33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Neural Network Based Classifier for Cardio Vascular Diseases Based on Vascular Aging

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Abstract— **Vascular Aging is a cardio vascular risk factor. Vascular aging and vascular disease go together. Cardio vascular diseases (CVDs) remain and will continue to be the leading cause of death in all countries. This rate is more, particularly in developing countries. This paper attempts to classify subjects tested as healthy or not based on the data obtained from the analysis of common carotid artery. The network taken for training and testing is a multilayer perceptron (MLP) with one hidden layer. Data obtained from the analysis has three parameters – diameter, distension and age of the subject under test. Subjects of varying age groups are taken for this. Network successfully classifies whether the person is 'healthy' or 'should meet the cardiologist for further treatment'. Since this is done at a very early stage, this will be a milestone in the treatment of cardio vascular diseases. Moreover, this uses data obtained from the analysis of ultrasound images of the carotid artery and therefore is a cost effective method.**

I. INTRODUCTION

Recent reports of world health organization alarm us with the fact that, if unchecked 50% of worlds cardiac diseases will be from India. Age is the major risk factor for cardiovascular diseases. Change in life style, work culture and high stress are other important contributing factors. Large arteries can be modeled with age. This is done with dilatation of the vessel, vessel lumen diameter, intima media thickness and endothelial dysfunction [1]. Aging blood vessels are fertile soil in which seeds of cardio vascular diseases flourish. Atherosclerotic diseases, chronic heart failure or stroke results from these diseases[2]. The epidemic of cardiovascular diseases is no longer restricted to Western societies. Cardiovascular diseases now spread their roots in India and are expected to surpass infectious diseases as the leading cause of mortality and disability. The major reasons for such changes in the pattern of diseases and massive increase in heart disease are reported to be (i) growing life expectancy (ii) decreasing infant mortality rate (iii) the decline in infections disease rate (iv) the increase in gross national product and in per capita income enabling the population of the nation to adopt to unhealthy life styles and behaviors of more developed countries and (v) interaction among genetic factors and newly altered environment.

Cross-sectional studies in humans have found that wall thickening and dilatation are prominent structural changes that occur within large elastic arteries during aging [3]. The age-associated increase in intima-media thickening and endothelial dysfunction are accompanied by both luminal dilatation and a reduction in arterial compliance or distension with an increase in vessel stiffness [3]. This gives a clear idea that altered mechanical properties of the vessel wall influence the development of atherosclerosis and the latter via endothelial cell dysfunction and other mechanisms influence vascular stiffness and hence cardiovascular diseases [4].

Aging alters the structure and function of large elastic arteries. To understand why age is so closely linked to cardiovascular disease and ultimately to understand the causes and develop cures for this group of diseases, it is essential to understand what is happening in the heart and arteries during normal aging – aging in the absence of disease. This work focuses on the effects of aging on blood vessels.

Common Carotid Artery(CCA) is an elastic artery. Studies [5] reveal that elastic arteries better suit the purpose than muscular arteries like femoral artery as they are not clearly altered by age. CCA diameter increases [6] as a consequence of hypertension and may also increase as the thickness of the arterial wall increases due to atherosclerosis and plaque deposits. Also, long-term outcome of patients with carotid artery disease rests on modifying risk factors for circulation problems that can also lead to blockage in heart and leg arteries [7]. Therefore CCA is a highly compliant artery for the study of elastic properties like distension.

The distension of an artery during a cardiac cycle depends on the elastic characteristics of the vessel wall. Distension is the change in diameter of the artery from diastole to systole. Measurement of distension helps to characterize the elasticity of the vessel and diameter helps to identify deposits and hence stiffness in the vessel wall. Therefore these two parameters are used for classifying the subject tested as healthy or not.

Manuscript was received on June 20,2011.
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I. DATA SET

The arterial movements are recorded in the Ultrasound machine **Prosound Alpha-10** from **Aloka**. ProSound Alpha 10 introduces the “Ultimate Compound Technology”, setting a new standard in diagnostic ultrasound. With the Compound Pulse Wave Generator Aloka is able to control the waveform on a performance level. The probe used is a multi-frequency probe of range 5-10 MHz. For this application the frequency is set at 7.5 MHz, since the CCA is at a optimum distance from the skin. The probe is placed about 2cm before the bifurcation of the common carotid artery for uniformity in measurement for the all the patients. The video is recorded for 2 to 3 cardiac cycles showing the longitudinal view as well as the blood pressure of the patient is also checked and recorded. ECG is also recorded by placing probes in the radial artery and posterior tibial artery for each patient so that systole and diastole variations are seen on the screen.

The recordings are done for subjects of varying age groups in Mediscan systems, Chennai. Dr. Suresh was instrumental in this work. 71 subjects of age varying from 22 to 75 are used for recording the function of the carotid artery. The movie recorded is sliced into frames. About 20-30 frames accounting to 2 to 3 cardiac cycles are obtained for each subject from the movie. Figure 1(a) shows a single frame obtained from the movie in the transversal view and figure 1(b) shows a single frame obtained from the movie in the longitudinal view. Diameter of the artery is measured for all the frames [8]. Segmentation of the transversal view of the artery is very complex. The diameter measured from transversal view of the artery had erratic variations. Also the boundary extracted did not fit exactly on the inner wall of the artery. This is seen from the graph which is shown in figure 2. Therefore the diameter is measured from the boundary extracted from the longitudinal view of the artery[9]. The graph is shown in figure 3.

For longitudinal section, distance of the lumen artery wall from the center to top as well as center to bottom is measured. The graph also shows the radius of the artery wall measured for each frame. Table 1 shows the values of diameter measured for various subjects of varying age groups. Age groups of the subjects tested varied from 22 to 75. The maximum diameter and the minimum diameter are measured.

The table shows the diameters measured during the systole and diastole i.e. when the vessel wall constricts and expands. The variations in diameter in the first category are from (6.7$\pm$0.7) mm to (7.3$\pm$0.7) mm whereas in the second category the variations are from (6.8$\pm$0.7) mm to (7.5$\pm$0.6) mm. This implies that many subjects in both categories have same diameter. Similar findings are seen in other categories also. Therefore, diameter of the subject alone can never be sufficient for evaluating the vascular age. The parameter, which greatly helps in evaluating the age, is the distension. Distension is another important parameter for the analysis of cardiovascular diseases. This helps to decide the functionality of the artery

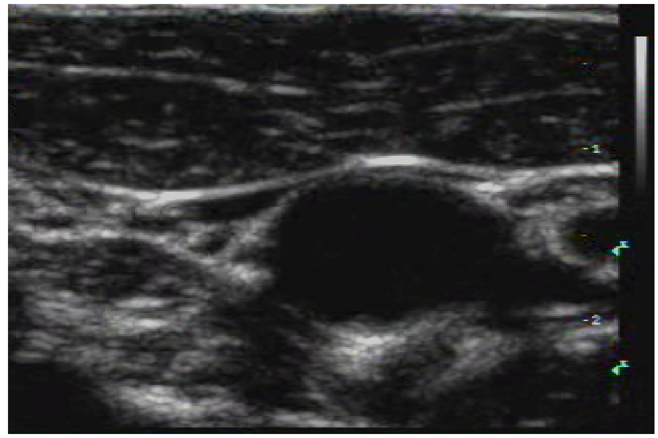

Fig.1(a) Sample frame showing transversal view of CCA

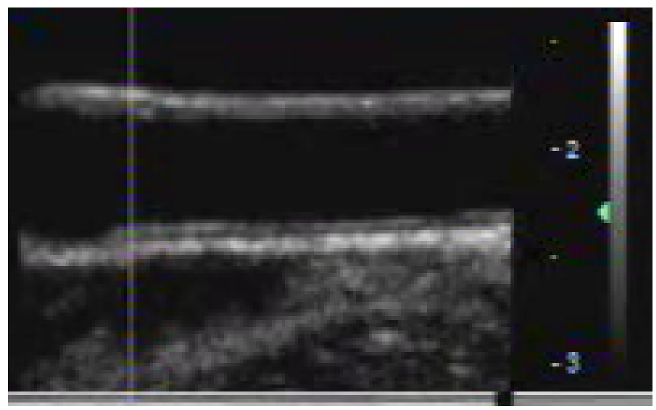

Fig.1(b) Sample frame showing transversal view of CCA

Distension is calculated from the diameter of the CCA. The distension for a particular subject under test is shown in figure4. This is calculated from the measured diameter. Changes in the diameter and distension are more pronounced only when age increases. The back propagation network is proposed for classification of the subjects under test. The input pattern for the BPN includes diameter, distension and age.

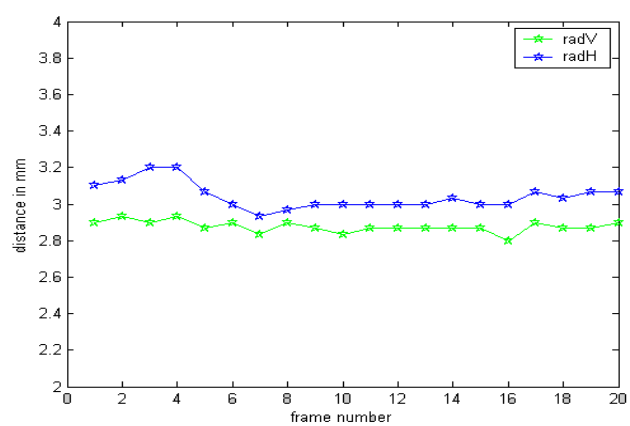

Fig.2 Diameter measured from transversal view of the CCA

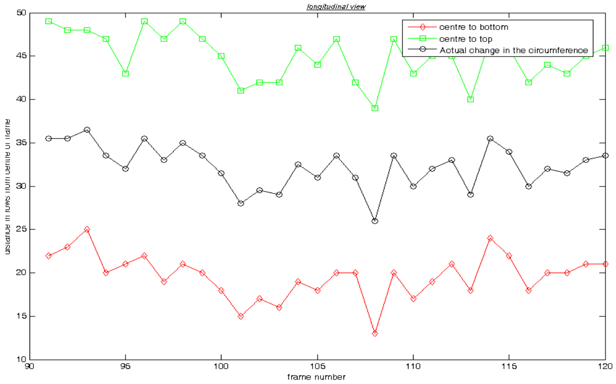

Fig.3 Diameter measured from longitudinal view of the CCA

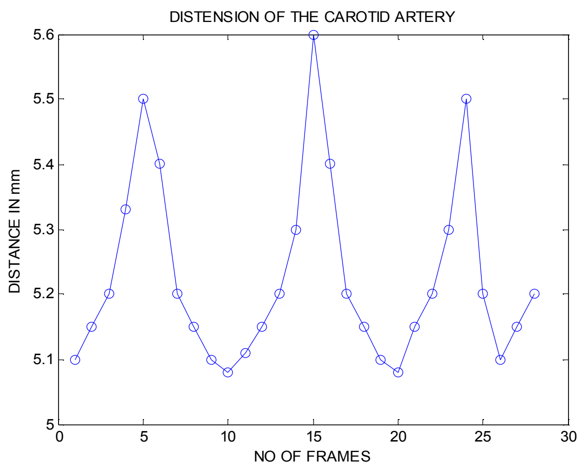

Fig.4 Distension of the CCA

II. NEURAL NETWORK CLASSIFIER

Artificial neural networks are computing elements which are based on the structure and function of biological neurons. This is useful in applications which involve pattern recognition, classification etc. The number of layers and nodes in a network may vary and the overall architecture may be feedback or feed forward. Single layer perceptron is sufficient to distinguish linearly separable classes. If the boundaries are complex then the number of layers must be increased.

Neural networks can perform the task of supervised classifier [10]. This work needs a decision making classifier which would identify the class or category that represents an input pattern. The net is expected to recognize through a learning process using training prototype from each class of inputs. Therefore a back propogation algorithm with sigmoid activation function is used.

Back propagation Network (BPN) learns a predefined set of input-output example pairs by using a two-phase *propagate-adapt* cycle. After an input pattern has been applied as a stimulus to the first layer of network units, it is propagated through each upper layer until an output is generated. This output pattern is then compared to the desired output, and an error signal, mean square error (MSE) is computed for each output unit. The error signals are then transmitted backward from the output layer to each node in the intermediate layer that contribute directly to the output. But each unit in the intermediate layer receives only a portion of the total signal, based roughly on the relative contribution the unit made to the original output. This process repeats, layer by layer, until each node in the network has received an error signal that described its relative contribution to the total error. Based on the error signal received, connection weights are then updated.

TABLE 1
DIAMETER OF CCA FOR SUBJECTS OF DIFFERENT AGE GROUPS

S. No.	Age Group (Years)	No. of subjects	Distension (mm)	Diameter	
				Max.(mm)	Min.(mm)
1.	22-35	21	0.7-0.8	7.3 ± 0.7	6.7 ± 0.7
2.	35-42	18	0.6-0.7	7.5 ± 0.6	6.8 ± 0.7
3.	43-50	10	0.6-0.7	8.0 ± 0.6	7.3 ± 0.6
4.	50-60	12	0.5-0.6	8.1 ± 0.6	7.5 ± 0.5
5.	60-75	10	0.4-0.5	8.1 ± 0.6	7.7 ± 0.6

By this process, the MSE of the network for the pattern presented is minimized. This procedure is summed up. After presenting the last training pattern, the network is considered to have learnt all the training patterns through iterations, but the MSE is large. To minimize MSE, the network has to be presented with all the training patterns many times. The significance of this process is that, as the network trains, the nodes I the intermediate layers organize themselves such that different nodes learn to recognize different features of the total input space. After training, when presented with an arbitrary input pattern that is noisy or incomplete, the units in the hidden layers of the network will respond with an active output if the new input contains a pattern that resembles the feature the individual units learned to recognize during training.

Figure 5 shows the BPN. The net input into the j[th] hidden unit is shown in equation (1).

$$net_{pj}^{\;h} = \sum_{i=1}^{N} w_{ji}^{\;h} x_{pi} + \theta_j^{\;h} \tag{1}$$

where w_{ji}^{h} is the weight on the connection from the i^{th} input unit, and θ_j^h is the bias term. The output of hidden layer is represented in equation (2).

$$i_{pj} = f_j^h(net_{pj}^{\;h}) \tag{2}$$

The weights on the hidden layer and output layer are updated according to equations (3-4)

$$w_{ji}^{\;h}(t+1) = w_{ji}^{\;h}(t) + \eta \partial_{pj}^{\;h} x_i \tag{3}$$

$$w_{kj}^{\;O}(t+1) = w_{kj}^{\;O}(t) + \Delta_p w_{kj}^{\;O}(t) \tag{4}$$

III. CLASSIFICATION

The BPN uses the steepest-descent method to reach the global minimum. The connections between nodes are initialized with random weights. It is seen that optimal results are obtained only when weight values are between 0.1 and 0.5. The error is propagated backwards towards the input layer and the weights are updated. Learning constant η is chosen as 1 for optimal results by trial and error process.

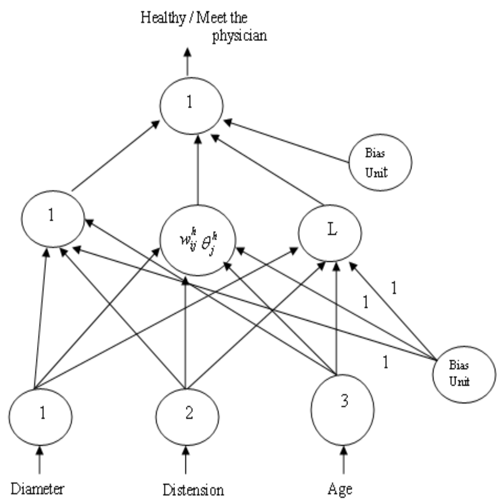

Fig. 5 Back Propogation Network with single output node

All the inputs and outputs are normalized. Only one node is decided in the output layer as there are only two classes of outputs. The user can decide the mean square error as well as the number of nodes in the hidden layer. Three inputs are decided i.e., diameter, distention and age of the subject. Therefore there are 3 nodes in the input layer. For the given input output patterns, the network converges faster when the mean square error is 0.01.

Patterns are provided for both normal and abnormal subjects. 50 inputs are taken for training the network and remaining are taken as test patterns. A pattern from the training set is presented in the output layer of the network and the error at the output layer is calculated. This procedure is repeated for all the training patterns with MSE of 0.0. The output displayed by the test network is **'Healthy Person'** if the diameter and distension are within the limits for the specified age group. If the distension is less due to the stiffness developed or the diameter is more due to abnormal aging of the vessel the output displayed is **'Should meet the physician'**. As this study has recorded only healthy subjects, the output obtained for the subjects tested shows that they are healthy. Some abnormal data obtained recommend them to meet the physician for further diagnosis and treatment. **This confirms that this system for evaluating the vascular aging is working perfectly.** Table 1 shows the diameter and distension measured for different age groups. This work takes the peak (systole) diameter measured for training and testing of all subjects.

IV. CONCLUSION

Table 1 shows the distension of CCA for subjects of different age groups. The first category is between 22-35 years. Changes in the diameter and distension are more pronounced only when age increases. Therefore more years are grouped in this category. The last category has 15 years group because only less number of subjects are available in this group. The variations in diameter in the first category are from (6.7 ± 0.7) mm to (7.3 ± 0.7) mm whereas in the second category the variations are form (6.8 V 0.7) mm to (7.5 ± 0.6) mm. This implies that many subjects in both categories.

The steady increase in the number of patients with myocardial infarcation or cerebral infarcation, both of which are considered to be the main cause of atherosclerosis is becoming a serious problem. Cross-sectional studies in humans have found that wall thickness and dilatation are prominent structural changes that occur within large elastic arteries during aging Vascular aging is characterized not only by age-associated increase in large vessel lumen and stiffness of vessel wall but also by wall thickening and endothelial dysfunction. This work considers only the first two parameters which is sufficient for vascular aging. Only healthy subjects are taken for study. If the subjects tested must know the severity of the problem, adding the IMT as the third parameter in determining the age can do it. Not only that, but, the severity of the unsuccessful vascular aging can also be informed clearly to the subjects tested.

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