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Blood pressure and ECG signal interpretation using Neural Network

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Abstract
Electrocardiogram (ECG) and blood pressure (BP) monitoring is very important in daily life. If a patient is suffering from any disease, then monitoring of these parameters becomes essential at every segment. BP hints of the power strived by circulating blood because major vessels are located on the upper left or right arm to take blood away from the heart. It points out the vessel where the pressure is examined which is called arterial pressure (AP). Activity traces by ECG exists due to potential differences (PD) according to placement of the electrodes and lead selection (3-lead, 12-lead arrangement, etc.) on the body. ECG and BP are related to each other. One can derive from other. Automated detection is very important for heart rate variability (HRV) analysis and arrhythmia detection. Classification phase is covered by the neural network. Detected R-peak (Total beats) and Mean square error (MSE) have been considered for detecting accuracy of the neural network classifier.

Keywords: Electrocardiogram (ECG), blood pressure (B.P), arterial pressure (A.P), potential difference (PD.

Introduction

The electrocardiogram (ECG) represents the cardiac status of the patient, including various pathological information [1]. It shows myocardium generated current in every heartbeat [2]. One heartbeat is known as cardiac cycle. Each heartbeat is the combination of the P wave, the QRS complex, and the T wave. Each of them has its amplitude, frequency during cardiac cycle those are used for detecting cardiac arrhythmias [1,3-5,6]. The heart transmits blood directly into the central elastic arteries. In literature survey, various study explained that the central pressure affects to target organ damage and the incidence of cardiovascular complications. Therefore, with the help of patient heart status, other parameters information can be extracted [7]. Heart attack still remains the key factor of death worldwide [8-9]. Various factors are responsible for heart attacks, including; smoking, diabetes, high cholesterol, diet, alcohol [10-11]. Cardio Vascular Disease (CVD) considers several types of heart abnormalities such as coronary heart [10,12-13], congenital heart, rheumatic heart, Atrial Fibrillation (AF), inflammatory heart disease, etc.

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[10,14]. ECG signal changes in the acquisition process due to respiration activity, poor electrode contact, body movement, etc., and of long length [15-16] which transforms its analysis in a complex zone. Every Arrhythmia has its specific orientation, so here good classifier is necessary [17]. Involvement of the computer increases accuracy of diagnosis, thus Computer-based ECG analysis is required here for classifying status of the arrhythmias.

In this paper Neural Network (NN) is used for classifying different types of arrhythmias. It extracts the diagnostic information and full evidence of arrhythmia presence in the patient electrocardiogram (ECG) signal [18-19].

Methods

The proposed methodology is shown in Figure.1. PCA, ICA was used for dimensionality reduction as well as noise reduction.

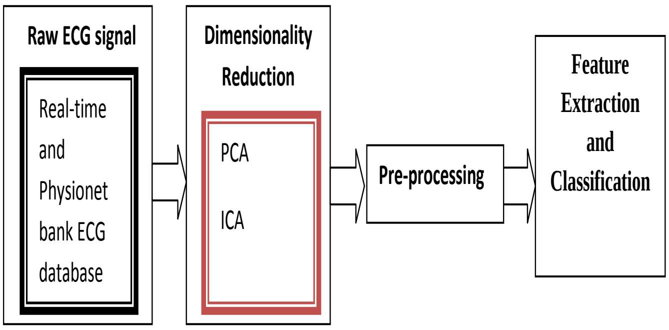

Figure:1 Proposed methodology in the paper

Raw ECG signal

Real-Time ECG database

This database prepared at 430 Hz sampling rate under the supervision of a skilled lab boy using two lead arrangements. 37 subjects were involved in this data acquisition program.

MIT-BIH Arrhythmia database

This database includes 48 recordings sampled at 360 Hz. This database was created by taking the recordings under the supervision of a cardiologist and technical expert for durations of 30 to 60 mins using two lead arrangements [20-21].

Dimensionality Reduction and Pre-processing

To analyze the long ECG dataset, it is very cumbersome. Thus dimensionality reduction process is followed throughout of the ECG dataset.

Principal Component Analysis (PCA)

PCA is a linear dimensionality reduction approach [22] based on least square criteria which indicates the essential diagnostic clue.

Independent Component Analysis (ICA)

ICA is a nonlinear approach [23-24] towards dimensionality reduction of the stored database (recording). It considers the observed signal is constituted by the linear mixing of source components and having the property of statistically-independent[25].ICA model with n linear mixtures $x_1, x_2, x_3 \dots\dots\dots\dots\dots . x_n$ of n independent components combined together in a mixture are expressed as;

$$x_j = a_{j1}S_1 + a_{j2}S_2 + .. + a_{jn}S_n, for\ all\ j$$

x is a random vector whose elements are a mixture of $x_1, x_2, x_3 \dots\dots\dots\dots\dots . x_n$ and S be the random vector with components $S_1, S_2, S_3 \dots\dots\dots\dots\dots . S_n$. The above equation model can be rewritten as the generalized form:

$$x = AS$$

The preprocessing step was followed by ICA [26] as first removing noise, the second segment of the ECG datasets into corresponding beats and last transforms uniform beats into uniform beats.

Feature Extraction and classification

Hilbert Transform (HT)

For extracting features hilbert transform were used which gives the analytic view of a real-valued signal. It gives the $\pm\frac{\pi}{2}$ phase shift in the output.

Neural Network (NN)

Neural Network (NN) is a well known classification technique. It consists of neurons as processing elements and their interconnections. It relies on weights for classifying the given datasets during the training phase. In general, it is the combination of an input layer, one or more hidden layer(s), and an output layer and these layers are attached together [27-28]. A different type of abnormality has its own characteristic, so it need various characteristics to be classified. Therefore, here versatile classifier is required for describing sets of features. For automatic diagnosing, NN classifies the disease effectively by changing its weights [29].

Results and Discussion

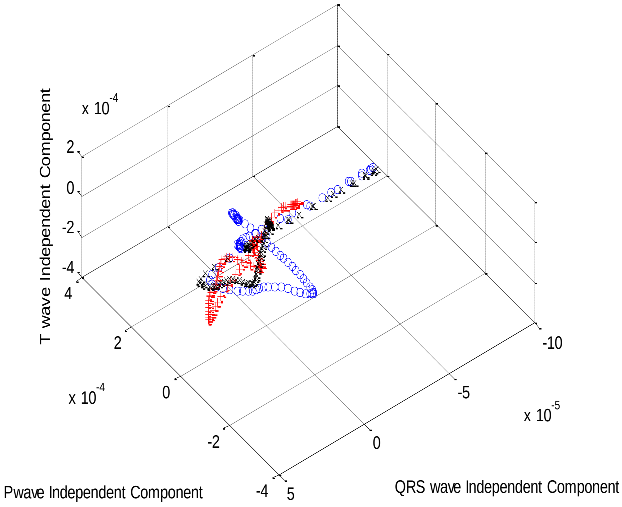

Figure:2 Principal Components (PC) of the ECG signal

$$\text{Eigen Values} = \begin{bmatrix} 19.3165 & 0 \\ 0 & 0.00884553 \end{bmatrix}$$

$$\text{Eigen Vectors} = \begin{bmatrix} 0.00023863 & -1 \\ 1 & 0.00023863 \end{bmatrix}$$

$$\%\ \text{Variance given by I}^{st}\ \text{P C} = \frac{19.3165}{(19.3165+0.00884553)} = 99.95$$

$$\%\ \text{Variance given by II}^{nd}\ \text{P C} = \frac{0.00884553}{(19.3165+0.00884553)} = 0.04577$$

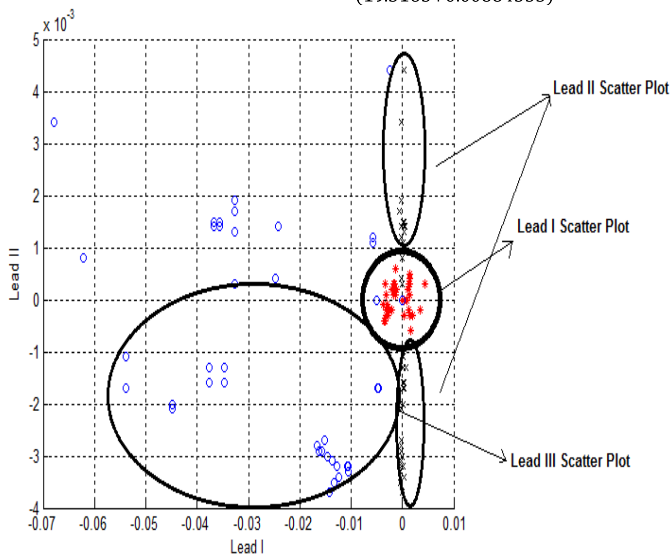

Figure:3 Noise removal using ICA(Scatter plot)

Due to variability in the ECG signal and its abnormalities from one patient's ECG to the next. These observations make an improper heart disease classification. That is why PCA used for pattern classification. PCA finds a set of the most representative projection vectors such that the projected samples retain the most information about original ECG samples. It has been found that the first principal component is the direction along which the samples show the largest variance. The second principal component is the direction uncorrelated to the first component along which the samples show the largest variance as shown in Figure.2. Signal processing time is lower in PCA other transform like a short time Fourier transform and wavelets. The main thing to choose ICA is that it helps in transforming the PCA corrupted signal into a noise free signal of independent decompositions as shown in Figure.3. It is given by the scatter plot. It has been found that ICA is a novel tool while being applied to the biomedical signal processing.

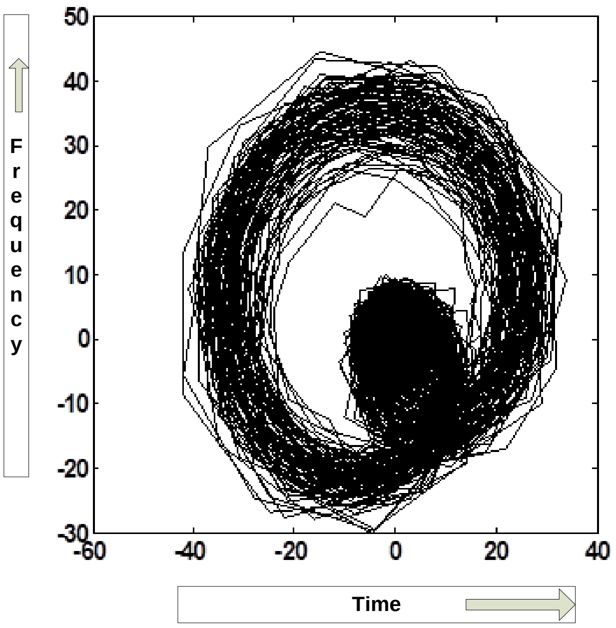

Figure:4 Hilbert Transform of normal ECG recording

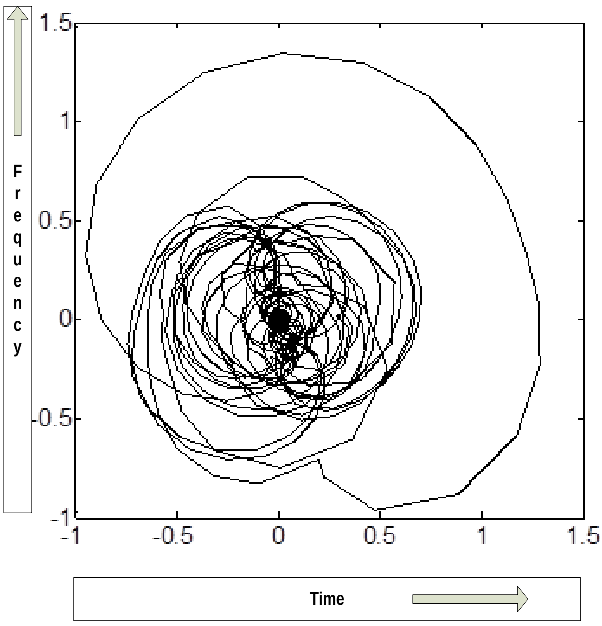

Figure:5 Hilbert Transform of abnormal ECG recording

Figure. 4 and Figure.5 are showing normal and abnormal feature extraction of the ECG signal. It clarifies the status of the patient before the NN classification stage. Artificial neural networks (ANN) work on the principle of biological neural networks. It is used for classifying nonlinear applications. In our application neural network constraints were considered as: 70% of data were used for training, 15% for validation and 15% for the test. Its structure is shown in Figure.6. The classification of each ECG to the normal or abnormal group was based on the final diagnosis provided by the cardiologists [28].

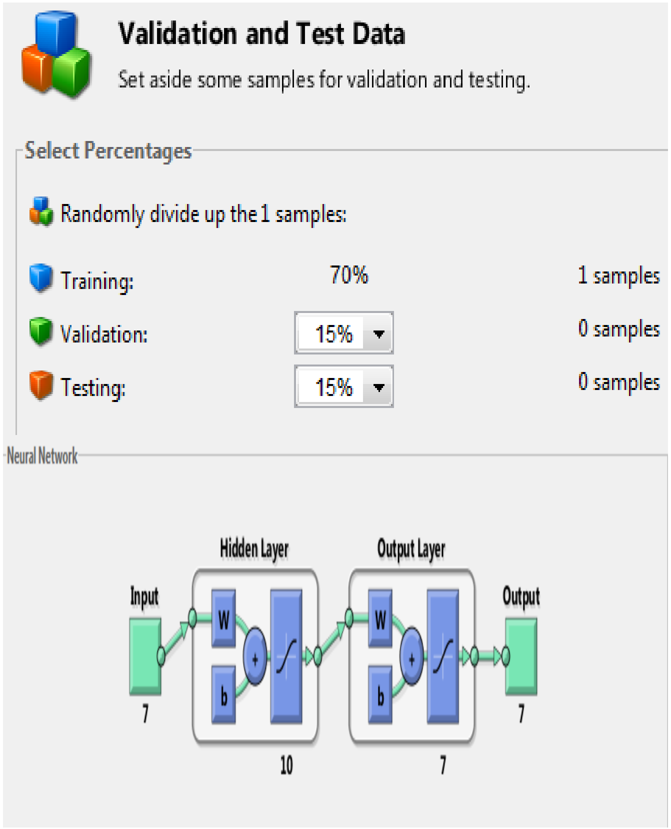

Figure:6 Validation and testing using Neural Network with considered Neural Network structure

In the validation process first of all comparison is done between outputs from NN with BP. After that estimated the correlation coefficient between the ECG, RSP and BP signals. It gave highest value of 0.977 the correlation coefficient between ECG and BP. In Figure.7 all signals (ECG1, ECG2, RSP, BP) were compared. Yellow line in Figure.7 is shown constant, but it is seeing constant due to large scale. In Figure.8 this original RSP signal is indicated.

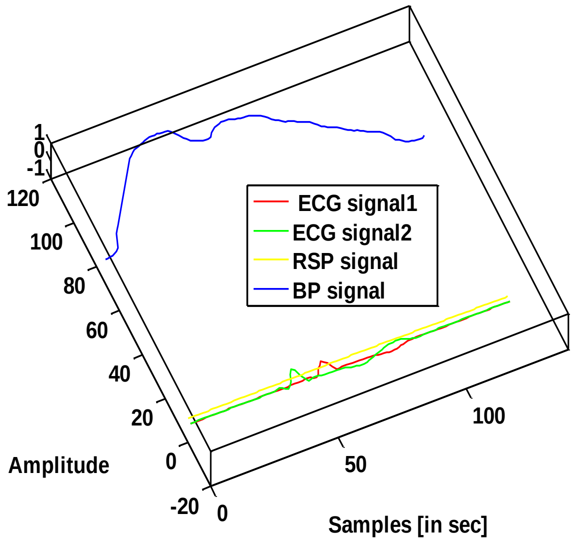

Figure:7 ECG signal, RSP signal and BP signal

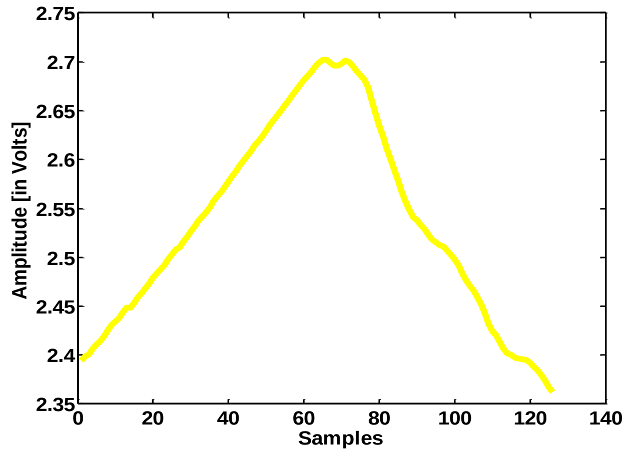

Figure:8 Respiratory (RSP) signal.

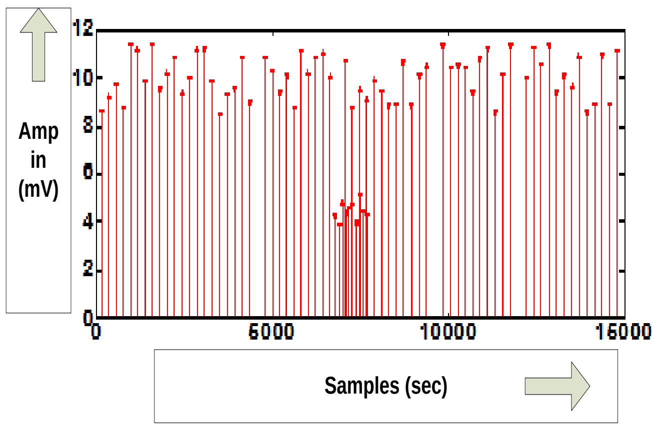

Figure: 9 R-peak detection in 111m MIT-BIH Arrhythmia database

Table. 1: TP, FP and FN calculation before applying Neural Network classifier

ECG	Actual	Detected	TP	FN	FP
Record	**R-peak**	**R-peak**			
MB-100	2270	2270	2266	5	2
MB-101	1867	1862	1855	5	2
MB-102	2187	2181	2175	11	7
MB-103	2081	2081	2081	2	3
MB-104	2233	2233	2225	7	5
MB-105	2589	2583	2584	5	5
MB-106	2038	2037	2032	11	7
MB-107	2144	2144	2143	7	7
MB-108	1773	1772	1771	4	3
MB-109	2535	2532	2523	9	7
MB-111	2126	2121	2122	7	4
MB-112	2539	2536	2532	5	2
MB-113	1797	1792	1793	2	2
MB-114	1885	1878	1876	5	6
RT_01	1770	1745	1738	4	2
RT_02	1232	1211	1189	5	1
RT_03	1210	1201	1179	5	4
RT_04	789	774	768	1	3
	35065	**34953**	**34852**	**100**	**72**

MB-MIT-BIH Arrhythmia database, **RT**-Real Time database

$$\text{R-peak detection \% accuracy} = \frac{TP}{TP+FN+FP} = 99.50\%$$

$$\text{Mean Square Error (MSE)} = \frac{(\text{Actual beats}-TP)^2}{\text{Actual beats}} = 1.2938$$

TP, FP and FN calculation after applying Neural Network classifier

$$\text{R-peak detection \% accuracy} = \frac{TP}{TP+FN+FP} = 99.71\%$$

$$\text{Mean Square Error (MSE)} = \frac{(\text{Actual beats}-TP)^2}{\text{Actual beats}} = 0.789$$

In [30] arterial pulse wave (APW) data set was analyzed including healthy and non-healthy patients. Support Vector Machine (SVM) and Artificial Neural Network (ANN) were used for classification in order to evaluate the performance. SVM achieved an average accuracy of 0.9917 ± 0.0024 and an F-Measure of 0.9925 ± 0.0019, in comparison with ANN, which reached the values of 0.9847 ± 0.0032 and 0.9852 ± 0.0031 for Accuracy and F-Measure, respectively. In [31] various architectures of Artificial Neural Network (ANN) were adopted for classifying more than 100 diseases. In [32] the synthesis of ECG cycles from arterial blood pressure (ABP) and central venous pressure (CVP) signals using Artificial Neural Network (ANN) have been given. In [33] ECG signal preprocessing and support vector machine-based arrhythmic beat classification has given. SVM classifier and different pattern recognized classifiers were used on noise removed feature extracted signal for beat classification. Results reveal that the performance of SVM classifier is better than other machine learning-based classifiers. In [34] SVM were incorporated to observe the blood pressure from the PPG signal. In [35] ICA and NN were used for an electrocardiogram (ECG) beat classification. The ICA was utilized for decomposing ECG signals into a weighted sum of basic components and the projections worked as a feature vector for the NN classifier. In [36] beat-to-beat optical blood pressure (BP) was analyzed using photoplethysmogram (PPG) signal from finger tips. Amplitudes and phases of cardiac components were used to train an artificial neural network. In[28] shallow neural networks with pretraining were used for the assessment of normal/abnormal heart function from raw ECG signals. In [37] In this research paper, Heart disease prediction system was developed using data mining. It reduces the burden on medical practitioner in efficient decision during diagnosis. It gave accuracy of 86.3 % in testing phase and 87.3 % in training phase. In [38] an artificial neural networks-based (ANNs) diagnostic model were developed for coronary heart disease (CHD) using a complex of traditional and genetic factors of this disease. The best accuracy achieved using a neural networks approach of multilayer perceptron with two hidden layers for models included by both genetic and non-genetic CHD risk factors. In [39] QRS detection algorithm was developed based on the Hilbert transform and the adaptive threshold technique. In this study PCA has been used for feature extraction of the QRS complex. Adaptive threshold was taken into account for detecting QRS complexes. In [29] ECG heartbeats classification was carried out using five heartbeat types according to AAMI recommendation, using an artificial neural network. Block-based Neural Network (BBNN) has been used as the classifier. Particle Swarm Optimization (PSO) was used for optimizing the Network structure and the weights. In [1] ECG signal was classified using projected and dynamic features. In which projected features are taken from a random projection matrix (RPM), in which each column is normalized and each row is transformed by a discrete cosine transform (DCT). Three weighted RR intervals are estimated as the dynamic features. A support vector machine classifier was used to cluster heartbeats into one of 15 or 5 classes by using those two kinds of features.

Table.2: comparison of Different work

Ref	SE	SP	PP	ACC	MSE
Present	-	-	-	99.50	1.2938
	-	-	-	99.71	0.789
[30]	-	-	-	99.56	-
[26]	99.97	98.7		99.5	-
[40]	97.85	-	-	99.05	-
[15]	99.92	-	99.85	99.77	-
[35]	-	-	-	98.71	-
[28]	95.60	71.43	-	86.39	-
[30]	-	-	-	99.17	-
[39]	96.28	-	99.71	-	-
[29]	-	-	-	97	-
[1]	-	-	-	98.46	-
[1]	-	-	-	93.1	-

Conclusion

ECG and BP signal are equally important for monitoring health status of the patient. With the help of patient heart status, other parameters information can be extracted. These parameters have a strong correlation. PCA and ICA reduced dimensionality and noise effectively. It reduces the load on Feature extraction process. Time/Frequency description of normal and abnormal patient using Hilbert transform provides a clear picture of the health status.Sometimes several signals are identical in view, but different in actuality. NN effectively classified such types of datasets effectively as shown in Table.2. It gave 99.71% detection accuracy and 0.789 mean square error. This approach is ready to use in laboratory to assist the cardiologist for taking decision in the critical condition.

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