*American Journal of Multidisciplinary Research & Development (AJMRD)*
*Volume 05, Issue 03 (March - 2023), PP 09-14*
*ISSN: 2360-821X*
www.ajmrd.com

**Research Paper** **Open Access**

# Adaptive Filter and EMD Based De-Noising Method of ECG Signals: A Review

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**ABSTRACT:** An ECG signal is usually corrupted by various types of noises. Some of these noises are power line interface, baseline drift, muscle contraction, motion artifacts, electrosurgical noise, instrumentation noise and electromyography noises. It is highly required to develop a method which can filter ECG signal noises significantly. In this work, an EMD along with Three iteration of Kalman adaptive filter (TKF) and new Customized Otsu Thresholding (COT) based new method for de-noising of ECG signal has been proposed. Unlike, conventional EMD based de-noising approaches, where only lower orders intrinsic mode functions (IMFs) are denoised, this work is capable to denoise lower and higher order IMFs. This work along with EMD, TKF operation has been employed for further signal quality improvement. The lower order IMFs are filtered through EMF applied on Kalman adaptive de-noising technique and high-frequency artifacts and retain the QRS complexes removed through COT. After considering first iteration, the effectiveness of TKF measure and, for further enhancement of signal quality using two more adaptive iteration of Kalman filter applied. The validity of the performance of the described technique is evaluated on standard MIT-BIH arrhythmia database. Gaussian noise at different signal to noise ratio (SNR) levels are added to the original signals for validation of proposed method in real time noisy environment.

**Keywords:** EMD: Empirical Mode Decomposition, SNR: signal to noise ratio, ECG: Electrocardiogram**,** LMS: Least Mean Square, EMF: Exploratory matrix *factorization, IMF:* Intrinsic mode functions

## I. INTRODUCTION

The ECG is nothing but the recording of the heart's electrical activity. The deviations in the normal electrical patterns indicate various cardiac disorders. There are various methods to help restore ECG from noisy signal corrupted by various noises. Flow diagram of required work for ECG signal filtering is explained below.

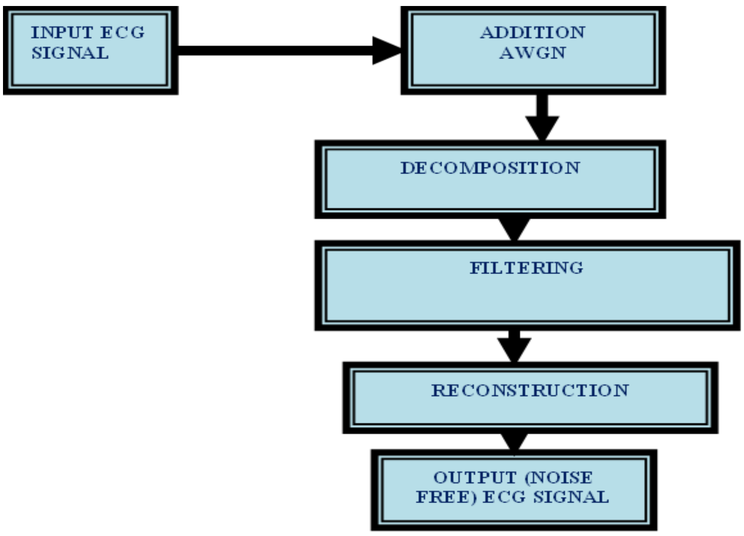


**Figure 1 Flow graph of the methodology**

While registering the ECG signal it may get contaminated by random noises uncorrelated with the ECG signal. These noises can be approximated by white Gaussian noise. Thresholding is used in wavelet domain to smooth out or to remove some coefficients of empirical mode decomposition of sub signals of the measured signal. This reduces the noise content of the signal under the non-stationary environment.

The Hilbert–Huang transform (HHT). The fundamental part of the HHT is the empirical mode decomposition (EMD) method. Breaking down signals into various components, EMD can be compared with other analysis methods such as Fourier transform and Wavelet transform. Using the EMD method, any complicated data set can be decomposed into a finite and often small number of components. The EMD method is a necessary step to reduce any given data into a collection of intrinsic mode functions (IMF) to which the Hilbert spectral analysis can be applied.

$$\mathrm{I(n)} = \sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{IMF_m(n)} + \mathrm{Res_M(n)}$$

where $\mathrm{I(n)}$ is the multi-component-signal. $\mathrm{IMF_m(n)}$is the $\mathrm{M_{th}}$ Intrinsic Mode Function, and $\mathrm{Res_M(n)}$ represents residue corresponding to M intrinsic modes.

ECG is nothing however recording for heart's electrical activity. Deviations in normal electrical shapes indicate various cardiac disorders. Cardiac cells, in simple state are electrically polarized. its internal sides are negative charged with respect to its out sides.

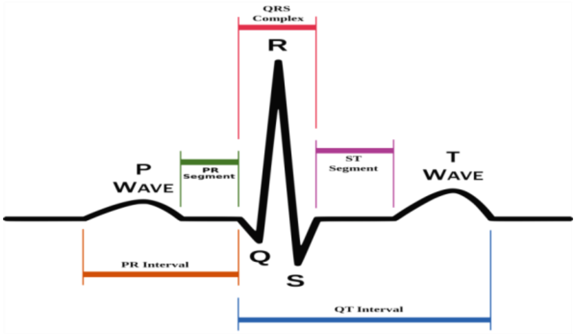


**Figure 2: Representative Signal Cycle for an ECG signal[2]**

## II. LITERATURE WORK

Binqiang Chen et al [4] discussed that, the noise cancellation in electrocardiogram (ECG) signal is very influential to distinguish the essential signal features masked by noises. The power line interference (PLI) is the main source of noise in most of bio-electric signals. Digital notch filters can be used to suppress the PLI in ECG signals. However, the problems of transient interferences and the ringing effect occur, especially when the digitization of PLI does not meet the condition of full period sampling. In this paper, to obtain a better cancellation of the PLI, a designing approach, generating adaptive notch filter (ANF) of sharp resolution, is proposed.

Chenxi Dai et al [3] recursive least square (RLS) notch filter was developed to effectively suppress electrocardiogram (ECG) artifacts from EEG recordings. ECG artifacts were estimated and modelled using the instantaneous frequency of the cardiac cycle. Then it was adaptively estimated using a RLS filter and directly subtracted from contaminated EEG data. Based on the validation measures of improvement of normalized power spectrum (INPS), mean square error (MSE) and information quantity (IQ), the performance of ECG artifacts suppression was compared among the proposed RLS approach, independent component analysis (ICA) and blind deconvolution method under information maximization (Infomax) on simulated and animal experimental data. Simulation data demonstrated that INPS of RLS method (19.75(18.37,20.95) dB) was significantly higher than that of ICA (4.35(3.35,5.41) dB) and Infomax (5.76(4.60,6.88) dB).

Hamed Danandeh Hesar et al [2] In this paper they discussed that marginalized particle extended Kalman filter (MP-EKF) has been known as an effective model-based nonlinear Bayesian framework in the field of electrocardiogram (ECG) signal denoising. In this paper, we reveal another potential capability of MP-EKF and propose a multi rate MP-EKF based framework for P and T wave segmentation in ECG signals. The proposed multi rate implementation of MP-EKF leads to better estimation of states and avoids unwanted errors in estimation procedure. Hamed Danandeh Hesar et al [1] In this paper, they propose a novel Bayesian framework based on Kalman filter, which does not need a predefined model and can adapt itself to different ECG morphologies. Compared with the previous Bayesian techniques, the proposed method requires much less preprocessing and it only needs to know the location of R-peaks to start ECG processing. Their method uses a filter bank comprised of two adaptive Kalman filters, one for denoising QRS complex (high frequency section) and another one for denoising P and T waves (low frequency section).

**Table 1: litrature work methods**

| SN | Author and Journal | Technique | Measurement Parameter | Advantages | Limitations |
|---|---|---|---|---|---|
| **1.** | Hamed Danandeh Hesar et al [1] IEEE Journal 2021 | EMD for ECG decomposition | Input Noise=0 DB SNR=7.195 $\pm$ 1.173<br>Input Noise=10 DB SNR=0.783 $\pm$1.901 | Decrease in preprocessing time and performs well in both stationary and non-stationary environments especially at low input SNRs. | single stage filtering using conventional thresholding method can produce wrong results if appropriate filtering is not performed. |
| **2.** | Hamed Danandeh Hesar et al [2] IEEE Journal 2019 | multi rate marginalized particle extended Kalman filter MP-EKF based framework | a) P Wave: Mean 5, Standard Deviation 34, RMSE 0.035<br><br>b) T Wave: Mean -3, Standard Deviation 24, RMSE 0.024 | 1) MP-EKF leads to better estimation of states and avoids unwanted errors in estimation procedure.<br>2) ECG wave segmentation performance showed promising results. | 1) MP-EKF is not capable to decompose ECG signal significantly to perform filtering.<br>2) Did not work on the most significant parameters QRS complex. |
| **3.** | Chenxi Dai et al [3] IEEE Journal 2019 | RLS method, Fast-ICA method &<br>Info-Max method | a) RLS method: Input Noise = 0 DB MSE = 0.53,<br>b) Fast-ICA method, Input Noise = 0 DB, MSE = 19.97<br>c) Info-Max method, Input Noise = 0 DB, MSE = 10.69 | RLS notch filter effectively eliminates ECG artefacts from EEG recordings. | RLS method is complicated and time-consuming adaptive mechanism |
| **4.** | Binqiang Chen et al [4] IEEE Journal 2019 | Adaptive notch filter (ANF) | Maximal Error=1.11601<br>RMS Error=0.4436 | 1) concise algorithm and achieves comprehensive reduction of the PLI.<br>2) Effectively preserves the QRS-complex features in the filtered signal. | ANF method is not suitable for all other types of ECG signal noises. |
| **5.** | Mojtaba Nazari et al [5] IEEE Journal 2018 | Variational Mode Extraction (VME) & Variational Mode Decomposition (VMD) | a) VMD: Mean = 31.527 Standard Deviation= 0.749<br><br>b) VME: Mean = 9.829 Standard Deviation = 0.121 | Better accuracy while performing at much lower computational cost and higher convergence rate. | Complex computations. |

## III. PROBLEM FORMULATION

Problem with [2] was that they never derive a new procedure they just study & select appropriate procedure from available methods as per input ECG signal its procedure is good if they use its procedure for research work however cannot guarantee to work accurate in practical conditions. [2] develop its own procedure for Thresholding & uses single stage filtering problem is that if filtering done is not appropriate than accurate Thresholding will also produce wrong results & second, they use conventional Daubechies wavelet for Thresholding. The ECG signal is time varying signal, includes the valuable information related to heart diseases, but frequently this valuable information is corrupted by various noises. As noise corrupts the ECG signal it is very important as well as difficult task to suppress noises from ECG signal. So de-noising is the method of estimating the unknown signal from available noisy data.

[1] develop their own method for adaptive EMD filter and uses single stage filtering problem is that if the filtering done is not appropriate in one iteration of adaptive filter than inaccurate Threshold may also produce wrong results. [3] uses empirical mode decomposition (EMD) along with adaptive switching mean filtering (ASMF) based ECG de-noising technique, their method was good but ASMF was time consuming process which further reduces the threshold. In near future they will develop a new modified adaptive EMD based ECG signal de-nosing method.

## IV. THEORETICAL ANALYSIS

**4.1 SIGNAL DECOMPOSITION METHODS:** This part of the thesis work addresses data-driven time-frequency (T-F) analysis of multivariate signals, which is achieved through the empirical mode decomposition (EMD) algorithm, and its noise assisted and multivariate extensions, the ensemble EMD (EEMD) and multivariate EMD (MEMD).

**Motivation for data-adaptive analysis**: Advances in sensor technology have enabled routine recordings of both multidimensional (e.g., three-dimensional RGB images) and multichannel (e.g., sensor arrays) signals. Such data are typically nonlinear and nonstationary, and their rigorous T-F analysis requires a multiscale approach at the accuracy level of instantaneous frequency (IF), attained through knowledge of joint intrinsic oscillatory modes across the data channels. The IF is also essential for a meaningful interpretation of nonlinear processes (containing subharmonics). To that end, it is convenient to employ the Hilbert transform (HT) in conjunction with the data model [5]

$$x(t) = \sum_{m=1}^{M} c_m(t) = \sum\nolimits_m a_m(t)\varphi_m(t)\ (+r \sim residual)$$

Where $a_m$ amplitude, $\varphi_m$ is oscillations

However, the HT produces meaningful IF only for mono component data while the Bedrosian and Nuttall theorems [2], [3] impose further constrains on the pair $[a_m, \varphi_m]$ , e.g., their nonoverlapping spectra.

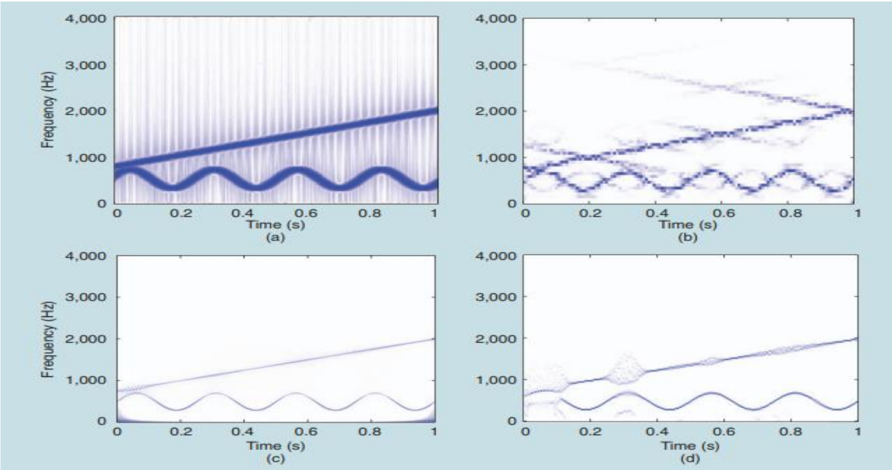


**Figure** 3 The T-F analysis of non-stationary signals: (a) STFT spectrogram, (b) wavelet packet, (c) synchro-squeezed transform, and (d) HHS.

The EMD models a signal x of length L as a sum of M oscillatory components called intrinsic mode functions (IMFs). These correspond to the bases $c_{m=1}^{M}$ in (1), and are sparse (with M << L), template free, and entirely data driven. Since the aim of EMD is for IMFs to represent intrinsic temporal modes (scales) that characterize the data, the residual r in (1) cannot contain a full oscillation and its role is to model the trend within a signal [10]. Recall that the estimation of IF via the HT gives 1) negative IF for data with a mismatch in the number of extrema and zero crossings, and 2) negative IF in the presence of a trend and dc offset.

**4.2 KALMAN ADAPTATION ALGORITHM:** In Kalman filter, to predict coefficient of filter with some uncertainty. Then measure the experimental position and velocity with some uncertainty. Finally, increase the certainty of our prediction by combining our prediction with the measurement information.

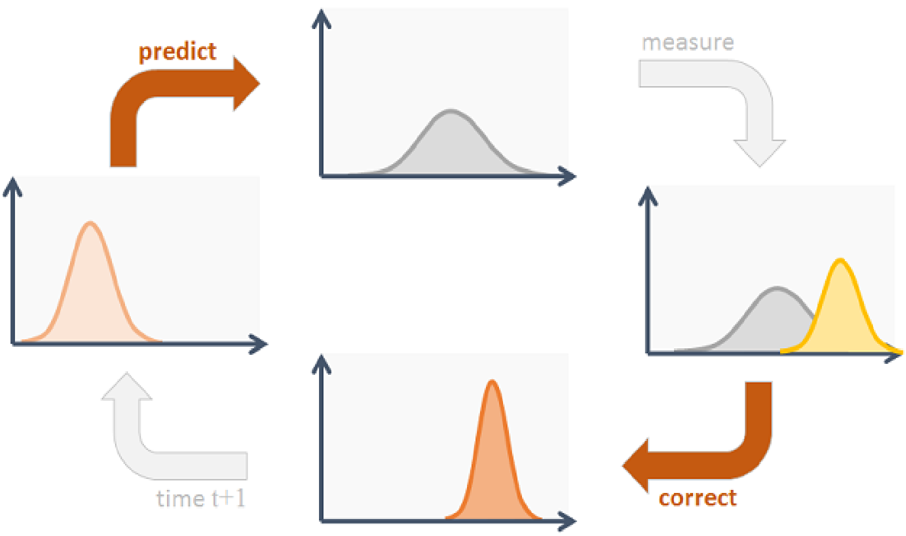


**Figure 4 Kalman predict and update process [3]**

For Kalman algorithm it is necessary to have a reference signal d[n] representing desired filter output. difference between reference signal & actual output for transversal filter (eq. below) is error signal

$$e[n] = d[n] - c^H[n]x[n].$$

A schematic for Kalman learning setup is depicted in figure 5.

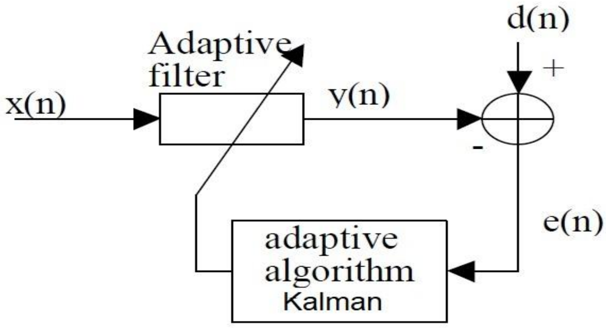


**Figure 5 KALMAN adaptive filter [6]**

**4.3 THRESHOLDING:** It can be also used in ECG signal filtering selection of threshold value plays an important role in de-noising of ECG signal. The parameters of this shrinkage function were optimized by comparing de-noised results of the simulative ECG signal at different contaminating levels. The choice of threshold and shrinkage function is the most important step for wavelet de-noising. For obtain the best de-noising results, a new shrinkage function which would be used in ECG signals de-noising was proposed here, expressed as formula:

$$\hat{Y} = \begin{cases} 0 & |Y| \leq T_L \\ sgn(Y)\left[\dfrac{|Y - T_L|^{\gamma}.T_H}{|T_H - T_L|^{\gamma}}\right] & T_L < |Y| \leq T_H \\ Y & |Y| > T_H \end{cases}$$

Where γ, TH, TL are alterable. This Formula is equal to formula of hard threshold when TL=TH; this formula is equal to formula of firm when γ=1, TL=2/3TH; and the same formula is equal to formula of Yasser when γ=3, TL=0.

## V. CONCLUSION

The de-noising effects for noisy ECG signal using various functions were compared here. Results show that shrinkage function proposed in this work is very good at noisy ECG signal de-noising. Not only may it get highest SNR, however also keep similarity & smoothness for de-noise signal. In fact, this function also may be used for all kinds for signals de-noised. Improvement for signal to noise ratio for proposed procedure proves that this is powerful technique for de-noising for non-stationary signals such as ECG signals. The proposed threshold & shrinkage function is useful while processing ECG signal & to improve signal-to-noise ratio (SNR) for obtaining clean recordings & preserve original shape for signal, especially peaks, without distorting waves & segments. main job is to recover a true ECG signal from noisy recording & successfully achieved by proposed method.

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