# Modeling of ECG Signal with Nonlinear Teager Energy Operator

**V.Sharmila and K.Ashoka Reddy,**

Kamala Institute of Technology &Science, Karimnagar, Andhra Pradesh, INDIA.

Kakatiya Institute of Technology &Science, Warangal, Andhra Pradesh, INDIA.

**Summary**
Objective of this paper is to analyze noise free ECG signal and to discriminate the arrhythmia data from normal sinus rhythm data. ECG data is characterized by its nonlinear dynamic behavior, which shows significant changes between normal and arrhythmia data. Presence of artifacts like 60Hz power line interference (PLI), low frequency base line wander noise (2Hz) and muscle artifacts will not allow the analysis of ECG. In this paper two nonlinear modeling techniques, Multi Scale Principle Component Analysis (MSPCA) and Higher Order Spectral Analysis (HOSA) used for denoising of ECG data. In MSPCA principal components (PC) at multi scale are computed and those PC's related to significant events are combined. MSPCA serves as powerful tool in denoising the ECG data from PLI noise. HOSA is valued for its characteristics of suppressing Gaussian noise for cumulants of higher order (3rdorder). This cumulant based method enhances the ECG data from artifacts like PLI, baseline wander , Gaussian noise and also improves the Signal to Noise Ratio. It is observed that HOSA is a simple nonlinear modeling technique that can be used to enhance the noisy ECG data. Teager Energy Operator (TEO), a nonlinear energy operator is applied on denoised ECG beat to find the energy generated by the source of signal rather than the energy of the signal itself. TEO of enhanced signal is valued for clear identification of arrhythmia data using parameters like Average nonlinear energy in time domain ANEt and average non linear energy in frequency domain ANEf . The performance measures are improvement in signal to noise ratio(SNR), Root Mean Square Error (RMSE), Root Mean Square Deviation (RMSD) [19]. TEO has successfully identified NSR data from arrhythmia data. The simulation work is carried out on a set of Normal sinus rhythm (NSR) and arrhythmia data taken from MIT-BIH database.

***Keywords:***
*ECG, MSPCA, HOSA, Principal components, Cumulants , TEO, Arrhythmia.*

## 1. Introduction

ECG is an graphical record of electrical activity of the heart required for diagnosing the problems associated with the heart. ECG data present in the frequency range of .05 to 100Hz gets corrupted with artifacts like PLI, Gaussian noise and low frequency baseline wander noise. ECG is envisioned to be a quasi periodic, dynamic, nonlinear and non-stationary signal [1-4]. It is required to obtain a clean ECG, free of artifacts for the purpose of diagnosis. Many linear algorithmic techniques like principal component analysis, AR [8] or ARMA modeling and LMS adaptive algorithm were presented in the literature to enhance the ECG data. Linear techniques can track changes appearing only in the linear components of stationary data, which does not give satisfactory results when applied on non-stationary data as it consists of underlying nonlinear dynamic components in addition to linear components. In this paper work is done using two nonlinear modeling techniques (1) MSPCA and (2) third order cumulants based on HOSA. MSPCA combines the significant PCA characteristics with wavelets to model the data whose behavior changes over time and frequency. In MSPCA, PC's of wavelet coefficients are computed at different scales and principal components at those scales of significant events are combined and corresponding power spectrum is computed in frequency domain. MSPCA reduces to conventional PCA if some of the insignificant PC's are not eliminated. HOSA is another nonlinear technique used to enhance the noisy data by computing the higher order cumulants in time domain. 3rd order cumulants are calculated for ECG data with maximum number of cumulant lags, and corresponding Bispectrum is computed in frequency domain. After denoising, a nonlinear energy operator TEO which tracks the changes in the nonlinear components of ECG data is used to derive the energy of the source (SA node) from which signal is generated rather than deriving the energy from the signal. Distance between the features for a set of NSR data and arrhythmia data is measured using Euclidean distance which distinguishes NSR data and arrhythmia data. This paper is organized as follows. Problem formulation of the work is illustrated in section 2 which includes brief description of MSPCA, HOSA and TEO. Proposed work is illustrated in section 3. In section 4, simulation results of both modeling techniques of MSPCA and HOSA on ECG data were discussed. Conclusion of the proposed work is covered in Section 5.

## 2.1 Problem Formulation:

Enhancing the noisy ECG data is very important for arrhythmia detection. In the previous work cited in [14] MSPCA was used to enhance the ECG data to reduce PLI , whereas in [15] a third order cumulant computation of

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HOSA has restored the ECG morphology against PLI, Gaussian noise, baseline wander noise and muscle artifacts. Cumulant based method improves the Signal to Noise Ratio when ECG signal is corrupted by Gaussian noise. TEO was used to extract the energy from the source of enhanced ECG in both TD and FD. To analyze nonlinear ECG data, work has been done to enhance the noisy data using the above nonlinear modeling techniques such as MSPCA and HOSA.

## 2.2. Principal component analysis

Principal component analysis (PCA) is suitable for analyzing the data that exhibits linear relationships between its variables by decomposing a larger matrix into smaller matrices.PCA can be performed by two ways of which one is by using covariance method and second by using singular value decomposition (SVD) method. PCA algorithm [10],[11] is discussed below.

$$X(t) = \left[x_1(t), x_2(t), x_3(t), ....x_m(t)\right] , \quad (1)$$

Where *X(t)* is a matrix of size *mxn*, $x_1(t)$, $x_2(t)$ … are periodic ECG beats. The mean of the $x_i$ are removed and the covariance matrix is computed. The covariance is defined as,

$$Y = \left[ XX^T \right], \quad (2)$$

Where *y* is an *mxm* square symmetric matrix from which Eigen values and Eigen vectors are computed. Eigen values are arranged in ascending order which gives Eigen vectors corresponding to highest Eigen values and less significant Eigen vectors corresponding to lowest Eigen values can be ignored. The above process forms the basis for compression. The ordered Eigen vectors of the covariance matrix are the principle components (PC) that can be obtained using

$$z_i = a_i \mathbf{x} \text{ Where i=1, 2 …n} \quad (3)$$

PCs are the linear transformation of the beats with Eigen values $a_i$ as the transformation coefficients. PCA is suitable for modeling the data which relates its variables at a single scale, whereas all the real time data is multi scale in nature that is variables of the data at different locations are related to time and frequency differently. So PCA is not suitable for modeling multi scale data such as ECG. PCA combined with Wavelets leads to the concept of MSPCA which gives improved performance.

## 2.3. Multi Scale PCA:

Multi scale principle component analysis uses the features of both wavelets and principal component analysis. Discrete wavelet transform[5]-[8] can be used for decomposition and reconstruction of the signal using wavelet filter banks as shown in figs.1and 2, the decomposition process is iterative where the signal is broken down into multiple levels of lower resolution. The decomposed components consist of approximate coefficients *Aj* and detailed coefficients *Dj*, of which the last level of approximation among all the details provide sufficient data is saved. Approximation coefficients are the outputs of LPF and the detailed coefficients are obtained at the output of HPF. Identity of the signal is defined by approximations and details impart gradation. Selection of mother wavelet that closely matches the signal is an important criterion. Though algorithm using Haar wavelets is simple to compute and Daubechies wavelet algorithm is complex but picks up the details missed by Haar wavelet algorithm. Wavelet transform which is capable of exploring the signals at different frequency bands with adjustable time frequency resolution is suitable to analyze the non-stationary ECG signal. Thresholding is used in wavelet domain in order to remove some of the coefficients from the decomposed components there by smoothing the signal. Noise corrupted ECG signal is first preprocessed by bandpass filtering. MSPCA algorithm uses the combined concepts of both PCA and wavelets[14]. Each column in the data matrix is subjected to wavelet decomposition at n levels or scales. Compute covariance of the wavelet coefficients at selected scales.PCA loadings are computed on the details of the wavelet coefficients at different scales. PCA is performed on wavelet coefficients greater than the threshold, at selected scales with significant events and data matrix is reconstructed from the selected and thresholded scores. Wavelet denoising procedure for the ECG signals constitutes the following steps as shown in the fig.3

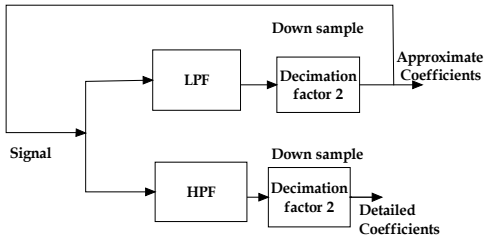


Fig.1.Wavelet Decomposition

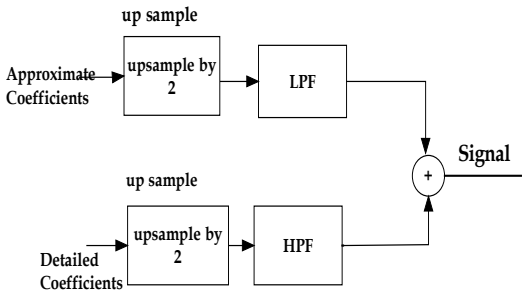


Fig.2.Wavelet Reconstruction

1. Decomposition**:** wavelet decomposition is performed by choosing the appropriate mother wavelet and decomposition level N.
2. Thresholding detail coefficients**:** For each level from 1 to N a threshold value is selected and soft or hard thresholding is applied to the detail Coefficients.
3. Reconstruction**:** wavelet reconstruction is performed by using the original approximation coefficients and modified detailed coefficients.

In hard thresholding process, any wavelet coefficient value less than or equal to the threshold is zeroed and in soft thresholding in addition to hard thresholding subtracts the threshold from the coefficient value greater than threshold.

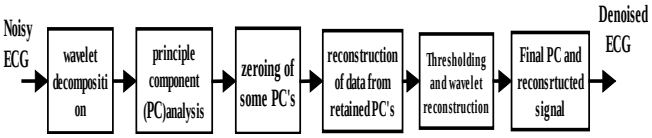


Fig.3.Block Diagram for enhancement of ECG signals using MSPCA

## 2.4. Higher Order Spectral Analysis:

Many real life signals which are nonlinear in nature cannot be modeled by second order measures like autocorrelation function (ACF) and power spectral density (PSD) . A set of parameters called higher order cumulants are used for detection of nonlinearities in a signal. HOS [16]-[18] are extensions to familiar second order measures in time domain and frequency domain for 3rd, 4th and higher orders. For a symmetrically distributed Gaussian random process higher order cumulants are zero. Second order statistics or moments retain amplitude information where as phase information is lost, HOSA retains both amplitude and phase information. In the time domain second order measure is called auto correlation function and third order measure is called third order moment given as

$$M(m1,m2) = x(n)x(n+m1)x(n+m2) \qquad (4)$$

Which by definition depends on two lags m1 and m2.Cumulants are nonlinear combination of moments in time domain whereas, in frequency domain Fourier transform of the higher order cumulants give the corresponding higher order spectra or polyspectra. Fourier transform of 3rd order cumulant called bispectrum is easy to compute and Fourier transform of 4th order cumulant gives trispectrum. Higher order cumulants and spectra may be used to characterize nonlinear, mixed phase and non-Gaussian signals. Cumulants are the coefficients in the taylor expansion of cumulant generating function about the origin, K(ε)=log M(ε). Relation between the first few moments and cumulants are as follows

$$\begin{aligned} K_1 &= \mu_1. \\ K_2 &= \mu_2 - \mu_1^2 \\ k_3 &= \mu_3 - 3\mu_2\mu_1 - 2\mu_1^3 \\ k_4 &= \mu_4 - 4\mu_3\mu_1 - 3\mu_2^2 + 12\mu_2\mu_1^2 - 6\mu_1^4 \end{aligned} \qquad (5)$$

$k_1$, $k_2$, $k_3$ and $k_4$ are 1st, 2nd,3rd and 4th order cumulants and $\mu_1$, $\mu_2$, $\mu_3$ , and $\mu_4$ are 1st,2nd,3rd and 4th order Moments respectively. For a zero mean stationary random process *x(t)*, $i^{th}$ higher order cumulants for *i*=3,4 are computed as

$$k_{i,x}(\tau_1,\tau_2,.....,\tau_{k-1}) = E\{x(\tau_1).....x(\tau_{k-1})\} - E\{g(\tau_1).....g(\tau_{k-1})\} \qquad (6)$$

Where *{g(t)}* is Gaussian random process with same second order statistics as *{x(t)}*. Cumulants compute higher order correlation and also measures the distance of *{x(t)}* from Gaussianity. If *{x(t)}* is Gaussian then all its cumulants are zero for all *i*. 2nd , 3rd and 4th order cumulants for zero mean signal *{x(t)}* are given as

$$\begin{aligned} k_{2,x}(\tau) &= E\{x(t)x(t+\tau)\} \\ k_{3,x}(\tau) &= E\{x(t)x(t+\tau_1)x(t+\tau_2\} \end{aligned} \qquad (7)$$

Mean of a signal can be determined by first order moment or cumulant. Variance of a signal can be determined by second order moment or cumulant. Skewness of a signal can be characterized by third order cumulant. Main drawback of higher order cumulants or polyspectra is that it requires longer data lengths than correlation based methods in order to reduce the variances associated with real time data. Cumulant computation involves expectations and must be approximated same as the correlations are approximated. Cumulants are approximated by replacing expectations with sample averages.

## 2.5 Teager Energy operator:

TEO is a nonlinear energy tracking operator [15]-[20] which tracks the changes occurring in the energy of the signal. TEO calculates the energy of the system that generated the signal rather than calculating the energy of the signal. TEO operation uses only three samples of the signal for calculating the energy, hence is simple and useful for real time applications. Suppose two signals of different frequencies exhibit same amplitude and energy, TEO reflects that the energy required for generating a signal of higher frequency is larger than the energy required for generating a signal with low frequency and tracks the amplitude envelope and instantaneous frequency. TE function reflects positive value of energy in time domain when the energy required to generate the signal is

from a single source and negative over some intervals when it models the energy from two different sources. Using this property any disturbance in the impulse generation from the sinoatrial node or deviation from normal sinus rhythm can be identified. In a normal subject SA node fires at a rate of 40 to 60 beats per minute whereas pacemaker cells in the bundle of His fires at a rate of 40 to 60 beats per minute in case of SA node failure. TE is directly proportional to the squared product of instantaneous amplitude and frequency where conventional energy is proportional to instantaneous amplitude of the signal only. Nonlinear energy in time domain for discrete time signal *x[n]* is measured using the equations below as

$$NE\{x(n)\} = x^2(n) - x(n-1)x(n+1) \quad (8)$$

Average nonlinear time domain energy is given as

$$ANE_t = 1/N \sum NE\{x[n]\} \quad (9)$$

Where N is the number of samples in the signal, $ANE_t$ is the mean of average energy in time domain.

Similarly nonlinear energy in frequency domain for discrete time signal *x[n]* is measured using the equation below as

$$NE\{x(n)\} = x^2(n) - x(n-1)x(n+1) \quad (10)$$

Average nonlinear energy in frequency domain is given as

$$ANE_f = 1/N \sum NE\{x[f]\} \quad (11)$$

Where $ANE_f$ is the mean of average energy in frequency domain.

## 3. Methodology:

The algorithm of the proposed method is as shown in the Fig.4 below.

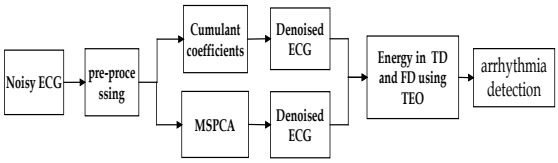


Fig.4. Block diagram of Proposed Scheme.

Steps involved in the algorithm are

1. NSR and arrhythmia ECG data which were originally sampled at different sampling rates were resampled to a common sampling rate of 200Hz as first step of preprocessing.
2. Noisy ECG data is de-meaned. DC or average value refers to a low frequency base line wander signal which carries no information so subtracting the mean or average value from the samples results in no consequences.
3. Noisy ECG data is modeled using MSPCA and higher order cumulants for denoising,
4. Improvement in $SNR_i$ ,RMSE, and RMSD are calculated for the enhanced ECG data.
5. Energy is extracted from the enhanced ECG data using nonlinear energy operator TEO
6. Mean of the average energy in time domain and frequency domains $ANE_t$ and $ANE_f$ are computed
7. The above steps are performed on a set of NSR and arrhythmia data.
8. The above steps are performed on a set of NSR and arrhythmia data.

### 3.1 Performance Measures:

*Root Mean Square Error (RMSE):* It is the RMS value of the difference between denoised ECG and filtered ECG. Smaller the RMS value, lesser is the distortion.

$$RMSE = \sqrt{\frac{\sum[y(i) - \hat{x}(i)]^2}{N}} \quad (12)$$

*Root Mean Square Deviation (RMSD):*It is the RMS value of the difference between pure ECG signal and denoised ECG signal. Smaller RMSD value indicates good enhancement.

$$RMSD = \sqrt{\frac{\sum[y(i) - x(i)]^2}{N}} \quad (13)$$

*Improvement in signal to Noise Ratio (SNRI):*It is the difference between signal to noise ratio at the output to signal to noise ratio at the input.

$$SNRI = SNR_{output} - SNR_{input} \text{ where}$$

$$SNR_{input} = 10\log_{10}\left[\frac{\sum_i [x_n(i)]^2}{\sum_i [x_n(i) - x(i)]^2}\right] \quad (14)$$

$$SNR_{output} = 10\log_{10}\left[\frac{\sum_i [y(i)]^2}{\sum_i [y(i) - \hat{x}(i)]^2}\right] \quad (15)$$

Where $x(i)$ is the original ECG, $x_n(i)$ is the noisy ECG signal, $y(i)$ is the denoised ECG signal, and $\hat{x}(i)$ is the filtered ECG , N is the number of samples.

## 4. Results and Discussion:

This paper presents an approach for enhancement of noisy ECG data using higher order cumulants and MSPCA. MSPCA is proposed to be a fault detection method for time series data analysis. MSPCA focused on combining the attractive properties of wavelets and principal components for multiscale data analysis. It is found to be a powerful tool in enhancing the ECG data corrupted with 50/60Hz PLI noise. Cumulants are a kind of measure closely related to moments which led to the development of HOS techniques. The attractive feature of third and fourth order cumulants becoming zero for a Gaussian noise motivated us to apply HOS technique for ECG enhancement. So third order cumulant coefficients are computed for noisy ECG data, which has eliminated the interferences and enhanced the ECG data. Higher order cumulants is found to be effective in reducing the artifacts like baseline wander, Gaussian noise and PLI, where as MSPCA is effective in enhancing the noisy data corrupted with only PLI.

To evaluate the statistical measures discussed above, MSPCA and HOSA are applied first on original uncorrupted ECG and then on noisy ECG data taken from MIT-BIH Arrhythmia database. The computed statistical observations for $ANE_t$ and $ANE_f$ is shown in table-I *RMSE, RMSD* and *SNRI* are shown in the tables II-III Results revealed that same values of RMSE and RMSD are obtained using both the modeling techniques. Higher order Cumulants contributed to larger *SNRI* than MSPCA. TE calculated using Higher order cumulants resulted in lower $ANE_t$ and $ANE_f$ for arrhythmia data than NSR data and TE calculated using MSPCA resulted in lower $ANE_t$ and higher $ANE_f$ for arrhythmia data than NSR data. both the techniques worked well in enhancing the data.

Mean of TE function in time and frequency domains $ANE_t$ and $ANE_f$ are the key measures for distinguishing NSR from arrhythmia data. $ANE_t$ for NSR data is higher than arrhythmia data. The proposed method is worked on a set of 30 records of NSR data and 30 records of arrhythmia data from MIT-BIH database. Selected ECG records constitute (a) NSR (b) PVC (c) LBBB and (d) RBBB. TE function is positive for normal beats and it reveals that strong energy is required by ventricles to contract during QRS interval. TE function in time and frequency domains for a set of records is shown in the figs.5-12 for normal and arrhythmia beats. ECG cycle for all records is windowed to reduce the artifacts due to edge effects. $ANE_t$ and $ANE_f$ for a normal beat (record 16272) are .072 and .019 respectively. TE in frequency domain for a normal beat shows that the energy is concentrated in the range 0-17Hz as shown in figs.7-8.

RBBB and LBBB are bundle branch blocks which appears due to depolarization delay through ventricular muscle. RBBB appears in the right side of the heart and LBBB is an indication of heart disease with which further ECG interpretation is not possible. TE in frequency domain for a LBBB record.111 shows that the energy concentration limits to 5 Hz as shown in figs.5-6. A LBBB record is identified with a broadened QRS complex absence of Q-wave, tall notched R wave, elevation or depression of ST segment are some indications of LBBB. TE function in time domain shows heavy ripple with negative peaks during the QRS interval. This is the reflection of disturbances in the impulse generation due to failure of SA node as shown in fig.2b. $ANE_t$ is .0073 and $ANE_f$ is 0.628. which shows that the time domain energy is lower for arrhythmia data than that of normal beat. For a RBBB record.118 $ANE_t$ is .0019 and $ANE_f$ is 0.504

A PVC beat from the record 208 is shown in figs.9-10. It arises from the ectopic focus within the ventricular muscle.QRS complex is wide bizarre and unrelated to the preceding p-wave. $ANE_t$ is 0.0069 which is lower than a normal ECG record and $ANE_f$ is 0.59 which is smaller than normal data. TE in TD consists of ripples (with negative peaks) during the inverted part of QRS interval and energy measured is lower than that of normal beat. .TE in frequency domain for all arrhythmia records show that the energy concentration limits to 5 Hz as shown in figs.11-12.

$ANE_t$ and $ANE_f$ are considered as feature vectors for Euclidean distance measurement. Euclidean distance between the feature vector of a known NSR ECG data and an unknown ECG data is measured. If the distance measured is less, unknown ECG data is identified as normal and if the distance is more it is considered as arrhythmia data. The Nonlinear TEO worked well in identifying the NSR data from arrhythmia data.

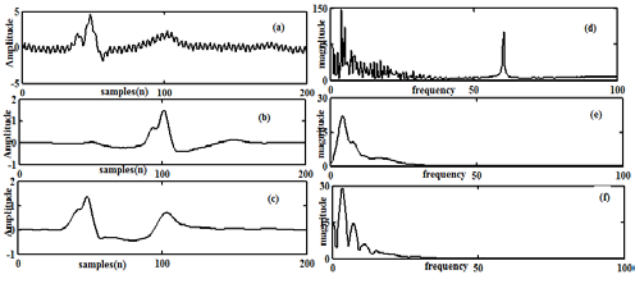


Fig.5. Record(111m,LBBB) PLI corrupted Noisy ECG in trace (a) denoised ECG beat using cumulants in trace (b) using MSPCA in trace(c) and their corresponding spectra in (d)-(f)

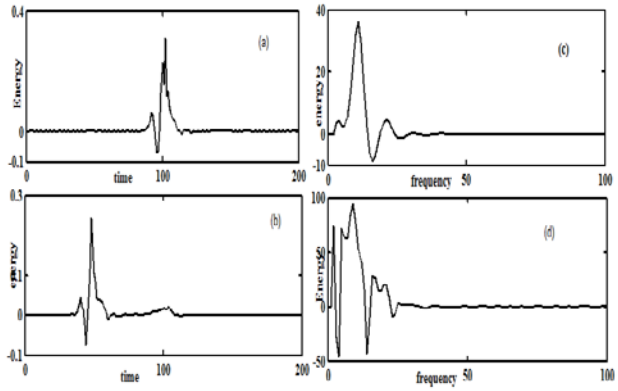


Fig.6. TE in TD and FD using cumulants in trace (a) - (b) and MSPCA in trace (c) - (d). for Record(111m).

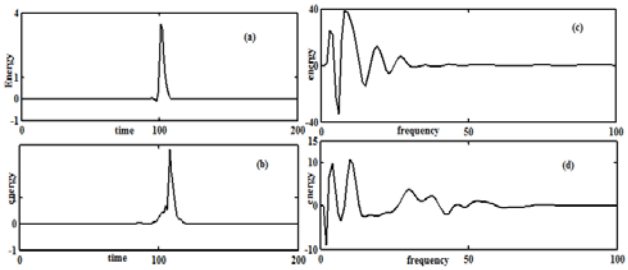


Fig.7. Record(16272,NSR).Teager Energy in TD and FD using Cumulants in trace (a) - (b) and MSPCA in trace (c) - (d).

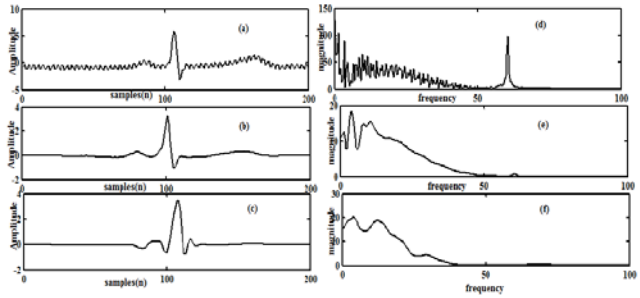


Fig.8. (Record 16272) PLI corrupted Noisy ECG beat in trace (a) denoised ECG beat using cumulants in trace (b) using MSPCA in trace(c) and their corresponding spectra in (d)-(f)

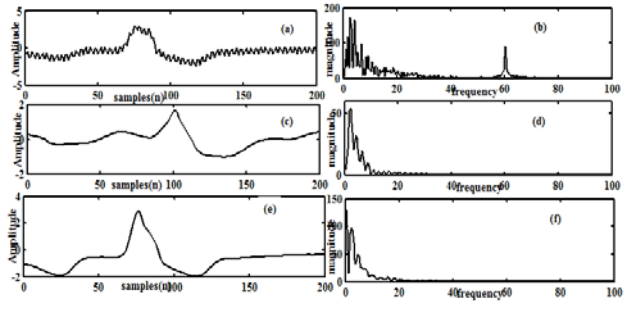


Fig.9. (Record 208) PLI corrupted Noisy ECG beat in trace (a) denoised ECG beat using cumulants in trace (c) using MSPCA in trace(e) and their corresponding spectra in (b),(d),(f)

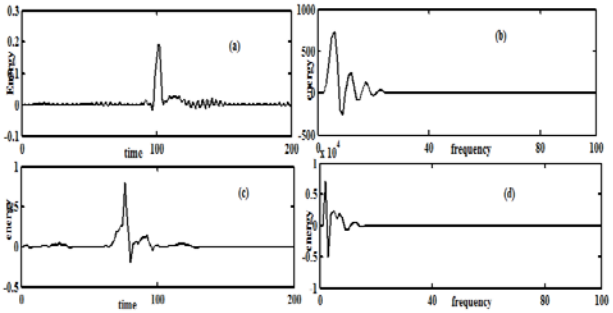


Fig.10 Record(208m-PVC).Teager Energy in TD and FD using Cumulants in trace (a) - (b) and MSPCA in trace (c) - (d).

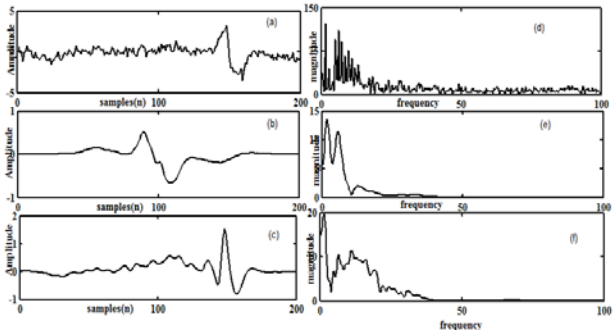


Fig.11.(Record 118-RBBB)Gaussian corrupted ECG beat in trace (a) denoised ECG beat using cumulants in trace (b) using MSPCA in trace(c) and their corresponding spectra in (d)-(f)

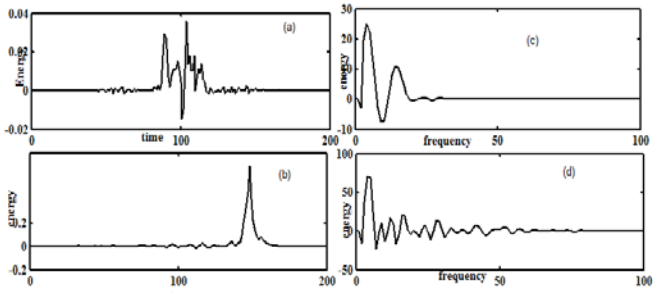


Fig.12 Record(118m).Teager Energy in TD and FD using Cumulants in trace (a) - (b) and MSPCA in trace (c) - (d).

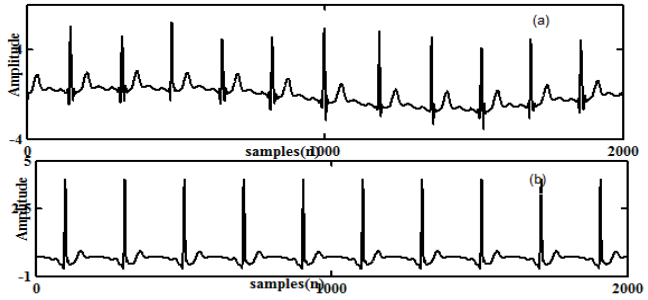


Fig.13. (Record 103-NSR) ECG beat with Baseline wander noise Using MSPCA in trace(a) using cumulants in trace (b)

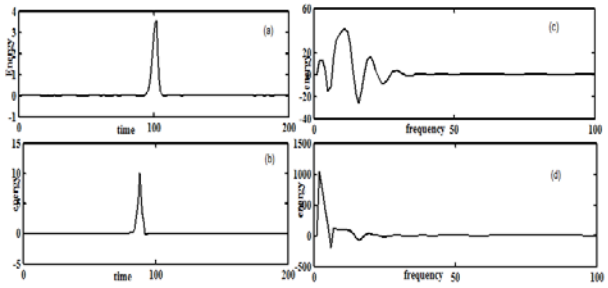


Fig.10 Record(103m).Teager Energy in TD and FD using cumulants in trace (a) - (b) and MSPCA in trace (c) - (d).

TABLE I. SUMMARY OF STATISTICAL MEASURES USING CUMULANTS AND MSPCA

| ECG beat | Using HOSA | | Using MSPCA | |
|---|---|---|---|---|
| | $ANE_t$ | $ANE_f$ | $ANE_t$ | $ANE_f$ |
| 16272 | .072 | .7019 | .085 | .2838 |
| 111 | .0073 | .628 | .0059 | 3.08 |
| 118 | .0019 | .504 | .017 | 12.86 |
| 208 | .0069 | .59 | .0071 | 2.51 |
| 231 | .0203 | .435 | .004 | 1.85 |
| 118e00 | .0021 | 1.84 | .069 | 5.48 |

TABLE-II. STATISTICAL MEASURES USING CUMULANTS

| ECG beat | RMSE | RMSD | $SNR_i$ |
|---|---|---|---|
| 16272 | .0008 | .0008 | 37 |
| 103 | .0025 | .0025 | 35 |
| 111 | .0532 | .0524 | 42 |
| 118 | .030 | .033 | 38 |
| 208 | .0355 | .0345 | 39.9 |
| 118e00 | .0129 | .0128 | 46 |

TABLE. III. Statistical Measures using MSPCA

| ECG beat | RMSE | RMSD | $SNR_i$ |
|---|---|---|---|
| 16272 | .009 | .009 | 27.2 |
| 103 | .00035 | .00035 | 3.05 |
| 111 | .00093 | .0017 | 12.33 |
| 118 | .023 | .025 | 9.7 |
| 208 | .0255 | .024 | 2.759 |
| 118e00 | .032 | .033 | 14.99 |

## Conclusions

ECG being a non-stationary, mixed phase biomedical signal is invariably corrupted with different artifacts while recording. Two nonlinear techniques MSPCA and HOSA are used to enhance the ECG signals by reducing the noise. MSPCA algorithm is used to enhance the noisy ECG data from 60Hz PLI noise, where it extracts the relationships between the variables by PCA and measurements by wavelet analysis by combining the attractive features of both wavelets and PCA. Third order cumulant computation of HOSA enhances the ECG signal from different artifacts. Statistical measures for both the techniques are shown as comparison in tables I-III. Higher order cumulants has an attractive feature of becoming zero for a Gaussian signal, which motivated us to use cumulants for enhancement of noisy ECG. TEO is a nonlinear energy operator applied on the enhanced ECG data which extracts the energy of the source that generated the signal. Results revealed that MSPCA restored the morphology of ECG signal by reducing PLI noise greatly where HOSA restored the morphology of ECG by reducing 60Hz PLI, Gaussian, baseline wander and EMG noises. TEO has successfully identified NSR data from arrhythmia data where the energy calculated from normal data lies in the range 0-15Hz and for arrhythmia data it is lying in the range of 0-5Hz. Euclidean distance is calculated between known parameters (ANEt and ANEf ) of NSR data and a set of unknown data. This distance is less from NSR to NSR data and more from NSR to arrhythmia data.

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**V. Sharmila** was born in Warangal, Andhra Pradesh, India in 1970. She received her B.Tech degree in Electronics & Communication Engineering from Siddhartha Engineering College, Vijayawada, Andhra Pradesh, India in 1994 and her M.Tech from NIT, Warangal, Andhra Pradesh in 2005. She is pursuing her Ph.D from JNTU, Hyderabad, A.P, India under the guidance of K.Ashoka Reddy. Presently she is working as Associate.Professor at Kamala Institute of Technology & Science, Karimnagar, Andra Pradesh INDIA.

**K. Ashoka Reddy** was born in Warangal, Andhra Pradesh, India, in 1970. He received The B.Tech. degree from Kakatiya University, Warangal, Andhra Pradesh, India, in 1992, the M.Tech. degree from Jawaharlal Nehru Technological University (JNTU), Kakinada, Andhra Pradesh, India, in 1994,and the Ph.D. degree in electrical engineering from the Indian Institute of Technology Madras, Chennai, Tamil Nadu, India, in 2008.He is currently a Professor with the Department of Electronics and Instrumentation Engineering, Kakatiya Institute of Technology and Science, Warangal, Andhra Pradesh, India. His current research interests include instrumentation, biomedical signal processing, and signal processing for communication and artificial neural networks.