Rule Based Identification of Cardiac Arrhythmias from Enhanced ECG Signals Using Multi-Scale PCA

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Abstract

The detection of abnormal cardiac rhythms, automatic discrimination from rhythmic heart activity, became a thrust area in clinical research. Arrhythmia detection is possible by analyzing the electrocardiogram (ECG) signal features. The presence of interference signals, like power line interference (PLI), Electromyogram (EMG) and baseline drift interferences, could cause serious problems during the recording of ECG signals. Many a time, they pose problem in modern control and signal processing applications by being narrow in-band interference near the frequencies carrying crucial information. This paper presents an approach for ECG signal enhancement by combining the attractive properties of principal component analysis (PCA) and wavelets, resulting in multi-scale PCA. In Multi-Scale Principal Component Analysis (MSPCA), the PCA's ability to decorrelate the variables by extracting a linear relationship and wavelet analysis are utilized. MSPCA method effectively processed the noisy ECG signal and enhanced signal features are used for clear identification of arrhythmias. In MSPCA, the principal components of the wavelet coefficients of the ECG data at each scale are computed first and are then combined at relevant scales. Statistical measures computed in terms of root mean square deviation (RMSD), root mean square error (RMSE), root mean square variation (RMSV) and improvement in signal to noise ratio (SNRI) revealed that the Daubechies based MSPCA outperformed the basic wavelet based processing for ECG signal enhancement. With enhanced signal features obtained after MSPCA processing, the detectable measures, QRS duration and R-R interval are evaluated. By using the rule base technique, projecting the detectable measures on a two dimensional area, various arrhythmias are detected depending upon the beat falling into particular place of the two dimensional area.

Keywords: ECG, Wavelet Transform, Principle Component Analysis, Arrhythmia Detection.

1. INTRODUCTION

In clinical applications, the arrhythmia condition, disturbing the rhythmic activity of heart, and its detection plays a vital role for diagnosing the patient's rhythmic status. The detection of abnormal cardiac rhythms became a potential area in clinical research. Arrhythmia detection is possible by analyzing the electrocardiogram (ECG) signal features. Several detection algorithms have been proposed earlier for arrhythmia detection, such as pattern matching, pattern subtraction etc., Rule base technique is one of the simple methods which can be utilized for arrhythmia detection after

obtaining the denoised ECG signal. Most of the physiological processes manifest themselves as signals reflecting their activity. Heart generated electrocardiogram (ECG), muscle generated electromyogram (EMG) and brain generated electroencephalogram (EEG) are some biomedical signals of interest [1]-[2]. The ECG signal, recorded with an electrocardiograph, is an electrical manifestation of the contraction and relaxation of the heart. ECG signal, whose frequency band of interest is 0.05 to 100Hz, is corrupted by different artifacts, which include 50/60 Hz power line interference (PLI), EMG interference and baseline wandering. PLI affects the complete ECG making it difficult for measurement of QRS complex and the QT interval. In order to remove 60 Hz PLI, an LMS adaptive filter can be employed by setting the 60Hz-component as a reference signal, so as to adjust the filter coefficient until the error is minimized from the input signal where the 60Hz-component is included [3]-[6]. The EMG, due to random contraction of muscles, is a high frequency component distributed in a wide frequency band which cannot be removed with a simpled filtering operation. The baseline wander, which is a low-frequency noise resulting from sudden movement of the body and respiration, has the same frequency band as of the ST segment of the ECG signal. Hence baseline wander is to be eliminated for the precise measurement of the ST segment. As a usual pre-processing phase, the real ECG is band pass filtered in order to remove the corrupted noise and to recover the signal waves (P, QRS and T). However, it has been established that the power spectral density (PSD) of the QRS complex (5-15 Hz) overlap with the muscle noise, while the PSD of P and T waves overlap with that of respiration, blood pressure at low frequency band usually (0.1 to 1 Hz). These different artfacts prevent considerably the accurate analysis of the ECG signal and eventual diagnosis of cardiac anomalies.

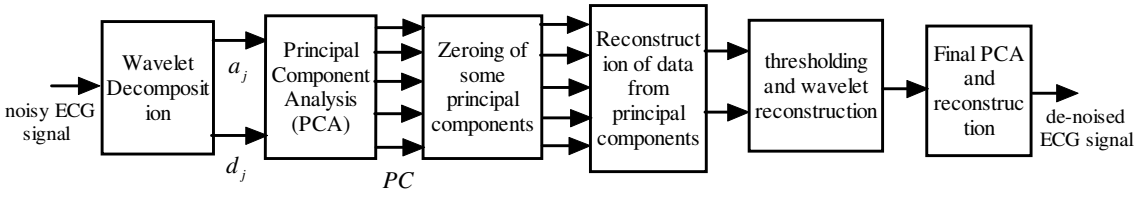

FIGURE 1: Block diagram for enhancement of ECG signal using multi-scale Principal Component Analysis.

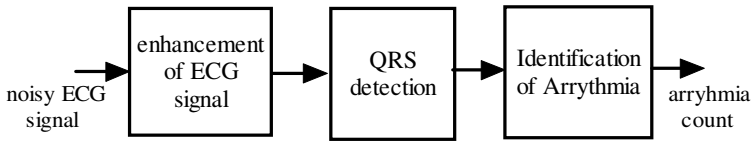

FIGURE 2: Block diagram for detection of cardiac arrhythmia from noisy ECG signal

Many solutions were reported in literature like digital filters (FIR or IIR), adaptive filtering methods and wavelet transform thresholding methods, in order to eliminate the noise of ECG signal [2]. The most widely used method, among the several other methods, used for ECG signal enhancement is the least mean square (LMS) adaptive algorithm [5]-[7]. But this algorithm is not able to track the rapidly varying non stationary signal, hence causes excessive low pass filter of mean parameters such as QRS complex. The wavelet transform (WT) has been proven to be a promising tool for non-stationary signal analysis, where in thresholding is used in wavelet domain to smooth out or to remove some coefficients of wavelet transform sub signals of the measured signal. Furthermore, the non-stationary behavior of the ECG signal, that becomes severe in the cardiac anomaly case, attracted researchers to analyze the ECG in both time and frequency planes simultaneously. The ability of the wavelet transform to explore signals into different frequency bands with adjustable time frequency resolution makes it suitable for ECG signal analysis and processing [8]-[13]. Many tools, methods and algorithms from signal processing theory have been proposed, described and implemented over the past few years to extract feature from ECG signals such as, total least squares based Prony modeling algorithm [14], correlation dimension and largest Lyapunov exponent [15], autoregressive model [16], multivariate autoregressive model [17], heartbeat interval combined with the shape and

morphological properties of the P, QRS and T waves [18], wavelet transform [19], multiple signal classification (MUSIC) algorithm [20], and efficient formation of morphological wavelet transform features together with the temporal features of the ECG signal [21].

Extracting the features from clean ECG signal has been found very helpful in identifying various cardiac arrhythmias. This could be difficult, when the size of the data of the ECG is huge and the existence of different noise types that may be contained in the ECG signals. Furthermore, manual analysis is considered a very time consuming and is prone to error. Hence arises the importance of automatic recognition and analysis of the ECG signals for extracting the different features available. Clean artifact free ECG signal is required exact identification of cardiac arrhythmias.

This paper presents multi-scale principal component analysis (MSPCA) based method for ECG enhancement as illustrated in Figure 1, which makes use of abilities of both the wavelets and the principal component analysis (PCA). This enhanced ECG is applied to the arrhythmia detector as shown in Figure 2. This basic idea is an extension to our previous work [22], where the enhanced ECG when presented to rule based arrhythmia classifier, resulted in a robust classification for arrhythmia.

2. WAVELETS

Since the useful ECG signal is corrupted with artifacts, the objective is to analyze accurately an ECG signal, to identify all the possible cardiovascular abnormalities. Wavelet analysis answers most of these problems [9]-[10]. In contrast to the classical Short-Time Fourier Transform (STFT) or Gabor transform, which uses a single analysis window, the WT uses long windows at low frequencies and short windows at high frequencies.

Discrete Wavelet Transform is referred as decomposition by wavelet filter banks as shown in Fig 3. and reconstruction in fig 4. Furthermore, the decomposition process, by which the signal is broken into many levels of lower resolution components, is iterative.

Only the last level of approximation is save among all levels of details, which provides sufficient data. A_j is the approximate coefficients and D_j is the detailed coefficients. The output coefficients of the LPF are referred to as 'approximations' and the output coefficients of the HPF are referred to as 'details'. The approximations of the signal are define its identity, while the details imparts gradation.

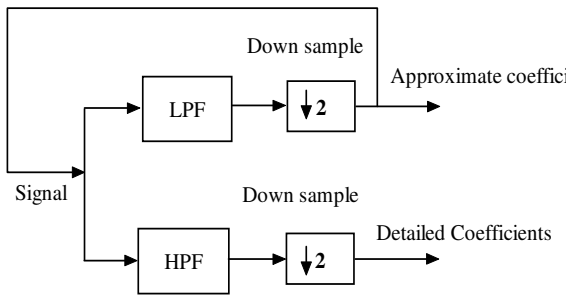

FIGURE 3: Wavelet Decomposition.

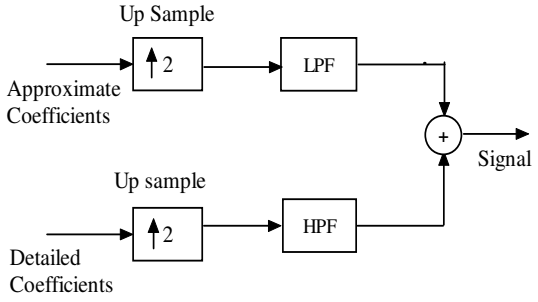

FIGURE 4: Wavelet Reconstruction.

Selecting a mother wavelet which closely matches the signal to be processed is of important in wavelet applications. The Haar wavelet algorithm is simple to compute, where the Daubechies algorithm is conceptually more complex and picks up detail that is missed by the Haar wavelet algorithm [11]. In practice, there is no absolute of choosing a certain wavelet. The choice of the wavelet function absolutely depends on the application. The energy spectrum of Daubechies

wavelet family is concentrated around low frequencies and more over similar in shape to QRS complex.

2.1 Wavelet De-noising

During denoising, the signals are transformed, thresholded and inverse-transformed as shown in Fig 5. The result is cleaned-up signal that shows important details. The general de-noising procedure follows the steps described below.

i. *Decomposition:* Perform wavelet decomposition by choosing a mother wavelet and a convenient level N for decomposition.

ii. *Thresholding detail coefficients:* For each level from 1 to *N*, select a threshold and apply soft or hard thresholding to the detail coefficients.

iii. *Reconstruction:* Perform the wavelet reconstruction using the original approximation coefficients and the modified detail coefficients obtained at different levels.

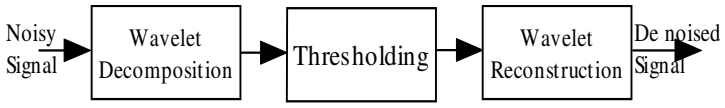

FIGURE 5: Wavelet Denoising Procedure.

There are two important issues with this: how to choose the threshold, and how to perform the thresholding [13]. Thresholding algorithm can be applied in two ways. One is hard thresholding process, which sets any wavelet coefficient less than or equal to the threshold to zero and the other is soft thresholding, which in addition to applying hard threshold, subtracts the threshold from any wavelet coefficient greater than the threshold.

2.2 Principal Component Analysis

Principal component analysis (PCA) is essentially a variable reduction procedure and it identifies the patterns in the data [27]. PCA can be performed using two methods, one of which using covariance matrix and the other using singular value decomposition (SVD). The essential steps involved in performing PCA on the data are discussed below.

Form a data set by using the periodicity of the ECG signal. Periodicity will be found using SVR profile i.e. the ratio of first principal component to the second principal component. The data matrix ***X*** is size of *m* x *n,* where *n* is the SVR computed periodicity and *m* is the number of periods considered.

$$\text{Let } X(t)=[x_1(t),\ x_2(t),\ x_3(t),\ldots\ldots x_m(t)] \quad (1)$$

is the time ordered collection of the feature at all beats into a single matrix to which PCA can be applied. The means of the x_i are removed and the covariance matrix computed. The covariance is defined as

$$\Sigma = {}^{1}\!/_{n}\left[X\ X^{T}\right] \quad (2)$$

Σ is an *m* x *m* square symmetric matrix, eigenvalues (***a**j)* and corresponding eigenvectors (***λ**j*) will be calculated, In general, once eigenvectors are found from the covariance matrix, the next step is to order them by eigenvalue, highest to lowest. This gives you the components in order of significance. The lesser eigenvalues can be ignored; this will form the basis for compression. The principal components (PC) are ordered eigenvectors of the covariance matrix. The PCs were obtained using

$$z_j = a_j\, x \qquad j=1,2,\ldots\ldots n \quad (3)$$

The PCs are a linear transformation of the beats with transformation coefficients given by the eigenvectors $\boldsymbol{\alpha}_j$. The performance of PCA an futher be improved by using PCA in conjunction with the wavelets, resulting in the concept of multiscale PCA.

2.3 Multi-Scale PCA

Multi-scale Principal Component Analysis (MSPCA) has been proposed as a fault detection method for the time series data [23]. This method combines the ability of PCA to extract the relationship among variables, then, to decorrelate the cross-correlation with that of wavelet analysis to decompose the time-series data into several frequency scales. Multiscale PCA reconcstructs simplified multivariate signal, starting from a multivariate signal using a simple representation at each resolution level. In MSPCA, the PCA will be performed (i) on the matrices of details of different levels, (ii) on the matrices of coarser approximation coefficients and (iii) on the final reconstructed matrix. Finally, the interested simplified signals can be obtained by retaining useful principal components. Such an approach is developed in this paper by efficiently combining the abilities of PCA and wavelets. The present work is focused on using wavelets for multi scale data analysis. The sequence of steps employed for implementing proposed MSPCA method for ECG signal enhancement are given below.

Step1: For each column in data matrix of ECG, perform wavelet decomposition process

Step 2: For each scale, compute covariance matrix of wavelet coefficients

Step 3: At selected scale, compute PCA loadings and scores of wavelet coefficients

Step 4: Select the appropriate number of loadings and wavelet coefficients (larger than appropriate threshold)

Step 5: For all scales together, compute PCA by including the scales with significant events

Step 6: Reconstruct approximate data matrix from the selected and thresholded scores at each scale

3. ARRYTHMIA DETECTION

Arrhythmia is a condition in which the rhythmic activity of heart is disturbed. It may be due to disturbance in impulse formation or conduction or both but it is not always an irregular heart activity. Arrhythmia can be detected by analyzing the ECG signal features particularly based on the detectable measures, QRS duration and R-R interval. The detection of abnormal cardiac rhythm, an automatic discrimination from rhythmic heart activity became a thrust area in clinical research. Several detection algorithms have been proposed earlier for arrhythmia detection, such as pattern matching, pattern subtraction etc., Rule base technique is one of the simple method which can be utilized for arrhythmia detection after obtaining the denoised ECG signal. In the present work, initially, noisy ECG signal is effectively processed by the MSPCA method for noise elimination from corrupted signals. The detectable measures, QRS duration and R-R interval, are evaluated for the restored artifact free ECG signal. Based upon these two values, arrhythmia can be detected by using rule base technique (two- parameter method). The rule base technique essentially projects QRS duration and R-R intervals on a two dimensional area. According to the beat falling into particular place of this two dimensional area, various arrhythmias can be detected. The two- parameter mapping method [27] can be clearly described by using the Figure 6 shown below.

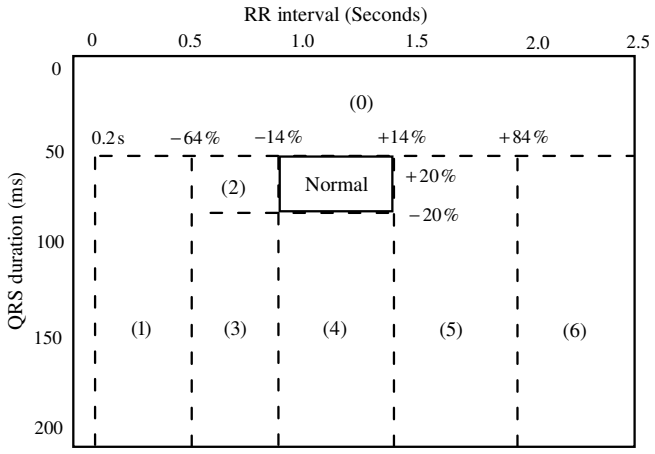

FIGURE 6: Two-Parameter Mapping.

In this two-parameter mapping, a region called normal is established by permitting the algorithm to first learn on a set of eight QRS complex defined by a clinician, as having normal rhythm and morphology for the specific subject. This learning establishes the initial center of the normal region in the two dimensional mapping space. Boundaries of all other regions in the map, except for region “0”, are computed as percentages of the location of the center of the normal region. Region “0“ has fixed boundaries based on physiological limits. Any point mapped into region “ 0 ” is consider to be noise because it falls outside, what we normally expect to be the physiological limits of the smallest possible RR interval or QRS duration.

An abnormality such as tachycardia condition causes the clusters of beats to fall in the region “1” (which represents very short RR intervals) whereas the bradycardia beats fall in region“6”. Abnormalities must be classified by considering sequences of beats .for example a pre mature ventricular contraction (PVC) with a full compensatory pause would be characterized by a short RR interval coupled with a long QRS duration, followed by a long RR interval coupled with a normal QRS duration. This would be manifested as a sequence of two points on the map, the first in the region “3” and the second in the region “5”. Thus, arrhythmia analysis consists of analyzing the ways in which the beats fall onto the mapping space.

S.No	Type of Beat	Description
1.	Normal	If a beat falls in the normal box
2.	Asystole	No R wave for more than 1.72 s; less than 35 beats /min
3.	Droped	A long RR interval;beat falls in region 6
4.	R-on-T	A beat falls in region 2
5.	Compensated PVC	A beat in Region 3, followed by another in Region 5
6.	Uncompensated PVC	Abeat in Region 3, followed by another in the normal region
7.	Couplet	Two consecutive beats in region 3 followed by beat in normal region 5
8.	Paroxysmal bradycardia	If there are at least three consecutive points in Region 5
9.	Tachycardia	Average RR interval is less than 120 beats /min
10.	Fusion	Beat with a wide QRS duration; falls in region 4
11.	Escape	Beat with a delayed QRS complex; falls in Region 5
12.	Rejected	Beat with RR interval of 200 ms or less QRS duration of 60 ms or less.

TABLE 1: Arrythmia Classification.

The center of the normal region is continuously updated, based on the average RR interval of the eight most-recent beats classified as normal. This approach permits the normal region to move in the two-dimensional space with normal changes in heart rate that occur with exercise and other physiological changes. The boundaries of other regions are modified beat-by-beat (adapts to normal changes in heart rate). The classification of the waveforms can be made by noting the regions in which successive beats fall. The rule base technique described above is an efficient method for extracting RR interval and QRS duration information from an denoised ECG signal. Based on the acquired information, different arrhythmias are classified as shown in the Table I.

4. RESULTS AND DISCUSSION

In order to test the performance of the proposed MSPCA algorithm, the MIT-BIH Arrhythmia Database records [24] were considered. To observe the enhancement, elimination of EMG, baseline wandering and PLI noise were considered. Steps described in section III were applied on corrupted ECG signals. Figure 7 illustrates EMG corrupted and eliminated ECG signal using multi scale PCA on two different subjects. Similarly, for the baseline wandering noise the result is shown in Fig 8. PLI corrupted and eliminated signals for two different subjects are portrayed in Fig 9. The principal components of the transformed ECG signal corresponding to record-103m are shown in Figure 10.

In order to test the efficacy of the proposed filtering method, different wavelets were used in the process of applying multi scale PCA on the PLI corrupted ECG and the resulted denoised signals were observed, wherein the morphological features of the ECG were clearly restored can be seen from fig 11. For the sake of comparison, the same ECGs were processed with only wavlets and the signals are portrayed as (e)-(g) in Figure 10. However, visual inspection of the enhanced signals did not reveal much information about the efficacy of the method used. Hence, for performance comparison, the following statistical measures were considered: RMSV, RMSE, RMSD.

1. Root mean square deviation (RMSD): It is the RMS value obtained from difference of pure ECG signal and the restored ECG signal that has been processed by the proposed method.

2. Root mean square error (RMSE): RMSE is the RMS value of the restored ECG minus filter output for clean ECG.

3. Root mean square variation (RMSV): It is the RMS value of the difference between the original input ECG and processed one.

A smaller values for RMSD, RMSE and RMSV indicates a better efficacy of the method in eliminating PLI and less distortion of signal after the processing; a lesser distortion of ECG morphology after the filtering operation; and less degree of variation of the ECG signal processed by the method respectively. In addition the restoring capacity can be evaluated using the effective measure, improvement in signal to noise ratio (SNRI).

4. Improvement in Signal to Noise Ratio (SNRI): It is the difference between Signal to Noise Ratio at Output (SNRout) in dB and the SNRinput in dB.

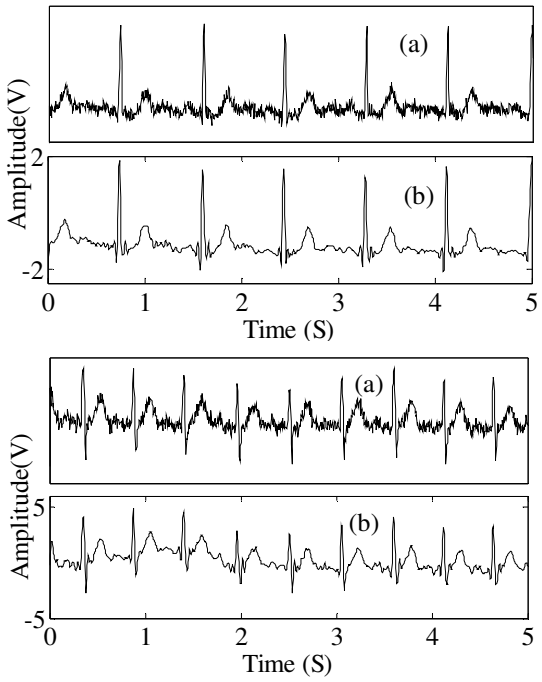

FIGURE 7: EMG corrupted ECG signal in trace (a) and eliminated ECG in trace (b) for two different subjects.

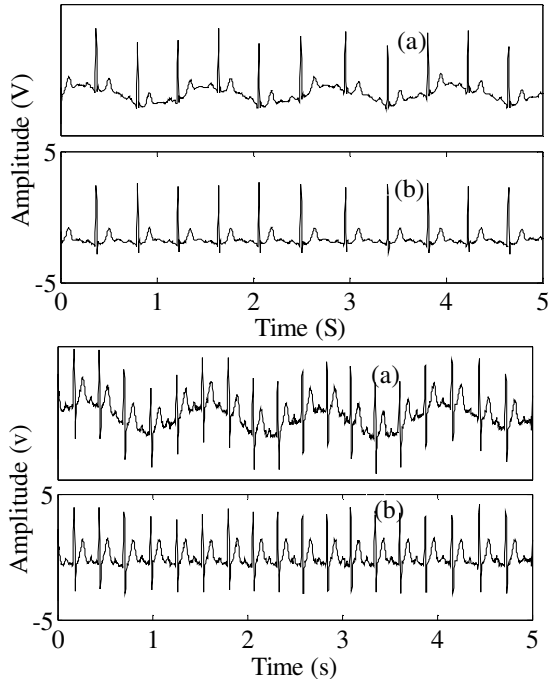

FIGURE 8: Baseline corrupted ECG signal in trace (a) and eliminated ECG in trace (b) for two different subjects.

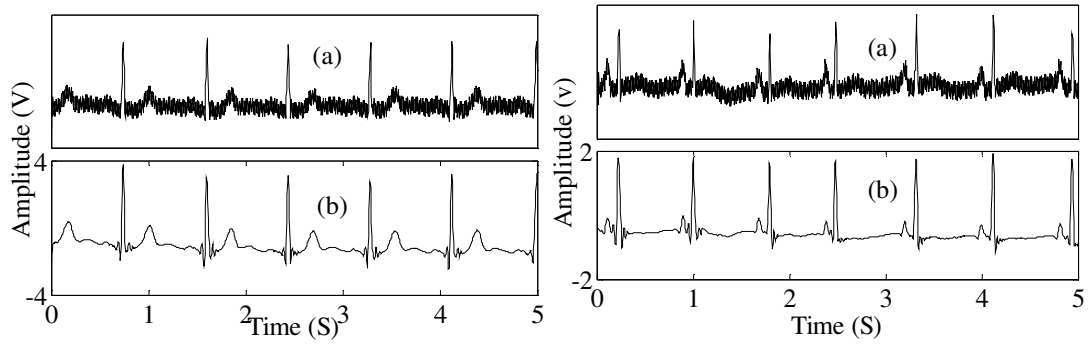

FIGURE 9: PLI corrupted ECG signal in trace (a) and eliminated ECG in trace (b) for two different subjects.

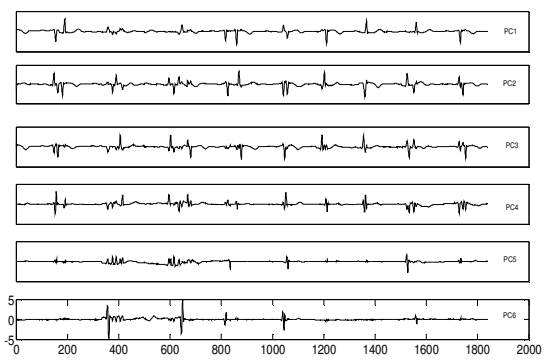

FIGURE 10: The Principle components of the transformd ECG record-103m.

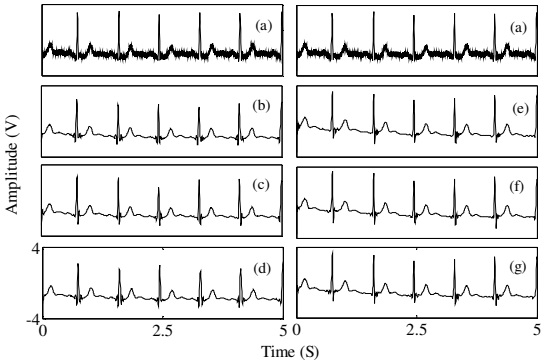

FIGURE 11: (a) PLI corrupted ECG and (b) PLI eliminated using Daubechies wavelet –MSPCA (c) Biorthogonal wavelt -MSPCA (d) coif wavelt- MSPCA (e) only Daubechies wavelet (f) only biorthogonal wavelet (g) only coif wavelet.

$$SNR_{Input} = 10\log_{10}\left[\frac{\sum_i [x_n(i)]^2}{\sum_i [x_n(i) - x(i)]^2}\right] \quad (4)$$

$$SNR_{Output} = 10\log_{10}\left[\frac{\sum_i [x_d(i)]^2}{\sum_i [x_d(i) - x(i)]^2}\right] \quad (5)$$

Where xn (i) is the noisy ECG signal, xd (i) is the de noised ECG signal and x (i) is the Original ECG signal.

To evaluate these measures, all the wavelets were initially applied on the original uncorrupted MIT-BIH Arrhythmia and then on the PLI corrupted ECG. The computed RMS statistics for MSPCA were compared with pure wavelet transform based ECG enhancement algorithm.

Tables II - V, revealed that MSPCA resulted in better statistics compared to only wavelets, which eventually facilitates accurate ECG signal analysis due to improved restoration of ECG morphology. Also the Daubechies wavelet based PCA efficiently eliminated the PLI. After enhancement, based on the signal's QRS duration and a rule base, the identification of cardiac arrythmias will performed. Two original ECG records (# record 103m, # record 215m), were enhanced by MSPCA, QRS locations and susequent classification is shown in Figure 12.

The sensitivity and positive predictivity of the beat detection algorithm are computed by

$$Se = \frac{TP}{TP + FN} \quad (6)$$

$$+P = \frac{TP}{TP + FP} \quad (7)$$

where TP is the number of true positives, FN the number of false negatives, and FP the number of false positives. The sensitivity Se reports the percentage of true beats that were correctly

detected by the algorithm. The positive predictivity +P reports the percentage of beat detections which were in reality true beats.

Table VI and Table VII give sensitivity and positive predictivity data for different cardiac arrythmias.

ECG Data base	WAVELET			MSPCA		
	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)
103	0.005± 1.5x10-4	0.005 ± 2.4 x10-4	0.002 ± 5.0 x10-4	0.004± 1.3x10-4	0.004 ± 2.2 x10-4	0.001± 2.9x10-4
215	0.005 ± 1.5 x10-4	0.003± 2.4 x10-4	0.004 ± 3.0 x10-4	0.004 ± 1.3 x10-4	0.003 ± 2.3 x10-4	0.003 ± 2.8 x10-4
219	0.005 ± 1.5 x10-4	0.004 ± 2.4 x10-4	0.004 ± 3.0 x10-4	0.004 ± 1.4x10-4	0.003 ± 2.3 x10-4	0.003± 2.8x10-4
222	0.005 ± 1.5 x10-4	0.005 ± 2.4 x10-4	0.149 ± 0.011	0.004 ± 1.4 x10-4	0.004 ± 2.3 x10-4	0.148 ± 0.010

TABLE 2: RMSV Measures.

ECG Data base	WAVELET			MSPCA		
	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)
103	0.005 ± 1.5 x10-4	0.005 ± 2.4 x10-4	0.149 ± 0.011	0.004 ± 1.4 x10-4	0.004 ± 2.3 x10-4	0.148 ± 0.009
215	0.005 ± 1.5 x10-4	0.005 ± 2.4 x10-4	0.148 ± 0.011	0.004 ± 1.4 x10-4	0.004 ± 2.1 x10-4	0.147 ± 0.010
219	0.005 ± 1.5 x10-4	0.005 ± 2.4 x10-4	0.146 ± 0.011	0.003 ± 1.0 x10-4	0.003 ± 2.3 x10-4	0.145 ± 0.010
222	0.005 ± 1.5 x10-4	0.005 ± 2.4 x10-4	0.147± 0.011	0.004 ± 1.0 x10-4	0.004 ± 2.3 x10-4	0.146 ± 0.009

TABLE3: RMSE Measures.

ECG Data base	WAVELET			MSPCA		
	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)
103	0.132 ± 0.008	0.132 ± 0.008	0.149 ± 0.011	0.132 ± 0.008	0.132 ± 0.008	0.148 ± 0.009
215	0.133 ± 0.007	0.005 ± 2.4 x10-4	0.148 ± 0.011	0.004 ± 1.4 x10-4	0.004 ± 2.1 x10-4	0.147 ± 0.010
219	0.131 ± 0.122	0.005 ± 2.4 x10-4	0.146 ± 0.011	0.003 ± 1.0 x10-4	0.131 ± 0.122	0.145 ± 0.010
222	0.005 ± 1.5 x10-4	0.005 ± 2.4 x10-4	0.147± 0.011	0.004 ± 1.0 x10-4	0.004 ± 2.3 x10-4	0.146 ± 0.009

TABLE 4: RMSD Measures.

ECG Data base	WAVELET			MSPCA		
	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)	db5 (Soft)	coif5 (Soft)	bior6.8 (Hard)
103	5.53	5.44	4.99	5.52	5.44	4.98
215	5.51	5.44	4.99	5.50	5.44	4.97
219	5.50	5.44	4.99	5.49	5.44	4.98
222	5.52	5.44	4.99	5.50	5.44	4.97

TABLE 5: SNRI Measures.

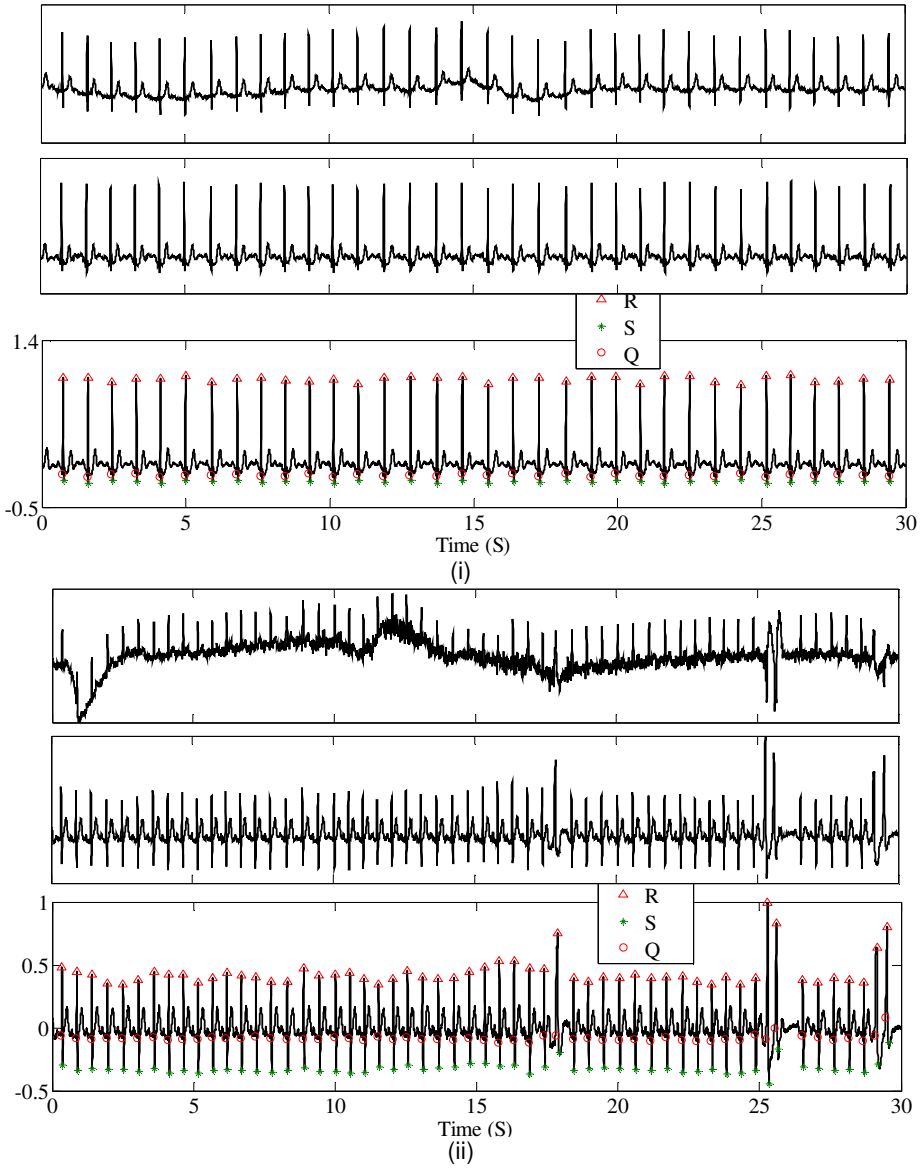

FIGURE 12: Noisy ECG signal shown in top trace, denoised using MSPCA in bottom trace and QRS detected signal in bottom trace for identification of cardiac arrythmias for a record of 103m in (i) and a record of 215m.

record #	Bradycardia					Escape					Normal				
	TP	FP	FN	Se (%)	+P (%)	TP	FP	FN	Se (%)	+P (%)	TP	FP	FN	Se (%)	+P (%)
100m	32	1	0	96.96	100.0	65	0	1	100.0	98.48	562	2	0	99.64	100.0
101m	20	0	1	100.0	95.23	30	1	0	96.77	100.0	04	0	0	100.0	100.0
103m	170	0	1	100.0	99.41	232	1	2	99.57	99.14	1812	20	16	98.90	99.12
107m	1092	10	12	99.09	98.91	1435	12	14	99.17	99.03	58	1	0	98.30	100.0
121m	110	1	1	99.09	99.09	150	0	1	100.0	99.33	09	0	0	100.0	100.0
215m	154	0	1	100.0	99.35	295	1	0	99.66	100.0	2278	30	12	98.70	99.47
219m	494	1	0	99.79	100.0	1056	14	17	98.69	98.41	964	1	2	99.89	99.79
222m	613	2	1	99.67	99.83	1254	12	16	99.05	98.74	311	1	1	99.67	99.67
Total	2685	15	17	99.44	99.37	4517	40	41	99.12	99.10	5998	55	31	99.09	99.48

TABLE 6: Arrythmia Beats of Eight Different Subjects.

record #	Noise					Fusion				
	TP	FP	FN	Se (%)	+P (%)	TP	FP	FN	Se (%)	+P (%)
100m	646	2	1	99.69	99.84	1069	20	2	98.16	99.81
101m	175	1	0	99.43	100	41	0	1	100.0	97.61
103m	162	1	1	99.38	99.38	43	0	1	100.0	97.72
107m	1486	25	24	99.00	99.06	175	1	1	99.43	99.43
121m	1017	10	2	99.02	99.80	257	1	2	99.61	99.22
215m	463	1	0	99.78	100.0	335	1	1	99.70	99.70
219m	140	0	1	100	99.29	39	0	0	100.0	100.0
222m	661	2	1	99.69	99.84	583	2	1	99.65	99.82
Total	4570	42	30	99.08	99.34	2542	25	9	99.02	99.64

TABLE 7: Arrythmia Beats of Eight Different Subjects.

5. CONCLUSION

In clinical applications, the arrhythmia condition, disturbing the rhythmic activity of heart, and its detection plays a vital role for diagnosing the patient's rhythmic status. The detection of abnormal cardiac rhythms, automatic discrimination from rhythmic heart activity, became a thrust area in clinical research. Arrhythmia detection is possible by analyzing the electrocardiogram (ECG) signal features. ECG is a non-stationary biomedical signal that is invariably corrupted with different artifacts during its recording. This paper presents an approach for ECG signal

enhancement by combining the attractive properties of principal component analysis (PCA) and wavelet processing, called multiscale PCA. The resulting multi-scale PCA extracts relationships between the variables by PCA, and between the measurements by wavelet analysis. In this application, the proposed MSPCA served as a powerful tool when addressing problems related to noise elimination. MSPCA eliminated the different types of noises present in the corrupted ECG signal. Experimental results revealed that Daubechies based MSPCA resulted in improved restoration of ECG morphology compared to simple wavelet processing. With enhanced ECG signal features obtained after MSPCA processing, detectable measures, QRS duration and R-R interval are evaluated. By using the rule base technique, projecting the detectable measures on a two dimensional area, various arrhythmias were detected depending upon the beat falling into particular place of the two dimensional area.

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