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Detection and Classification of Cardiac Arrhythmias based on ECG and PCG using Temporal and Wavelet features

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Abstract: Arrhythmias are abnormal rhythms of heart. Sudden Cardiac Arrest is most often caused by life threatening arrhythmias such as Ventricular Tachycardia (VT) and Ventricular Fibrillation (VF). Early detection of life threatening arrhythmias is crucial for successive defibrillation therapy. In general heart diseases have been investigated by various methods. Among these Electrocardiography (ECG) test is considered as the best noninvasive method of investigation. ECG test is varied if the heart sound from the Phonocardiogram shows any abnormalities. So Phonocardiography (PCG) is also considered for more efficiency. Commonly used arrhythmia detection and classification algorithms are only based on surface Electrocardiogram analysis. So an algorithm corresponds to multiresolution wavelet analysis using temporal and wavelet features of Electrocardiogram and Phonocardiogram along with Electrocardiogram-Phonocardiogram relationships is designed so as to increase the efficiency of the heart diagnostics. Temporal and wavelet features of ECG and PCG along with the linear prediction coefficients representing ECG and PCG are fed to the classifier for classification. The goal of this work is to achieve an efficient arrhythmia detection system that can lead to high performance heart diagnostics.

Index Terms: DWT,ECG, HRV,LPC, Multiresolution, Massachusetts Institute of Technology/Beth Isrel Hospital (MIT-BIH) ECG arrhythmia database, PCG, SVM.

I. INTRODUCTION

Cardiac Arrhythmia (dysrhythmia) is any of a group ofconditions in which the electrical activity of the heart is irregular or is faster or slower than normal [1]. They cause the heart to pump blood less effectively. During an arrhythmia, the heart may not be able to pump enough blood to the body. Lack of blood flow can damage the brain, heart, and other organs. Although many arrhythmias are not life-threatening, ventricular arrhythmias can cause Cardiac Arrest. Arrhythmias can occur in the upper chambers of the heart (atria), or in the lower chambers of the heart (ventricles). Arrhythmias may occur at any age. Some are temporary and benign, whereas others can be more dramatic and can even lead to sudden cardiac death [2].

So, the study on the detection of abnormal life-threatening cardiac rhythms (Arrhythmias) is of important clinical significance. Ventricular Fibrillation (VF) and Ventricular Tachycardia (VT) are life-threatening ventricular arrhythmias. During the last decade, attention was focused on early detection and treatment of arrhythmias and the emphasize of treatment switched from resuscitation to aggressive Defibrillation therapy. Defibrillation is the process of converting arrhythmia into an efficient rhythm, by applying a high energy electric shock to the patient's heart. The instrument delivering the shock is called the defibrillator. In order to effectively offer high-energy defibrillation to VF and low-energy cardio-version to VT, Automatic external defibrillators (AEDs) and implantable cardioverter defibrillators (ICDs) require arrhythmia classification algorithms that can distinguish abnormal cardiac rhythms from normal cardiac rhythms.

In general, heart disease has been investigated by various methods [3], [4]-[8]. Among these Electrocardiography

(ECG) test is considered as the best noninvasive arrhythmia detection method, because it is a simple and noninvasive diagnostic tool. Besides an ECG signal, a phonocardiogram (PCG) signal is also employed for heart disease diagnosis. The heart is a two part pump, one part mechanical and one part electrical. The mechanical function of the heart is governed by the electrical system within the heart. ECG shows the electrical activity and PCG, phonocardiogram shows the mechanical (opening and closure of valves) activity of humanheart.Thus, a relationship between the waves of the ECG and the heart sounds of the PCG exists. So both signals are considered in this algorithm.

The present study aimed to frame an arrhythmia detection algorithm based on multiresolution wavelet analysis of ECG and PCG using temporal and wavelet domain features. The objective of this study is to improve the arrhythmia detection efficiency by using both the ECG and PCG. Previous studies have used time delay methods [10], time domain methods [11], and frequency domain methods etc., as arrhythmia detection methods. This methodology is applied to detect the presence of arrhythmia based on Electrocardiogram (ECG) and Phonocardiogram (PCG) analysis.

II. METHODOLOGY

Cardiac Arrhythmia detection based on multiresolution wavelet analysis using temporal and wavelet features of

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Electrocardiogram and Phonocardiogram is a novel arrhythmia detection method. This methodology also uses the Linear Prediction Coefficients (LPC) representing the wavelet coefficients of ECG and PCG as ECG-PCG relationship.By combining the relationship between the Electrocardiogram and Phonocardiogram signals, this methodology increases the efficiency of the heart diagnostics.

The block diagram showing the Arrhythmia detection system is as shown in Figure1. Data in the form of ECG signals and PCG signals are acquired, and then are processed.

Then the Discrete Wavelet Transform is applied to obtain the waveletdomain features. Feature Extraction based on ECG-PCG relationship is also performed. The obtainedfeatures are finally fed to Support Vector Machine Classifier (SVM) to detect thepresence or absence of arrhythmia. The processing steps, feature extraction and the arrhythmia detection employed in the work are explained in the following section.

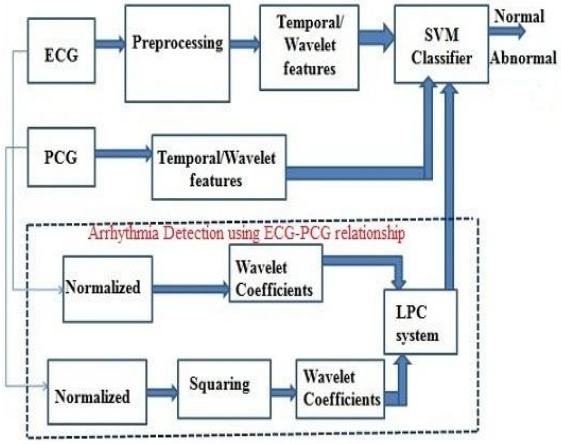

Figure 1: Block diagram for Arrhythmia Detection

A. ECG and PCG Collection

The analysis of ECG and PCG signals provide relevant information for Arrhythmia detection. In this work, normal ECG from the MIT-BIH (Massachusetts Institute of Technology/Beth Isrel Hospital) Normal Sinus Rhythm database is used.And for abnormal ECG signals, ECG signals from the MIT-BIH arrhythmia database are used.

In this work, PCG signals are generated from the ECG signals by using the ECG-PCG relationship. The normal and abnormal PCG signals are generated by using the preprocessed normal and abnormal ECG signals respectively based on the ECG-PCG relationship, as shown in Figure 2.

The S1 occurs 0.04s-0.06s after the onset of the QRS complex [9], the S2 occurs towards the end of the T wave, and the fourth heart sound S4 occurs after the P wave. Both ECG and PCG signals play important roles in heart abnormality detection.

However, diagnosis based on ECG signal or PCG signal alone cannot detect all cases of heart symptoms. Some abnormalities cannot be analyzed via ECG but can be analyzed with PCG.

So preprocessing of PCG signals is not required here.

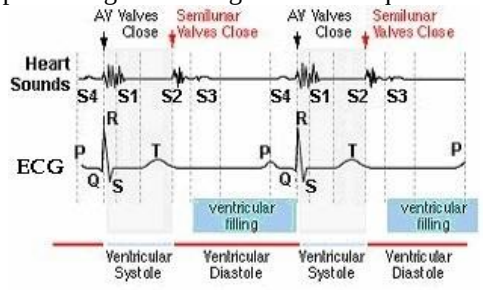

Figure 2: Relationship between ECG and the 4 Heart Sounds by PCG[9]

- QRS wave indicates depolarization of the ventricles,and this stimulates contraction. The rise in intraventricularpressure that results causes the atrioventricular (AV)valves to close, so that S1, is produced immediatelyafter the QRS wave.[9]
- T wave indicates repolarization of the ventricles. The fall in intraventricular pressure that results causes the aortic and pulmonary semilunar valves to close, so that S2, is produced shortly after the T wave.
- Occasionally, S3 is heard at the beginning of the middlethird of diastole, as shown in Figure 2.
- P wave indicates the atrial contraction. S4 iscaused by vibration of the ventricular wall during atrialcontraction, and S4 follows the P wave as shown in Figure 2.

B. ECG Preprocessing

At first, it is necessary to preprocess the ECG signal as it is frequently corrupted with different types of noises. All ECG signals are preprocessed using the filtering process, which works in three successive steps:

1) Five-order moving average filtering (Electromyographic noise removal).

$$y(n) = \sum_{k=0}^{N} b_k x(n-k) \quad (1)$$

2) Butter worth high-pass filtering with cutoff frequency, fc =0.5 Hz (drift suppression).

$$|H(\omega)^2| = \frac{1}{1+(\frac{\omega_c}{\omega})^{2N}} \quad (2)$$

3) Butter worth low-pass filtering with fc = 45 Hz (power line interference removal).

$$|H(\omega)^2| = \frac{1}{1+(\frac{\omega}{\omega_c})^{2N}} \quad (3)$$

Now, the unwanted noise segments were removed from the input ECG signals.

C. Feature Extraction

1) ECG Feature Extraction: The main objective of the ECG feature extraction process is to derive a set of parameters that best characterize the ECG signal.

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These parameters should contain maximum information about the ECG signal. Hence the selection of these parameters is an important criterion to be considered for proper classification.Arrhythmia classification, therefore, involves determination of several characteristic features of the ECG signal.

The DWT (Discrete Wavelet Transform) has been used to obtain the characteristic waves of the ECG signal from which a set of features are derived.The 8 level waveletdecomposition based on Daubechies 6 wavelet functions are considered here. The Daubechies6 wavelets are chosen based on their shape and their ability to analyze the signal in this particular application. The shape of Daubechies wavelets is similar to that of the shape of an ECG signal. To obtain the ECG features, the characteristic points P, Q, R, S and T are obtained at different decomposition levels based on the following steps as shown in the following Figure 3.

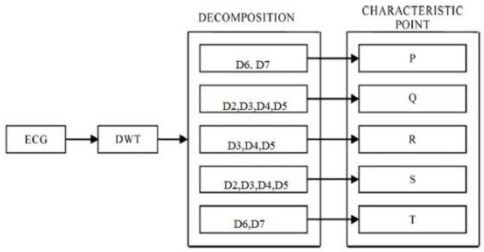

Figure 3: Characteristic points extraction from ECG signal [12]

- Segment selection.
- 8-level wavelet decomposition using Daubechies 6
- wavelet functions.
- Detection of R peak at level obtained by combining detailcomponents D3, D4, and D5 using adaptive thresholdvalue. The values greater than threshold is taken as Rpeak.

Threshold value= Max [signal]*Mean [signal] (4)

- Detection of Q peak, as local minimum point at levelobtained by combining detail components D2, D3, D4 and D5, before R wave.
- Detection of S peak, as local minimum point at level obtained by combining detail components D2,D3,D4 and D5, after R wave
- Detection of P wave at level obtained by combining detail components D6 and D7 before Q wave.
- Detection of T wave at level obtained by combining detail components D6 and D7 after S wave.

From the values obtained the following five wavelet-domain parameters have been calculated.

- P-P interval, which is the mean of P-P intervaldurations. The P-P interval is obtained by the following equation.

$$T_{PP} = P_{i+1} - P_i, i = 1,2, \dots N-1 \quad (5)$$

- R-R interval, which is the mean of R-R interval durations.The R-R interval is obtained by the following equation.

$$T_{RR} = R_{i+1} - R_i, i = 1,2, \dots N-1 \quad (6)$$

- P-R interval, which is the time duration between successiveP and R waves in each beat. The P-R interval isobtained by the following equation.

$$T_{PR} = R - P_{on-set} \quad (7)$$

- QRS Duration, which is the time duration from thebeginning of the Q wave to the end of the S wave. TheQRS duration is calculated by :

$$T_{QRS} = T_S - T_Q \quad (8)$$

- QT Interval Duration, which is the time from the beginning of the Q-wave to the end of the T wave. It is obtained by:

$$T_{QT} = T_{off-set} - Q \quad (9)$$

The following parameters of the HRV signal are directly extracted from the RR interval time series.

- Mean HR: The mean value of the heart rate within oneminute in each segment. Instantaneous heart rate (beat per minute) is equal to 60 divided by each R-R interval (second).
- STD HR: The standard deviation of Instantaneous Heart rate in each segment.
- HRV triangular index: This refers to the integral of thehistogram (i.e. total number of RR intervals) divided by the height of the histogram (maximum of histogram).

2) PCG Feature Extraction: From the generated heart sound signal, the durations of S1-S2 interval (systolic S) and S2-S1 interval (diastolic D) are extracted. These wavelet domain parameters can be used to detectthe cardiac arrhythmias.

- The S1-S2 (systolic) interval is calculated by the following equation.

$$T_{S1S2} = T - S1_{off-set} \quad (10)$$

- The S2-S1 (diastolic) interval is calculated by the following equation.

$$T_{S2S1} = R - S2_{off-set} \quad (11)$$

3) Features based on ECG-PCG Relationship: Linear prediction coding coefficients representing the wavelet coefficients of normalized ECG and PCG signals are considered here. These linear prediction coding coefficients are fed to the classifier along with the temporal and wavelet features of ECG and PCG. For generating the LPC coefficients, the normalized ECG and PCG signals are considered. The equation for signal normalization is shown below.

$$x_{norm} = [x - \min(x)]/[\max(x) - \min(x)] \quad (12)$$

After signal normalization, the LPC coefficients of the ECG and PCG signals are generated based on the following equation.

$$x'(n) = \sum_{k=1}^{P} a_p(k) x(n-k) \quad (13)$$

where x(n) is a signal sample, $x'(n)$is a predicted signal, p is the order of LPC and, a_p (k) are LPC coefficients. These

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LPC coefficients are used to train the SVM classifier along with the wavelet domain features of ECG and PCG.

D.SVM Classification

In this method, the presence of arrhythmia is detected by a Support Vector Machine classifier.SVM simultaneously minimizes the empirical classification error andmaximize the geometric margin. So SVM is also called Maximum Margin Classifiers.

If an SVM classifier is trained with pattern vectors $\boldsymbol{x}_i$, and that r of these are determined to be support vectors. Denote them by $\boldsymbol{x}_i$, $i = 1,2, \ldots, r$. The decision surface for pattern classification then takes the form

$$f(\boldsymbol{x}) = \sum_{i=1}^{r} \alpha_i y_i K(\boldsymbol{x}, \boldsymbol{x}_i) + b \qquad (14)$$

whereα_i is the Lagrange multiplier associated with pattern $\boldsymbol{x}_i$ and $K(\boldsymbol{x}, \boldsymbol{x}_i)$ is a kernel function that implicitly maps the pattern vectors into a suitable feature space.

If support vector $\boldsymbol{x}_k$ is linearly dependent on the other support vectors in feature space, *i.e.*

$$K(\boldsymbol{x}, \boldsymbol{x}_k) = \sum_{\substack{i=1 \\ i \neq k}}^{r} c_i K(\boldsymbol{x}, \boldsymbol{x}_i) \qquad (15)$$

where the c_i are scalar constants.Then the decision surface (14) can be written

$$f(\boldsymbol{x}) = \sum_{\substack{i=1 \\ i \neq k}}^{r} \alpha_i y_i K(\boldsymbol{x}, \boldsymbol{x}_i) + \alpha_k y_k \sum_{\substack{i=1 \\ i \neq k}}^{r} c_i K(\boldsymbol{x}, \boldsymbol{x}_i) + b \qquad (16)$$

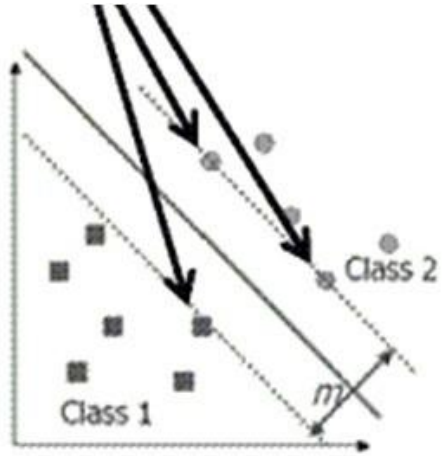

Figure 4: SVM classification

The Figure 4 shows the SVM Classification. In this work, the extracted features are finally fed to an SVM classifier, sothat the classifier detects the presence or absence of arrhythmia.

III. RESULTS AND DISCUSSIONS

In this study an arrhythmia detection algorithm based on ECG and PCG using temporal and wavelet features along with the Linear prediction coding coefficients based on the wavelet coefficients of normalized ECG and PCG signals has been presented. ECG signal is frequently corrupted with different types of electrical and mechanical noises. Generally, many interfering signals such as 50/60Hz power line interference, Electromyogram (EMG) signals and also the baseline wandering can affect the ECG signal. Hence, removal of artifacts in ECG signal is as a preprocessing operation in most analysis of disease diagnosis and clinical applications. So preprocessing is necessary to avoid these noises. All ECG signals are preprocessed using the filtering process. Simulation is performed using the MATLAB R2010b.

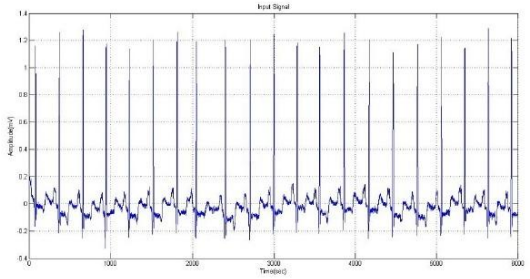

Figure 5: Input ECG signal

For ECG preprocessing, First, a moving average filter oforder 5 is applied to the signal. This filter removes highfrequency noise like muscle noise..

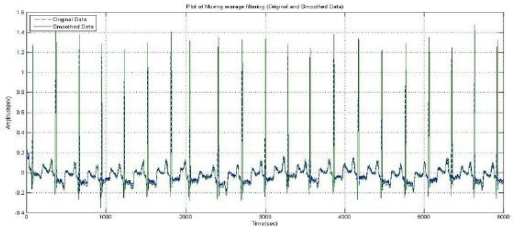

Figure 6: Moving average filtering

Then, a drift suppression is applied to the resulting signal. This is done by a Butter worth high pass filter with a cut off frequency of 0.5 Hz.

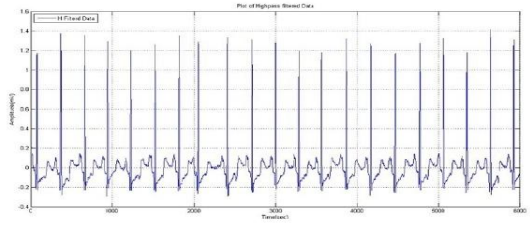

Figure 7:Butterworth high pass filtering

Finally, a low pass Butter worth filter with a limiting frequency of 45 Hz is applied to the signal in order to suppress the high-frequency power-line interference.

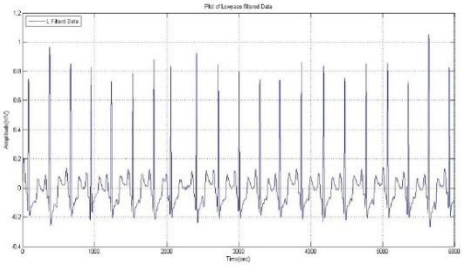

Figure 8:Butterworth low pass filtering

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Then PCG signals are generated from the preprocessed ECG signals. The generated PCG signal is shown in the following figure 9.

The S1-S1 interval in PCG signal is equivalent to the one cardiac cycle. It is equivalent to the RR interval in the ECG signal. Similarly, the S1S2 interval in thePCG signal is equivalent to the ventricular diastole or filling phase and the S2S1 intervalis equivalent to the ventricular systole or pumping phase. So any change in the valueof these intervals from the normal durations indicates the presence of arrhythmia.

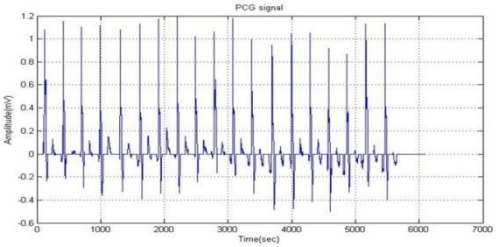

Figure 9:PCG signal

After preprocessing the feature extraction of ECG and PCG signals are performed. Wavelet domain features of ECG and PCG are extracted first [Figure14]. For ECG feature extraction, the characteristic points P.Q, R, S and T peaks are detected first. This is done by an algorithm explained in section C.

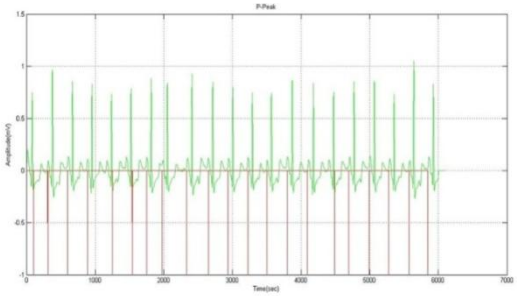

Figure 10: P peak

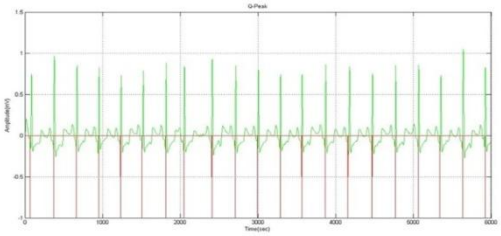

Figure 11: Q peak

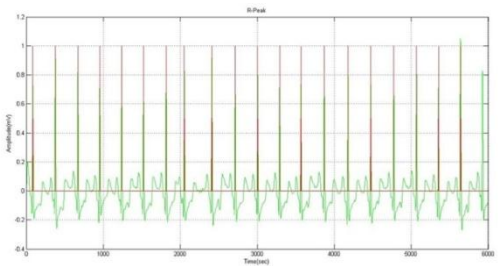

Figure 12: R peak

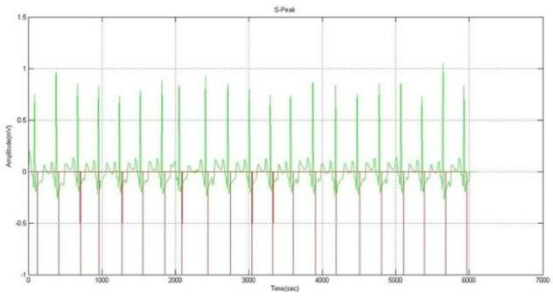

Figure 13: S peak

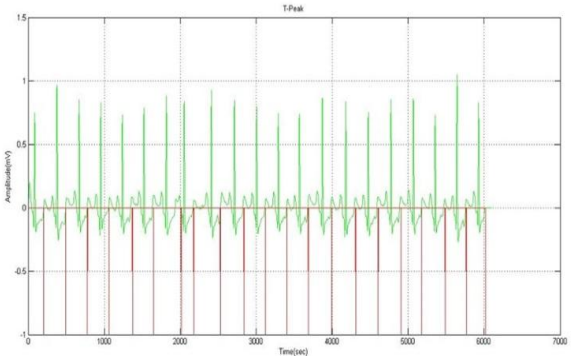

Figure 14: T peak

After characteristic point detection the ECG features are extracted, which includes RR interval, PP interval, QT interval, PR interval, QRS duration, Mean Heart Rate (HR), Standard Deviation of HR, and HRV Triangular Index.

Then features are extracted from the generated PCG signal, which includes the S1-S2 interval and S2-S1 interval. The S1-S2 duration indicates the systolic (pumping) interval and S2-S1 duration indicates the diastolic (filling) interval of human heart.

NORMAL		ABNORMAL	
Features	Value	Features	Value
RR interval	0.9583	RR	0.5389
PP interval	1.0528	PP	0.7861
QT interval	0.31670	PR	0.8222
PR interval	1.1056	QT	0.3028
QRS duration	0.0667	QRS	0.0917
Mean HR	60.8052	Mean HR	95.4129
SD of HR	3.5420	SD of HR	17.0570
HRV	4	HRV	3.1250
s1s2	0.211	s1s2	0.2889
s2s1	0.389	s2s1	-0.3833

Figure 15: Wavelet domain features of ECG and PCG

Then the parameters based on ECG-PCG relationship are extracted. These feature parameters include the LPC coefficients of ECG and PCG.

```
LP coefficients of ECG
ap1
    1.0000   -1.9611    1.7199   -0.6996

ap2
    1.0000   -2.0294    1.6395   -0.5467

ap3
    1.0000   -2.1782    1.3699   -0.1881
```

Figure 16: LPC coefficients of ECG

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For ECG signal, the LPC coefficients of the ECG wavelet coefficients which are used for the generation of the five characteristic points (P, Q, R, S and T) are considered.

For PCG signal, the LPC coefficients of the PCG wavelet coefficients are calculated.

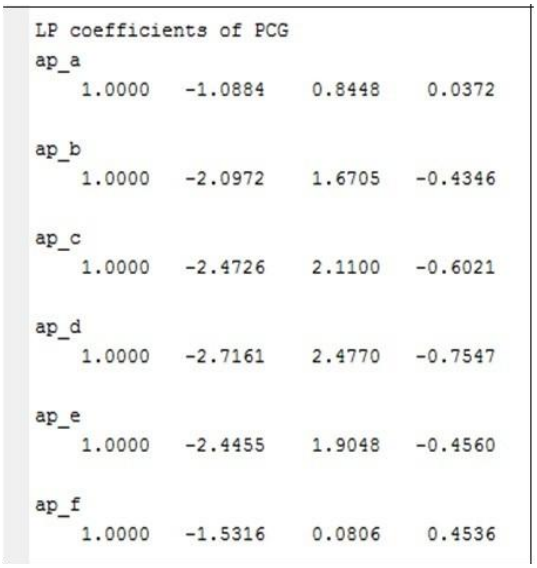

Figure 17: LPC coefficients of PCG

The obtained temporal and wavelet domain features and the LPC coefficients of ECG and PCG are finally fed to SVM classifier for Classification. Then the classifier classifies the data into two classes, a normal class and an abnormal class based on the feature values.

IV. CONCLUSION

An arrhythmia detection algorithm based on multiresolutionwavelet analysis using temporal and wavelet featuresof Electrocardiogram and Phonocardiogram along with Electro cardiogram-Phonocardiogram relationships is designed so as to increase the arrhythmia detection efficiency. Electrocardiogram signals maycontain noise. So effective preprocessing should be done toremove these noises. From the preprocessing steps it is clearthat, the noise present in the ECG signals areremoved. After feature extraction obtained featuresfrom the ECG and PCG are finally fed to the SVM classifierfor classification. Based on the obtained features, the classifierclassifies the data into a normal rhythm or an abnormalrhythm. Since the traditional arrhythmia detection algorithms are only based on surface Electrocardiogram analysis, this methodology can provide an efficient heart diagnostic approach by considering both ECG and PCG signals.

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