Classification of Carotid Artery Abnormalities in Ultrasound Images using an Artificial Neural Classifier

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Abstract: *This work presents a computer-aided system for the identification of plaques and atherosclerosis of carotid abnormalities and the individuals at risk of stroke. Intima Media Thickness (IMT) of carotid artery is the standard biomarker of subclinical atherosclerosis and plaques. Conventional IMT measurement by expert sonologist is time consuming, associated with subjectivity and the process becomes difficult when the number of patients is very large. This paper proposes a standard protocol to diagnose patients efficiently and the process is made extremely fast. In this paper, the decision making ability of an artificial learning machine is investigated in carotid ultrasound artery image classification. Architecture with multilayer Back Propagation Network (BPN) using Levenberg-Marquardt training with good generalization capabilities and extremely fast learning capacity that overcomes the local minima problem of generalized BPN has been proposed. Carotid images are preprocessed, normalized and segmented to extract eighteen different feature sets and given as input to Artificial Neural Network (ANN). The selected features are found to be the good choice of feature vectors and have the ability to discriminate between normal and abnormal image. The proposed system is robust to any ultrasound image artifact. ANN classifier is evaluated using 361 ultrasound images. The efficiency is measured by validating the outputs of this decision support system with that of medical experts. This system improves the classification rate, reaching the diagnostic yield of 89.43%. The simulation results depicts that ANN achieves good classification accuracies with less implementation complexity when compared with manual operation.*

Keywords: *Artificial neural network, multilayer back propagation network, ultrasound carotid artery, carotid intima-media thickness, subclinical atherosclerosis, decision assist system.*

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1. Introduction

Cardiovascular Diseases (CVDs) comprise a major portion of non-communicable diseases which leads to sudden disability and death. In fact, CVDs in 2030 would be the single largest cause of death in the world accounting for more than a third of all deaths [5]. Progression of plaque in the carotid artery is detected and monitored by using high resolution ultrasound carotid Intima Media Thickness (IMT) measurement. Thickness measured between two layers of innermost arterial wall tunica intima and tunica media is called IMT. Determination of IMT is a complicated task because the layers of Carotid Artery (CA) are thin and moreover the relatively low contrast structures of CA are affected by ultrasound artifacts. Many semiautomatic techniques were developed for Intima Media Complex (IMC) segmentation. Conventional method of IMT measurement is by manual delineation of the intima and the adventitia layers.

The manual IMT tracing methods are tedious, time consuming and unreliable in addition to requirement of well-trained sonologist and the measurements also suffer from intra observer and inter observer variability. In recent years, for better diagnosis of diseases medical imaging have provided powerful non-invasive tool to probe various pathologies of human body [11]. The extraction of internal structures and the removal of noise artifacts present in the medical ultrasound images is a challenging task for many clinical applications. Computer-Aided Diagnosis (CAD) scheme has been developed that aids the sonologist to investigate in a quantitative manner regarding the nature of the subjects. Gutierrez *et al*. [6] suggested a novel semi-automated method of carotid diameter measurement and thickness of walls in ultrasound images where the manual selection of CA in the image frame is required. Retraining is required when there is a change in the image characteristics which is the limitation of dynamic programming [10] method and this method of segmentation are often device-dependent.

Loizou *et al*. [12] proposed snake-based algorithms for the carotid segmentation and was effective for processing both normal and abnormal carotids, but severely suffered from the initialization problem [2]. Cohen *et al.* [3] proposed a balloon snake model, where the authors used finite element method to calculate the continuity function. Gustavson *et al.* [7] implemented four different methods, namely maximum gradient, dynamic programming, mathematical models, and matched filter for segmenting the carotid IMT and the lumen. The results showed that the dynamic programming algorithm performed better than the others in respect of speed and boundary continuity, although the detected boundaries could not be drawn correctly.

Present work develops an Artificial Neural Network (ANN) classifier based decision-assisting system that aids in ultrasound CA diagnosis. Multilayer back propagation network using Levenberg-Marquardt training algorithm has been developed and implemented for ultrasound CA classification. The performance of the developed scheme is evaluated based on classification efficiency, testing time and training time and for all the 361 CA images taken under study. The efficiency of the system is measured by cross validating the classification results with that of expert radiologists.

The paper is organized as follows. Section 3 proposes an ANN classifier for CA diagnosis. The theory of backpropagation network and the application of backpropagation algorithm using Levenberg-Marquardt training are explained in subsection 3.1. Section 3.2, describes the extraction of texture features that aids in diagnosis. Section 4 deals with accuracy of the proposed classification scheme along with relevant data. Summary of the results and few issues to be addressed are presented in section 5.

2. Overview of Intima Media Complex Neural Tracking System

Aim of this paper is to discriminate healthy subject and patients with manifest disease related to CVD in a practical and scientifically contemporary manner. The four stages involved in designing a computer aided system are (a) Image acquisition (b) Image Preprocessing (c) Region of Interest (ROI) extraction and segmentation (d) Classification of CA by ANN.

Figure 1 gives the overall view of the developed scheme to realize a CA medical diagnosis decision-assisting system. From the ultrasound scanning system images are acquired which is then provided as input to the CAD system. Ultrasound VOLUSON E8 with the frequency of 5Mhz is used to acquire images. Image obtained is normalized and filtered to remove the speckle noise using anisotropic diffusion filter. Geodesic active contour is used to extract ROI and thus helps in segmenting intima media layer from CA image. This segmented image is used for extracting and calculating features from which 18 different features have been extracted and given as input to ANN. The ANN model captures the local statistical regularities of textures and can map the input data into different classes directly with one network [16]. This is useful in predicting the level of the medical indicator and also useful for classifying images as normal and abnormal [1].

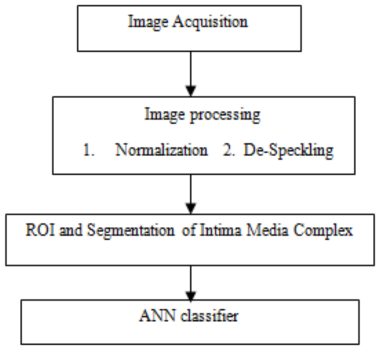


Figure 1. Overall view of the proposed scheme.

3. Proposed Artificial Neural Network Classifier for Carotid Artery Diagnosis

This paper presents an automated IMC tracking and classification of ultrasound CA images based on IMT. The schematic diagram for the proposed neural tracking system is depicted in Figure 2. Segmentation of CA-IMT using geodesic active contour algorithm is illustrated. The ultrasound CA image is first filtered using Kuan filter and then using anisotropic diffusion process. Moreover, it avoids blurring of images at larger scales. It is then applied to gradient filtering and the result of applying the gradient to the image is mainly to indicate the boundaries of the object and to filter out the less important portions of the image. Next the region of interest is selected and geodesic active contour is applied for a specified number of iterations. Thus, the edges of the artery walls are detected and segmented.

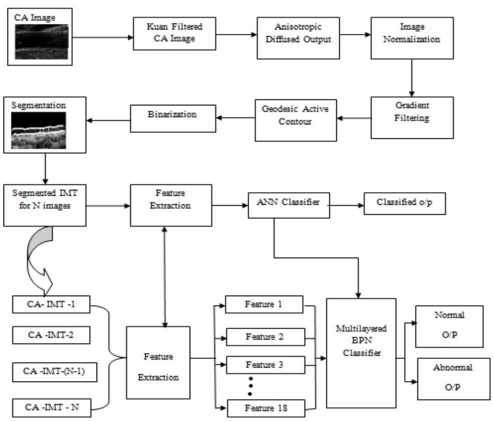


Figure 2. The proposed multilayer BPN based ANN-CA classification scheme.

The IMC neural classifying scheme of the proposed method is also given in Figure 2. The feature extraction module, extracts eighteen different features like moment, intensity profile, instantaneous amplitude, instantaneous frequency etc. The extracted features are given to the nodes of the input layer of ANN classifier. Based on the weights, thresholds, extracted features and IMT, the classifier predicts the output and classifies the CA.

3.1. Multilayer Back propagation Network

The back propagation learning method is the most popular method to train networks in problems like sonar detection, character recognition, speech recognition and many more applications of image processing. The MBPN architecture is a network of nodes arranged in layers like input, hidden and output layers as shown in Figure 3. A feed forward ANN needs a training scheme to tune weights and biases of all of the layers. Conventional neural network schemes uses back propagation ANN that usually adopts gradient-based learning, that are susceptible to various convergence problems and also the curvature of the error surface may not be the same in all directions. This paper proposes a neural network training algorithm that uses Levenberg-Marquardt (LM) algorithm to overcome such convergence problems and evaluate it for multicategory CA plague diagnosis. In LM algorithm the parameters are updated adaptively between the Gauss-Newton and gradient descent update, i.e., when algorithmic parameter λ is small it results in a Gauss-Newton update and when λ is large it takes gradient descent update.

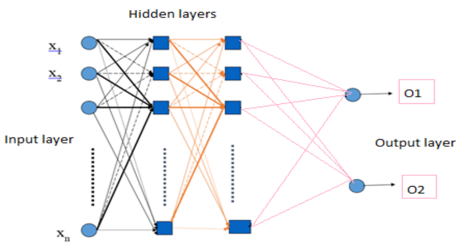


Figure 3. Multilayered backpropagation network with 18 input nodes and 2 output nodes.

Thus, the LM utilizes the best features of both the Gauss-Newton and gradient-descent method. The input layer of the ANN is built with 18 neurons one for each of the 18 different features that have been extracted. These neurons provide the weights to all the hidden layer nodes. In output layer we have one output node and if it is 1 it belongs to normal class and 0 for abnormal class. This paper presents a nonlinear least squares optimization algorithm, and the ways to incorporate it into the backpropagation algorithm. The LM algorithm converges fast for networks that contains only few hundred weights and results in accurate training. Marquardt's suggested update relationship [15] as:

$$[J^T WJ + \lambda \, diag(J^T WJ)] \, h_{lm} = J^T \, W(y_m - y_f) \tag{1}$$

where, J=jacobian matrix, W=weight matrix, λ=algorithmic parameter, y_m=measured data y_f=curve fit function, h_{lm}=perturbation. The backpropagation algorithm using LM training [16] is given as a flowchart in Figure 4.

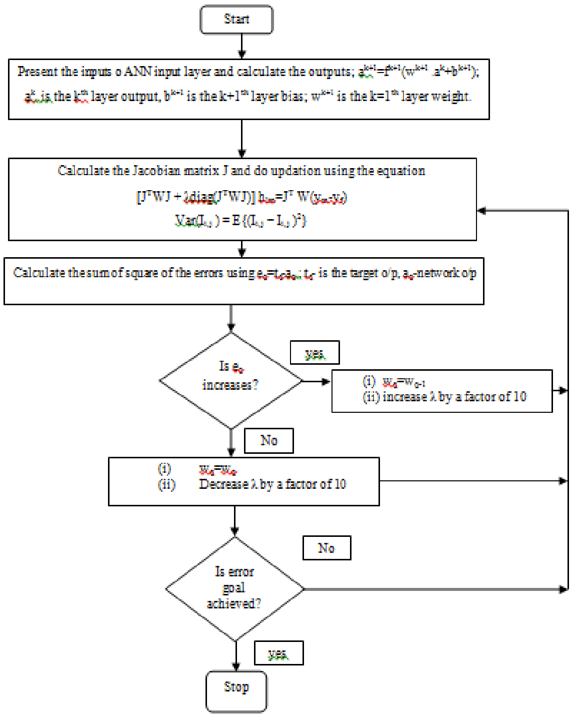


Figure 4. Flowchart for the backpropagation algorithm using Levenberg-Marquardt training.

3.2. Diagnostic Texture Feature Extraction

The feature extraction processes of CA images are discussed in this section. Each CA image was selected starting from 10 mm proximal to the carotid bifurcation and extends till 10 mm distal. For the ROI, binarization is applied from which IMT is formulated. The next features are the local variance and mean of an image *I* and is defined as:

$$Var(I_{i,j}) = E\{(I_{i,j} - I_{i,j})^2\} \tag{2}$$

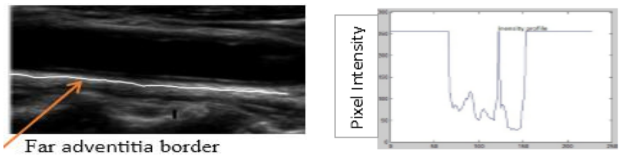
$$I_{i,j} = E\{I_{i,j}\} \tag{3}$$

The estimated local variance of the image gives the quality measure of the structural similarity between the cropped images. Standard deviation measures how the data's are spread around the mean, and it is the square root of the variance. Skewness measures the asymmetry of the probability distribution of a real-valued random variable. Kurtosis is a descriptor of the shape of a probability distribution.

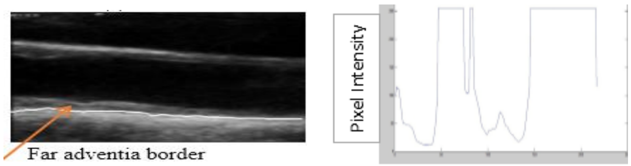
To analyse the significant texture changes [4], the Instantaneous Amplitude (IA) and the magnitude of the Instantaneous Frequency (IF) over each layer are extracted [13]. The 2D image acquired is represented using the following complex function as

$$f^{\wedge}(x, y) = f(x, y) + j \, H_{2d}[f(x, y)] \tag{4}$$

Where $f(x, y)$ denotes the input image and H_{2d} denotes the two-dimensional Hilbert transform operator applied along the columns. Hilbert transform of the preprocessed image yields the mean value of magnitude of the complex expression and the phase part of the transformation yields the instantaneous frequencies. Intensity profile is a plot of the intensity values along the line segment. Figure 5 gives the intensity profile for the normal and abnormal sample image.



a) Normal CA image. b) Intensity profile of a.



c) Abnormal image. d) Intensity profile of c.

Figure 5. Intensity profile for a normal and an abnormal CA sample image.

From the Figure 6-a, it is evident that for normal CA image the real and imaginary part variation follows the same and regular pattern. Instantaneous amplitude varies rhythmically and the peak is found to be 130 and the minimum value less than 5. Instantaneous frequency is very high and the peaks are found to be at normal intervals and the variations between the peaks are same for a normal carotid artery of age group more than 60.

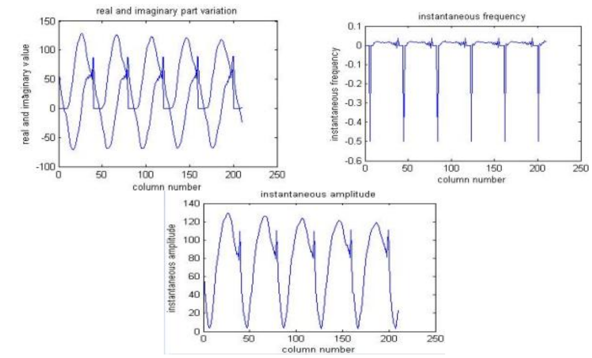
From the Figure 6-b it is clear that the real and imaginary part variation follows different and irregular patterns. Instantaneous amplitude graph shows the peak value as 15 and the minimum value as 1. Instantaneous frequency plot shows that the variations between the peaks are different for an abnormal carotid artery of age group more than 60.

Thus eighteen features were extracted from the pre-processed CA image are listed in Table 1.

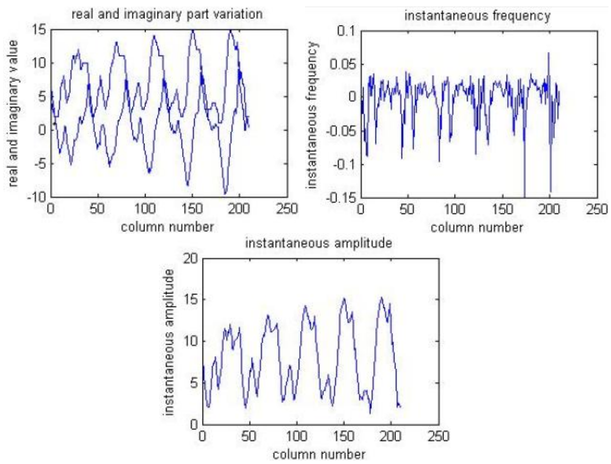
Table 1. List of extracted feature from preprocessed ultrasound CA image.

No	Features
1	Starting point of Intima
2	Thickness of the extracted image
3	Gaussian distribution of the extracted image
4	Random permutation of row of cropped image R1
5	Random permutation of column of cropped image R2
6	Minimum point between R1 and R2
7	Maximum point between R1 and R2
8	Difference D= R1-R2
9	Standard deviation of D
10	Variance between of D
11	Skewness between of D
12	Kurtosis between of D
13	Moment between of D
14	Intensity Profile
15	Instantaneous Amplitude
16	Instantaneous Frequency
17	Mean
18	Median

These feature vectors consists of extracted feature and calculated features of CA image which were given as the input to the nodes of input layer of ANN classifier.



a. Variations of IA and IF for a normal image.



b. Variations of IA and IF for an abnormal image.

Figure 6. Variations of IA and IF for a normal and abnormal image.

4. Results and Discussions

4.1. Data Sets and Criteria used

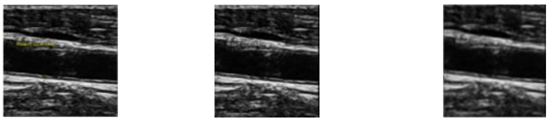
This section presents the experiments made to evaluate the proposed method on real ultrasound images. 361 ultrasound carotid artery images were collected from M/s Bharat scans, Chennai, Tamilnadu, India for analysis and evaluation of the proposed classifier. Studies were done using a MATlab environment-MATlab R2011b on an Intel® Core i3, 2.40 GHZ PC with 3 GB memory.

The ultrasound carotid artery image database is created consisting of total 361 images spanning normal and abnormal classes. These samples include 167 normal CA and 194 abnormal CA. The 361 samples of CA are randomly split into 256 training sets and 105 testing sets.

4.2. Simulation Results of Carotid Artery Segmentation

The output at each stage of segmentation process is presented below in Figure 7. The original input image is despeckled using Kuan filter. Kuan filtered image is allowed for anisotropic diffusion. PSNR achieved using anisotropic diffusion is good compared to all other filters and mean square error is also reduced. The edges of the artery wall are detected using geodesic active contour and binarization is done to calculate IMT. From the selected ROI and binarization output IMT is formulated by using three steps.

- *Step 1*. Total thickness=total number of white pixels in the ROI.
- *Step 2*. Average thickness =total thickness / no of columns.
- *Step 3*. Thickness (cm)=average thickness * (2.54/96dpi).



a) Ultrasound CA image. b) Kuan filtered CA image. c) Anistorpic diffused output.

d) Gradient output. e) Geodesic active contour output. f) Binarization output.

Figure 7. Outputs for the CA-IMT segmentation algorithm.

Table 2. IMT measurement for a sample normal and abnormal CA image.

No	Nature of Image	Iterations	No. of White Pixels	Algorithm IMT	Expert IMT
1	Normal image	250	1768	0.0583 cm	0.06cm
2	Abnormal image	400	2793	0.1170 cm	0.12cm

Carotid IMT is the total of Thickness of Intima (IT) and Thickness of Media (MT). ROI and binarization of the sample normal and abnormal image is given in Figures 8 and 9. The number of iterations required to draw ROI and the IMT measurement obtained using the algorithm is compared with expert IMT measurement for the two samples is given in Table 2.

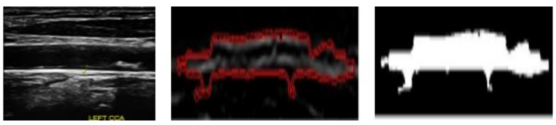


Figure 8. Sample Normal image, ROI and Binarization.

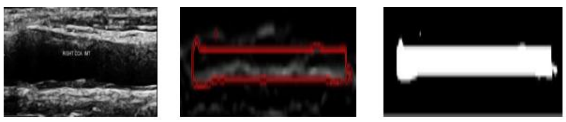


Figure 9. Sample abnormal image, ROI and Binarization.

4.3. Medical Expert Validation

ROI is segmented and then IMT is calculated and the results are tabulated and compared with the manual measurement taken by the sonologist.

From the Table 4, it is clear that automated IMT values are very much close to the manual measurement done by specialized and experienced sonologist. We have classified the images in to three age groups like less than 40, between 40 to 60 and greater than 60. It has been simulated and tested for all these types of images and found that it works well for both normal and abnormal carotid artery images of all age groups. Table 3 shows that results obtained by the proposed method are more or less similar to the manual measurement by well-trained sonologist.

Table 3. First set of evaluation parameters.

No.	Evaluation Parameters	Formula	Calculated Values
1	Classification accuracy	(TP+TN) /(TP+TN+FP+FN)	0.8943
2	PPV	(TP)/(TP+FP)	0.8667
3	NPV	(TN)/(TN+FN)	0.5385
4	Sensitivity	(TP)/(TP+FN)	0.8842
5	Specificity	(TN)/(TN+FP)	0.7778
6	Positive likelihood ratio	S/(1-Sp)	3.9789
7	Negative likelihood ratio	(1-Se)/Sp	-0.1369

Table 4. Comparison of IMT values for manual and automated algorithm in pixel units.

Nature of the image	$IMT_{Automated}$	IMT_{manual}
Normal image (<40)	2.25	2.268
Normal image (40-60)	1.86	1.89
Normal image (>60)	3.01	3.024
Abnormal image (<40)	3.82	3.78
Abnormal image (40-60)	6.62	6.426
Abnormal image (>60)	4.53	4.536

4.4. Artificial Neural Network Classifier Outputs

The 361 ultrasound CA images are randomly split into 256 training sets and 105 testing sets at each trial and 100 trials were carried out to obtain average performance. Accuracy of classification is defined as the proportion of correct tests to all tests performed. Positive Predictive Value (PPV) is the likelihood that a subject with a positive test actually has the disease. Negative Predictive Value (NPV) is the likelihood that a subject with a negative test does not have the disease. Sensitivity is the likelihood that a result will be positive if the subject actually has disease. Specificity is the likelihood that a result will be negative when the subject is truly free from disease. Positive likelihood ratio is the probability of a positive test in those with disease compared with the probability of a positive test in those without disease. Negative likelihood ratio is the probability of a negative test in those with disease compared with the probability of a negative test in those without disease [9]. The Table 3 gives the obtained values as the result of ANN classification of ultrasound CA. Evaluation is based on calculating the parameters like True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

Training time and testing time are estimated for 256 training and 105 testing samples respectively. TANSIG is used as the activation function at hidden layer and PURELIN is used at output layer. The training time and testing time taken by CPU in seconds for momentum β=0.0042 and the learning rate η=0.7 is given in Table 5.

Table 5. Second set of evaluation parameters.

No.	Evaluation Parameters	Obtained Values
1	Training time (sec)	45.3495
2	Testing time (sec)	04.71
3	Accuracy %	89.43
4	Best learning rate (η)	0.7
5	Best momentum (β)	0.0042

Self-Organizing Map (SOM), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) classifiers were also tested and the results were reported. The efficiency achieved using RBF-SVM was 86.7%. SOM classifier and the statistical KNN classifier which was implemented for the classification of the carotid plaques achieved a diagnostic yield of 73.1% and 67.1% respectively while this proposed methodology achieves a diagnostic yield of 89.43%.

5. Conclusions

In the present work, an attempt has been made to implement a decision assist system using artificial neural classifier that facilitates automated classification of ultrasound CA using 18 different extracted and estimated features of CA. This work develops a computer assists to experts to perform accurate diagnosis of CA images on large scale.

A well-structured and robust ANN classifier is proposed for the ultrasound carotid artery classification. Among the main novelties of the proposed approach is the classification of CA based on 18 different features. The training time is greatly reduced with the feed forward backpropagation network with LM training algorithm. The convergence obtained is much faster because it adaptively updates the parameters. The success of the classifier is based on the 18 extracted features that aids in classification. Results shows that ANN classifier has good generalization performance and is best suited for networks with a few hundred weights. This scheme developed represents a generalized and standard methodology of automated segmentation and better IMT measurement. The presented modeling scheme may aid to develop an algorithm for multicategory classification of carotid images.

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