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Analysis of MRI and OCT Images for the Early Diagnosis of Alzheimer's Disease Using Wavelet Networks

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Abstract

Alzheimer disease (AD), a progressive neurodegenerative disorder, is the most common cause of dementia in the old age population. Previous clinical and histological studies suggest that the neurodegenerative process, which affects the brain, may also affect the retina of AD patients. Any disease modifying treatments which are developed are most possibly to be achieving success if initiated early in the process, and this needs that we tend to develop reliable, validated and economical ways to diagnose Alzheimer's kind brain disease. However, despite comprehensive searches, no single test has shown adequate sensitivity and specificity, and it is likely that a combination will be needed. Profiling of human body parameter using computers can be utilized for the early diagnosis of Alzheimer's disease. In this paper we have focused on Magnetic Resonance Imaging (MRI) and Optical Coherence Tomography (OCT) imaging techniques for the early diagnosis of AD. For this purpose we have developed a method based on Wavelet Networks (WN) known as Fixed Grid Wavelet Networks (FGWN) for the analysis of OCT and MRI images. This method provides reliable and validated results for both OCT and MRI images.

Key words

Alzheimer's disease, Early Diagnosis, FGWN, MRI and OCT.

1. Introduction

Alzheimer's disease (AD) is one of the most prominent types of dementia that leads to permanent memory loss and disrupt the daily life. The relevant incidence shows that the prevalence of AD increases as the age of population increases [1]. AD is characterized by continuous memory impairment, cognitive dysfunction, aphasia, apraxia, agnosia and visual abnormalities [2, 3]. The most usual visual complaints seen in AD are loss of spatial contrast sensitivity, unable to identify motion perception, cannot discriminate color and visual loss, affecting the primary visual cortex and other selected areas of the brain [4, 5]. For the diagnosis of AD, a noninvasive neuroimaging technique like magnetic resonance imaging (MRI) is widely used. It is now becoming the most used tool that provides detailed information about brain structure and cerebral imaging in AD [6, 7]. The evidence and studies made on clinical and histological AD suggests that the similar neurodegenerative process that occurs in the brain, may also affect the eye retina, since the latter is an extension of central nervous system. The morbid changes in retina were observed in animal models and in post mortem studies of human eyes of AD patients [8, 9].

From the above, it is clearly understood that in addition to MRI another technique can be used for obtaining the changes in eye for the early diagnosis of AD. Most prominent of them are Fundus Imaging and Optical coherence tomography (OCT). As AD leads to the thinning of Retinal Nerve Fiber Layer (RNFL), OCT method gives a clear scan of RNFL [10]. So we have used MRI and OCT scanned images for the preparation of this paper. After obtaining the MRI and OCT images of AD patient, next step is to make a computer based assessment of these images. For this assessment we have followed different image analyzing techniques like segmentation, feature extraction, feature selection and classification of MRI and OCT images.

2. Literature Review

Segmentation is the most important process in the artificial intelligence (AI) field for medical image analysis. Most important and popular AI techniques for segmentation of medical images are fuzzy logic and artificial neural networks (ANNs) [11, 12]. Another promising field of AI technique that has been popularly used for various applications in different areas of analyzing the medical images is wavelet networks (WNs). The advantages of Wavelet Networks are noise reduction, reduction in back ground, recovery of the characteristic information, overcome the different limitations in computational intelligent methods like ANNs and optimization of WN structure with efficient deterministic construction algorithms over multilayer perceptrons (MLP) and radial basis functions (RBFs) [13,14]. In this paper, we have developed a method based on WNs for the segmentation of both MRI and OCT images. WNs can be classified into two different categories, adaptive wavelet networks (AWNs), uses continuous wavelet transforms (CWTs) and fixed-grid wavelet networks (FGWNs), uses discrete wavelet transforms (CWTs). The main limitations of AWNs are complex calculations and sensitivity to initial values [15].

The following features of FGWNs over AWNs made us to select the predecessor. The parameters such as number of wavelets, scale, and shift parameters value can be determined easily. The neuronal weights are determined by algorithms similar to the least squares. After segmentation, necessary features are extracted and finally the classification of images has done. Therefore, the purpose of this paper is to address the main findings on MRI and OCT in AD patients, to discuss the role of MRI and OCT in AD patients and how MRI and OCT scans involved in the early diagnosis of AD. The author’s previous works in the area of Biomedical Engineering will definitely help to develop a new proposed tool using latest biomedical methods for the solution of the early Diagnosis of AD [1-6].

3. FGWN Method of Segmentation

Image acquisition is the first step in the analysis of MRI and OCT images. This is done by using MRI scanner and OCT camera which is shown in figure 1. Preprocessing is by using median filter which removes unwanted noise like salt pepper noise on the obtained MRI and OCT images. Next step is to build a FGWN as explained in the previous section. During processing, at first a wavelet scan is formed from a function, called "mother wavelet," which is confined in a finite interval. A single scaling multidimensional wavelet frame is employed for mother wavelet creation which provides better regularities and also the ease of frame generation in comparison with wavelet basis.

Fig.1. (a) MRI Scanner (b) OCT device

Wavelets are mostly useful for reducing the size of MRI image as well as OCT image data from a larger one. The output signal of a wavelet network with one output, d inputs and q wavelons in the hidden layer is given by the equation (1).

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

where w_i, $i=1,2,...,n$,are weight coefficients ,ψpi ,qi are dilated and translated versions of a mother wavelet function, ψ , pi, qi are scale , shift parameters, respectively [16]. In most of the experiments, input data of wavelet network changes within a wide range, this variability reduces the efficiency of wavelet network. Therefore in the first stage called data preprocessing stage, the input data are normalized to a specified range in order to avoid data scattering. Hence the red, green and blue values of RGB matrix of each MRI as well as OCT image are mapped into [0, 1] range by performing normalization [17] process using the equation (2).

$$x_{n,new}^{(k)} = \frac{x_{n,old}^{(k)} - t_k}{T_k - t_k} \tag{2}$$

where $x_{n,new}^{(k)}$ is the value of each red, green and blue color matrix after normalization, t_k is the minimum value and T_k is the maximum values of these matrices, respectively. Next is to select the mother wavelet. For providing better regularities and ease of frame generation, wavelet frame with multi-dimensional single scaling is employed. Hence d-dimensional Mexican hat radial wavelet is used as the mother wavelet [18] as in equation (3).

$$\psi(x) = \eta\|x\| = (d - \|x\|\hat{}2)e\hat{}(-\|x\|\hat{}2|2) \tag{3}$$

Next step is to select the scale and shift parameters. In this stage, minimum and maximum scale levels in the form $[p_{\min}, p_{\max}]$ and shift parameter are to be employed. A hyper shape on the wavelet parameters space that was selected previously in the wavelet function is calculated for all input vectors as in equation (4).

$$\psi_{pi.qj}(x) = 2^{-p_i d/2}\psi(2^{p_i}x - q_j) \tag{4}$$

For the creation of wavelet lattice two screening stages are involved, primary and secondary screening. After the formation of a wavelet matrix, a fast and efficient model structure determination approach has been implemented using the orthogonal least squares (OLS) algorithm [19]. After employing this stage, wavelet network is constructed as in equation (5)

$$f = \sum_{i=1}^{s} w_i\psi_i(x) \tag{5}$$

where s is the number of wavelons in the hidden layer and w_i is the weight of wavelons. By selecting the ideal number of wavelons [20], index of the wavelet network can be calculated as in equation (6).

$$MSE = \frac{1}{P}\sum_{k=1}^{P}(\hat{f}^{(k)} - f^{(k)})^2 \quad (6)$$

Finally the number of wavelons will change until the desired error measure is achieved. The algorithm from the previous stage of FGWN is used in the present stage for segmentation of MRI and OCT images. From images database, a number of images are selected in a random fashion for the creation of FGWN. During the initial stage, the values of RGB matrix of each color MRI and OCT image are mapped into [0, 1] range by performing normalization process. In order to form the FGWN, the values of three color matrices are considered as network inputs. The matrices formed are related to the ten images selected separately from MRI and OCT images used for segmentation in the database. From these images, some pixels are selected in a random fashion to construct FGWN. After this process, the value of the three matrices R, G, B for each pixel are considered as FGWN inputs, and the output of FGWN is a binary image that shows the segmentation of original image. The figure 2 shows the different process of segmentation in MRI and OCT images: (a) input image, (b) Median filter image (c) Mexican hat feature output (d) FGWN output (e) Post Processing and (f) Segmented image.

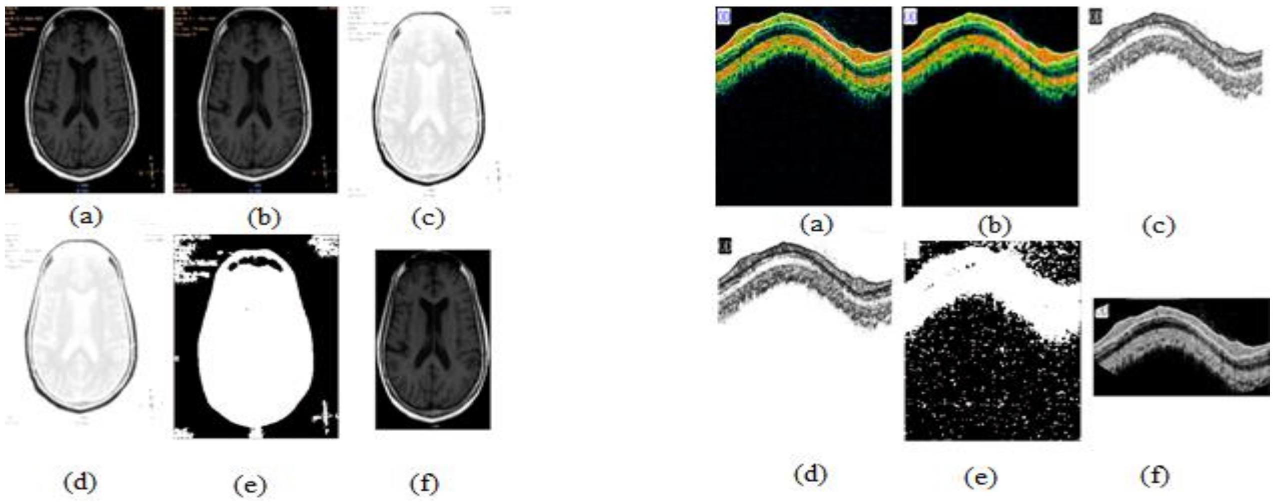

Fig.2. MRI Segmentation (left) and OCT Segmentation (right)

As mentioned above, segmentation is the most important and critical stage of the different stages of Automatic Diagnosis of AD using MRI and OCT images, it has a very significant role in the final outcome. Due to this reason, the performance of this state should be examined by means of appropriate criteria. Here the brain region and the retinal fiber layer which are the most significant feature in detecting Alzheimer’s disease is extracted by FGWN with an acceptable accuracy. Our method is quite simple and considering the satisfactory results of this study, it is very applicable for detecting AD by means of the computer. For this purpose we have to consider Ground Truth (GT), obtained by medical experts and Segmentation Algorithm (SA). Therefore, for comparing the different segmentation algorithms we have to take in account of GT as the base image. Also the criteria should be defined based on the parameters like True Acceptance (TA); False Acceptance (FA); True Rejection (TR) and False Rejection (FR). As shown in table 1 we compared the features like accuracy, precision, sensitivity, specificity, similarity and border error (all values are in percentage) of FGWN segmentation with Neural networks (NN), Fuzzy-Based Split-And-Merge algorithm (FBSM), Gradient Vector Flow (GVF) and AT. FGWN shows considerable results than all the other segmentation algorithms.

Method	Accuracy	Precision	Sensitivity	Specificity	Similarity	Border Error
FGWN	99.65	94.77	94.32	99.82	99.67	11.32
NN	99.53	92.15	93.34	99.73	98.43	17.82
FBSM	99.21	88.54	87.06	99.15	89.93	22.44
GVF	98.83	82.28	83.94	98.63	82.14	33.07
AT	97.72	81.04	82.19	96.44	81.82	36.63

Table.1. Comparison of FGWN, NN, FBSM, GVF and AT (values are in percentage)

4. Feature extraction and Classification

After segmentation of OCT images, next step is to extract the features. Since extracting the features of brain region and retinal layers is the most essential part of diagnosing AD. For this, after segmentation with FGWN the space between two shapes is filled, extra parts are eliminated, and the noise is removed. Then, the exact boundary of the layer is extracted. This is done by appropriate morphological processes, including erosion, dilation. In this paper feature extraction of MRI and OCT images is done using different features like ellipticity, ratio between thickness calculation, curvature variance, salience variance, average number of regional minima in the gradient image inside the object, perimeter, area finding the second, third and fourth moments [21].

After selecting the most significant features, the next process is the classification of OCT images. To classify input feature vectors into target vectors, we used Back Propagation (BP) and Radial Basis Function (RBF). For the classification using BP, the weighting factor of the input-to-hidden neurons can be calculated by equation (7).

$$w_{ij}^{k+1} = w_{ij}^{k} - \eta \frac{\partial E^{(k)}}{\partial w_{ij}} \quad (7)$$

where *k* is iteration number; *i, j* are index of input and hidden neuron, respectively; and η is step size. Back Propagation networks usually having hidden layers one or more of sigmoid neurons succeeded by an output layer of linear neurons. Multiple layers of neurons with transfer functions that are nonlinear allow learning of linear-nonlinear relationships between input and output vectors. The linear output layer produces values outside the range -1 to +1 in the network [22]. For the classification using RBF, the RBF classifier is having the input layer with a set of *n* units that can receive the *n* -dimensional input feature vector elements. The *n* elements having input vector *x* are given to the input of *l* hidden functions. The output from the hidden function is multiplied by the weighting factor *w(i, j),* which is given as input to the output layer of the network *y(x).* Therefore for each RBF unit *k, k = 1, 2,3,..., l* the center is selected as the mean value of the sample patterns belong to class k as in equation (8).

$$\mu_k = \frac{1}{N_k}\sum_{i=1}^{N_k} x_k^i \tag{8}$$

where x_k^i is the eigenvector of the i^{th} image in the class *k,* and N_k is the total number of trained images in class *k*. As the RBF neural network is type of neural networks, the hidden layer activation function is determined by input vector and prototype vector distance [23]. We have compared the above techniques for the OCT images and found that RBF produces better results than BP. Also RBF requires less time than BP during execution.

5. Experimental Results

The database of MRI and OCT images is taken from Sree Gokulam Medical College and Research Foundation, Trivandrum, India. For this purpose the AD patients diagnosed by Neurologist through MRI are selected. Then those patients were sent to Ophthalmologist for further investigation through OCT. The dataset includes 100 MRI and OCT images taken under the same environmental conditions. All of these images are saved as bitmap file for further processing. The size of each image was 535,974 byte; the database images employed in this paper were made free from noise or other artifacts by filtering or preprocessing stage. In case of noisy images (images which are not of desired quality or the results of segmentation are not satisfactory), or necessity of elimination of the hairs, a preprocessing stage be used [36]. Among the 100 images selected for segmentation using the proposed FGWN, 10 images are used for the formation of the wavelet lattice, determination of the shift scale parameters, calculation of the network weights and the rest are used for testing it. In our experiments, 10–12 wavelons are enough to achieve good results. The images that selected are previously saved as bit map file. The dimension of the saved image is high. So it must be reduced to a low dimension, 256X256 sizes as we have done. The proposed FGWN segmentation process is compared with NN, FBSM, GVF and AT, FGWN achieves considerable result than the other four as explained in the previous section. The feature extraction has been done after the segmentation part is over. The feature classification has been done using Back Propagation and Radial Basis Function, the later showed considerable results. Out of 100 images selected, 50 images are normal and the remaining are AD victims. We have calculated the True Acceptance Rate

(TAR), False Acceptance Rate (FAR), True Rejection Rate (TRR) and False Rejection Rate (FRR) with the proposed system and achieved good results compared to FBSM, GVF and AT as shown in table 2.

Method	TAR in %	TRR in %	FAR in %	FRR in %
FGWN	98.93	98.79	1.07	1.21
FBSM	93.43	92.33	6.51	7.65
GVF	88.48	87.23	11.23	12.56
AT	78.71	76.43	21.37	13.83

Table.2. Comparison of TAR, TRR, FAR and FRR of FGWN with FBSM, GVF and AT

6. Conclusion

In this study a new approach for the analysis of MRI and OCT images based on fixed grid wavelet network for segmentation and Neural network for classification has been employed. By comparing the changes in brain as well as retina between AD and control subjects we can diagnose early. For performing this, a wavelet lattice is formed. Parameters of wavelets are determined with two screening stages. Orthogonal least squares algorithm is used to calculate the network weights and to optimize the network structure using the developed algorithm. After that different features of MRI and OCT images are extracted. Also the proposed method is compared with other methods, the former shows better results. Unlike NN, the results from FGWN not change in several experiments, i.e., training and testing a WN several times with the same data would lead to the same results. After that feature selection has done and classified the features using NN. Then we compared the TAR, TRR, FAR and FRR of the proposed method with other methods and achieved better results. Therefore the proposed method provides a useful tool for the analysis of MRI and OCT retina images for predicting AD. The main finding is that both the MRI and OCT images can be segmented with WNs and produced almost same results. But OCT scanning is more economical than MRI; therefore we can go for OCT than MRI for the early diagnosis of AD. From the existing work analysis of MRI and OCT images using FGWN and NN has been done. In future we can compare FGWN with other segmentation techniques other than those which has not mentioned in this paper. Also for defining the network structure of a WN, an efficient constructive algorithm could be used.

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