Development of a Novel ECG signal Denoising System Using Extended Kalman Filter

Nagendra Sen¹, Chinmay Chandrakar²
PG Student, Dept. of Communication Engineering, SSCET, Bhilai, India¹
Head of Dept., Dept. of Electronics & Communication, SSCET, Bhilai, India²

ABSTRACT - ECG signal plays a crucial role in diagnosis of a Variaty of diseases. At the time of diagnosis the proper information from the ECG signals helps to make a proper and efficient diagnosis for the patient. Most often it is found that treatment of the patient suffers due to improper information of ECG signals. The cause behind this problem is the noise added in the ECG signals at the time of signal acquisition. Hence to overcome this problem efficient denoising of ECG signals is required. This paper presents efficient denoising scheme for electrocardiogram (ECG) signals based on extended Kalman filter (EKF) structure. The basic idea is to overcome the disadvantages of conventional techniques like median filter by utilizing the adaptive nature of EKF structure. For the comparative analysis this paper deploys three important parameters; mean square error (MSE), Peak signal to noise ratio (PSNR), and most importantly RR interval estimation. On the basis of the three parameters a comparative analysis has been presented to explore efficient denoising capability of EKF over median filter. The results obtained indicated that EKF provides very less MSE and very high PSNR as compare to median filter. On the other side the estimated RR interval obtained using EKF is the closest match with original signal RR intervals, while median filter provides so many RR intervals, which are not even presents in the original signal.

Keywords - Denoising, ECG dynamical model (EDM), extended Kalman filter (EKF), hidden state variables, lossy compression.

I. INTRODUCTION

ECG recordings obtained by a noninvasive technique is a harmless, safe, and quick method of cardiovascular diagnosis. The accuracy and content of information extracted from a recording require proper characterization of waveform morphologies, which, in turn, require the preservation of the phase and amplitude important clinical features and high attenuation of noise. ECG signals are usually corrupted with unwanted interference such as muscle noise, electrode artifacts, line noise, and respiration. 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 multi resolution characteristics such as the ECG [8]–[13].

On the other hand, a synthetic model has been proposed for generating artificial ECGs, which has unified the morphology and pulse timing in a single nonlinear dynamic model [16]. Concerning the simplicity and flexibility of this model, it can be easily used as a base for ECG processing, as demonstrated by Clifford et al. [17], where the use of the model to filter, compress, and classify the ECG was first proposed. This approach was based on the least squares error (LSE) optimization. The model may be further used in dynamic adaptive filter, such as the Kalman Filter (KF). Sameni et al. proposed the use of a KF framework to update the model on a beat-to-beat basis in order to filter noisy ECGs [18]–[21]. The polar form of the dynamical equations was also used for Kalman-based ECG denoising [20].

II. DYNAMICAL SYSTEM AND EXTENDED KALMAN FILTER

Let us consider nonlinear dynamical systems of the following form:

\[ x_{t+1} = f(x_t) + w_t \]  

\[ \text{(1)} \]
As in [3], we will use the matrix identity
\[
\begin{eqnarray*}
I - (A + B)^{-1}A &=& (A + B)^{-1}
\end{eqnarray*}
\]
Copyright to IJAREEIE www.ijareeie.com
Applying (13) and substituting the definition of $e_t$ from (8),

$$
x_t^1 = V_t^1(C^tR_t^{1/2}(y_t - e_t) + (V_t^{1/2})^{-1}x_t^1)
= K_t(y_t - e_t) + (I - K_tC)x_t^{1-1}
= x_t^{1-1} + K_t(y_t - g_t)(x_t^{1-1}).
$$

...(14)

The time update for the mean can be found by conditioning on $x_{t-1}$ and substituting the definition of $d_t$ from (7)

$$
x_t^{1-1} = E_{x_{t-1}}(E(x_t|x_{t-1}, \{y_l\}^t_{l=1}|\{y_l\}^{t-1}|\{y_l\}^{t-1})
= A_{t-1}x_{t-1}^{1-1} + d_{t-1}|\{y_l\}^{t-1}
= f_{t-1}(x_{t-1}^{1-1}).
$$

...(15)

The recursions start with $x_0^0$ and $x_{t-1}^{1-1} = V_t$. Equations (10), (11), (12), (14), and (15) together form the Extended Kalman filter forward recursions, as shown in [24], [25].

The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems as shown below in Figure 2-1.

Figure (2.1) the ongoing discrete Kalman filter cycle.

The time update projects the current state estimate ahead in time. The measurement update adjusts the projected estimate by an actual measurement at that time. The specific equations for the time and measurement updates are presented below in Table 1 and Table 2.

**Table 1: Discrete Kalman filter time update equations.**

$$
\log P(x_t|y_1^t) = \log P(y_t|x_t) + \log P(x_t|y_1^{t-1}) + ...
$$

**Table 2: Discrete Kalman filter measurement update equations.**

$$
K_t = \frac{V_t^{1/2}C_t^{1/2}(R_t + V_t^{1/2}C_t^{1/2})^{-1}C_t^{1/2}}{V_t^{1/2}C_t^{1/2}(R_t + V_t^{1/2}C_t^{1/2})^{-1}C_t^{1/2}}
\text{x}_t^1 = x_t^{1-1} + K_t(y_t - g_t)(x_t^{1-1}).
$$

Figure (2.2) a complete picture of the operation of the Kalman filter, combining the high-level diagram of Figure 2.1 with the equations from table 1 and table 2.
III. METHODOLOGY

The proposed work of this paper, deals with the implementation of extended Kalman filter (EKF) for the efficient ECG signals denoising and RR interval estimation in comparison with available median filter. Figure (3.1) shows the flow chart representation of proposed work.

IV. RESULTS AND DISCUSSIONS

The proposed work has been successfully implemented in the MATLAB. This section presents the results obtained and comparative analysis with median filter and extended kalman filter. For the testing phase, we have used MIT-ANSI ECG data base. Figure (4.1) to figure (4.3) shows the results obtained after ECG signal denoising using EKF and median filter. For example figure (4.1a) shows original ECG signal, figure (4.1b) shows Noisy ECG signal to be filter, figure (4.1c) shows resultant image after median filtering and figure (4.1d) shows resultant image after EKF filtering.
Figure (4.3a) Original ECG

Figure (4.3b) Noisy

Figure (4.3c) Median filtering output

Figure (4.3d) EKF Output

Table 3

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Database Signal</th>
<th>RR intervals of original ECG signal</th>
<th>RR intervals Obtained for Median Filter</th>
<th>RR intervals Obtained for EKF Filter</th>
<th>MSE for Median Filter</th>
<th>MSE for EKF Filter</th>
<th>PSNR for Median Filter</th>
<th>PSNR for EKF Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>aami3a</td>
<td>58</td>
<td>9</td>
<td>0.0027</td>
<td>0.8124</td>
<td>0.0027</td>
<td>73.7539</td>
<td>73.7539</td>
</tr>
<tr>
<td>2</td>
<td>aami3b</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>0.1357</td>
<td>0.00025</td>
<td>84.1015</td>
<td>84.1015</td>
</tr>
<tr>
<td>3</td>
<td>aami3d</td>
<td>54</td>
<td>6</td>
<td>6</td>
<td>0.6424</td>
<td>0.0017</td>
<td>75.8117</td>
<td>75.8117</td>
</tr>
</tbody>
</table>
Table 3 shows the complete comparative analysis of the ECG signal denoising using median filter and EKF filter on the basis of MSE, PSNR and estimated RR intervals. From the Table 3, following things are clearly observable

i. MSE values obtained from EKF filter are much smaller than the available median filter for all the three ECG signals.

ii. PSNR values obtained from EKF filter are much higher than median filter for all the three ECG signals.

iii. The most important parameter is RR interval, from the table it is evident that median is not able to preserve RR interval of original ECG signal during the denoising process, while the EKF filter is found very efficient as far as RR interval preservation is concerned. Hence EKF provides exact estimation of RR interval as in the original ECG signal.

V. CONCLUSIONS

The aim of this paper was to overcome disadvantages of conventional techniques of ECG signal denoising, like median filter by utilizing the adaptive nature of EKF structure. For the comparative analysis, this paper included three important parameters; mean square error (MSE), peak signal to noise ratio (PSNR), and most importantly RR interval estimation. On the basis of the three parameters a comparative analysis has been done to explore efficient denoising capability of EKF over median filter. The results obtained indicated that EKF provides very less MSE and very high PSNR as compare to median filter. On the other side the estimated RR interval obtained using EKF is the efficient estimation of RR interval as the original signal RR intervals, while median filter provides so many RR intervals, which are not even presents in the original signal.

Hence EKF provides exact estimation of RR interval as in the original ECG signal as well as simultaneously able to highly suppress the noise contents added in the original ECG signal.

REFERENCES


