A Review on Different Denoising Technique of ECG Signal

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ABSTRACT

In today medical prevention, the early diagnosis of cardiac diseases is one of the most important topic. the heart sound signal stores a huge amount of information regarding the pathological status of every part of the heart and the interaction among them. Unfortunately, detection of relevant symptoms and diagnosis based on heart sound through stethoscope is difficult. Analysis of heart sound requires a quiet environment with minimum ambient noise. In order to address such issues here we are comparing different techniques of denoising of ECG signal. Here we are compairing kalman filter, extended kalman filter and Adaptive filter to reduce noise from the signal and we concluded that kalman filter is best for denoising ECG signal as it show best result in linear transformation.

***Keyword**: ECG signal, kalman filter, EKF, heart sound, Adaptive filter.*

1. INTRODUCTION

The human heart is an organ that provides a continuous blood circulation through the cardiac cycle and is one of the most vital organs in the human body. An ECG can be defined as the graphic record that detects the minute differences in potential caused by heart action and occurring between different parts of the body.[2] ECG is among the most valuable clinical tests available to medicine because it is quick, completely safe, painless, inexpensive, and rich in information. Supervision and analysis of ECG allows diagnosis of a wide range of heart conditions. [3]

The heart signals are taken from ECG, which is known as Electrocardiography. That the heart signals are picked by using electrodes in arms, leg, chest of our body. By using this signal heart disorder can be find out. Depend on the shape of the ECG waveform, find out the cardiac health. ECG signal readings and their analysis are carried out from signal processing. The ECG signal is characterized by six peaks and valleys, which are traditionally labeled P, Q, R, S, T, and U, shown in figure 1. [1]

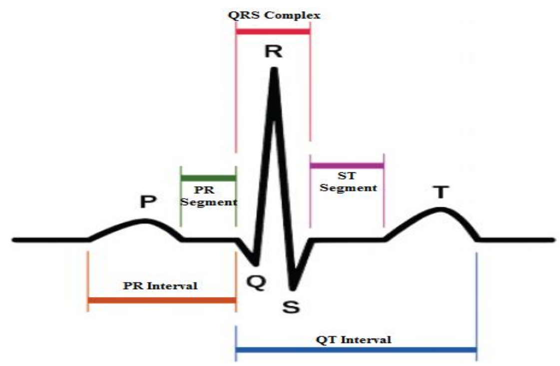

Figure.1:ECG Waveform

Figure 1 shows stethoscope positions to listen to normal S1, S2, S3, and S4 sounds. The intensity of S1 depends on the rate of pressure development in the ventricle, the structure of the valve leaflets, and the position of the AV valves at the beginning of the ventricle contraction. The goal is to listen to the four areas corresponding to the valves, which provide valuable information to GPs and can be a very valuable diagnostic tool to examine the hearts of patients.

Several techniques have been proposed to extract the ECG components contaminated with the background noise and allow the measurement of subtle features in the ECG signal. One of the common approaches is the adaptive filter architecture, which has been used for the noise cancellation of ECGs containing baseline wander, electromyogram (EMG) noise, and motion artifacts [2], [3]. Statistical techniques such as principal component analysis [4], independent component analysis [5], [6], and neural networks [7] have also been used to extract a noise-free signal from the noisy ECG. Over the past several years, methods based on the wavelet transform (WT) have also received a great deal of attention for the denoising of signals that possess multiresolution characteristics such as the ECG [8].

There are various method are used for denoising input signal which shows best result in different environment. Here we are use kalman filter, adaptive filter and extended kalman filter and compare their values using linear transformation. section 2 and 3 shows the methodology used and compare their output signal to conclude which filter perform better in linear transformation.

2. METHODOLOGY

I. KALMAN FILTER:-

The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance—when some presumed conditions are met. The Kalman filter has as objective the minimization of the estimation square error of a non-stationary signal buried in noise. The estimated signal itself is modelled utilizing the state-space formulation describing its dynamical behaviour.
The heart sound signal is the desired signal and the lung sound signal is the undesired signal which is noise. The lung sound signal is assumed to be white additive noise. The heart sound signal [2] and lung sound signal are assumed to be uncorrelated with each other.
The Kalman filter [3] addresses the general problem of trying to estimate the state x of a discrete-time controlled process that is governed by the linear stochastic difference equation

$$X_\kappa = AX_{\kappa-1} + W_{\kappa-1} \quad (1)$$

with a measurement z that is

$$Z_\kappa = HX_\kappa + V_\kappa \quad (2)$$

The random variables W_κ and V_κ represent the process and measurement noise (respectively). They are assumed to be independent (of each other), white, and with normal probability distributions

$$P(w) \sim N(0,Q) \quad (3)$$

$$P(v) \sim N(0,R) \quad (4)$$

In practice, the process noise covariance Q and measurement noise covariance R matrices might change with each time step or measurement, however here we assume they are constant. The measurement noise here is the lung sound signal. The process noise takes into account the inaccuracies due to state transform model is completely unknown and the uncertainty incorporated because of the process models. The state x here is the weight which when multiplied with the mixed heart and lung sound sample gives the desired heart sound.
The n X n matrix A in the difference equation – equation (1) relates the state at the previous time step k-1 to the state at the current step k. Kalman filter algorithm uses feedback. The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback—i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.
Discrete Kalman filter time update equations

$$X_\kappa = AX_{\kappa-1} + W_{\kappa-1}$$

$$P_k^- = AP_{k-1}A^T + Q$$

Discrete Kalman filter measurement update equations

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$$

$$X_k = X_k^- + K_k (Z_k - H X_k^-)$$

$$P_k = (I - K_k H) P_k^-$$

II. ADAPTIVE FILTER:-

An *adaptive filter* is a computational device that attempts to model the relationship between two signals in real time in an iterative manner. Adaptive filters are often realized either as a set of program instructions running on an arithmetical processing device such as a microprocessor or DSP chip, or as a set of logic operations implemented in a field-programmable gate array (FPGA) or in a semicustom or custom VLSI integrated circuit. However, ignoring any errors introduced by numerical precision effects in these implementations, the fundamental operation of an adaptive filter can be characterized independently of the specific physical realization that it takes. For this reason, we shall focus on the mathematical forms of adaptive filters as opposed to their specific realizations in software or hardware. In general, any system with a finite number of parameters that affect how y(n) is computed from X(n) could be used for the adaptive filter in Fig.2. Define the parameter or coefficient vector W(n) As

$$W(n) = [w0(n) w1(n) \ldots\ldots wL\text{-}1(n)]^T$$

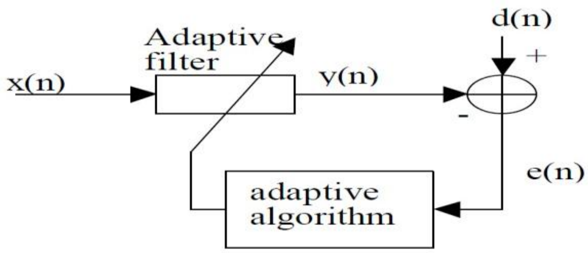

Figure: The general adaptive filtering

where {w(n)}, 0 <=i<= L − 1 are the L parameters of the system at time n.With this definition, we could define a general input-output relationship for the adaptive filter as

y(n)=f(**W**(n), y(n−1), y(n−2)…… y(n−N), x(n), x(n−1)………… x(n−M+1)) (3)

where f(.) represents any well-defined linear or nonlinear function and M and N are positive integers.
Implicit in this definition is the fact that the filter is causal, such that future values of x(n) are not needed to compute y(n). While noncausal filters can be handled in practice by suitably buffering or storing the input signal samples, we do not consider this possibility.
Although (3) is the most general description of an adaptive filter structure, we are interested in determining the best linear relationship between the input and desired response signals for many period.

III.EXTENDED KALMAN FILTER :-

The EKF is a nonlinear extension of conventional Kalman filter that has been specifically developed for systems having nonlinear dynamic models [22]. For a discrete nonlinear system with the state vector *xk* and observation vector *yk* , the dynamic model and its linear approximation near a desired reference point may be formulated as follows:

$X_{k+1} = f(x_k, w_k, k)$
$\approx f(\hat{x}_k, \hat{w}_k, k) + A_k (x_k - \hat{x}_k) + F_k (w_k - \hat{w}_k)$
$Y_k = g(x_k, v_k, k)$
$\approx g(\hat{x}_k, \hat{v}_k, k) + C_k (x_k - \hat{x}_k) + G_k (v_k - \hat{v}_k)$
(1)
where

$A_k = \partial f(x, \hat{w}_k, k)/\partial x$ when $x = \hat{x}_k$
$F_k = \partial f(\hat{x}_k, w, k)/\partial w$ when $w = \hat{w}_k$
$C_k = \partial g(x, \hat{v}_k, k)/\partial x$ when $x = \hat{x}_k$
$G_k = \partial g(\hat{x}_k, v, k)/\partial v$ when $v = \hat{v}$.
(2)

Here, wk and vk are the process and measurement noises, respectively, with covariance matrices Qk = E{wkwTk} and
Rk = E{vk vTk}. In order to implement the EKF, the time propagation and the measurement propagation equations are summarized as follows:
$X_{k+1}^{-} = f(\hat{x}_k^{+}, w, k)/ w=0$
$P_{k+1}^{-} = A_k P^{+} A_k^{T} + F_k Q_k F_k^{T}$
$\hat{X}_K^{+} = \hat{X}_k^{-} + K_k [y_k - g(\hat{x}_k^{-}, v, k)|v=0]$
$K_k = P_k^{-} C_k^{T} [C_k P_k^{-} C_k^{T} + G_k]^{-1}$
$P_k^{+} = P_k^{-} - C_k K_k P_k^{-}$
where $\hat{x}_k^{-} = E\{x_k|y_{k-1}, y_{k-2}, \ldots, y_1$ is the a prior estimate of the state vector, xk, at the kth update, using the observations y1 to yk−1 , and $\hat{x}_k^{+} = \hat{E}\{x_k|y_k, y_{k-1}, \ldots, y_1\}$ is the a posteriori estimate of the state vector after adding the kth observations yk . P−k and P+k are defined in the same manner to be the estimations of the covariance matrices in the kth stage, before andafter using the kth observation, respectively.

3. RESULT

ECG test signals were chosen from CSE and MIT-BIH database. The sampling frequency of these signals is of 500 and 360 Hz. In this section we compare the performance of kalman filter, adaptive filter and extended kalman filter for noise cancellation. The algorithm are implemented according to the steps shown in methodology. Figure 2,3 and 4 shows the simulation result of the algorithm.

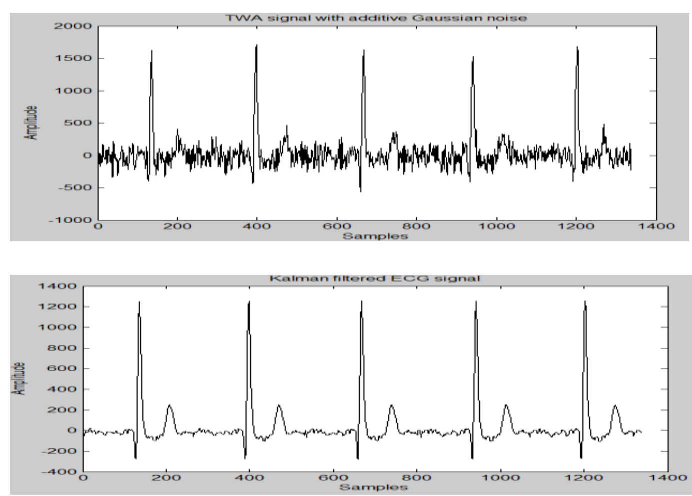

Figure 2: input ECG signal and kalman filtered output signal

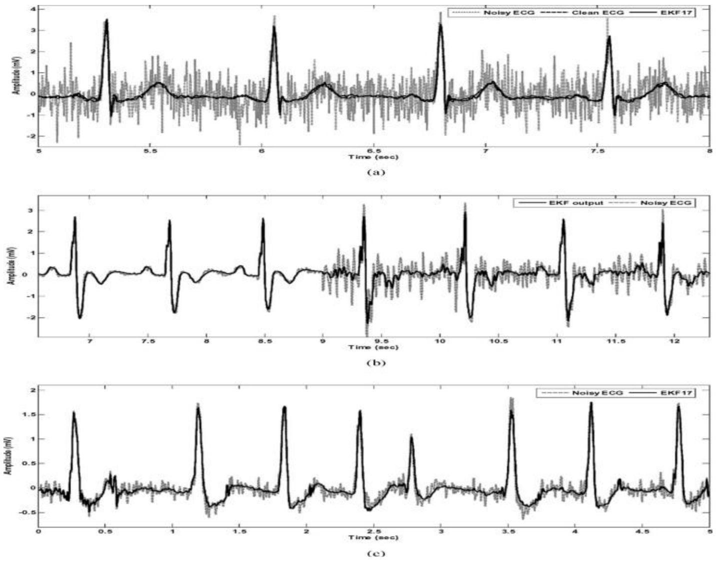

Figure 3: input ECG signal and extended kalman filter output signal

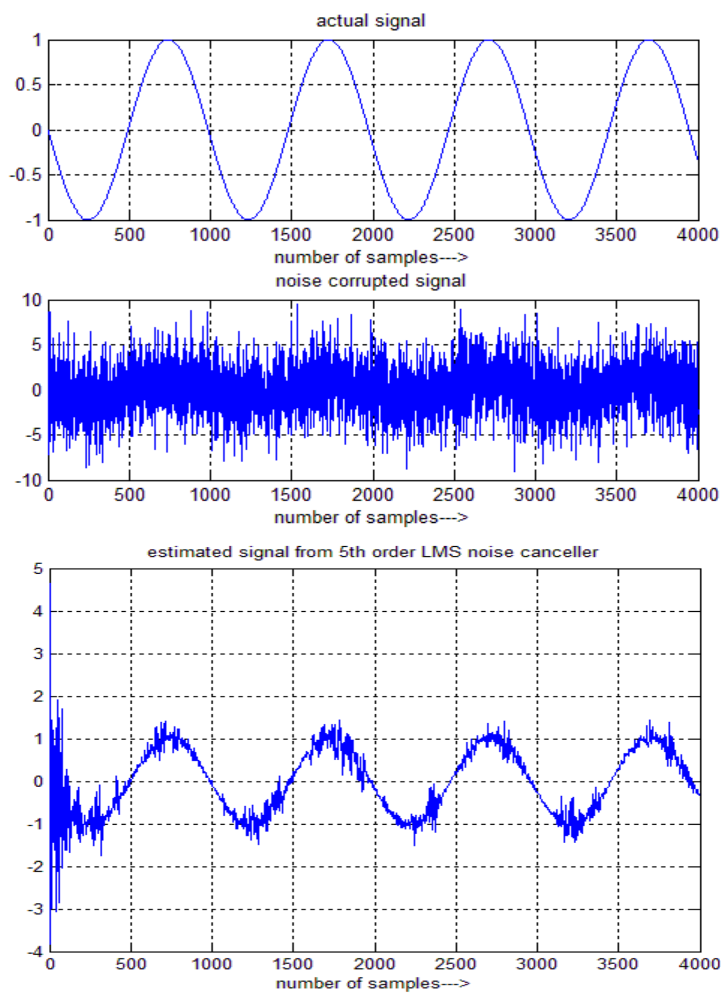

Figure 4: input signal, noise signal and adaptive filtered output signal

4. CONCLUSION

Various denoising technique are used to denoise ECG signal. Here we are using kalman filter, adaptive filter and extended kalamn filter in linear transformation. The main goal of this investigate the application of filter used to noise cancellation. From the result we conclude that the kalman show the best result in linear transformation of noise cancellation.

5. REFERENCE

1. Rovin Tiwari, Rahul Dubey "Analysis of different denoising technique of ecg signal", in IJETAE ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 4, Issue 3, March 2014.
2. Jashvir Chhikara, Jagbir Singh "Noise cancellation using Adaptive filter", in IJMER Vol.2, Issue.3, May-June 2012 pp-792-795 ISSN: 2249-6645.
3. Sarang Patil, Nikhil Chaughule, Pranali Choudhari, "Heart Sound Enhancement using Kalman filter and Independent component analysis Algorithm", in IJETAE ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 6, June 2013 .
4. Sheik Hussain Salleh, Hadrina Sheik Hussain, Tan Tian Swee, Chee-Ming Ting, Alias Mohd Noor, Surasak Pipatsart, Jalil Ali, Preecha P Yupapin, " Acoustic cardiac signals analysis: a Kalman filter–based approach", in INTERNATIONAL JOURNAL OF NANOMEDICINE.
5. Gaurav Mithal, "Denoising of ECG signal using Kalman Faddeev Filter", in International Society of Thesis Publication (ISTP) Volume1. Issue1 Nov 2012.
6. Vahid Fathabadi, Mehdi Shahbazian, Karim Salahshour, Lotfollah Jargani, "Comparison of Adaptive Kalman Filter Methods in State Estimation of a Nonlinear System Using Asynchronous Measurements", in WCECS 2009, October 20-22, 2009, San Francisco, USA.
7. Lindsay Kleeman, "Understanding and Applying Kalman Filtering", Department of Electrical and Computer Systems Engineering Monash University, Clayton.
8. Douglas, S.C. "Introduction to Adaptive Filters" Digital Signal Processing Handbook Ed. Vijay K. Madisetti and Douglas B. Williams Boca Raton: CRC Press LLC, 1999.
9. Omid Sayadi, Student Member, IEEE, andMohammad Bagher Shamsollahi, Member, IEEE, "ECG Denoising and Compression Using a Modified Extended Kalman Filter Structure", IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 55, NO. 9, SEPTEMBER 2008.
10. Mahsa Akhbari, Mohammad B. Shamsollahi, Christian Jutten and Bertrand Coppa , "ECG Denoising using Angular Velocity as a State and an Observation in an Extended Kalman Filter Framework", 34th Annual International Conference of the IEEE EMBS San Diego, California USA, 28 August - 1 September, 2012