International Journal of
Emerging Research in Management &Technology
ISSN: 2278-9359 (Volume-4, Issue-3)

Research Article

March 2015

A Novel Technique for ECG Signal Denoising

Alpana Sahu
Research Scholar, ECE, C.S.V.T.U.
Bhilai, Chhattisgarh, India

Chinmay Chandrakr
Associate Professor, ECE, C.S.V.T.U.
Bhilai, Chhattisgarh, India

Abstract-

The diagnosis of ecg signal is very complex process because it involve many types of noises which affect the proper processing of heart signal. There are various techniques to distinguish the heart signal from noise. In this paper we are taking the original heart signal from MIT BIH database and then further processing it using kalman filter and bounded robust kalman filter which are used for linear and non-linear estimation respectively. In robust kalman filter we bound the upper boundary of signal so we can easily calculate the noise present in signal .Then comparing their performance according to the result obtained by it.

Keywords: ECG signal, MIT BIH database, kalman filter, robust kalman filter

I. INTRODUCTION

ECG is used to measure the rate and regularity of heartbeats, as well as the size and position of the chambers, the presence of any damage to the heart, and the effects of drugs or devices used to regulate the heart, such as a pacemaker. See also test and Halter monitor (24h).Most ECGs are performed for diagnostic or research purposes on human hearts, but may also be performed on animals, usually for diagnosis of heart abnormalities or research.

According to the medical definition, the most important information about ECG signal is almost concentrated on the P wave, QRS complex and T wave. These data include the positions and/or magnitudes of PR interval, QRS interval, QT interval, ST interval, PR segment, and ST segment.

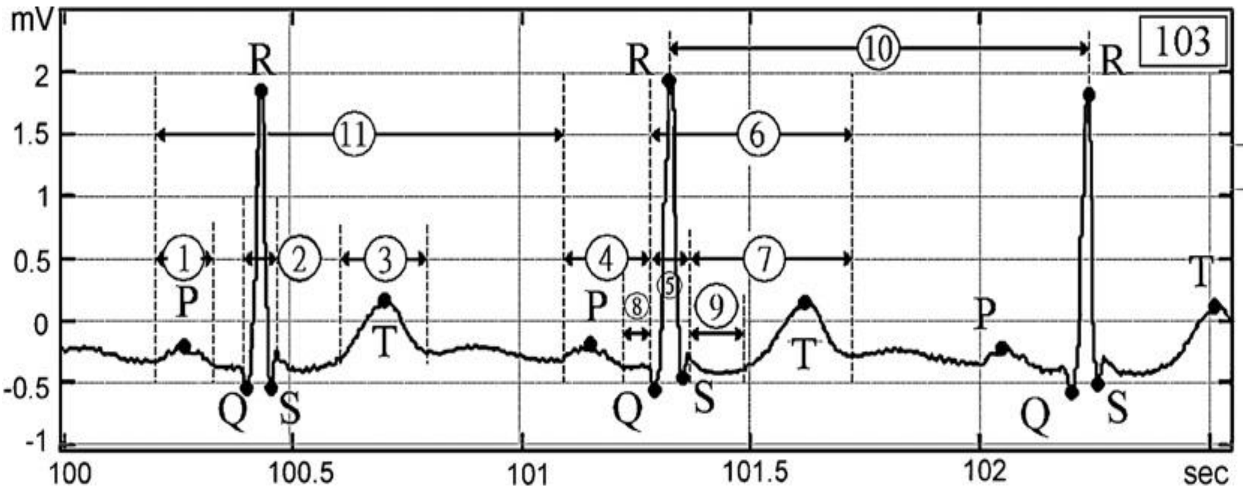

Fig. – ECG waveform: (1) P wave; (2) QRS complex; (3) T wave; (4) PR interval; (5) QRS interval; (6) QT interval; (7) ST interval; (8) PR segment; (9) ST segment; (10) R–R interval (or beat); (11) cardiac cycle

ECG signal has many types of noises that are innocent murmur noise, baseline noise etc which affect the proper functioning of signal. Here we are using kalman filter and robust kalman filter for denoising the ecg signal. The kalman filter has been used as a forecasting tool in several special cases[2-5]. The standard kalman filter works properly when the process and measurement noises are in Gaussian form and Kalman filter shows best result for optimal linear system using state space variable which are recursive in nature[1].

State estimation has been one of the fundamental issues in the control area and there have been many works following those of kalman[6].When we are taking discrete value Using covariance matrix we can easily obtain the result of kalman filter but it works properly for state space variable that limit its performance. But the robust kalman filter shows best result on the minimum value of uncertainty which makes it better then kalman filter.

In this paper we are using the original heart signal from the MIT-BIH database after that adding white Gaussian noise and denoised it using kalman filter and robust kalman filter. We are doing it in 2 steps: first we generate ecg signal using the mit bih database than convert it into discrete form and than denoise it using kalman filter in state space equation using covariance matrix. Second using the ecg signal in matrix form we again denoise it using robust kalman filter with bounded parameters.

II. METHODOLOGY

1. KALMAN FILTER :-

The kalman filter is a method for estimating the state space vector of a linear dynamic system from noisy observation. The discrete linear system with the state vector X_k and observation vector $Y_{k.}$ the equation is given by

$X_k = AX_{k-1} + BW_{k-1}$

$Y_k = HX_{k-1} + V_k$

Where A and B are the matrix which relates to state at time step k-1 and time step k. H is a measurement equation matrix relates state X_k to measurement $Y_{k.}$ Wk and Vk represent the process noise and measurement noise. Kalman filter works on two method: 1. Time update 2. Measurement update.

In time update the prediction of next state is done using the information of previous state. The equation of projected state and projected error covariance is given by the following equation:

$X_{k/k-1} = X_{k-1/k-1} + BW_k$

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

In measurement update the value is computed using equation and correct the predicted value of time update equation. The equation for computed kalman gain and update estimate with measurement and update the error covariance is given by:

$K_k = P_{k/k-1}H^T (H P_{k/k-1}H^T + R)^{-1}$

$X^{\wedge}_{k/k} = {}^{\wedge}X_{k/k-1} + K_z (Z_k - HX^{\wedge}_{k/k-1})$

$P_{k/k} = (I - K_kH) P_{k/k-1}$

Using this equation the final equation of kalman filter and kalman gain is given by

$X^{\wedge}_{k+1} = A_fX^{\wedge}_k + K_fY_k$

2. ROBUST KALMAN FILTER:-

In robust kalman filter we bound the system noise by the following equation $E ((X_k - X^{\wedge}_k) (X_k - X^{\wedge}_k)^T) <= S_k$ this equation is known as posteriori estimate of error covariance. Where S_k is the upper boundary of error equation. Now we are using a vector which combine both error and state equation, called as augmented vector and estimated error $e_k = X_k - X^{\wedge}_k$

$£_k = [e_k \quad X^{\wedge}_k] = [X_k - X^{\wedge}_k \quad X^{\wedge}_k]$

For the next state space equation is given by

$£_{k+1} = [e_{k+1} \quad X^{\wedge}_{k+1}] = [X_{k+1} - X^{\wedge}_{k+1} \quad X^{\wedge}_{k+1}]$

$e_{k+1} = (A-K_fC)X_k - (A-K_f C)X^{\wedge}_k + (A-K_f C)X_k^{\wedge} + BW_k - A_fX^{\wedge}_k + K_f V_k$

$X^{\wedge}_{k+1} = (A_f + K_f C)X^{\wedge}_k + K_fC e_k + K_fV_k$

In above equation we are using the method of mean square method. When we combining both the equation we get a new matrix which called as matrix inequality equation is given by

$£_{k+1} = A_{c1}£_k + G ŋ_k$

Where $£_k = [e_k \quad X^{\wedge}_k]$ and $ŋ_{k=} [W_k \quad V_k]$

$A_{c1} = [A-K_fC \quad A-A_f - K_f C \quad K_f C \quad A_f - K_f C]$

$G = [B \quad -K_f \quad 0 \quad K_f]$

$£[£_k \quad £_k^T] \leq \sum_k$

For the next state space equation is given by

$£[£_{k+1} \quad £_{k+1}^T] \leq \sum_{k+1}$

$E[\{ A_{c1}£_k + G ŋ_k\} \{ A_{c1}£_k + G ŋ_k\}^T] \leq \sum_{k+1}$

$E[\{ A_{c1}£_k + G ŋ_k\} *\{ A_{c1}£_k + G ŋ_k\}^T] \leq \sum_{k+1}$

$E[\{ A_{c1}£_k A_{c1}^T £_k^T + G ŋ_k A_{c1}^T £_k^T + A_{c1}£_k G^T ŋ_k^T + G ŋ_k G^T ŋ_k^T] \leq \sum_{k+1}$

$£_k \; £_k^T = \sum_k \qquad ŋ_k ŋ_k^T = W \text{ bar}$

$E[A_{c1} A_{c1}^T \sum_{k} + G ŋ_k G^TW] \leq \sum_{k+1}$

$\sum_k = [£_k \quad £_k^T]$

When we put values in the equation we calculate the value as

$\sum_k = [S_k \quad 0 \quad 0 \quad P_k - S_k]$

Our main aim to reduce the value of this error $P_k - S_k \leq S_k$. for the next state the value of S_k is given by

Kalman gain $K_f = (AQ_kC^T) R^{-1}$

$S_{k+1} = AQ_kC^T - (AQ_kC^T) R^{-1}(AQ_kC^T)^T + BWB^T$

III. RESULT

Here we are using standard Kalman filter and robust kalman filter for denoising the ecg signal. From figure we conclude that the error in true state and estimated state is minimal in robust kalman filer.

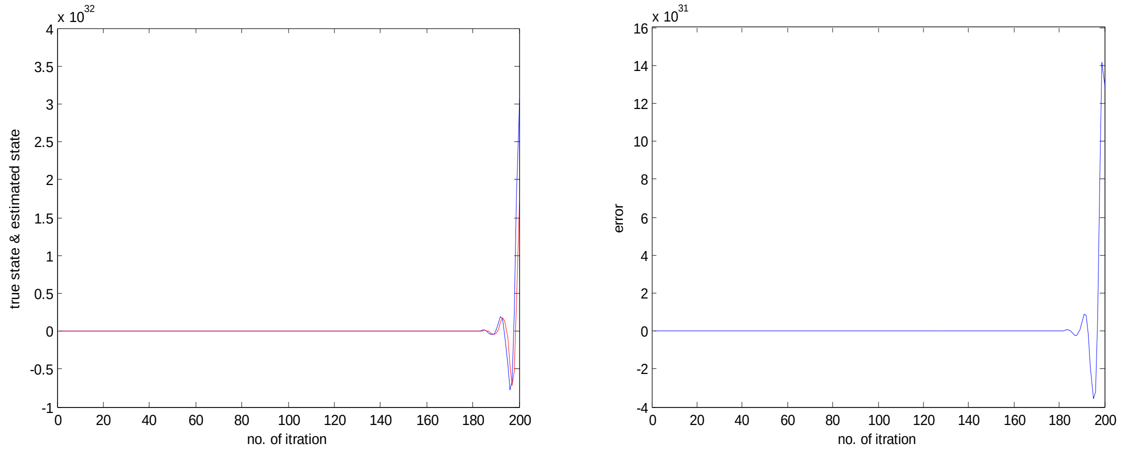

Figure : 1st fig shows the true state and estimated state of kalman filter and 2nd fig shows the value of error in given filter

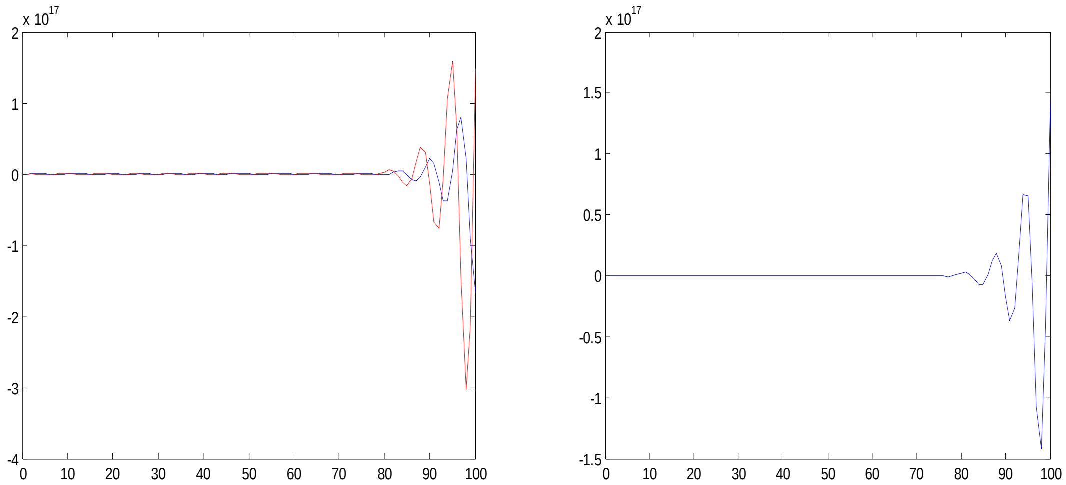

Figure2: 1st figure shows the difference of true state and estimated state and 2nd fig shows the error of robust kalman filter.

IV. CONCLUTION

A robust kalman filter with bounded parameter and uncertainty is presented in this paper. It extends the standard kalman filter the value of covariance matrix shows that robust kalman filter shows better result for denoising it. There are many other method which shows better result than kalman filter but here we were focus only robust kalman filter. The extended kalman filter and UKF also show better result in denoising the ECG signal.

The covariance matrix obtain in robust kalman filter:-

0.6920	-1.5085	0.6920	-1.5085
-1.5085	3.3083	-1.5085	3.3083
0.6920	-1.5085	0.6920	-1.5085
-1.5085	3.3083	-1.5085	3.3083

The covariance matrix obtain in kalman filter:-

2.1927	-2.7459	2.1927	-2.7459
-2.7459	7.8502	-2.7459	7.8502
2.1927	-2.7459	2.1927	-2.7459
-2.7459	7.8502	-2.7459	7.8502

REFERENCE

[1] Chan, Zhang,Tse,"A NEW ROBUST KALMAN FILTER ALGORITHM UNDER OUTLIERS AND SYSTEM UNCERTAINTIES" IEEE 2005.http://hdl.handle.net/10722/45785.

[2] Carlos E. de souza, Minyue fu, karina A barbosa," ROBUST FILTERING FOR UNCERTAIN LINEAR DISCRETE TIME DESCRIPTOR SYSTEM", 30.2317/02-3/PQ and PRONEX0331.00/00. Brazil

[3] Huan xu and shie mannor,” A KALMAN FILTER DESIGN BASED ON THE PERFORMANCE/ ROBUSTNESS TRADEOFF” IEEE vol 54, no 5 may 2009.

[4] Liyu cao, Howard M. Schwartz, “ANALYSIS OF THE KALMAN FILTER BASED ESTIMATION ALGORITHM: AN ORTHOGONAL DECOMPOSITION APPROCH” 0005-1098, 2003.

[5] G. W. Morrison, D. H. pike, “KALMAN FILTERING APPLIED TO STATISTICAL FORECASTING”, management science vol 23, n0 7, march 1977.

[6] XIA yuanqing, HAN jingqing, “ROBUST KALMAN FILTERING FOR SYSTEM UNDER NORM BOUNDED UNCERTAINTIES IN ALL SYSTEM MATRICES AND ERROR COVARIANCE CONSTRAINTS”, JSSC vol 18 no 4, oct 2005.

[7] Mahsa Akhbari, Mohammad B. Shamsollahi, Christian Jutten, Bertrand Coppa,” ECG DENOISING USING ANGULAR VELOCITY AS A STATE AND AN OBSERVATION IN AN EXTENDED KALMAN FILTER FRAMEWORK” IEEE 2012 california USA.

[8] Laurent El ghaoui, Giuseppe calafiore, “ROBUST FILTERING FOR DISCRETE TIME SYSTEM WITH BOUNDED NOISE AND PARAMETRIC UNCERTAINTY”, IEEE vol 46, no 7, july 2001.

[9] Tansel yucelen, Farzad pourboghrat, “KALMAN FILTER BASED MODELING AND CONSTRAINED H∞ OPTIMAL CONTROL FOR ACTIVE NOISE CANCELLATION”, IEEE.

