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A NOVEL APPROACH FOR THE EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE

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Abstract: Alzheimer disease (AD) is the most common dementia type disease after the age of 65. This leads to cognitive disability to the person being affected. The existing methods are not able to definitely diagnose the disease at an earlier stage. Also, if we can diagnose the disease earlier, treatments can be given at a proper time. Accordingly, an innovative technique should be developed with good accuracy, specificity, and sensitivity. In this scenario, the Magnetic Resonance Imaging (MRI) can be utilized. In this research work, a method has been proposed using Discrete Wavelet Networks (DWNs). This method gives better results in case of MRI images.
Keywords: Alzheimer's disease; DWNs; Early Diagnosis; Feature Selection; and MRI

INTRODUCTION

Alzheimer's disease is considered as a neuronal disease that upsets neuron cells. Once the nerve cells are damaged due to this disease, it cannot reproduce the cells and causes damaged to the nearby cells. This permanent damage of the cells leads to permanent memory impairment. The disease progression is classified according to the progressive nature of the disease [1, 2]. When the disease progresses to the severe stage, the patient conditions become more critical. In addition to the patient, the family members are also affected. AD normally occurs due to protein accumulation called as plaques, and tangles [3, 4].
Plaques are present outside the nerve cells and tangles are those that present inside the nerve cells. In AD patients, the deposits of plaques and tangles are seen more than normal subjects. The main parts of the brain that is affected by AD in the earlier stage are hippocampus, frontal, temporal, occipital and, parietal lobes. In these areas, there is a loss of neuronal cells and more deposits of proteins. Also, there is cortical atrophy in these areas [5-7]. Therefore, brain imaging techniques can be used for the diagnosis of this disease. At present, there is several brain imaging methods for diagnosing AD. From those Magnetic Resonance Imaging (MRI) gives considerable results than other because it reveals relevant information about the most critical areas that are causing AD. MRI is non-invasive equipment for determining cross-sectional areas of brain as well as records the changes in the tissue region including the hippocampus, frontal lobes, temporal, occipital lobes, and parietal lobes [8, 9]. Due to this, MRI scans are becoming popular. The images obtained from MRI devices show more reliable and consistent in the case of AD. After selecting the most suitable brain imaging technique, next is to make an automated expert system using computers for the diagnosis of the disease. For this purpose, we can use the advanced Biomedical Engineering technology for making an automated system using computers.

REVIEW OF LITERATURE

Feature selection is a substantial process in the automatic computer diagnosis of brain pictures. The different techniques for this process are genetic algorithm, artificial neural networks (ANNs), fuzzy logic; and support vector machines (SVMs). Another method that can be used in conjunction with the above is wavelet Networks (WNs). In this research, we are using WNs for the segmentation process. The WNs can overcome the different limitations caused by other segmentation techniques. By using WNs, we can reduce noise from the images to minimum; avoid complex calculations, efficient image retrieval and separation of background from the image [10].
In this paper, feature selection of MRI images has been developed based on WNs. They can be characterized into adaptive wavelet networks (AWNs) that uses Continuous Wavelet Transforms (CWTs) and the other is discrete wavelet Networks (DWNs) which uses Discrete Wavelet Transform (DWT) [11]. In this research, DWN has been used extensively. The advantages of DWN over AWN are as follows. Unlike AWN, DWN uses simple computations and are not as sensitive to initial values as AWN [12]. The other factors to choose DWN to construct the networks are wavelets, scale and shift parameters. In addition to inner parameters there are outer parameters like the weight of the wavelet neurons, calculated using least squares estimation [13, 14].
Therefore, in this research work we are using DWNs for the segmentation of MRI images for the feature selection process. After the segmentation process is over, necessary features of MRI are extracted and select the appropriate features for the classification of images.

FEATURE SELECTION OF MRI IMAGES

During the feature selection of MRI pictures, segmentation is a prominent task. Figure 1 shows the feature selection method using MRI. The different block represents Image Acquisition, Preprocessing, WN Construction, Segmentation, Image

Postprocessing, Extraction of features, and Feature Selection. The first step in this method is to acquire the MRI scans using MRI scanner as in figure 2. The second step is the removal of noise from the images using filters.. Filters can be classified into linear and non-linear filters. In this research, we are using a non-linear median filter to removes the unneeded noise on the obtained MRI image before proceeding to the segmentation process.

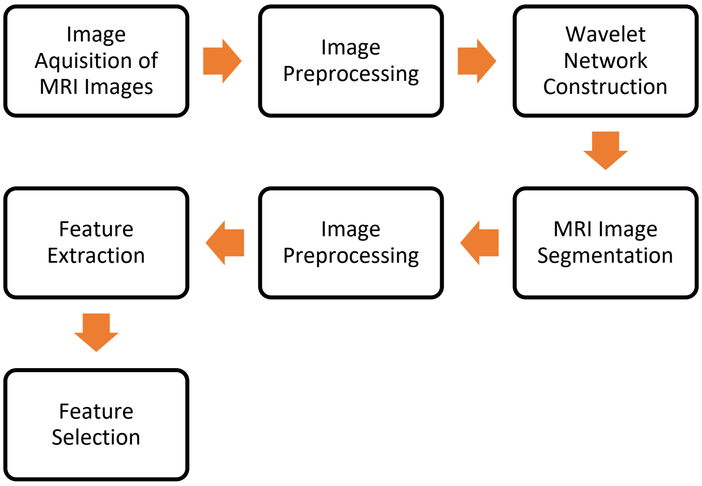

Figure 1.Block diagram of MRI Feature Selection Process

The third step is the WN construction from the MRI scans stored in the computer using DWNs. Once the network construction is completed, segmentation can be done [15]. In the pre-processing stage, the edges and heirs that are no longer needed has been removed. After that various features connected with MRI has been extracted. The final step is the feature selection method in which only the optimum features are selected.

Figure 2. MRI device

THE SEGMENTATION ALGORITHM USING WAVELET NETWORKS FOR THE FEATURE SELECTION PROCESS

Figure 3 shows the block diagram of the segmentation algorithm for the feature selection process. Wavelets are mainly used to reduce the magnitudes of MRI picture information from a bigger value. A Discrete Wavelet Network consisting of one output, d inputs and q Wavelet neurons can be calculated as in equation (1).

$$\sum_{i=1}^{n} w_i \psi_{pi,qi}(X) = \sum_{i=1}^{n} w_i 2^{-p_i d/2} \psi(2^{pi} X - qi) \qquad (1)$$

From the above equation, wi is the weight coefficients, ψpi, qi are the parameters of primary wavelet network [16].

While using DWNs, the Red Green Blue (RGB) matrix values of MRI data that is given as DWN input changes from a minimum value to maximum. These variations will cause problems in the segmentation as well as classification process. Therefore, the RGB data is to be normalised in the range [0,1]. This stage is also called as pre-processing stage of the feature selection process [17]. The normalisation of input data is calculated as in equation (2).

$$x^{(k)}_{n,new} = \frac{x^{(k)}_{n,old} - t_k}{T_k - t_k} \qquad (2)$$

From the equation (2), $x^{(k)}_{n,new}$ is the value of the matrix, t_k denotes lowest value and T_k denotes highest value of the matrix.

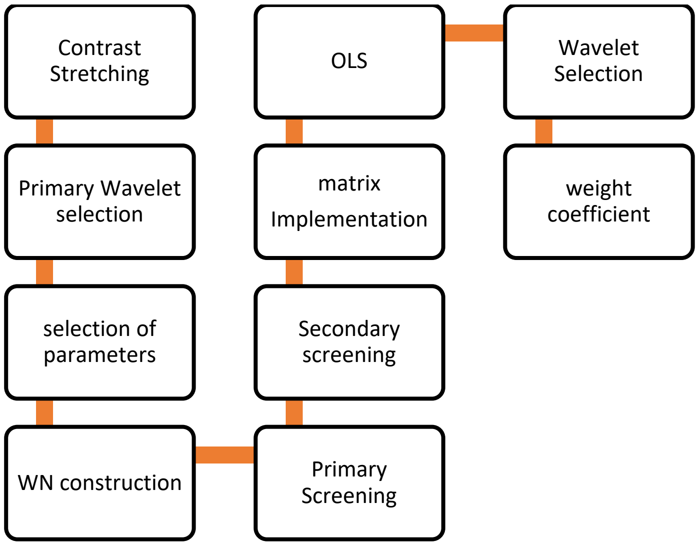

Figure 3.Block diagram for the feature selection process

The next step in this algorithm is to select the principal wavelet for the construction of DWN for the segmentation process. For the purpose of creating a DWN with good efficiency, the wavelets must be chosen with utmost care. In this scenario, we cannot use a single dimensional wavelet. Therefore, multi-dimensional wavelets should be employed. There are different types of wavelets available in biomedical processing. After executing the program for feature extraction with different wavelets, Marr and Morlet Wavelet combination has been chosen as the principal wavelet [18]. The Marr function is represented as in equation (3)

$$\psi_1(x) = [(d - abs(x^2) * e^{\wedge}(-abs(\tfrac{x^2}{2})] \qquad (3)$$

Likewise, the Morlet wavelet function is given by the equation (4).

$$\psi_2(x) = Ce^{\frac{-x^2}{2}} * \cos(5x) \qquad (4)$$

By using dimension d=2 and constant C=1, the equation changed as shown in equation (5).

$$\psi(x) = [((d - \mathrm{abs}(x^2) * e\hat{}(-\mathrm{abs}(\tfrac{x^2}{2}))) * (Ce^{\frac{-x^2}{2}} * \cos(5x))] \qquad (5)$$

After selecting the principal wavelet, the succeeding step is to select the scaling and shifting parameter functions for crating the wavelet lattice. The lowest scale level with P_{min} and the highest scale level with P_{max} have been selected [19]. After choosing the shift and scale parameters, a wavelet lattice is constructed with d=2 as in equation (6).

$$\psi_{pi.qj}(x) = 2^{-p_i d/2}\psi(2^{p_i} x - q_j) \qquad (6)$$

After the construction of Wavelet lattice, there are there exist so many redundant wavelets that cause inaccuracies in the segmentation section. Therefore the most suitable wavelets should be selected with shift and scale parameters. For this purpose, the primary screening is used. In this screening, the matrix I_k is formed from the selected wavelets [20]. In the next stage, the secondary screening is employed in which matrix I is formed from the matrix I_k. In the next stage, the wavelet matrix is calculated from the selected shift and scale parameters after the screening process [21]. Therefore, in the next stage is the employing of Orthogonal Least Square algorithm to select the suitable parameters from the matrix. After employing the OLS estimation, the wavelet network is computed by the equation (7)

$$f = \sum_{i=1}^{s} w_i \psi_i(x) \qquad (7)$$

From the equation (7), s denotes neurons and wi is the weight. In the next only the required Wavelet neurons are selected and index of WN is given by equation (8).

$$MSE = \frac{1}{P}\sum_{k=1}^{P}(\hat{f}^{(k)} - f^{(k)})^2 \qquad (8)$$

Finally, the weight coefficients have been calculated successfully [22, 23].

IMAGE PRE AND POST PROCESSING

MRI pictures acquired digitally are exposed to different Digital Image Processing Techniques. The standard picture ratio is taken as 360x360 pixels. Normally, the picture comprises of unwanted distortion in the form of hairs, bubbles and so on. These commotions cause errors in the final output. So as to stay away from that, pictures are exposed to different image processing schemes such as Image Pre-processing and Post-processing. Pre-processing is the removal of commotions in the picture such as hair and bubbles. The principal strategy of pre-processing is to carefully evacuate the hairs and bubbles and makes the image smooth for the segmentation process. After the segmentation process, there are some unwanted regions are formed near the boundaries and edges. This can be removed by image post-processing in which unneeded regions are removed and region of interest is calculated.

EXTRACTING MRI FEATURES

The features that can be extracted from MRI images are are described as below.

Ellipticity is a grade of resemblance with the oval contour that is achieved in-between the area of the utmost real fitted area elliptically. It shows larger values during normal and smaller values during abnormal conditions.

Texture feature is an arranged group of metrics in image processing to evaluate the deceptive surface. It provides evidence of spatial arrangement of color or intensities in an MRI image.

Red average value is the mean value of the pixels in the red region.

Regional minima are to seizure the consistency calculated using number of minima and the area of object. Moment is defined as the histogram of the MRI image inside the object. Median is measured by arranging all initial value of the pixel from the adjacent neighborhood into numerical order. Contrast is the difference in the luminance or colour of the MRI image, thereby the objects can be easily found out. Entropy is a statistical degree of uncertainty to characterize input image. Maximally Stable Extreme Regions (MSER) features are used for spot recognition in images. Min-Eigen feature find corners using Eigenvalues and returns a corner point's object in a two-dimensional grayscale image. Curvature variance is the measurement of curvature that is usually present in the objects outline. It shows maximum for AD and minimum for normal by measuring the variance of their assessment dissemination. Salience variance is used as the precise enlargements of an outline forming discrete regions. Some of the features obtained are shown in figure 4.

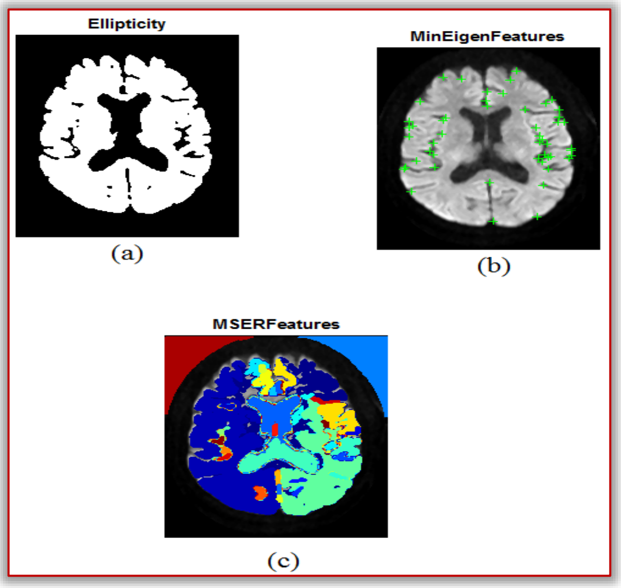

Figure 4. (i) Ellipticity (ii) Min-Eigen (iii) MSER feature

FEATURE SELECTION OF MRI IMAGES

The next process is to find out the best features that are more suitable for the diagnosis of AD. For finding out the optimal feature, we have executed the MRI images with each feature separately for the classification of images. Finally, we have selected six features for the classification stage. The features are Ellipticity, Texture feature, curvature variance, MSER features, Min-Eigen, and saliency variance.

RESULTS AND DISCUSSION

The dataset includes 100 MRI images taken under same environmental conditions. The size of image obtained is 5 megabyte, images have been made noise free using non-linear median filter. Figure 5 shows the different process of segmentation in MRI images.

Table.1. Comparison of MMDWNS, NN, FCM, and ED

Method	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	Similarity (%)	Border Error (%)
proposed	99.55	94.57	94.22	99.72	99.57	11.12
GA	99.45	92.15	93.34	99.65	99.12	13.14
NN	99.43	92.05	93.24	99.63	98.43	17.72
SVM	99.11	88.44	86.96	99.05	89.93	22.34
FCM	98.73	82.18	83.84	98.53	82.14	32.97

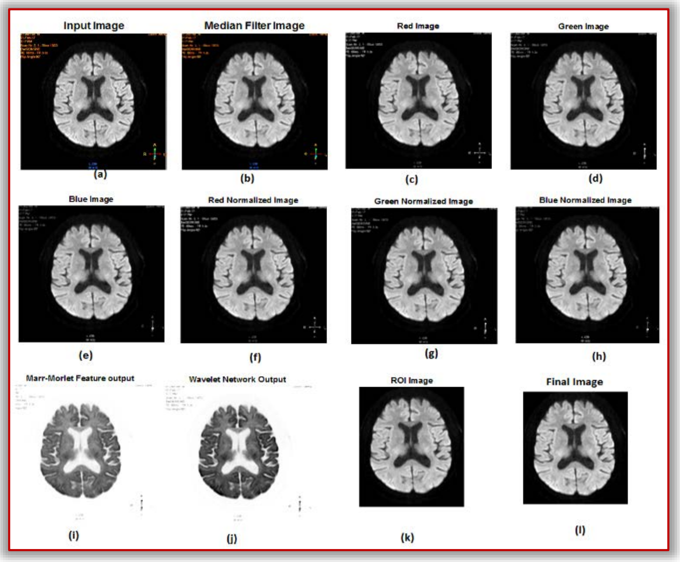

Figure 5. The different process of segmentation in MRI images: (a) input image, (b) Median filter image (c) Red image (d) Green image (e) Blue image (f) Red Normalized image (g) Green Normalized image (h) Blue Normalized image (i) Marr-Morlet feature output (j) Wavelet Network Output (k) ROI image (l) final output.

In this research, feature selection of the MRI images has been done with DWNs for the early diagnosis of AD. We have compared the proposed work with genetic algorithm GA, Neural networks (NNs), Support Vector Machines (SVM), and Fuzzy C- Means (FCM) for accuracy, precision, sensitivity, specificity, similarity and border error rate, our method is better than the other four as in table 1.

CONCLUSIONS

In this paper, feature selection of MRI has been done using Discrete Wavelet Network. For the feature selection process, images are obtained through MRI scanner and stored as a database. After that, normalisation has been done before image segmentation. Image pre-processing has done before segmentation stage and Image post-processing has been done after segmentation and then region of interest is calculated to get the final segmented image. After segmentation, feature extraction of MRI has been done and features have been extracted, in which 6 significant features have been selected. The proposed method has been compared with other relevant methods and shows better results. Therefore, this innovative method can definitely helpful for diagnosing Alzheimer's disease affectively.

Acknowledgment

We would like to express our gratitude to Sree Gokulam Medical College and Research Foundation, Trivandrum, India for providing the necessary MRI images for the preparation of this paper. Also we are thankful to the professors Dr.K.Mahadevan, Ophthalmology department and Dr.Manoj.P, Neurology department for their support in this research work.

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ACTA TECHNICA CORVINIENSIS – Bulletin of Engineering
ISSN: 2067-3809