Artificial Neural Networks (ANN) Approach to PPG Signal Classification

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Abstract: *Ageing and disease states associated with an increase in cardiovascular events alter the physical characteristics of blood vessel walls and impair the pulsatile function of arteries. A variety of techniques are employed to evaluate the mechanical properties of arteries. All techniques have theoretical, technical and practical limitations that impact on their widespread application in the clinical setting and use as measurement tools to improve cardiovascular risk stratification [2]. This paper presents Artificial Neural Network (ANN) approaches that classify a PPG signal into two distinct classes. Multistage based on time-series data mining framework for building classification models in the presence temporal high dimensional data, was suggested. First we reduce the dimensionality by smoothing the input signal and we assume that the smoothing accuracy serve features by exploring the highly parallelised nature of multilayer feed-forward networks (MFN). The classification results showed that multilayer perceptron neural network employing back propagation-training algorithm was effective to distinct between the two classes, based on the good selection of the training data set samples. The correct classification rate was 100% for the training data sets and 94.7% for testing data sets. We used for testing the algorithm 170 samples, in which 56 samples are pathologies and 114 are healthier. The paper also discusses the future research directions.*

Keywords: *PPG Signal, Multilayer perceptron neural network, vascular disease and diabetes.*

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1. Introduction

Finger photoplethismography (PPG) is a commonly used technique in medicine [4]. Photoplethysmography is based on the determination of the optical properties of a selected skin area. For this purpose non-visible infrared light is emitted into the skin. More or less light is absorbed, depending on the blood volume in the skin. Consequently, the backscattered light corresponds with the variation of the blood volume. Blood volume changes can then be determined by measuring the reflected light and using the optical properties of tissue and blood [8]. Neural nets emerged from psychology as a learning paradigm, which mimics how the brain learns. There are many different types of neural networks, training algorithms, and different ways to interpret how and why a neural network operates [6]. Over the past few years, an explosion of interest in ANN models and their applications has occurred. ANNs posses a number of properties which make them articularly suited to complex classification problems. Unlike traditional classifiers, ANN models can examine numerous competing hypotheses simultaneously using massive interconnections among many simple processing elements. In addition, ANNs perform extremely well under noise and distortion [10] [11].

2. Pre- PPG non-invasive blood pressure measurement techniques

The oscillometric method is the oldest one used in man. In 1866 this method was described by Marey. He used a small cuff, snugged around a limb, which was inflated with water above systolic pressure. During deflation he registrated the oscillations of a mercury column on a carbon drum. Pressure was read from a mercury manometer. The point of maximal oscillations was decided to be the mean arterial pressure. In 1896 Riva-Rocci introduced the palpatory method, only suitable to determine the systolic pressure. He used a cuff with air connected to a mercury manometer to measure the pressure applied to the brachial artery. The pulse was determined by palpation of the a. radialis at the wrist and the pressure was increased until the pulse disappeared (systolic pressure). The oscillation of the cuff pressure with the heartrate, when the cuff was smoothly being deflated, was noted. It results from pressure transmission from the artery to the cuff, which is the basis of all oscillometric measurements. The problem where to locate the point of diastolic pressure in the sequence of oscillations could not be solved. In 1905 a solution was proposed by Korotkoff, who introduced the auscultatory blood pressure measurement. He described the characteristic sounds (named after him) heard with a stethoscope in the "elbow" when the pressure in the inflated cuff was lowered through systolic and diastolic pressure. He used the same cuff as Riva-Rocci. This method still is the basis of the auscultatory method used today. The method slightly improved after 1940, when intra-arterial measurements had become available that could be used as a "gold standard". In particular attention was given to the small size of the cuff, which especially in the obese turned out to overestimate the blood pressure level. The American Heart Association recommends for the cuff-bladder dimension a width of 40% of the circumference of the limb, long enough to encircle 80% of the circumference, to be placed such that it is centered over the artery to be compressed. The automated oscillometric devices currently used still follow the oscillometric principle described by Marey, using a cuff snugged around a limb. A detailed description, characteristic for many of these devices, is given by Ramsey. The cuff is inflated to approximately 160 mmHg for the first determination, or to 30 mmHg above the previous systolic pressure found. Some automated devices use microphones or a Doppler signal to determine the systolic, diastolic and mean pressure points during deflation of a cuff. The microphone instruments use the abrupt change of frequency content of the Korotkoff sound. A filter circuit is able to detect the muffled end point of the sound at diastolic pressure, which is more reliable than the detection of disappearance of sound. Nevertheless, errors may occur due to ambient sounds or sounds generated by patient movement. Doppler blood flow detection under the cuff can be used to determine the systolic pressure in specific small arteries. It is useful in the evaluation of peripheral vascular disease. Only recently a continuous *non-invasive* measurement of finger arterial blood pressure in adults and children older than one year has introduced as photoplytismography (PPG) [3].

3. Research Methods

3.1 Data Measurements

The PPG sensor is intended for clinical use in conjunction with any standard PC. Three basic modules are needed for its operation the sensor head (fingertip probe with amplifier), standard AD-card and a standard hard disk. With the signal processing software and space for storage of the recorded data [1]. The system consists of two PPG pulse amplifiers, each with bandwidth of 0.005-15Hz.

The transmission PPG probe of the commercial pulse Oximetry OEM 601 from Digital Dolphin consisted of a light emitting diode (LED) of 865 nm and a PIN photo-detector (peak spectral response 865 nm) located on different sides of the probe, so that they were attached to the two contra-lateral surfaces of the finger [9]. The PPG probe were attached to the right or left hands or right and left legs. For data acquisition we use a software driver provided with the instrumentation; the computerized system allowed to optimally adapting the amplification level for obtaining a non-saturated signal. The PPG signal was digitized (275 Hz) and stored in ASCII format. Data processing was performed off-line.

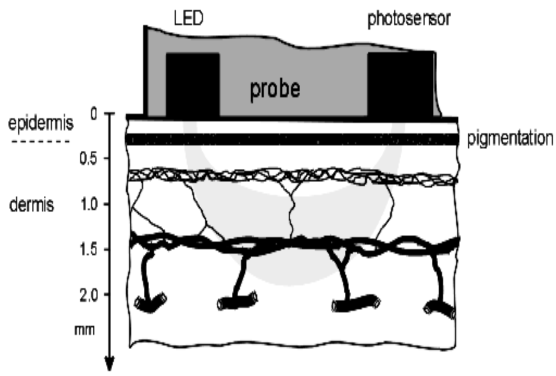

Figure 1: Photoplethysmography Measurements[8]

A PPG Data recordings were from two experimental groups of healthy and pathologies volunteers aged 21-64 years groups were composed of 11 pathologies and. 37 healthier. The subjects were seated during examination, with their hands laid comfortably on the table at the level of the heart. Recording time was between 1 to 2 min after a rest period of 10-min. Room temperature was 25^{o} C.

3.2 Data Pre-processing Strategy and Feature Extraction

The Data collected are highly dimensional, by considering the 60 seconds of the time recording the file database contain (16500 samples).

The curse of dimensionality related to high-dimensional data sets in classification or data analysis has attracted numerous researchers and ignited vivid research activities with regard to dimensionality reduction Techniques.

Over the last three decades, empirical modeling approaches based on linear time series analysis such as ARMA (auto-regressive moving average) have commonly used and have been found to show satisfactory results in many applications to data pre-processing and dimensionality reduction. However, these linear empirical approaches are not always guaranteed to provide certain results due to the inherent non-linearity of components that consisted the systems and the uncertainty with respect to the states and characteristic of those systems.

Due to rapid innovation of computer technology, the artificial neural network (ANN) technique, which is a powerful tool for nonlinear modeling. The main advantages of using ANN are: (1) it has the ability to learn a complex nonlinear relationship with limited prior knowledge of the system structure and (2) it can perform inferences for an unknown combination of input variables.

We propose a two stages Networks Based On multi-layer perceptron with back-propagation strategy. The sequence of layers is selected to resemble feature extraction procedures performed in living systems [10].

First we segment the data and after we apply a successive smoothing than we use a simple mean square error regression based on inverse of covariance at the end the prediction accuracy are assumed as features and labeled and used to feed the pattern recognition stage.

In first stage Network, we perform a smoothing of the original signal: $X = \{x_1, x_2, \dots, x_n\}$:

$$y_k^{Smoothed} = \sum_{i=-w}^{w} \prod_i x_{k-1}$$

Where $\prod_{-w}, \prod_{-w+1}, \prod_{-w+2}, \dots, \prod_{w-1}, \prod_w$ are values of a smoothing window, such that

$$\sum_{i=-w}^{w} \prod_i = 1$$

and w represents the window with; $i = 1, 2, \dots, n.$ and the parameters $\prod = \{\prod_i\}$ was the weight of the network layer and was a task specific.

In second stage network**,** the high frequency signal $\Delta Y = \{\Delta y_1, \Delta y_2, \dots, \Delta y_n\}$ are reconstructed from the original signal, using the smoothed one:

$$\Delta y_k = yk - y_k^{Smoothed}, k = 1,2,..,n$$

No training is required in both pre-processing stages of neural networks.

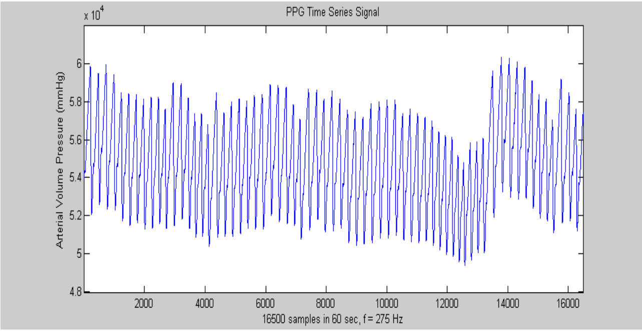

Figure 2: Subject_1 Left Arm (LA) raw_ppg signal

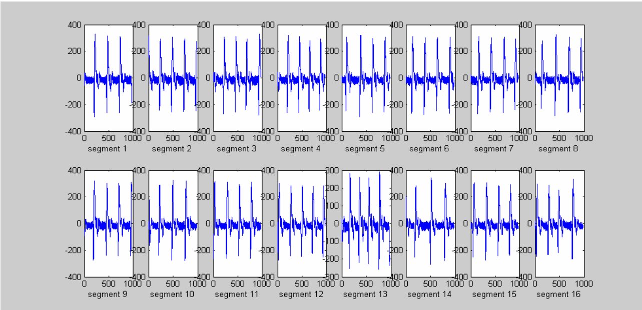

Figure 3: Subject_1 Left Arm (LA) raw_ppg signal after segmentation and smoothing.

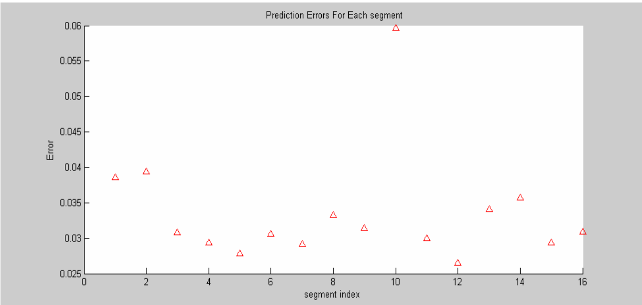

Figure 4: Subject_1 Left Arm (LA) raw_ppg signal reconstruction accuracy.

3.3 Multilayer Perceptron (MLP) Neural Network

A multilayer perceptron (MLP) is a network architecture in which has been formulated with two adaptive parameters, the scaling and translation of the postsynaptic function at each node [7].

ANNs consist of a great number of processing elements (neurons), which are connected with each other; the strengths of the connections are called weights. For the modeling of physical systems, a MLP neural network is commonly used. It consists of a layer of input neurons, a layer of output neurons and one or more hidden layers. In order to cope with nonlinearly separable problems, additional layer(s) of neurons placed between the input layer (containing input nodes) and the output layer are needed leading to the MLP architecture. The most popular approach to finding the optimal number of hidden layers is by trial and error [11][5]. In the present study, the MLP neural network consisted of one input layer, two hidden layers, and one output layer and the decision about the number of determined empirically.

In ANNs, the knowledge lies in the interconnection weights between neurons. Therefore, training process is an important characteristic of the ANN methodology, whereby representative examples of the knowledge are iteratively presented to the network, so that it can integrate this knowledge within its structure [11][5]. There are a number of training algorithms used to train a MLP and a frequently used one is called the back-propagation training algorithm [11][5]. However, back-propagation has some problems such as slow convergence for many applications. The quick propagation training algorithm, is a modified back-propagation algorithm developed to speed up the training of the network [5].

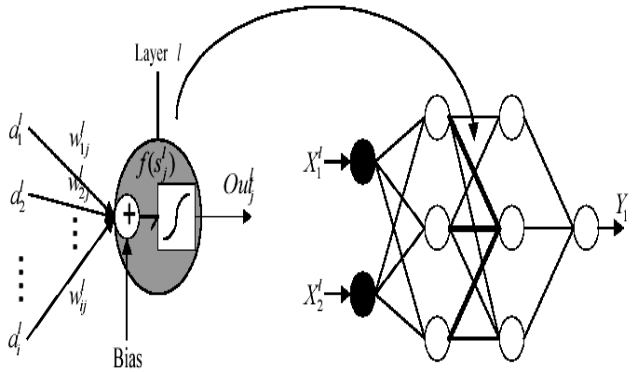

Figure 5: Architecture of the multi-layer feed-forward neural network (MFNN).

In MLP neural network, each neuron *j* in the hidden layer sums its input signals x_i after multiplying them by the strengths of the respective connection weights w_{ji} and computes its output y_j as a function of the sum:

$$y_j = f(\sum w_{ji} x_i)$$

Where *f* is activation function that is necessary to transform the weighted sum of all signals impinging onto a neuron. In this study, the activation function for hidden neurons was the conventional sigmoidal function with the range between zero and one. The sum of squared differences between the desired and actual values of the output neurons *E* is defined as:

$$E = (1/2) * \sum_j (y_{dj} - y_j)^2$$

Where y_{dj} is the desired value of output neuron j and y_j is the actual output of that neuron. Each weight w_{ji} is adjusted by adding an increment Δw_{ji}. To it. Δw_{ji}. Is selected to reduce *E* as rapidly as possible. How Δw_{ji}. Is computed depends on the training algorithm adopted. Quick propagation algorithm is then invoked to adjust all the weights in the network and gives the change $\Delta w_{ji}(k)$. In the weight of the connection between neurons *i* and *j* at iteration *k* as:

$$\Delta w_{ji}(k) = -\alpha(\partial E / \Delta w_{ji}(k)) + \mu \Delta w_{ji}(k-1)$$

Where α is called the learning coefficient, $\Delta w_{ji}(k\text{-}1)$, is the weight change in the immediately proceeding iteration and μ is the momentum coefficient and defined as:

$$\mu = \frac{(\partial E / \Delta w_{ji}(k))}{(\partial E / \Delta w_{ji}(k-1)) - (\partial E / \Delta w_{ji}(k))}$$

In this study, learning coefficient was determined empirically and α was taken as 0.1, the momentum was taken as 0.1, the input scaling [-5 5] and the output scaling [.2 .8].

3.4 Gaussian Mixture Model (GMM)

Mixture Models are a type of density model which comprise a number of component functions, usually Gaussian. These component functions are combined to provide a multi-modal density. A Gaussian mixture density is a weighted sum of M component densities and is given by the form:

$$p(x \setminus \lambda) = \sum_{i=1}^{M} c_i b_i(x)$$

Where x is a d-dimensional random vector, $b_i(x); i = 1,.., M$ is the component density and $c_i; i = 1,.., M$ is the mixture weight. Each component density is a d-variate Gaussian function of the form:

$$b_i(x) = \frac{\exp\{-1/2(x-\mu_i)^2 (\Sigma_i)^{-1}(x-\mu_i)\}}{(2\pi)^{1/2} |\Sigma_i|^{1/2}}$$

With mean vector μ_i and covariance matrix $\sum_i$. The mixture weights satisfy the constraint:

$$\sum_{i=1}^{M} C_i = 1$$

The complete Gaussian mixture density is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities. These parameters are collectively represented by the notation: $\lambda = \{C_i, \mu_i, \Sigma_i\}$ i=1,..,M each feature is represented by such GMM and is referred to by his/her model. GMM parameters are estimated using the standard Expectation Maximization (EM) algorithm. Then using logarithms and the independence between observations, the feature identification system normalizes and computes $p(x \setminus \lambda)$ to make features recognition decisions.

4. Simulation Results

PPG classification is important in determining the health of an individual. Doctor's and Vascular Scientists are trained to examine a PPG and make a diagnosis. In some situations though, there is not always a trained Doctor's and Vascular Scientists on hand. Airports, amusement parks, and shopping malls are just a few of the places where computers are used to diagnosis a person's vascular condition if a life threatening condition occurs. This research attempts to mimic a Doctor's and Vascular Scientists diagnosis by implementing a neural network diagnosis algorithm. The scope of this project does not cover all the possible vascular diseases abnormalities. Instead, classifies a PPG into two distinct classes, which are Healthy and Diabetic. Having 14 feature vectors already extracted from the UKM/MALAYSIAN-HOSPITALS database, the next step was to develop a neural network to classify each of the samples. The network tested was a multilayer perceptron network with back propagation and Gaussian Mixture Model neural network.

Netlab toolbox was chosen to be the platform in this work. It is convenient for training and testing MLP, GMM and also provides many configuration choices for achieving better classification accuracy.

Success with MLP and GMM algorithms were achieved after appropriate scaling of data, and selection of the number of hidden layers.

The constants used to determine the 'optimal' MLP. Which were determined by several preliminary runs and then used for all successive MLP models That Used to Test the Data.

The 48 Subjects numbered From 1 to 48 in which The Subjects [2 3 5 6 42 43 44 45 46 47 48] are pathologies and others are healthier from four body sites Data Measurement, RA: Right Arm, LR: Left Arm, RL: Right Leg and LL: Left Leg.

Training Data Sets_1:

Subject: [LA] [1 4 3 7 8 5 9 10 6 11]

Table 1: The classification Rate Testing Data Sets_1

Testing Data Sets_1	MLP	GMM
LA [10 11 12 13 14 15 1 2 3 4]	90%	80%
RA [10 11 12 13 14 15 1 2 3 4]	90%	90%
LA [5 6 7 8 9 36 37 38 39 40]	100%	100%
RA [5 6 7 8 9 36 37 38 39 40]	90%	80%
RA [16 17 18 19 20 21 22 23 24 25]	100%	100%
RA [26 27 28 29 30 31 32 33 34 35]	100%	100%
LA [1 4 7 8 9 41] & RA[2 3 5 6]	100%	100%
LA[10 11 12 2 36 37 3 41 5 6]	80%	70%
LA[2 3 5 6 7] & RA [2 3 5 6 7]	90%	90%

Training Data Sets_2:

Subject: [1][LA RA], [4][LA LL RL],
[3][LA RA],[5][LA RA LL]

Table 2: The classification Rate Testing Data Sets_2

Testing Data Sets_2	MLP	GMM
[2][RA LA], [7][LA LL RL RA], [8][LA LL RA RL]	100%	90%
[9][LA LL RA RL],[15][LL RL],[13][RLLL], [6][RL RA]	100%	100%
[11][LA LL RA RL],[12][LA LL RA RL], [13][LA LL]	100%	100%
[2][RA LL], [5][RA LL], [6][RA LL] [14][LA LL RA RL]	80%	80%

Training Data Sets_3:

Subject: [40][LA RA], [41][LA RA],
[44][LA RA],[47][LA RA],[46][RL LL]

Table 3: The classification Rate Testing Data Sets_3

Testing Data Sets_3	MLP	GMM
[46][LA RA RL LL], [47][LA LL], [41][RA RL LA], [43][LL]	90%	90%
RA[20 21 22] [44][LA RA], [48][LA RA RL], [45][LA RL]	100%	90%
[41][RA RL LA] [46][LA RA RL LL], [47][LA LL], [43][LL]	100%	100%
[RA][23 25 28 29 20 30], [LA][40] [45][RL], [46][LA RA]	100%	100%

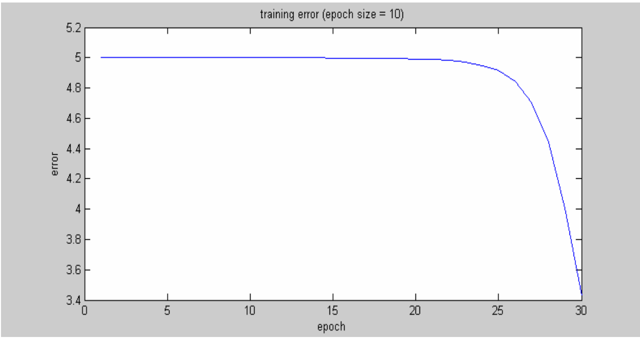

Figure 6: MLP Training Error Experiment2_1

Training Data Sets_2:

Subject: [1][LA RA], [4][LA LL RL],
[3][LA RA],[5][LA RA LL]

Testing Data Sets_1:

Subject: [2][RA LA], [7][LA LL RL RA],
[8][LA LL RA RL]

Training Rate: 100% & Testing Rate: 100%

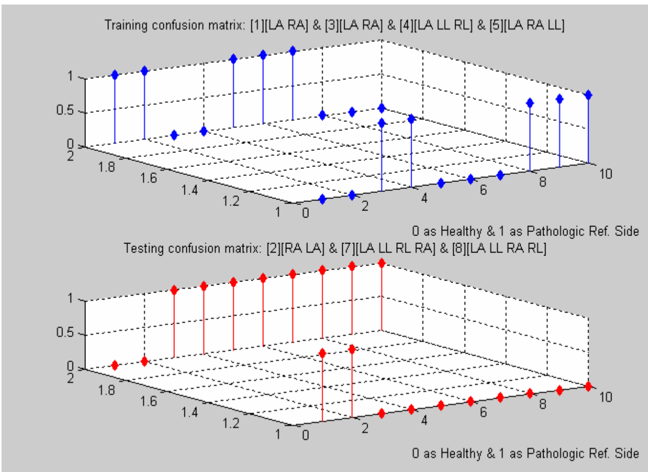

Figure 7: MLP Training & Testing confusion matrix Experiment2_1

5. Conclusion & Discussion

The first topic that needs to be discussed is the data that was sampled to train and test the MLP and GMM. The data were collected from Seremban Hospital using a commercial transmission PPG probe, the Pulse Oximetry OEM 601 manufactured by Digital Dolphin.

The PPG data were recorded from two experimental groups of volunteers consisting of 37 healthy (Type 1) and 11 pathologies (Type 2) aged between 21 and 64 years old. 170 data samples were used for training and testing. The data samples are then evaluated using the MLP and GMM classification methods. An artifact reduction algorithm was developed for pre-processing the data and shown to perform satisfactory. However, the satisfaction of the pre-processing stage cannot be judged before the feature recognition stage. Hence, the signals are inspected empirically and visually before using them for further analysis. An analysis was performed and a classification rate of over 94% was achieved. Upon further investigations, this classification rate was found to be useless, if the training data was chosen randomly from all the 170 samples. As a result, almost all of the training data was of Type 1 (Healthy) due to the fact that the PPG signal is not unique for each person. This is because, the PPG signal measured from different points on the body site are different and also the PPG signal measured from same body points at different times are different. For this reason, three different data sets based on three different training data sets are tested. Analysis of the data show that the classification accuracy becomes loose with the increase of the data size, and the Type 1 data are found to outnumbers Type 2. With this respect, a bin size of 10 data samples are found to be of the best size for testing the performance of the algorithm. From the 170 training and testing data samples with bin size of 10 data samples, 56 data samples were found of Type 2 with the remaining of the data sets are classified as Type 1, resulting in classification rate of 67% (114/170). This shows that the MLP is efficient in discriminating the two classes of the data using small data bin. It was found that for bin size of 15 data samples or greater; the accuracy of MLP decreases. Further examination of the MLP results showed that building the MLP was very volatile for a small size data. Upon examining, the best configuration obtained is 6-3-2. It was also found that the overall classification rate could vary by quite a bit, where in some situation there would be a 100% classification rate. The cumulative classification rates obtained are 94.7% for MLP and 91.17% for GMM. These results show the pre-processing algorithms employed to reduce dimension and extract features are effective and are applicable. However, the second stage of the features recognition was limited to the small size data (a bin of 12 data samples). Base on these analyses, it can be concluded that the PPG approach as a non-invasive way to investigate the vascular diseases still not an optimum method for vascular diseases diagnosis.

6. Future Research Suggestions Directives

PPG signal is not unique for each person and it depends on the psychological state of the person. For this reason, the analysis based on the quantity of data solely did not pose a great challenge. The real challenge is to investigate the anatomy of the data inside the veins of the target and to derive the projected artificial intelligence model of the vascular systems.

Based on this perspective, method of knowledge discovery using genetic algorithm based on fuzzy neural network is believed to be a better approach for classification of vascular disease. This approach involves the expert system in the data collection and preparation.

Another approach that could expand this work for future research is to apply the concept of multi-channels blind system identification used in wireless communication system. This is because, based on the medical fact, the channel dynamics from the central aortic flow to the peripheral pressure are expected to be different under different diseases. Hence, it would be useful to study the pressure waveforms of the target under different condition of the circulation.

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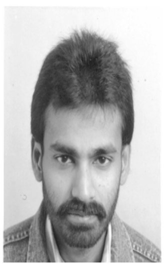

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