An Adaptive Kalman Filter for Removing Baseline Wandering in ECG Signals

MA Mneimneh, EE Yaz, MT Johnson, RJ Povinelli

Marquette University, Milwaukee, WI, USA

Abstract

Baseline wandering interference misleads ECG annotators from accurate identification of the ECG features. Previous work that deals with baseline wandering removal requires the identification of the QRS complex or other ECG features prior to baseline removal. This paper proposes an adaptive Kalman filter for the real time removal of baseline wandering using a polynomial approximation independent of the signal characteristics. A state space model is used with an adaptive Kalman filter to estimate the state variables, including the baseline wandering approximation from the previous values of the original ECG signal. This approach is applied to the (PTB) Diagnostic ECG Database and to a ECG signal disturbed by white noise and a second order baseline wandering. The results show accurate and improved baseline wandering estimation and removal as compared to moving averaging and cubic spline techniques.

1. Introduction

Baseline wandering is one of the noise artifacts that affect ECG signals. This wandering, caused by the subject's movement or breathing, might induce misleading measurement and annotation of the signal's features. Usually, the baseline wandering is expected to have the same frequency content as the T-wave. However, due to certain tests such as the stress test, the baseline wandering may vary unpredictably. This work presents a Kalman filter based approach for the online estimation and removal of baseline wandering in ECG signals.

Most of the previous adaptive techniques that deal with baseline wandering make the assumption that the extremities of the features of the signal are known. The first is the adaptive technique proposed by Jane et al. that applies a combination of a Least Mean Squares (LMS) driven adaptive impulse correlated filter and a two stage cascade filter for the removal of baseline wandering. This technique requires the detection of the QRS complex and the frequency analysis of the signal in order to determine the transfer function of the cascade filter [1]. Additionally, Daqrouq et al. have proposed a baseline wandering reduction technique that requires the decomposition and reconstruction of the signal after the signal is filtered [2]. Therefore, these techniques require certain knowledge (RR interval) of the patient prior to applying the filtering technique. Lisheng et al. used a combination of Meyer wavelet filter and spline interpolation for the removal of the baseline wandering [3].

Additional well known techniques include the window moving averaging method [4] and the cubic spline technique [3]. Since these methods can be applied without the knowledge of the heart rate of the signal, these techniques will be used for validating the proposed adaptive Kalman filter approach.

The technique proposed in this work is an application of the Kalman filter for the prediction and removal of the baseline wandering in ECG signals. The proposed approach is based on the hypothesis that the ECG signal can be characterized by an autoregressive model, while the baseline wandering is estimated as a first order polynomial. The State Space model is integrated with the Kalman filter in order to estimate state variables, which in this case are the coefficients of the autoregressive model and the coefficients of the baseline wandering estimated curve. The proposed approach suggests an accurate way for the estimation of the baseline of an ECG signal, and is compared to the Cubic Spline Method (CSM) and the Moving Averaging (MVG) technique.

2. Datasets

The proposed approach is applied to two data sets. The first dataset is the PTB Diagnostic ECG database [5]. This database is taken from Physiobank. This dataset was collected by Physikalisch-Technische Bundesanstalt (PTB), the National Metrology Institute of Germany.

The database consists of 549 records taken from 294 subjects. Each record contains measurements taken from 15 leads, where the first 12 leads are the conventional leads and the last 3 are the Frank leads (X, Y, and Z). The data is digitized at 1000 samples per second.

The second dataset is simulated data with additional baseline wandering. Since there is no quantitative measurement of baseline wandering, the use of simulated data can be used to measure the error between the original signal (before applying baseline wandering) and the signal after applying the baseline wandering removal techniques.

The simulated ECG signal is generated using a piecewise linear function, where the features of the signals are represented by triangles. The signal is then smoothed using a third order Savitzky-Golay FIR filter of frame size of 17 samples, and is repeated 150 times.

The baseline wandering is represented as a second order polynomial dependent on the discrete sample time. The simulated baseline wandering is added to the original signal.

3. Method

The proposed approach is used to identify and remove the baseline wandering in ECG signals without adding any distortion to the signal. The Kalman filter approach is chosen because of its ability to simultaneously model both the ECG signal and the baseline wandering.

3.1. State space model

The ECG signal without the baseline wandering is assumed in this work as an autoregressive model such as:

$$y_{e_i} = a_1 y_{i-1} + a_2 y_{i-2} + \ldots + a_{n-1} y_{i-n}, \tag{1}$$

and the baseline wandering is represented as

$$b = a_{a1}k + a_{a2}, \tag{2}$$

where k is time sample of the signal. Therefore, the signal with the baseline wandering is

$$y_n = a_1 y_{i-1} + a_2 y_{i-2} + \ldots + a_{n-1} y_{i-n+1} + a_{a1}k + a_{a2} \tag{3}$$

With the assumption of stationarity the general form of the update equations can be written as follows:

$$X_{k+1} = A \bullet X_k \tag{4}$$

$$Y_k = C_k \bullet X_k \tag{5}$$

where X_k is an n-dimensional vector, Y_k is the scalar valued measurement.

Using the proposed model in equation (3), and replacing X with the set of coefficients, a_k ,and C with $C = \begin{bmatrix} y_{i-1} & y_{i-2} & y_{i-3} & y_{i-4} & \bullet & \bullet & \bullet & \bullet & y_{i-n} & 1 & 0 \end{bmatrix}$ the update equations (4) and (5) are written as follows:

$$\begin{bmatrix} a_{1k+1} \\ a_{2k+1} \\ a_{3k+1} \\ \vdots \\ a_{nk+1} \\ a_{a_1k+1} \\ a_{a_2k+1} \end{bmatrix} = \begin{bmatrix} & & & & & 0 & 0 \\ & & \boldsymbol{I} & & & 0 & 0 \\ & & & & & 0 & 0 \\ & & & & & \vdots & \vdots \\ & & & & & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 1 & 1 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a_{1k} \\ a_{2k} \\ a_{3k} \\ \vdots \\ a_{nk} \\ a_{a_1k} \\ a_{a_2k} \end{bmatrix} \tag{6}$$

$$\hat{y}_i = \begin{bmatrix} y_{i-1} & y_{i-2} & y_{i-3} & y_{i-4} & \bullet & \bullet & \bullet & \bullet & y_{i-n} & 1 & 0 \end{bmatrix} \begin{bmatrix} a_{1k} \\ a_{2k} \\ a_{3k} \\ . \\ . \\ . \\ . \\ a_{nk} \\ a_{a_1k} \\ a_{a_2k} \end{bmatrix} \tag{7}$$

where I_n is the n-dimensional identity matrix.

3.2. Kalman filter solution

The solution for the State Space model presented in (6) and (7) is determined using an iterative approach. The solution is presented in terms of equations (4) and (5) as follows [6]:

$$\begin{aligned} K_k &= A \bullet P_k \bullet C_k^{\,T} / (C_k \bullet P_k \bullet C_k^{\,T} + \varepsilon) \\ \hat{X}_{k+1} &= A \bullet \hat{X}_k + K_k \bullet \left(y_k - C_k \bullet \hat{X}_k \right) \\ P_{k+1} &= (A - K_k \bullet C_k) \bullet P_k \bullet (A - K_k \bullet C_k)^T + \varepsilon K_k K_k^T \end{aligned} \tag{8}$$

Where K is the Kalman gain, k is the discrete time sample, P is the uncertainty covariance matrix and $0 < \varepsilon \ll 1$ is added to model measurement noise.

The mean convergence time for the KF approach was 4.4 ms for the original setup. The convergence time is the time needed by the KF approach in order to accurately predict and remove the baseline wandering. However, the equations shown in (8) are iterated over the input signal, y. During the iteration process, equation (8) is updated for the first 2 iterations as follows to accelerate the convergence of the Kalman filter.

$$\hat{X}_{k+1} = 1.01(A \bullet \hat{X}_k) + K_k \left(y_k - C_k \hat{X}_k \right) \tag{9}$$

The initial condition of X is chosen as a zero vector, while that of the error covariance vector is chosen to be $50 * I_{n+2}$.

4. Validation techniques

4.1. Window moving averaging (MVG)

The Window Moving Averaging technique is used to smooth the input curve. The method averages over a window of data as follows

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i , \tag{10}$$

where x is an element in the dataset and n is the number of elements in the window

4.2. Cubic spline method (CSM)

This method uses a cubic spline estimation of the baseline from the PR segments solely. In this work, the baseline wandering was determined using a cubic spline interpolation over a window in order to determine the baseline wandering of ECG signal as suggested by [3].

5. Results

These techniques are applied to PTB Diagnostic ECG database and simulation data. The reason for using simulated data is to be able to determine precisely the error in each of the methods, because both the original and the baseline wandering are known. The validation of the Kalman Filter approach with respect to the window moving averaging and the spline technique for the PTB Diagnostic ECG database is qualitative, while that for the simulated data is quantitative.

5.1. PTB Diagnostic ECG Database

The approach was applied to a sample record taken from the PTB database. The comparison between the three methods is shown in Figure 1. This signal is taken from the lead I of record ID s0027lre of the sixth patient. The simulation was applied with the same window size of 70 samples to all three methods.

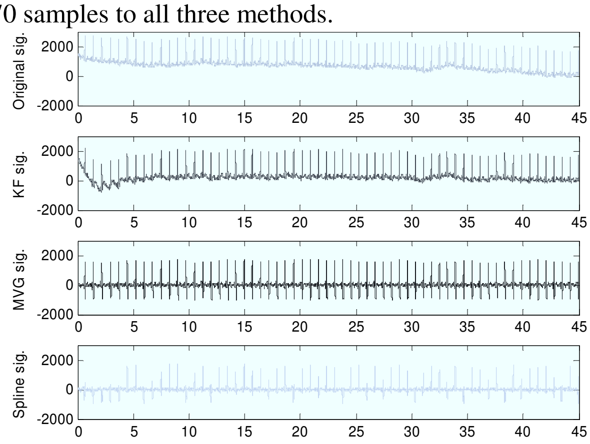

Figure 1 Comparison of the different techniques.

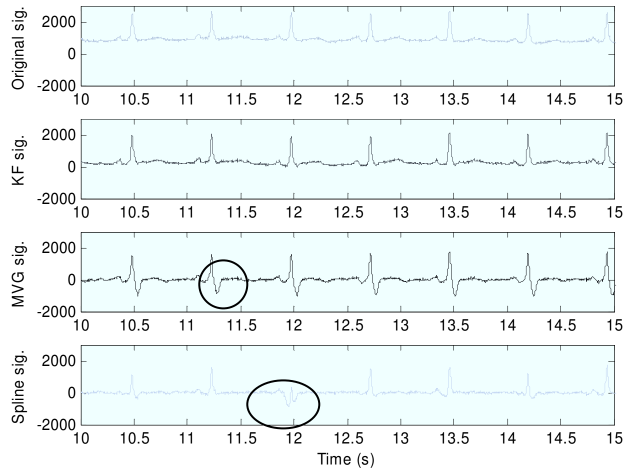

Figure 2 Comparison of the distortion in the signals.

Figure 2 shows that the KF approach aligned the ECG signal successfully and managed to keep the signal without any distortion for the same window size. Although the other approaches, MVG and Spline, were able to remove the baseline wandering, an additional artifact was added to the signal, as shown in the S-wave for the MVG and some of the QRS complex for the Spline approach.

5.2. Simulated data

The simulated ECG signal provides a quantitative comparison amongst the techniques. The simulate signal for a single beat is shown in

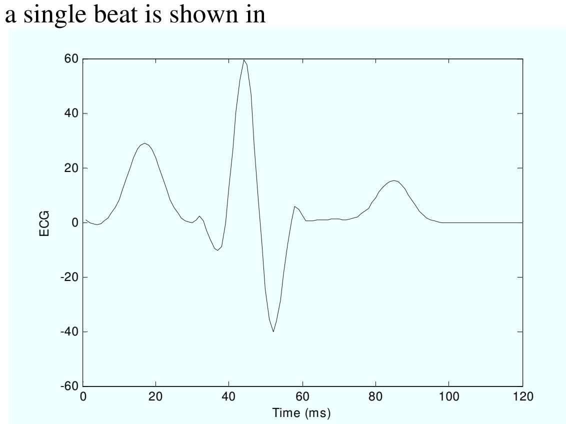

Figure 3 Simulated ECG signal for one beat.

The KF approach is applied to the simulated data over 150 beats. The window size for the KF approach is the same as for the real patient data (70 samples). The window size for the MVG and the CSM was chosen to be 90 samples. This was done to improve the performance of the MVG and the CSM. The result from applying the KF, MVG, and CSM techniques is shown in Figure 4.

As it can be seen from the results, all three techniques successfully remove the baseline wandering in the modified ECG signal. These resulting signals are compared to the original signal to study the distortion resulting of each of the techniques.

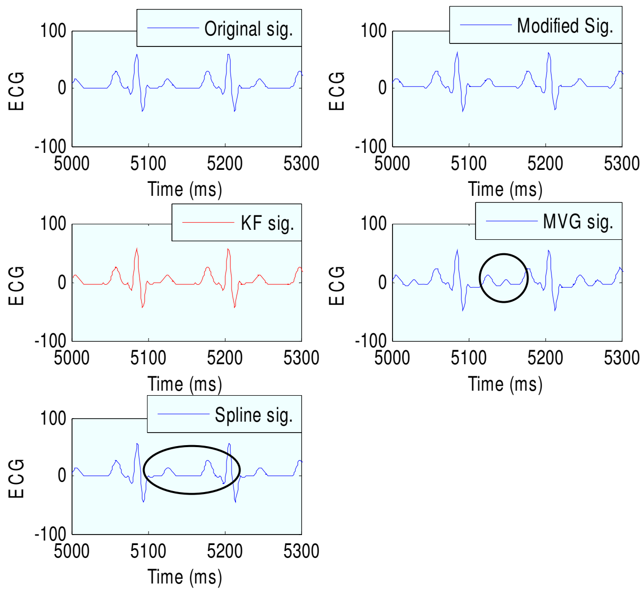

Figure 4 Comparison between the three techniques.

The mean and standard deviation of the error resulting from the difference between the original signal and the signal generated from each of the techniques are shown in Table 1. It is to be noted that the comparison is performed after the convergence of the KF.

Algorithm	Mean Error	Error STD
Kalman Filter	0.073	0.076
Moving Avering	0.215	1.858
Cubic Spline	1.010	3.666

Table 1 Comparison between baseline removal techniques.

As can be seen from the table above, the level of distortion is minimal for the KF approach. This is because the MVG and the CSM techniques are highly dependant on the window size and the heart rate of the patient. However, the KF approach can be applied to different signal as shown previously, for the same window size.

6. Discussion and conclusions

This paper presented a method used in real time baseline removal. However, this was adjusted as mentioned in Eq. (9) by using exponential weighting on the state variables update equations of the SS model. The reason for this weighting is to accelerate the convergence of the Kalman Filter. As shown in the results, the KF approach had minimal distortion, specially in the ST segment, when compared to the other techniques. The KF approach for the removal of baseline wandering failed for the condition under high frequency changes. This is due to the adaptability and convergence factor of the KF. This problem can be fixed by increasing the window size for the time samples; however, this is not favorable due to the increase in the computational time during estimation.

In conclusion, although the Kalman filter approach did not accommodate for quick baseline changes, this approach was successful in the online estimation and removal of the baseline wandering for real-patient and a simulated test signal.

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Address for correspondence

Mohamed Mneimneh
EECE Department, Marquette University
1515 W. Wisconsin Ave.
Milwaukee, WI 53233
Mohamed.Mneimneh@Marquette.edu