Research on Various Enhancing Algorithms for ECG

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Abstract— Electrocardiogram (ECG) is an electrical signal used for measuring activity of the heart on the body surface via electrodes (leads). It is a primary diagnostic tool for analysis of cardio vascular problems. As ECG signal gets corrupted by different artefacts like power line interference, baseline drift and muscle contraction, diagnosis becomes a difficult task. To get an artefact free ECG signal various techniques employed for de-noising are wavelet transforms, (MSPCA) Multi scale Principal Component Analysis, (HOSA) Higher Order Spectral Analysis and Empirical mode of Decomposition (EMD). Performance comparison of these techniques is achieved by calculating the statistical parameters such as (RMSE) Root mean square error, (RMSV) Root mean square variance and (RMSD)Root mean square deviation.

1. INTRODUCTION

1.1. ELECTROCARDIOGRAM

ECG is an important diagnostic tool that decides the heart condition of a person is [1]. The cardiac cycle refers to the sequence of events occurring between two consecutive triggering of the SA node. It is represented by the ECG beat as shown in figure.1.1. It has three significant features of P-wave, QRS wave, T and sometimes U wave.
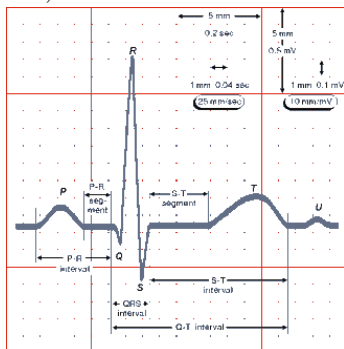

Fig 1.1: Normal ECG waveform.

1.2. ECG ARTIFACTS

Noise is omnipresent. Artifacts are something undesired. Unwanted signals generated from external sources called artifacts contaminate the ECG while recording. As a result of this contamination components of the ECG signal gets distorted making the clinical diagnosis difficult. AC power line noise (PLI) [2], Electromyogram, and Baseline- wander noise are some of the common undesired signal which corrupt the ECG signal. PLI [2] is of frequency 50 Hz, may corrupt the ECG due to improper grounding of recording machine, with amplitude equal to as high as 50% of the QRS complex. Due to the movement of electrodes and patient, zero reference line of the signal shifts up/ down resulting in baseline wander noise with frequency of 1Hz. EMG is a 2KHz noisy signal that corrupts the signal due to the movement of the muscles by patient with an amplitude equal to nearly 10% of that of QRS wave.

1.3 MOTIVATION AND OBJECTIVE

Requirement of an enhanced ECG signal for clinical diagnosis motivated this study and implementation of various enhancing methods for arrhythmia detection. Over the past four decades several signal enhancement techniques were presented in the past using IIR and Finite impulse response digital filters, [3-5] adaptive filtering and [6-11]wavelet thresholding techniques. Being a linear energy operator LMS adaptive method poses difficulties in following the changes happening in nonstationary signals like ECG, though it is a widely used method for noise cancellation. Linear energy operator calculates the energy of a signal based on only amplitude variations, neglecting phase relations. Hence nonlinear algorithms with improved performance measures for ECG enhancement are welcome. Objective of work in this paper is to make a comparative study and implement some nonlinear techniques like wavelets, multi scale principal component analysis [12-14], higher order spectral (HOS) cumulant based AR modeling [15-18], Empirical mode Decomposition method [19], and to quantify the significant differences among them. The contaminating artifacts considered are power line interference (PLI), baseline wander (BLW). Practical input SNR considered was from -10 dB to 10 dB. It is a difficult task for the physician to decipher the minute changes in amplitude and duration of the ECG signal by a naked eye to monitor the cardiac health. So the performance measures [20] considered for evaluation of the proposed methods are RMSE (root mean square error), RMSD (root mean square deviation) and RMSV (root mean square variance). Required data is extracted from MIT-BIH physionet archive.

2. METHODOLOGY:

2.1. Algorithm1: Multiscale Principal Component analysis (MSPCA)

2.1.1 WAVELETS

Time frequency description of a signal can be obtained by Wavelets [6-8]. WT (Wavelet transform) gives the information of a signal about its frequency and time localization.

WT can break down the signal into low/high frequency modules with reference to a transformation function which matches the signal to be broken down. Choice of the a transformation function depends on the application. Algorithm using Haar wavelet can be computed easily whereas the details missed by Haar wavelet can be picked up by Daubechies wavelet [9] but complexity increases. Low frequency Energy spectrum of Daubechies wavelet family matches the energy spectrum of the ECG signal. In contrast to short time Fourier transform, length of the window is long for low frequency signals and short for high frequency signals in WT. In discrete wavelet transform, the signal is decomposed into lower resolution components like 'approximation' and 'detail' coefficients using wavelet filter banks, as shown in fig.2.1 and reconstruction in fig.2.2. Low pass filter produces an output termed as Approximate coefficients A_j which describes the identity of the signal and output of high pass filter (HPF) are detail coefficients D_j which convey gradation. Dividing the signal at various levels is a repetitive method of decomposing approximate coefficients at different levels, shown in fig.2.3 as a wavelet decomposition tree. sufficient information is present in approximate coefficients so the last level of A_j are saved
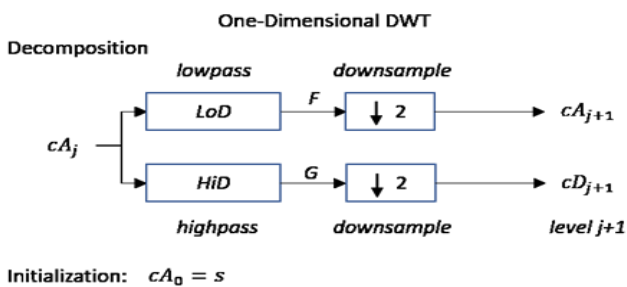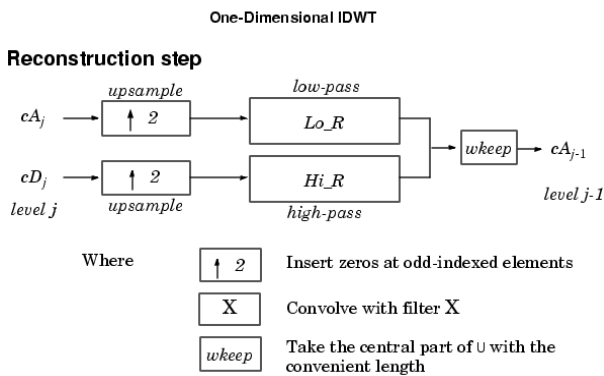

Fig 2.1 Wavelet Decomposition
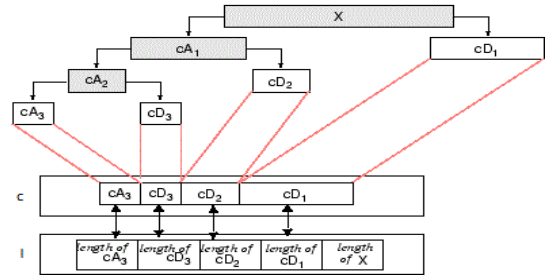

Fig 2.2 Wavelet Reconstruction

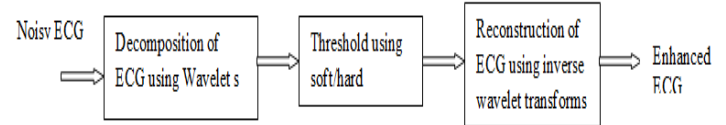**Fig 2.3 Wavelet Decomposition tree**

2.1.2. DENOISING

Figure 2.4: Block diagram of Wavelet Denoising

Block diagram for Wavelet Denoising [10-11] is shown in fig.2.4 and the steps for denoising are.

(i) Decomposition: Breakdown the ECG signal at various levels of N using appropriate choice of mother wavelet.

(ii) Thresholding: Choosing a threshold value based on hard or soft thresholding methods of detail coefficients at various levels from 1 to N so as to obtain modified detail coefficients. Theoretical considerations yield the following value of the threshold:

$$t = \sqrt{2\sigma^2 \log(n)/n} \qquad (2.1)$$

where t is the threshold value , σ^2 is the variance of noise and n is the length of input vector. Two important factors for selecting a threshold value are a) value of the threshold and b) method of threshold. All the wavelet coefficients with lesser amplitude than threshold are set to zero in hard threshold method, and wavelet coefficients with greater amplitude than threshold are shrinked to zero in soft thresholding. Detail coefficients that carry the critical information are thresholded. output is a clean signal with required details.

(iii) Reconstruction: original signal is reconstructed from the modified detail coefficients and approximation coefficients at all levels.

2.1.3. PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is a variable reduction method [12-13], used to identify the patterns. PCA can be obtained in two methods, by covariance matrix method or using Singular Value Decomposition (SVD) method. Procedure required for computing Principal components of the data are explained below.

(i)consider a the ECG data which is periodic.

(ii) Arrange the above data as a matrix P of size i x j, where j represents the periodicity and i represent the number of periods considered.

Let

P(l)=[p$_1$(l),p$_2$(l),p$_3$(l),….,p$_m$(l)]   (2.2)

Where P(t) represents the arrangement of ECG beats into a matrix from which principal components are computed. Singular Value Ratio (SVR) profile is used to obtain Periodicity, consider the ratio of first principal component to the second principal component.

(iii) Subtract the mean of pl from all samples and, compute the covariance matrix. Covariance is defined as

$$C = \frac{1}{N}\left[P\,P^T \right]$$ (2.3)

where C is m x m square symmetric matrix.

(iv) Compute the Eigen values, Eigen vectors for the covariance matrix C.

(v) Arrange the Eigen vectors as per the Eigen values from highest to lowest.

Neglect the minimum Eigen values as the first step for data reduction, and Eigen vectors of higher values are considered as principal components (PC). These are linear transformation coefficients for eigenvectors ai of ECG beats where i=1, 2,…,n

Disadvantages of Principal Component Analysis (PCA):

i. PCA can be processed only at one level.

ii. It suits steady state processes with linear relationships.

iii. With limited ability it can reduce the error by neglecting least significant component

Multi-scale Principal Component Analysis (MSPCA) combines the concepts of PCA and wavelets to gain the advantages of both PCA and wavelets.

2.1.4. Multi-scale principal component analysis

MSPCA [14] uses both the concepts of PCA and wavelet transforms. ECG data is decomposed into coefficients at various frequency bands using wavelet transform and thresholded to smoothen out few of the sub coefficients. PCA is computed which de-correlates the variables in complex data and brings out only the linear relationships. Various sets of ECG data subjected to MSPCA technique. Statistical parameters used as performance measures are RMSE, RMSD, RMSV and improvement in signal to noise ratio (SNRI). In addition to the above parameters another important measure evaluated is correlation coefficient to show the likeness between the original data l and enhanced data of ECG. These parameters justified that the MSPCA method is a fine enhancement method for signals like ECG by use of Db5 wavelet in comparison with empirical mode decomposition (EMD) method. The enhanced signal may be used for arrhythmia detection. In

TABLE 2.1: VARIOUS RECORDS OF ECG DATA

S.No	ECG data record	Type
1	103m	Normal
2	16272m	Normal

3	16265	Normal
3	117	Normal
4	215	Normal
5	219	Normal
6	222	Normal
7	30	SCD
8	31	SCD
9	52	SCD
10	208	PVC
11	111	LBBB
12	124	RBBB

2.1.5. TEST PROCEDURE AND MEASURES:

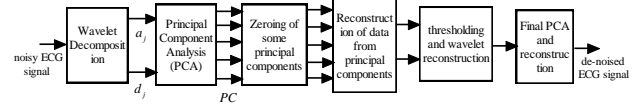Proposed MSPCA method is shown in fig 2.5.

Fig 2.5 MSPCA method for enhancement of ECG signals

Sequence of steps for enhancement of ECG signals using MSPCA are

• Apply wavelet decomposition technique to each column in ECG data matrix ,

• Work out on wavelet coefficients to form a covariance matrix for each scale

• Estimate loadings of PCA and scores of wavelet coefficients at required scale,

• choose the required number of wavelet coefficients and loadings

• Calculate Principal components for all scales on considering important scales having major events

Statistical parameters used as Performance measure of the algorithm

Root Mean Square Deviation (RMSD): It is the root mean square value of the difference between clean ECG and denoised ECG.

$$RMSD = \sqrt{\frac{\sum [q(i)-p(i)]^2}{N}}$$

(2.4)

• Root Mean Square Error (RMSE): It is the root mean square value computed for the difference between enhanced ECG and filter output.

$$RMSE = \sqrt{\frac{\sum [q(i)-p'(i)]^2}{N}}$$ (2.5)

• RMSV (Root Mean Square Variation): It is obtained by calculating root mean square value of subtracting filtered ECG signal frompure ECG signal.

$$RMSE = \sqrt{\frac{\sum [q(i)-p'(i)]^2}{N}}$$ (2.6)

2.1.6. RESULTS AND DISCUSSION:

The proposed MSPCA based algorithm is applied on ECG records from MIT-BIH Arrhythmia database. The signal is enhanced after reducing the PLI and baseline wandering noises. Procedure explained in the above section is implemented on the noisy ECG signal. Fig.2.6 depicts

the ECG affected by baseline wandering which is deviated from iso-electric line and enhanced ECG. Noisy ECG with PLI and enhanced ECG with corresponding frequency spectrum is portrayed in fig.2.7. Power spectrum for a noisy signal shows an impulse at exactly 50/60HZ (AC power line frequency) where as the enhanced data doesn't show this as it free of PLI

noise. MSPCA algorithm with different wavelets is used to process the noisy ECG signals and it was observed that the mother wavelet dB5 enhanced the ECG signal effectively to restore the morphological features of the ECG signal. To prove the reliability of the proposed method, it is compared with the empirical mode decomposition (EMD) [19] method and cumulant based AR method. Spectrum of the noisy ECG and enhanced ECG with suppressed PLI for record 103m is clearly demonstrated using MSPCA. Similarly the performance of the proposed method is compared with EMD and cumulant based AR algorithm in removing BLW. The results demonstrate the efficacy of the proposed MSPCA based method.
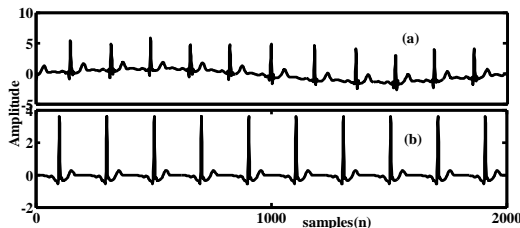

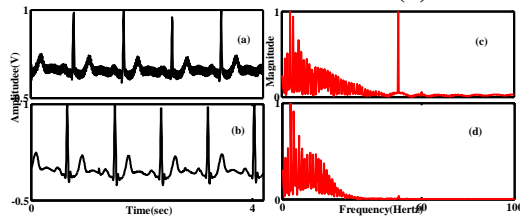**Fig 2.6 ECG signal with baseline wander in trace (a) and denoised ECG in trace (b)**

Fig 2.7 ECG with PLI noise in trace (a) and denoised in trace (b) with corresponding spectra in (c)-(d)

2.2. Algorithm 2

2.2.1. HIGHER ORDER STATISTICS (HOS)

Higher order statistics [15-17], refer to the spectrum of cumulants of 2nd order or higher. In this domain signal to noise is high. Two main properties which inspired to exercise on HOS are its (i) capability to hold back Gaussian noise whose mean and variance are not known (ii) ability to reconstruct the magnitude as well as phase response of the signal.

Precise character of second order cumulant is, it is equivalent to variance whose Frequency transformation gives frequency spectrum. Third order cumulant whose Frequency transformation gives Bispectrum. Analogy of fourth order cumulant is kurtosis of the signal around zero mean whose Frequency transformation is trispectrum. Definition of cumulants is given below.

$$k_1 = cumulant\left[m_1\right] = K_1 \qquad (2.7)$$

i.e., k_1 the 1st order cumulant of m1 and is the 1st moment or mean.

$$k_2 = cumulant[m_1, m_1] = K_2 - K_1^2 \qquad (2.8)$$

i.e., k_2 is 2nd order cumulant of m2 ,is 2nd moment.

$$k_3 = cum[m_1, m_1, m_1] = K_3 - 3K_2 K_1 - 2K_1^3 \quad (2.9)$$

Where k_3 is third order cumulant of m1 , is 3rd moment.

Attributes that allows to use the cumulants effectively to analyze non-stationary and no-minimum phase ECG signal are

- Their arguments are symmetric.
- Their arguments are additive .
- They hide additive constants
- Linearity property can be satisfied.

Autoregressive (AR) model algorithm using HOS cumulants [18] is presented to achieve noise free ECG signal. As a first step third order cumulants are calculated for corrupted ECG signal, and next an AR model filter is designed with these cumulant coefficients using Yule-walker method. A noise free ECG signal can be obtained by allowing the corrupted ECG signal to pass throughout this AR model filter. Statistical parameters such as RMSE, RMSD, RMSV are calculated to prove the efficiency of the designed algorithm.

2.2.2. Autoregressive (AR) Model

AR model is used for computing power spectrum density using autocorrelation function. It is a linear model which is widely used due to 2 causes. This model presents narrow peaks in the spectrum by estimating AR parameters using plain linear expressions. This method expects the system output by considering past results. This may be analysed as an IIR filter output with input as white noise. In this work, AR concept models the ECG data as a linear system the output with input as white noise whose mean is zero and variance unknown. Parameters of AR filter are computed using Yule-walker method which estimates the autocorrelation of the signal. AR model has the form

$$x[j] = \sum_{l=2}^{n+1} b_j x[j-l+1] + n[j] \qquad (2.10)$$

Where x[j] is the ECG time domain signal, n[j] is the white Gaussian noise of zero mean, bj's are AR coefficients, and n is the AR order. AR model is a linear model which expects the signal to have minimum phase. Spectral estimate using autocorrelation function and Yule-walker method may not give an appropriate fit for ECG as it is a non-linear and combined phase signal. So 3rd order cumulants for ECG data are estimated first and from the estimate required AR parameters are computed. The expression for observed data is

$$q(m) = \sum_{i=1}^{p} b_i \exp(j2\pi mfi + j\phi_i) + w(m) = y(m) + w(m) \rightarrow \quad (2.11)$$

Where, w(m) is additive noise, bi 's are the amplitudes, fi's are the frequencies and φi's are the phases. This way combined phase and non-linear ECG data can be made to fit into AR model of least order.

2.2.3. TEST PROCEDURES AND MEASURES

Steps involved in ECG Enhancement using cumulant based AR modelling [18] is shown in the fig.2.8.

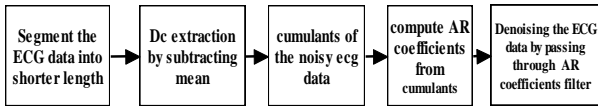| Segment the ECG data into shorter length | → | Dc extraction by subtracting mean | → | cumulants of the noisy ecg data | → | compute AR coefficients from cumulants | → | Denoising the ECG data by passing through AR coefficients filter |

Fig. 2.8 Block diagram for enhancing the ECG data

(i) Various ECG data records with different sampling rates are re-sampled to 200 samples/sec

to have a common sampling rate.

(ii) Shorter length segments of ECG data are considered.

(iii) DC noise is eliminated by subtraction of the average value from all sample values.

(iv) Higher order cumulants are calculated for the ECG data segments.

(v) 3rd order cumulants are used to calculate AR coefficients using Yule-walker algorithm.

(vi) Enhanced ECG signal can be obtained by passing the noisy ECG signal through AR filter,.

2.2.4. DISCUSSION on RESULTS

Normal sinus rhythm of ECG data taken from MITBIH database are subjected the proposed algorithm.. Fig 2.9 shows the BLW corrupted ECG and enhanced one using cumulant based AR algorithm. Fig 2.10 shows noisy and noise free ECG data with respective frequency spectrum. Minimum values of RMSE, RMSV and RMSD justify that cumulant based HOSA model is able to reduce the artifacts while preserving the morphology of ECG.
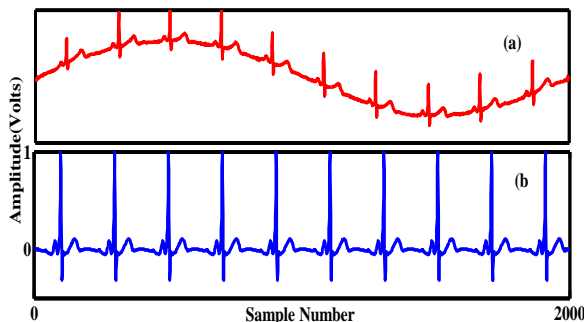

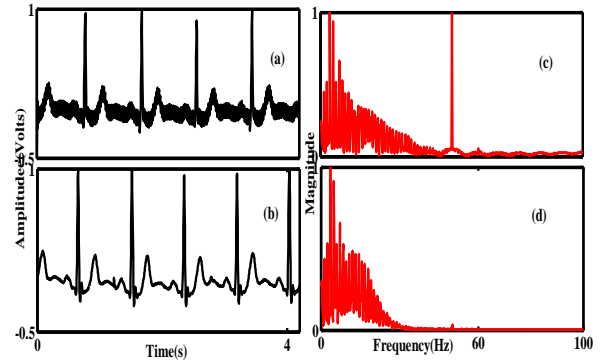**Fig 2.9 BLW interfered ECG record in trace (a) and enhanced ECG using AR model in trace (b)**

Fig 2.10 ECG signal with PLI corruption in trace(a). ; Enhanced ECG in trace (b) and their respective spectrum in (c)-(d) using AR model

2.3. Algorithm 3: Empirical Mode Decomposition

Empirical mode decomposition (EMD) [19] is the basic concept of HHT. Dividing the signal into various segments, EMD is comparable to other frequency analysis techniques like Fourier transform and Wavelet transform. EMD is an effective and adaptive method. EMD can be applied to non-linear and non-stationary processes as the signal is divided based on the local characteristic time scale of the data. This method is useful for the analysis of natural signals, which are non-linear and non-stationary. Functions which are orthogonal to the original signal are eliminated by EMD method. Completeness is based on the method of the EMD, the way it is divided implies completeness. Intrinsic Mode Functions (IMFs) or components of EMD can describe the signal very well even though they are not exactly orthogonal. IMF is defined a simple oscillatory mode analogous to the simple harmonic function, but it is much more general with constant amplitude and frequency in a simple harmonic component. An IMF may have varying amplitude and frequency on time scale. The truth is that all the IMFs of the signal are in time-domain, of equal length as the original signal and allows the signal frequency to be preserved. Extracting IMFs of real world signals is important as there are multiple reasons for natural processes, and each of these reasons may occur at particular time intervals. EMD analysis such type of data is observed whereas, it is hidden in the Frequency domain or in wavelet coefficients.

Sequence of Steps for EMD on ECG signals

• In EMD the signal is divided into intrinsic mode functions (IMF)

• The method of extracting an IMF is called sifting.

• The sifting process is as follows: Identify all the local extrema in the test data.

• Connect all the local maxima by a cubic spline line as the upper envelope.

• Repeat the process for the local minima to produce the lower envelope.

• The IMF's are used to divide the time series into superposition of components with well-defined instantaneous frequency.

• The IMF's are added and the signal is reconstructed again.

3.RESULTS AND DISCUSSION

Fig.2.11 depicts the PLI corrupted ECG, enhanced ECG with their corresponding spectra respectively. Fig. 2.12 depict the performance of EMD in enhancing the ECG data against BLW noise. Statistical parameters RMSE, RMSV and RMSD reveal that EMD technique is best applicable for nonstationary and nonlinear signals like ECG. It reduces the artifacts while preserving the morphology.
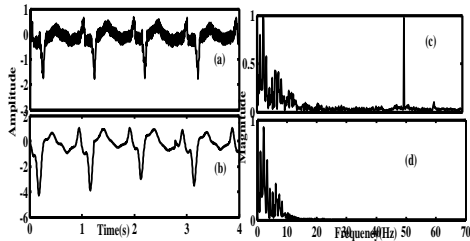

Fig.2.11 ECG record with PLI corruption in trace(a); denoised ECG in trace (b) and their respective spectrum in (c)-(d) using EMD
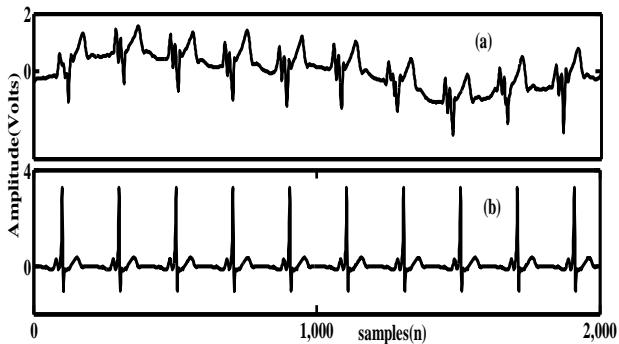

Fig. 2.12 BLW interfered signal in trace(a); noise free ECG using EMD in trace (b)

CONCLUSION

Being a non-stationary biomedical signal, recorded ECG signal is contaminated with different unwanted signals like PLI and baseline wander. This paper discussed three different algorithms in comparison based on MSPCA, cumulant based AR model and EMD. MSPCA combines the advantageous features of PCA and wavelets for enhancement of ECG signal. In MSPCA, PCA brings out the linear relationships between the variables, and required measures using multilevel wavelet analysis. The MSPCA algorithm serves as a powerful method when addressing noise elimination problems related to ECG. MSPCA reduces different types of artifacts like PLI, BLW from the corrupted ECG signal. Statistical measures RMSE, RMSD, RMSV have shown that MSPCA using Daubechies wavelet gave better reconstruction of ECG wave shape when compared to the continuous wavelets, adaptive filter and EMD methods in minimizing PLI noise. Algorithm Complexity for decomposition of ECG data at multiple level for enhancement of ECG data is the matter of concern. To overcome the disadvantage of MSPCA algorithm, a new algorithm based on Higher order statistical analysis is

discussed. This algorithm, combines the concept of HOSA with AR model called cumulant based AR model which was implemented for enhancement of ECG data. Least values of statistical parameters justified that this algorithm is also efficient in enhancing ECG against PLI and baselinewander.th. third algorithm EMD is adaptive and highly efficient, as the decomposition is based on the local characteristic time scale of the data, it can be applied to nonlinear and non-stationary processes. So, for the removal of BLW the EMD is the best method. Performance comparison of the above algorithms is shown in tables 3.1 and 3.2 reveal that the Empirical Mode Decomposition removes the Base line wandering noise effectively with low RMSE value in the ECG signal, whereas MSPCA is efficient in removing PLI noise with low RMSE value compared to other two methods.

Table 3.1 Comparative table of the enhancement techniques to reduce BLW noise.

Name of the Technique	RMSD	RMSV	RMSE
	Mean± STD	Mean± STD	Mean± STD
Cumulant based AR modeling	0.754±0.0161	0.732± 0.019	0.077±0.0071
EMD	0.7034±0.0144	0.7102±0.0153	0.0168±0.0101
DWT	0.8969±0.1389	0.9295±0.0424	1.3616±0.1567
MSPCA	0.7234±0.0331	0.7295±0.0345	0.0168±0.0101

Table 3.2 Comparative table for all the enhancement techniques to reduce PLI noise.

Name of the Technique	RMSE	RMSD	RMSV
	Mean± STD	Mean± STD	Mean± STD
Cumulant based AR modeling	0.872±0.0118	0.1594±0.0216	0.148± 0.121
EMD	0.7820±0.1391	0.7887±0.1398	0.0168±0.0101
DWT	0.8931±0.1372	0.9334±0.0432	1.3616±0.1567
MSPCA	0.7226±0.0877	0.7287±0.0888	0.0168±0.0101

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