Automated Technique for Medical Images Using Neural Network

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Abstract– **This article raises a new automated technique for medical images. It has been implemented using a neural network. Automated technique is an important process that helps in identifying objects of the image. Existing automated technique methods are not able to exactly segment the complex profile of the medical images accurately. Automated technique of every pixel in the medical images correctly helps in proper location of tumor. The presence of noise and object raises a stimulating problem in proper automated technique. The proposed model is an assessment method with energy minimization. The assessment property helps in better automated technique of the complex profile of the medical images. The performance of the new automated technique method is found to be better with higher peak signal to noise ratio of 61 when compared to the existing automated technique method.**

Keywords– Neural Network, Intelligent Automated Technique, Medical Images, Feature Extraction and Signal-to-Noise-Ratio

I. INTRODUCTION

Medical imaging plays a crucial role in the field of bio-medical engineering. Some of the organs of the human body require non-invasive approach to understand the defects such as tumor, cancer in different parts of the body. Study and analysis of brain are done through the images obtained by various modalities like X-ray, Computer Tomography, Positron Emission Tomography, Ultrasound, Single Photon Emission Computed Tomography, etc. The present day to day study of brain is much preferred through medical images. The obtained medical images need to be preprocessed, registered and segmented for understanding the defects in the brain by physician. Current topographic technologies in medical imaging enable studies of brain function by measuring hemodynamic changes related to changes in neuronal activity. The signal changes observed in medical images are mostly based on blood oxygenation level dependent contrast and are usually close to the noise level. Consequently, statistical methods and signal averaging are frequently used to distinguish signals from noise in the data. In most medical images setup, images are obtained during alternating task and control conditions [1], [2].

Automated technique approaches for 3D magnetic resonance images for brain have been advanced under three broad algorithms, namely classification-based, region-based and contour-based approaches. Anatomical knowledge, used appropriately, boosts the accuracy and robustness of the automated technique algorithm. MRI automated technique strive toward improving the accuracy, precision and computation speed of the automated technique algorithms [10].

Statistical methods are used for settling non-parametric thresholds for medical images statistical maps by take another sample medical images data sets containing block shaped responses. The complex dependence structure of medical images noise precludes parametric statistical methods for finding appropriate thresholds. The non-parametric thresholds are potentially more accurate than those found by parametric methods. Three different transforms have been proposed for the take another sample: whitening, Fourier, and wavelet transforms. Take another sample methods based on Fourier and wavelet transforms, which employ weak models of the temporal noise characteristic, may produce erroneous thresholds [9].

A commonly used method based on the maximum of the background mode of the histogram, is maximum. A fully automated, parametric, unsupervised algorithm for tissue classification of noisy MRI images of the brain has been done. This algorithm is used to segment three-dimensional, T1-weighted, simulated and real MR images of the brain into different tissues, under varying noise conditions [10]. Parametric and non-parametric statistical methods are powerful tools in the analysis of medical images data [7].

A method for somewhat automatic automated technique of brain structures such as thalamus from MRI images based on the concept of geometric surface flow has been done. The model evolves by incorporating both boundary and region information following the principle of deviating analysis. The deformation will stop when a steady state is achieved [8]. Energy minimization algorithm provides a high quality automated technique due to region homogeneity and compactness. The graph algorithm for multistage automated technique of three dimensional medical data sets has been presented [4].

Artificial neural networks are computing elements which are based on the structure and function of the biological neurons [2]. These networks have nodes or neurons which are described by difference or differential equations. The nodes are interconnected layer-wise or intra-connected among themselves. Each node in the successive layer receives the inner product of synaptic weights with the outputs of the nodes in the previous layer [1]. The inner product is called the activation value.

II. PROPOSED METHOD

The proposed method focuses on a new automated technique approach using energy minimizing neural network. Due to the complex profiles of the brain, the new method helps in segmenting the profiles by learning the different states of the profile of medical images. Statistical features are calculated from the medical images. These features are learnt by the training phase of the model. The learnt weights are further used for automated technique of the medical images during the testing phase.

The minimizing neural network condition is defined in terms of the spectral radius, denoted by (‖ ‖) of the reservoir's weight matrix (‖ W ‖ < 1)). This condition states that the dynamics of the model is uniquely controlled by the input, and the effect of the first states vanishes. The current design of model parameters relies on the selection of spectral radius. There are many possible weight matrices with the same spectral radius, and unfortunately they do not all perform at the same level of mean square error for functional approximation. Model is composed of two parts a fixed weight (‖ W ‖ < 1) repeated network and a linear readout. The repeated network is a reservoir of highly interconnected dynamical components, states of which are called echo states. [5]:

The memory less linear readout is trained to produce the output [6]. Consider the repeated discrete-time neural network with M input units, N internal PEs, and L output units. The value of the input unit at time n is:

$$u(n) = [u_1(n), u_2(n), \ldots, u_M(n)]^T,$$

The internal units are $x(n) = [x_1(n), x_2(n), \ldots, x_N(n)]^T$, and

Output units are $y(n) = [y_1(n), y_2(n), \ldots, y_L(n)]^T$.
The connection weights are given

i). in an (N x M) weight matrix $W^{back} = W_{ij}^{back}$ for connections between the input and the internal PEs,

ii). in an N × N matrix $W^{in} = W_{ij}^{in}$ for connections between the internal PEs

iii). in an L × N matrix $W^{out} = W_{ij}^{out}$ for connections from PEs to the output units and

iv). In an N × L matrix $W^{back} = W_{ij}^{back}$ for the connections that project back from the output to the internal PEs.

The activation of the internal PEs (echo state) is updated according to:

$$x(n+1) = f(W^{in} u(n+1) + Wx(n) + W^{back} y(n)), \quad (1)$$

Where,

$f = (f_1, f_2, \ldots, f_N)$ are the internal PEs' activation functions.

All f_i's are hyperbolic tangent functions $\frac{e^x - e^{-x}}{e^x + e^{-x}}$. The output from the readout network is computed according to

$$y(n+1) = f^{out}(W^{out} x(n+1)), . \quad (2)$$

Where

$f^{out} = (f_1^{out}, f_2^{out}, \ldots, f_L^{out})$ Are the output unit's nonlinear functions.

In this paper, much careful attention is done for improving automated technique of medical images by implementing the model. The progression of steps involved in medical images intelligent automated technique is:

i). Acquire automated technique
ii). Preprocess slice for canceling noise
iii). Train statistical features and obtain trained weights
iv). Testing trained weights
v). Segment image

Obtaining the image is done through standard medical images equipment. The image is preprocessed to make sure that the noise is deleted. Noise canceling is mostly preferred by using adaptive filtering methods. Depending on the severity of noise, the internal parameters of the filtering method can be fine tuned. Contrast intensification of the image is done to have better clearness of the image. This process is very important for further study of the medical images slices. The model is first ized with random weights. The statistical features obtained from the medical images are used to train the model. The process of training is used to obtain set of trained weights. Testing of model is done for medical images automated technique using the trained weights.

III. EXPERIMENTAL RESULTS

The medical image[a] is considered for analyzing the performance of automated technique by model algorithm. As the first image is affected with electronic noise, it has been adaptively filtered to remove the noise and subsequently registered.

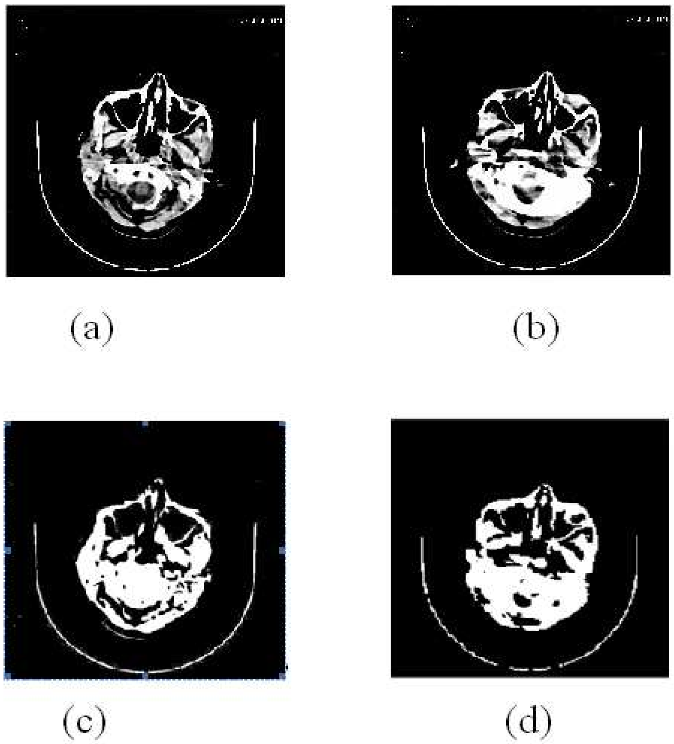

Fig. 1: Automated technique of medical images

For the comparison of the automated technique execution of the model, automated technique is taken as the reference, since model is the oldest neural network method used earlier for image automated technique. The segmented image through is shown in Fig. 1(c). Similarly the segmented image using model is shown in Fig. 1(d).

One of the important automated technique performance comparisons is PSNR. The PSNR is expressed as:

$$PSNR = 10*\log10 (255*255/MSE) \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$MSE= \sum (\text{Original image} - \text{segmented image})^2$$

Where,

MSE is the mean squared error

Fig. 2 display peak signal to noise ratio for different threshold used in both model algorithms. The PSNR values starts with minimum 59 and goes up to approximately 64. The PSNR value for the segmented image by model ranges from 62 to 64. The maximum PSNR value is obtained in case of model automated technique is for threshold of 0.01 with 62.58. By comparison, the maximum PSNR is obtained at lower threshold for the MODEL algorithm. The PSNR can be further improved by further modifying the model algorithm in terms of number of nodes I the hidden layer.

The Fig. 3 displays the model assessment and the corresponding input patterns. The estimate is based on the number of reservoirs used during the training process.

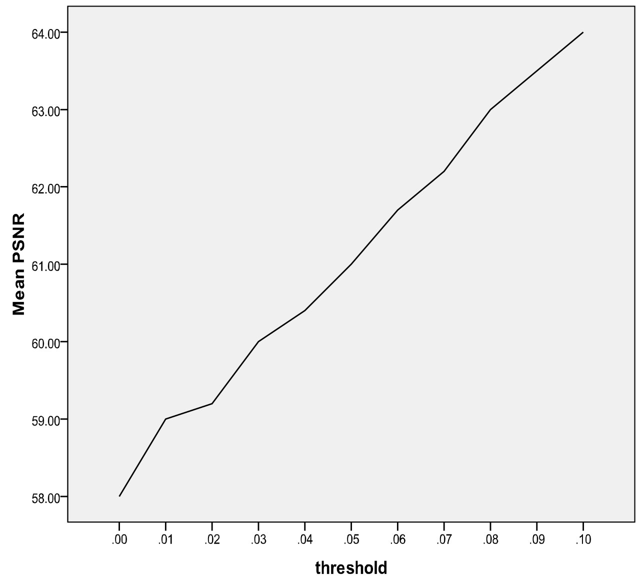

Fig. 2: Comparison performance of model

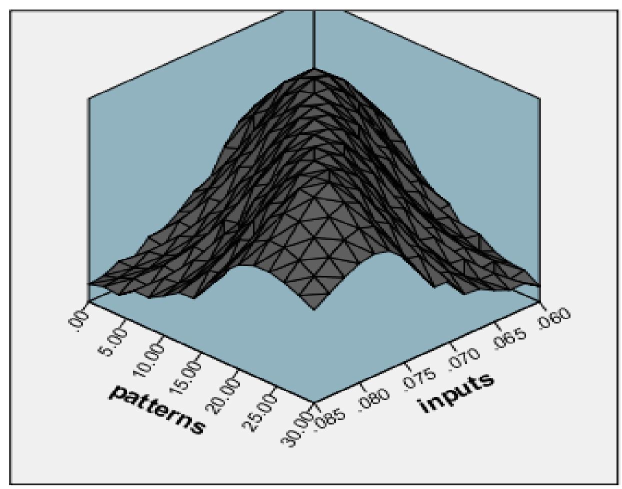

Fig. 3: Training performance of the model

IV. CONCLUSION

In this paper the medical images automated technique has been done with a repeated model that provisions the different states of medical images. The proposed method focuses on a new automated technique approach using energy minimizing neural network. Due to the complex profiles of the brain, the new method helps in segmenting the profiles by learning the different states of the profile of medical images. The PSNR value for this method is 62.6667. Whereas, the PSNR value for the automated technique done by is 56.87. The work can be further extended by incorporating modifications of internal states in model and fine adjusting the noise filtering methods.

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