IOSR Journal of Electronics & Communication Engineering (IOSR-JECE)
ISSN(e) : 2278-1684 ISSN(p) : 2320-334X, PP 06-13
www.iosrjournals.org

PCA Enhanced Kalman Filter for ECG Denoising

Febina Ikbal[1], Prof.M.Mathurakani[2]
[1](*Department of Electronics and Communication, TocH Institute of Science & Technology, India)*
[2](*Head of Department (M.Tech), Department of Electronics and Communication, TocH Institute of Science & Technology, India)*

ABSTRACT: *Technological developments in the medical industry have contributed to significant improvements in patient care. Non-aggressive monitoring of critical biological functions is an important need to provide appropriate care to patients and leads to their improved health. Supervision and analysis of ECG has long been used in clinical practice. The technological developments of ECG monitoring have made it more mobile and convenient, but this has resulted in decreased signal quality. In this paper, PCA is used along with an optimal filter developed using Bayesian framework to enhance the signal quality of ECG signal. This filter has the form of a Kalman Filter. Also, the method of PCA allows efficient estimation of QRS complexes from the noisy ECG data. The adaptive estimation of the process noise covariance is performed based on earlier parameter estimates and on newly arriving data. The measurement noise covariance is obtained by the spatial correlation between several simultaneously recorded ECG signals. The filter has been evaluated on TWA signals and Fetal ECG signals.*

Keywords -*Electrocardiogram, PCA, Kalman Filter, Noise Estimation.*

I. 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 [1]. 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.

A typical ECG waveform comprises of 3 important parts, an initial P-wave, followed by the main 'QRS' complex and then a trailing T-wave. Each of them represents a vital process in the heart.

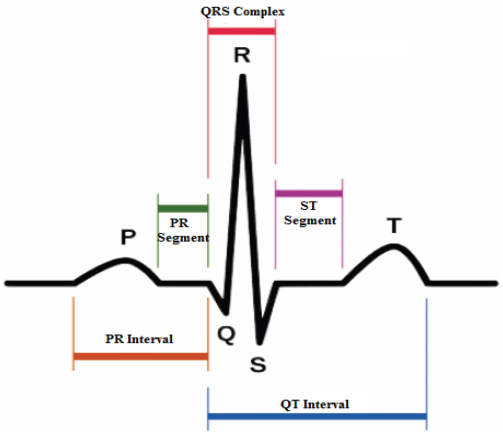


Figure.1:ECG Waveform

In the recent years, new mobile cardiac monitors have been developed for continuous ECG monitoring. The portability of these devices is improving with the development of low-power microelectronics. Sensor devices which are of wear-around type have been introduced in the field [2]. However, in such mobile

conditions, noise increases with higher levels of activity [3]. The extraction of high-resolution cardiac signals from a noisy ECG remains an important problem for the biomedical engineering community.

Artifacts are the noise induced to ECG signals that result from movements of electrodes. This in turn causes deformation and change in the electrical characteristics of the skin under and around the electrodes. These electrical changes appear in the ECG as motion artifacts and baseline drifts. Motion artifacts could reduce signal quality, making ECG interpretation very difficult.

The numerous non-cardiac ECG contaminants, such as electromyographic (EMG) noise, overlap with the cardiac components in the frequency domain, particularly in the 0.01 Hz to 100 Hz range. Other contaminants include power line interference, baseline wander due to respiration, electrode contact noise etc. Band pass filtering is therefore inadequate to suppress such contaminants. Another technique involves the adaptive filtering, in which a filter is applied after adjusting its parameters in time to a time varying noise. This is particularly useful when the noise is non-stationary as it is the case in ambulatory motion artifacts. However, a reference signal has to be additionally recorded together with the ECG.

Consecutive ECG complexes correspond to one another and are uncorrelated in terms of noise. Thus, by averaging several complexes together, signal quality can be improved. But, along with noise, the morphological dynamics of ECG signal will also be removed. In this paper, the method of PCA is made use along with an optimal filter to effectively enhance the signal quality of a variety of ECG signals, while at the same time preserving relevant morphological dynamics in the ECG. This filter has the form of a Kalman filter [4]. The statistical technique of PCA is used to extract a statistical-based model of the signal and noise, allowing the removal of in-band noise by discarding the dimensions corresponding to noise. The noise estimation is based on the earlier estimate and all newly arriving data.

The rest of this paper is organized as follows. Section II deals with the state-space model of ECG. PCA is dealt with in Section III. Section IV deals with the data used and the separation of individual ECG complexes. Kalman filter is described in section V and the Simulation results are provided in Section VI. Finally, conclusions are provided in Section VII.

II. STATE-SPACE MODEL OF ECG

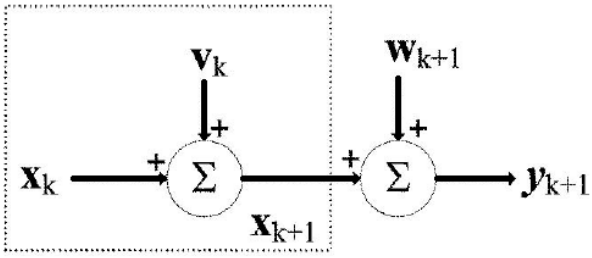


Figure.2:State-space model describing evolution of ECG over time

Consecutive ECG complexes are very similar, but not identical. An ECG complex differ from its succeeding complex by a component called process noise. Also, the signals are corrupted by noise and artifacts. The relation between consecutive complexes and the addition of noise to the recorded ECG can be described by a state-space model as shown below:

$$\begin{cases} x_{k+1} = x_k + v_i \\ y_{k+1} = x_{k+1} + w \end{cases} \quad (1)$$

where x_k denotes the [T×1] ECG complex for heartbeat k and y_k denotes the [T×1] recorded signal, where T is the length of the ECG complex. v_k is a [T×1] vector and denotes the process noise. The measurement noise which includes motion artifacts, power line interference, EMG noise, electrode contact noise etc., are represented by the [T×1] vector w_k.

From fig.1 and (1), we cannot distinguish between measurement noise and process noise. Thus a separate model is used for measurement noise estimation. The process noise v_k is assumed to be zero mean with adaptive covariance Λ_k. The measurement noise is assumed to be zero mean with adaptive covariance Σ_k.

III. PRINCIPAL COMPONENT ANALYSIS

PCA (Principal Component Analysis) is a statistical technique whose purpose is to condense the information of a large set of correlated variables into a few uncorrelated variables called Principal Components. The Principal Components are derived as a linear combination of variables of the data set, with weights chosen so that the principal components become mutually uncorrelated. The first Principal Component is in the direction of greatest variability or covariance in data, second Principal Component in the next orthogonal direction of greatest variance and so on. Since the first few components are of greatest importance, they are retained for further use thus reducing the dimensionality.

PCA is applied using the NIPALS Algorithm. PCA involves decomposing a data matrix X into two parts: structure part composing of TP^T and a noise part.

$$X = TP^T . \tag{2}$$

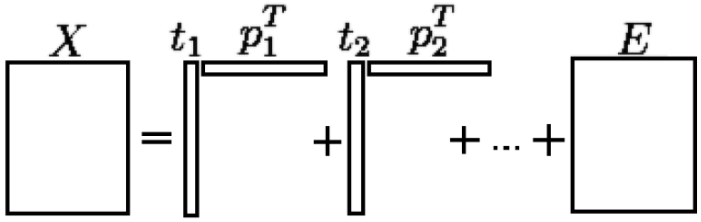


Figure.3:Collection of Scores & Loadings

T , known as scores, gives summary of the original variables in X that describe how the observations relate to each other. P, known as loadings gives the weights or influence of variables in X on the scores T.

Here, PCA is applied prior to QRS complex detection. The first Principal Component is then used for detecting QRS peaks in the ECG complexes. The signals are then reconstructed and then further used for filtering.

IV. DATA ACHIEVEMENT AND SEPARATION OF ECG COMPLEXES

4.1. Data Achievement

The proposed system was tested on mainly two types of ECG signals: TWA signals and Fetal ECG signals recorded from fetal scalp. These signals were obtained from MIT-BIH TWA Challenge database and Abdominal and direct Fetal ECG database respectively. TWA signals comprises of 12-lead ECG signals obtained from patients suffering from T-Wave Alternans. T-wave Alternans is a condition that changes the amplitude or shape of the T-wave in an ECG signal. The fetal ECG signals consists of a reference direct fetal ECG registered from fetal head and four different signals acquired from maternal abdomen. Gaussian noise of various amplitudes was then added with these signals for the evaluation of the developed filter.

4.2. Separation of Individual ECG Complexes

Each recorded signal has to be separated based on their QRS peaks. The QRS peaks are detected on these signals after performing PCA. The ECG complexes are then defined as samples in a predefined time window around corresponding peaks. The value of T chosen is about 120% of mean interval between consecutive heartbeats. After filtering of complexes, the signals are reconstructed by placing the complexes back on their original positions.

V. KALMAN FILTER

5.1. Measurement Noise Estimation

The standard electrocardiogram is simply a graphical representation of the direction and magnitude of the electrical field of the heart as it changes with time. In a 12-lead ECG, each lead looks at this electrical field from a different angle. The theoretic basis of electrocardiography depends upon the assumptions that the heart is a single dipole generator, the body is a homogeneous conductor, and all electrodes are equidistant from the dipole generator. The magnitude of the electrical field as measured by an electrode is proportional to the distance between the electrode and the dipole, and to the size of the dipole. Thus, each ECG signal is the projection of the electric field generated by this dipole on the vector describing the position of electrode. Hence, each ECG signal can be represented as linear combination of three independent ECG signals [4].

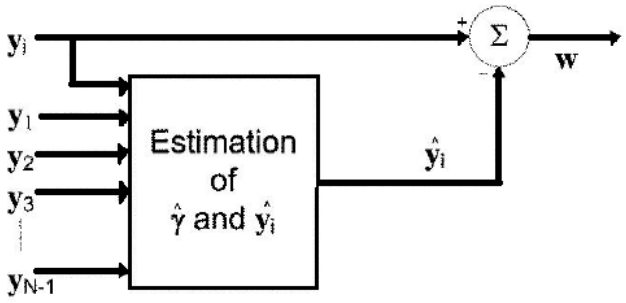


Figure.4: Measurement Noise Estimation

For recorded ECG signals, ECG signal can be modeled as:

$$x_i = \gamma \tag{3}$$

where is a matrix, of which the ECG signals constitute the column vectors, and for which the th column is to be found. The vector γ comprises the coefficients of linear combination.

The morphological variations in ECG are reflected in all the recorded ECG signals . Thus, the measurement noise can be found from these signals as the one not spatially correlated to the other signals. The measurement noise vector can be estimated as using the estimate as:

$$\hat{w}_i = \quad - \tag{4}$$

thus obtaining an estimate for measurement noise covariance Σ.

The estimate that minimizes the mean squared error (MSE) between and its estimate is:

$$\hat{\gamma} = (Y_{-i}^T Y_{-i})^{-1} Y \tag{5}$$

5.2. Kalman Filter

The Kalman filter is an efficient recursive filter that estimates the state of a linear dynamic system from a series of noisy measurements. This property of Kalman filter makes it suitable for the sequential estimation of the unknown parameters of ECG. Sequential estimation refers to the estimation of unknown parameters based on earlier estimates and newly arriving data.

The Kalman Filter equations are given as:

$$\hat{x}_{k+1} = \hat{x}_k + K_{k+1}(y_{k+1} - \hat{x}_k) \tag{6}$$

$$_{k+1} = _k + \Lambda_k - K_{k+1}(_k + \Lambda_k) \tag{7}$$

$$K_{k+1} = \frac{_k + \Lambda_k}{\Sigma_{k+1} + _k} \tag{8}$$

where is known as the Kalman gain. is the variance of optimal estimate .

5.3. Process Noise Estimation

The model residual is defined as

$$\rho_{k+1} = y_{k+1} - \tag{9}$$

While finding the model residual for each complex, the preceding complexes are also taken into account by averaging their corresponding model residuals.

From (8), it can be seen that the Kalman gain can be simplified to be a scalar matrix (a diagonal matrix with all entries equal) or even a scalar. By changing this value of , the weights provided to the newly arriving ECG complexes y can be varied, thus changing the effect of preceding ECG complexes to the estimation of $\hat{x}$. Since Kalman gain is assumed to be a scalar, , and can be assumed to be scalar and represented as , and .

The process noise covariance is estimated as follows:

$$\lambda_k^2 = \begin{cases} \frac{1}{T}\rho_{k+1}^T\rho_{k+1} - \psi_k^2 - \sigma_{k+1}^2, if\ posit \\ 0, otherwise \end{cases} \tag{10}$$

If the model error $\frac{1}{T}\rho_{k+1}^T\rho$ is greater than its theoretical value σ, increases and this results in increased Kalman gain. Thus, more weight is given to newly arriving ECG complexes.

5.4. Algorithm

1. Initial estimate of ECG complex $\hat{x}_0$ and the measurement noise vector $\hat{w}_1$ are obtained as the mean ECG complex over heartbeats and after projection respectively.
2. Initial estimates for noise variances ψ_0^2 and σ_1^2 are taken as the variances of vectors $\hat{x}_0$ and $\hat{w}_1$respectively.
3. Estimation of measurement noise covariance from (5) and (4).
4. Estimation of process noise covariance from (9) and (10).
5. Calculation of Kalman gain from (8).
6. Calculation of estimate of ECG complex and its variance from (6) and (7).

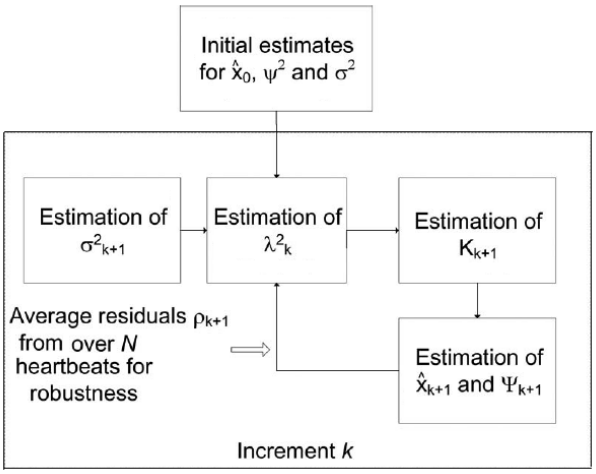


Figure.5:Algorithmic Implementation of Adaptive Kalman Filter

VI. SIMULATION RESULTS

6.1. TWA Signals

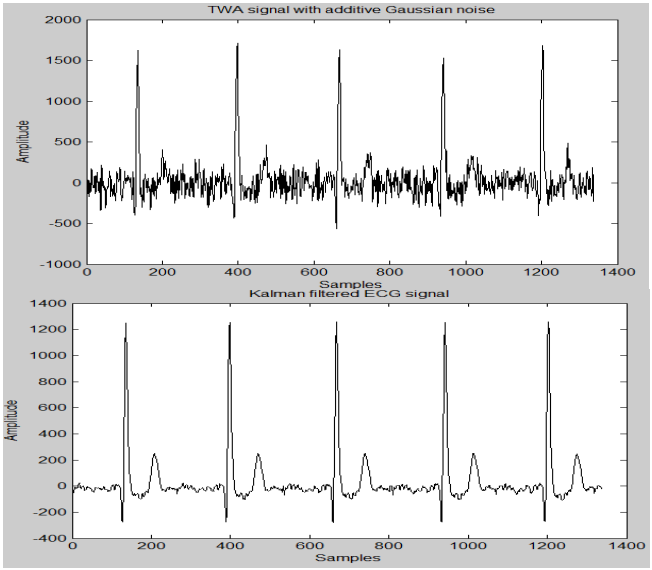
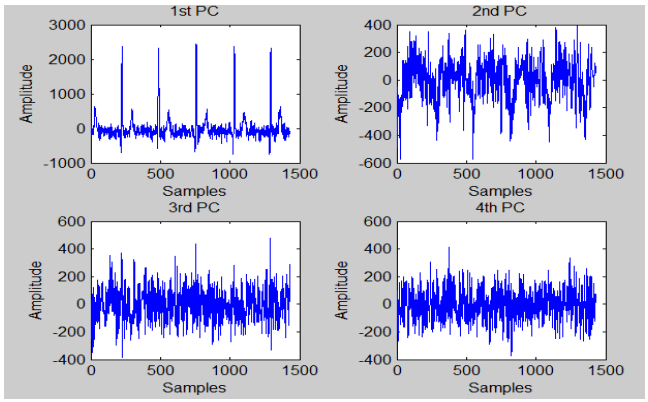
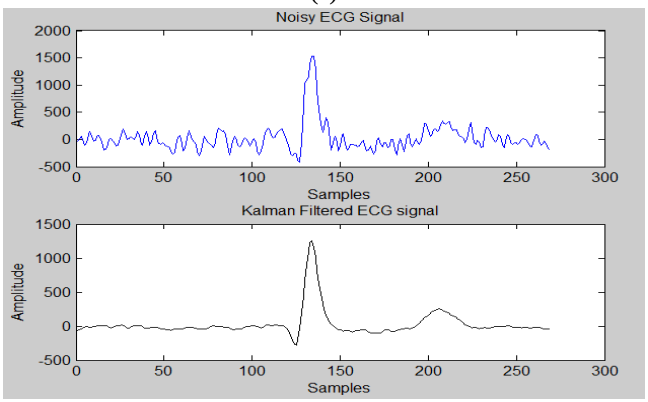


Figure.6: TWA signals before filtering (top panel), after filtering using adaptive Kalman filter (bottom panel).



(a)



(b)

Figure.7: (a) Principal Components obtained after PCA. (b) ECG complex before filtering (top panel), filtered ECG complex (bottom panel).

6.2. Fetal ECG Signals

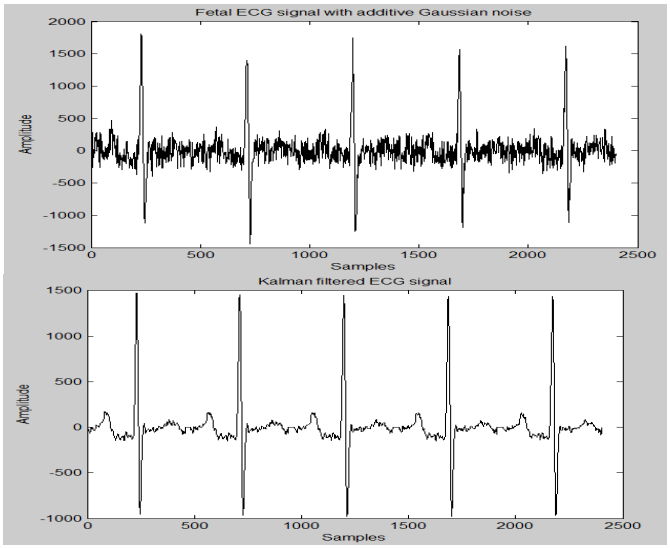
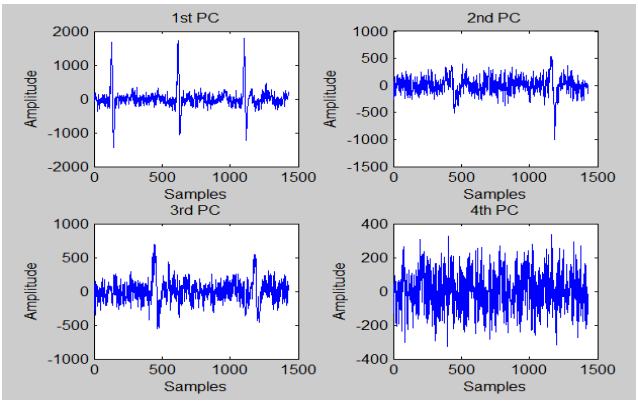
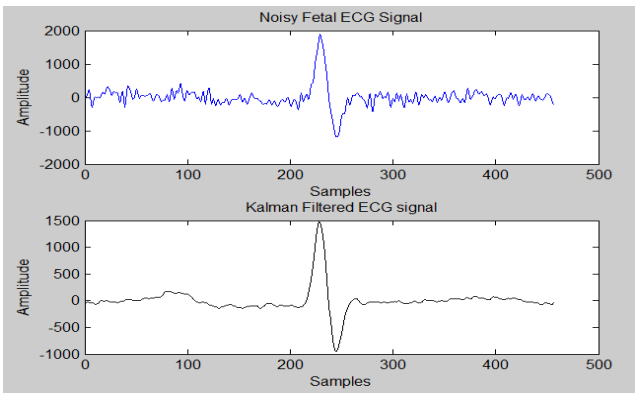


Figure.8: Fetal ECG signals before filtering (top panel), after filtering using adaptive Kalman filter (bottom panel).



(a)



(b)

Figure.9: (a) Principal Components obtained after PCA. (b) ECG complex before filtering (top panel), filtered ECG complex (bottom panel).

The performance of the filter is assessed by using the normalized MSE (Mean Square Error) between the filtered ECG signals $\hat{x}$ and the original ECG signals x used (signals without additive Gaussian noise).

$$\epsilon = \frac{\sum_k (x_k - \hat{x}_k)^T (x_k - \hat{x}_k)}{\sum_k x_k{}^T x_k} \tag{11}$$

Here, ϵ is averaged over all heartbeats in the ECG signal.Normalized MSE for TWA and Fetal ECG signals using N=5 is given in the following table.

TABLE I. NORMALIZED MSE FOR TWA & FETAL ECG SIGNALS

Type of ECG Signal	Normalised MSE
TWA Signal	-17.08dB
Fetal ECG Signal	-28.21dB

Normalized MSE was calculated for different values of number of ECG Complexes N and is plotted as shown below. The Mean square error was found to be decreasing in a small scale with increase in number of ECG complexes used.

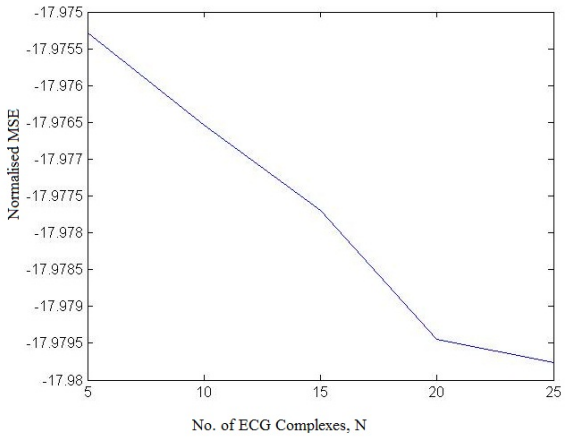


Figure.10. Normalized MSE vs. Number of ECG complexes, N

VII. CONCLUSION

The paper presents an adaptive Kalman filter for the enhancement of ECG signals. The filter was evaluated on a variety of ECG signals and its performance was assessed based on the normalized MSE between the filtered signals and the original ECG signal.

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