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An Accurate Plaque Characterization using Feed Forward Neural Network

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***Abstract*- Computer Aided Diagnosis CAD is useful in detection of carotid atherosclerosis into symptomatic or asymptomatic in cardiac health. With the help of patents CAD system the symptomatic versus asymptomatic plaque is classified in ultra sound images. The system involves four steps preprocessing, feature extraction, feature selection and classification using feed forward neural network. Preprocessing is used to remove unwanted portions in the image, feature extraction is used to extract the required image portion, feature selection is used to select the required matrix values for classification of images into symptomatic or asymptomatic and blood clot will be detected using feed forward neural network. Feed forward neural network classifier classifies symptomatic or asymptomatic plaque and detects the condition of plaque and blood clot. The system was evaluated with 93 ultra sound carotid images and obtained classification accuracy is 94.50%.**

Keywords- Computer Aided Diagnosis (CAD), Region Of Interest, Discrete Wavelet Transform (DWT), Feed Forward Neural Network(FFNW).

I. INTRODUCTION

Stroke is the one of the leading cause of death in the world. Stroke will disrupt the blood flow which block the oxygen supply to the part of brain cells and the cells will die with lack of oxygen supply to the cells. This disturbance is due to blockage or leakage in blood vessels. Stroke and heart disease are related to high blood pressure and atherosclerosis. Presence of plaque in blood vessels will block the blood flow and cause stroke or heart disease [2],[3],[4].

For atherosclerotic cardiovascular diseases diagnosis of plaque can make real difference in the treatment. To reduce the risk of stroke and heart disease plaques are surgically removed from affected area [6],[7]. The diagnosis system, detection and carotid surgery leads to the quality of the successful treatment. Ultrasound imaging is cost effective and it will produce good result for medical imaging. Even though the ultrasound imaging has significant advantages in detecting cerebrovascular disease it still has some limitations. The correlation between histological evaluation of carotid plaques and ultrasonographic features are poor. Due to the low spatial resolution and ultrasound artifacts these limitations appear. By improving the ultrasonographic image quality using extraction of good features and adequate image preprocessing techniques the diagnosis of plaque may improve [8],[9].

To detect the carotid atherosclerosis into symptomatic or asymptomatic using computer-aided diagnosis (CAD) is useful in the analysis of cardiac health. With the help of the patented CAD system called Atheromatic the symptomatic and asymptomatic plaque classification is done in carotid ultra sound images. This operation involves four steps 1.pre-processing 2.feature extraction using discrete wavelet transform 3.feature selection with averaging algorithms 4.classification using feed forward neural network.The block diagram of the classification system is shown in the fig 1. The ultra sound image is pre-processed and given for feature extraction. The feature extraction is done using discrete wavelet transform. From the feature extracted image feature selection is obtained. The feature selected values are fed to the feed forward neural network for symptomatic and asymptomatic plaque classification.

II. MATERIALS AND METHODS

Fig 1 shows the proposed system block diagram. The ultrasound images are preprocessed and fed to feature extraction using DWT. The extracted features are selected and classified using feed forward neural network.

A. Ultrasound images and preprocessing

In this paper we use 93 ultra sound carotid plaque images out of that 46 were asymptomatic and 47 were symptomatic. Ultrasound imaging is the second popularly used technique after x-ray to map the human body and its functions.

Ultrasound imaging uses same principle used by bats and sonar. In medical imaging the operation of x-ray is a sound wave that is passed on human body it will strike the body organs and bounce back a echo which consist of information about the patient body as image. This image consists of the information about body organs to diagnose the symptoms about several diseases.

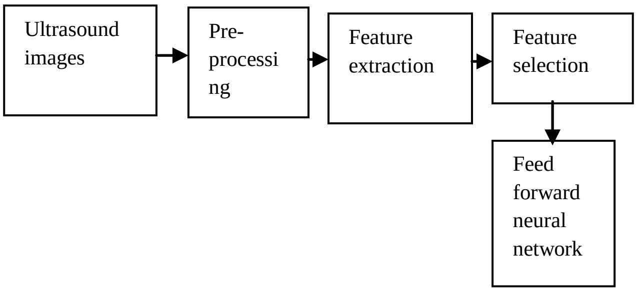

Fig 1. Block diagram for classification

The images obtained from ultrasound scan of the human body may contain some unwanted portions which may not be useful for diagnosis of plaques. To remove the unwanted portions in image the region of interest (ROI) is calculated for the images to be processed on the system. The ROI calculated image constitutes less than 25% of the original image, so the classification process will become more easily by calculating ROI and it will be useful to detect the symptomatic and asymptomatic plaques with this method. Figure 2(a), 2(b) and 2(c) shows the symptomatic plaque, asymptomatic plaque and blood clot. Figure 3(a), 3(b), 3(c) shows the ROI selected symptomatic plaque, asymptomatic plaque and blood clot.

B. Feature extraction

For feature extraction 2-D DWT and its averaging algorithms are used in this paper. In image processing feature extraction is the form of dimensionality reduction, the dimensionality reduction is achieved when the input to an algorithm is too large to be processed in it. Feature extraction is the process of transforming the input data into set of features that can be applied to the classifier. The extracted features are properly chosen that the features should have relevant information from the input data in order to get reduced representation of input data instead of full size input.

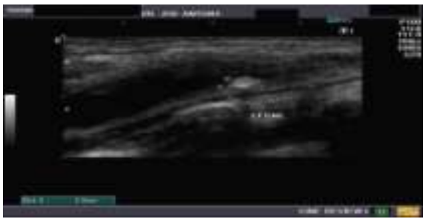

Fig 2. (a) symptomatic carotid image

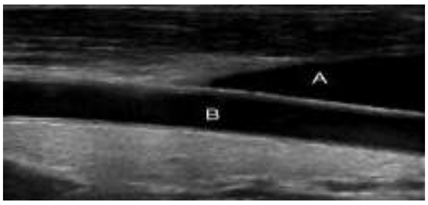

Fig 2. (b) asymptomatic carotid image

Fig 2 . (c) blood clot

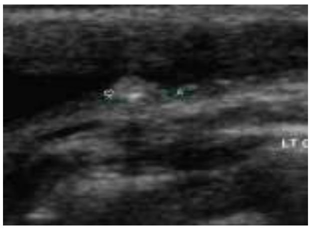

Fig 3 . (a) ROI selected symptomatic carotid image

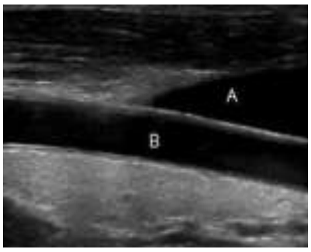

Fig 3(b) ROI selected asymptomatic carotid image

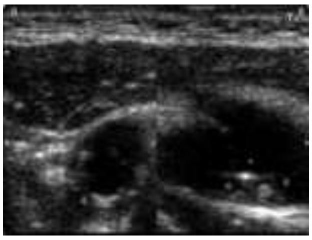

Fig 3(c) ROI selected blood clot

The detail and approximation coefficients are calculated using The equations (1) and (2).

$$H_o=\sum_{i=-\infty}^{\infty} x[i]h[2n-i] \qquad (1)$$

$$G_o=\sum_{i=-\infty}^{\infty} x[i]g[2n-i] \qquad (2)$$

In this paper we have evaluated the image with several wavelet functions. Out of those functions biorthogonal 3.1 (bior3.1) produced better result hence bior3.1 family is used in this work [5] .

In 2-D DWT the input image rows are filtered with one high-pass filter and one low-pass filter combination. The high-pass filter output is known as detailed coefficient and low-pass filter output is known as approximation coefficient. These high pass filter and low-pass filter output are down-sampled to get the redundant sampled value which has high information content. With this operation the bandwidth gets reduced and the frequency resolution gets doubled. The down sampled output of high-pass and low-pass filter is filtered with sets of high and low-pass filters for columns. The first level 2D-DWT produces four matrices values namely Dh_1, Dv_1, Dd_1 and A_1, the second level 2D-DWT produces four matrices in each of the obtained matrices Dh_1, Dv_1, Dd_1 and A_1.The figure 4 and 5 shows DWT decomposition and image decomposition. The elements of these matrices are intensity values and its number of elements is too high which cannot be used for classification directly. Therefore we used two averaging methods and energy of the intensity values to select the features used for classification in feed forward neural network. Two averaging methods and the energy of the intensity values are calculated using the equation (3),(4) and (5). The features obtained using these equations for symptomatic and asymptomatic plaques are shown in the table I.

Avg Dh1= (1/L×M)

$$\sum_{x=(L)} |\, Dh1(x,y)| \sum_{y=(M)} |Dh1(x,y)| \quad (3)$$

Avg Dv1= (1/L×M)

$$\sum_{x=(L)} |\, Dv1(x,y)| \sum_{y=(M)} |Dv1(x,y)| \quad (4)$$

Energy (E)=(1/L²×M

$$\sum_{x=(L)} (Dv1(x,y))^2 \sum_{y=(M)} (Dv1(x,y))^2 \quad (5)$$

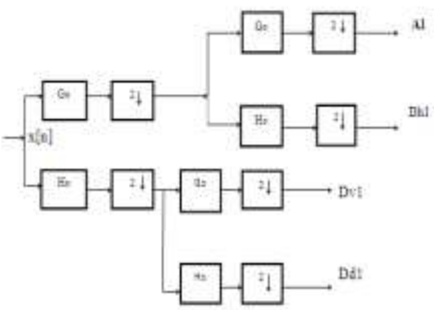

Fig 4. DWT decomposition

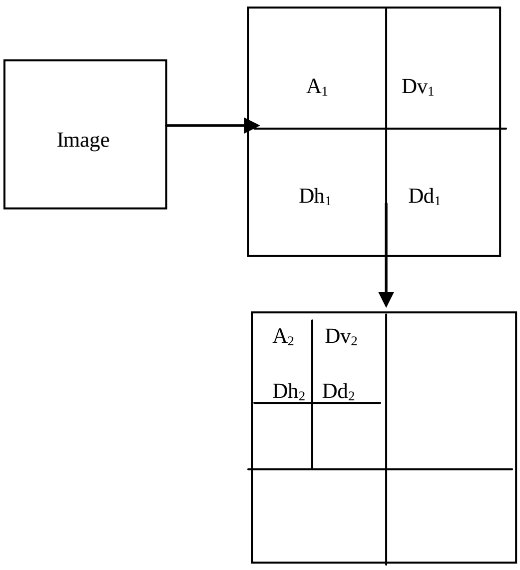

Fig 5. image decomposition

TABLE I .Symptomatic versus asymptomatic features obtained using DWT BIOR 3.1 wavelet function.

Features	Symptomatic	Asymptomatic
Avg Dh1	0.1411	-0.4069
Avg Dv1	0.0727	0.1427
Energy(E)	0.0051	0.0045

C .Feed Forward Neural Network

Artificial neural networks are very popular image processing and data mining tool. The function of artificial neural networks is attempts to model the algorithm like human thought which can be efficiently run on a computer. The human brain is formed with neurons which send activation signals in the brain to control the human function, likewise human brain the artificial neural network also contains artificial neurons which sends activation functions between one another and calculate the outputs according to their inputs. Therefore neural networks can be useful for several applications such as clustering, classification, function approximation, time series prediction, and descriptive modeling. In this paper the system is evaluated with feed forward neural network.

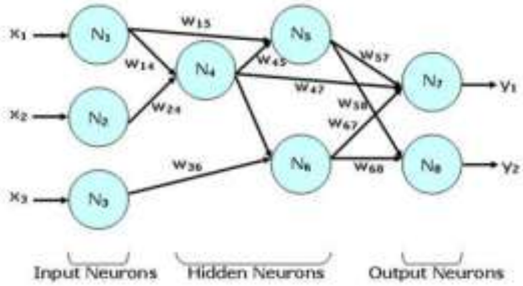

Fig 6 . feed forward neural network

Information's in feed forward neural network will moves only in forward direction, from the input neurons to the output neurons through hidden neurons. To activate the inputs in network the input activation function is activated at input neurons and to get the output the output activation function is activated at the output neurons. The equation (6) and (7) shows the input and output activation functions. The classification operations are performed accurately in hidden neurons and output is transferred to output neurons. The neurons in each layers sends activation to the other neurons in next layers called weights. The weights consist of source and destination addresses which delivers the data to the proper destination the weights are given by $W_{i,j}$ where i is the source and j is the destination.

$$a(X)= b+\Sigma_i w_i x_i \quad (6)$$

$$h(X)= g(a(X)) \quad (7)$$

In the classification of plaque and blood clot using feed forward neural network the symptomatic plaque and blood clot are given a value of 1 and the asymptomatic plaque and blood clot are given a value of -1. The feed forward neural network provides better classification accuracy by separating the 1 and -1 by a hyperplane.

In this paper three sets of images are used, two sets are used for training and one set is used for testing. The input image is compared with testing set of images, if the input image value is -1 or near to -1 the feed forward neural network will classify it as asymptomatic and if the input image value is 1 the feed forward neural network will classify it as symptomatic.

III. RESULTS

A. Significant features

The feature selected values such as horizontal coefficient, vertical coefficient and energy are fed to the feed forward neural network for detection of unknown class. The features are obtained using DWT with bior3.1 wavelet.

B. Classification results

In this paper we compared the performance of several wavelet functions. The biorthogonal bior3.1 function performed better compared to other wavelet functions. In this paper three sets of images are used, two sets are used for training and one set is used for testing. In this method 93 images are used for testing among those 46 images were asymptomatic and 47 images were symptomatic. These images are classified using feed forward neural network to find the unknown class.

The feed forward neural network performs better result than the previous classification methods. In this method its performance is calculated by number of true positive (TP), true negative (TN), false positive (FP) and false negative (FN). True positive (TP) is the number of symptomatic samples identified as symptomatic. True negative (TN) is the number of asymptomatic plaques classified as asymptomatic. False negative (FN), is the number of symptomatic samples classified as asymptomatic, and false positive (FP) is the number of asymptomatic samples classified as symptomatic. The probability that the technique will classify the symptomatic cases which are calculated by the formula TP/ (TP + FN) called as sensitivity. The probability that the technique will identify the asymptomatic cases which are calculated by the formula TN/ (TN +FP) called as specificity. The ratio of the number of correctly classified samples to the total number of samples which are calculated by the formula (TP + FP)/ (TP + FP + TN + FN) called as accuracy. PPV is the consideration of symptomatic subjects among those who were labeled symptomatic by the technique. NPV is the consideration of asymptomatic subjects among those who were labeled asymptomatic by the technique. Our result shows that the feed forward neural network offers better result than the previous methods with accuracy of 94.5%, sensitivity of 93.61% and specificity of 95% for the classification of symptomatic and asymptomatic plaques. The performance calculation is shown in the table II.

TABLE II
Performance calculation of symptomatic and asymptomatic plaques

FFNW input	93
True negative(TN)	42
False negative (FN)	3
True positive (TP)	44
False positive (FP)	2
Accuracy (%)	94.5
Specificity (%)	95
Sensitivity (%)	93.6
PPV (%)	95.6
NPV (%)	93

IV. CONCLUSION

It is very difficult to diagnose the blood clot symptomatic and asymptomatic plaques from ultrasound images using image processing. Only experienced surgeons can able to detect the difference between blood clot, symptomatic and asymptomatic plaque in ultrasound scanned images. Our present system diagnoses some of the difficulty in classification of plaques and blood clot. It can be used as a diagnostic tool in modern clinical practice in detection of carotid plaques. Our system uses DWT for feature extraction and diagnoses the classes with accuracy, specificity and sensitivity. With this method we obtained highest classification accuracy of 94.5%. This accuracy is higher than the methods implemented in similar studies in the literature. Therefore we believe the proposed method can be considered as an effective technique which serves as a effective tool for the vascular surgeons in patients for treatment of risky stenosis. To improve the accuracy furthermore, our feature work includes in studying more feature extraction methods to improve accuracy.

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