stationary nature, it is often beneficial to be able to acquire a correlation between the time and frequency domains of a signal. The Fourier transform, provides information about the frequency domain, however time localized information is essentially lost in the process. The problem with this is the inability to associate features in the frequency domain with their location in time, as an alteration in the frequency spectrum will result in changes throughout the time domain. In contrast to the Fourier transform, the wavelet transform allows exceptional localization in both the time domain via translations of the mother wavelet, and in the scale (frequency) domain via dilations.

The translation and dilation operations applied to the mother wavelet are performed to calculate the wavelet coefficients, which represent the correlation between the wavelet and a localized section of the signal. The wavelet coefficients are calculated for each wavelet segment, giving a time-scale function relating the wavelets correlation to the signal. This process of translation and dilation of the mother wavelet is depicted below.

The dilation function of the discrete wavelet transform can be represented as a tree of low and high pass filters, with each step transforming the low pass filter as shown in Figure. The original signal is successively decomposed into components of lower resolution, while the high frequency components are not analyzed any further. The maximum number of dilations that can be performed is dependent on the input size of the data to be analyzed, with 2N data samples enabling the breakdown of the signal into N discrete levels using the discrete wavelet transform.

The waveletdecomposition at various levels shown in fig 2.

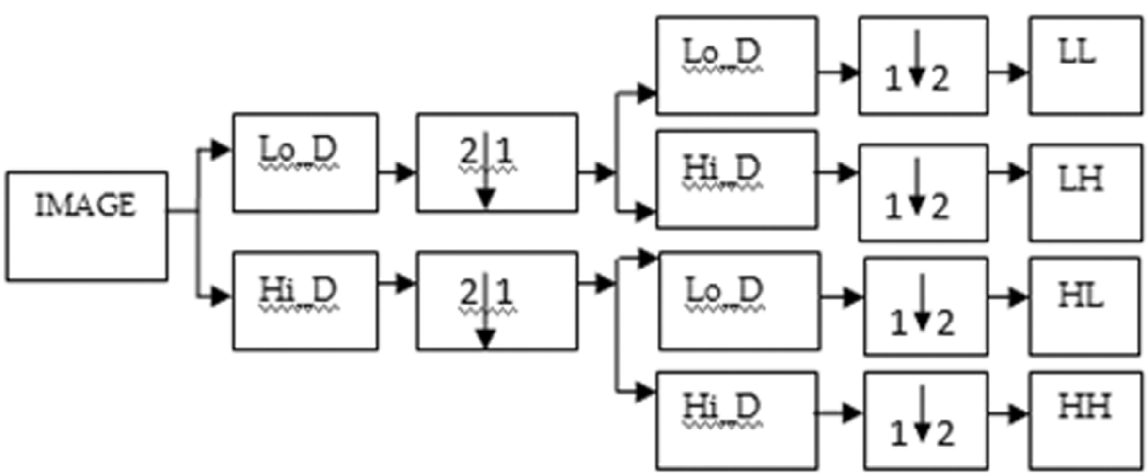


Figure 2: Wavelet decomposition

6. CLASSIFICATION

6.1. Back propagation algorithm

Back-Propagation Neural Network (BPNN) Back propagation is a supervised learning method. In supervised learning, each input vector needs a corresponding target vector. Input vector and target vector are presented in training of the network. The output vector (i.e. actual output) which is result of the network is compared with the target output vector then an error signal is generated by the network. This error signal is used for adjustment of weights until the actual output matches the target output. Algorithm stages for BPN are initialization of weights, feed forward, back propagation of Error and Updation of weights and biases. By using this BPA the various features are extracted from normal and abnormal MRI brain imges.The extracted features were fed into BPA network to define the images are normal are abnormal. The statistical texture features taken into consideration are as follows:

Mean: The mean is defined as below:

$$Mean(m) = \frac{1}{x+1} \sum_{i=1}^{x} \sum_{j=1}^{y} x(i, j)$$

Variance: It is square of mean. The variance is defined as below:

$$Variance(v) = \frac{1}{x+1} \sum_{i=1}^{x} \sum_{j=1}^{y} \left(x(i, j) - m \right)^2$$

Contrast: A measure of difference moment and is defined as below:

$$Contrast = \sum_{i=1}^{N} \sum_{j=1}^{N} (i-j)^2 \left(\frac{P(i, j)}{R} \right)$$

These statistical features can be further fed to the BPNN classifier for training and testing the performance of the classifier in classifying the brain MR images into normal, benign and malignant.

6.2. Results and discussion

It is found that the directional features extracted from LH and HL sub bands of the wavelet transform, which gives information along the horizontal and vertical directions respectively, are more efficient at characterizing changes in the biological tissue.

The above five factors has been taken into account for 50 numbers of normal and abnormal brain images. The same has been listed in the following table for 5 patients.

For normalimages

The following Table 1 gives details of the various features extracted for normal brain images.

Images/ Features	*Mean*	*Standard deviation*	*Entropy*	*Contrast*	*Correlation*	*Energy*
1	1.2417n	16.4258	0.0539	0.0360	0.9399	0.9870
2	0.9776	14.3836	0.0426	0.1246	0.7257	0.9870
3	0.6113	11.9167	0.0273	0.0585	0.7827	0.9933
4	0.4913	10.8738	0.0212	0.0525	0.7383	0.9948
5	0.3927	9.4463	0.0185	0.0706	0.5870	0.9951

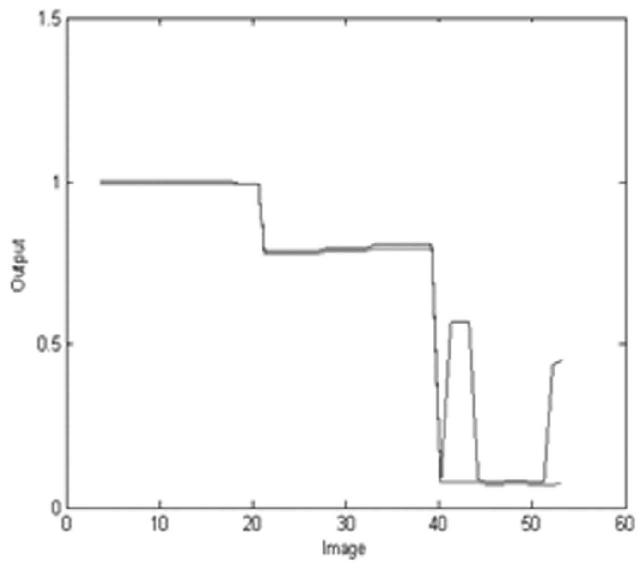
For abnormal images

The following Table 2 gives the various features extracted for abnormal brain images.

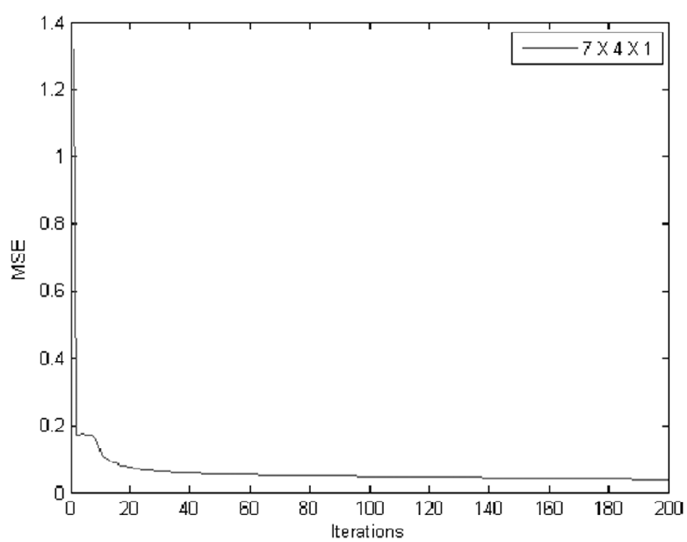
Images/ Features	*Mean*	*Standard deviation*	*Entropy*	*Contrast*	*Correlation*	*Energy*
1	14.8844	55.0689	0.3600	0.1036	0.9835	0.8699
2	4.3586	31.7704	0.1329	0.0736	0.9588	0.9621
3	101.5625	86.4825	0.9563	0.3468	0.9849	0.5542
4	4.8523	34.5557	0.1378	0.1561	0.9164	0.9587
5	92.7775	79.5200	0.9112	0.3918	0.9817	

The following graph shows the performance analysis for brain images. From Figure it is evident for the abnormal brain images have a close association between target and predicted values (range 0.9 to 1.5) and for normal brain images the match between target and predicted values is in the range of 0.3 to 0.89. The network parameters for training the ANN is tabulated in Table 3.

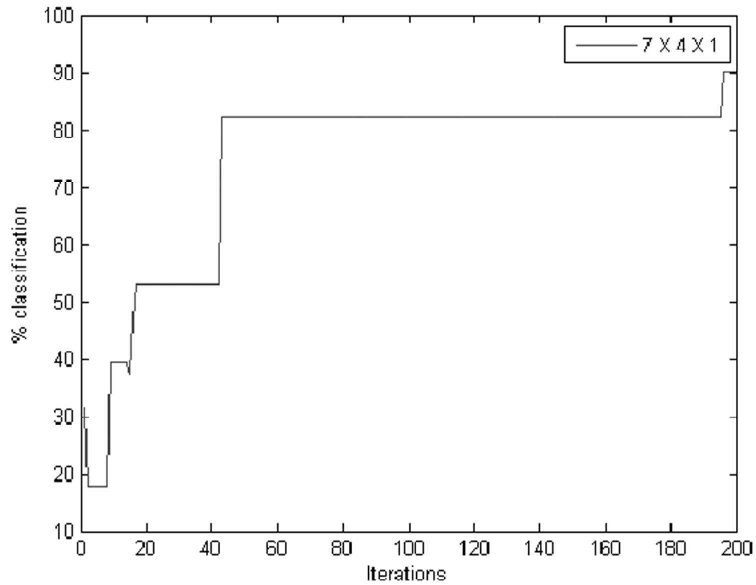
Classification efficiency is 93.28%. The efficiency can be improved using an extensive data base.



(a) Target Vs Estimated output



(b) Iterations Vs MSE



(c) Classification Efficiency

Table 3
ANN parameters

S. No	*Network parameters*	*Value*
1.	No. of nodes in input layer	7
2.	No. of nodes in hidden layer	4
3.	No. of nodes in the output layer	1
4.	Activation function for hidden layer neurons	Sigmoid
5.	Activation function for Output layer neurons	Sigmoid
6.	Mean Squared Error	0.0198
7.	No. of iterations	120
8.	Learning factor	0.998

7. CONCLUSION

This research paper is more efficient method for classification of brain images into normal, benign and malignant tumorusing back propagation algorithm. The proposed method use the texture feature obtained from LH and HL subbands,is able to classify MRI brain images into normal or abnormal. Based on experimental results BPN is more efficient over conventional neural network. This method of automatic early detection and classification of MR brain images into normal, benign and malignant, based on their statistical texture features, not only replaces conventional invasive techniques, but also helps in reducing the fatality rate.

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