



Comparative Analysis of Kalman Filtering and Machine Learning Based Cardiovascular Signal Processing Algorithms

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Abstract. Cardiovascular (CV) disorder is one of the critical health problem that cause economical and social impacts, even death to lots of peoples globally. Electrocardiogram (ECG) signal is the signal taken from the human body to study the status of CV and heart conditions. Before the introduction of computers, those tasks were done by the experts that cause various mistakes. Currently, the use of advancing signal processing devices manage to reduce these effects. Besides, it allows to develop various signal detection and parameter estimation algorithms. By studying the parameters of ECG signals, it is possible to determine whether the person is in critical condition or not. This helps to take an appropriate action. In the last decades, both classical and machine learning methods have been used to study and characterize the essential properties and parameters of CV signals.

In this work, we study different algorithms that are useful for ECG based CV parameters estimation. We evaluate the performance of both classical (Kalman Filtering) and machine learning algorithms with Butterworth low pass filter, wavelet transform and linear regression for parameter estimation. Besides, we proposed an algorithm that combines adaptive Kalman filter (AKF) and discrete wavelet transform (DWT). In this algorithm, the ECG signal is filtered using AKF. Then segmentation is performed and features are extracted using DWT algorithm. Numerical simulation is done to validate the performances of these algorithms. The results show that the proposed algorithm gives better performance than Kalman filtering and has nearly the same performance with machine learning methods.

Keywords: ECG signal · Cardiovascular parameters · Kalman filter · Machine learning · DWT

1 Introduction

Cardiovascular disease (CVD) is the most widespread chronic disease that cause enormous amount of economic and social problems. It is also one of the main cause for death of lots of people within all age ranges [1]. In order to combat the effect of this disease, a better estimation and prediction of heart state and diagnosis mechanism is required. ECG is one of the devices that capture the electrical activity of the heart, which in turn is used for the diagnosis of cardiac problems [1,2]. The study of cardiovascular parameters from ECG signal is mostly depend on the PQSRT pattern (a cardiac cycle due to the cardiac muscle depolarization and repolarization), which varies from person to person and from time to time. As shown in Fig. 1, one cycle has P-wave (atrial contraction), QRS-complex (contraction of the ventricles) and T-wave (relaxation of the ventricles). The amplitude of these waves and the RR, PR, QT, and QRS complex intervals indicate the condition of the heart. Although the variation of such waves might be visible to the physicians, the time to make the decision may be very long. This endangers the life of the patient at risk since the variation might occur within a fraction of seconds. Hence, due to such variation in addition to the noise and other motion artifacts, having a signal processing system with efficient algorithms is vital to study the condition of the patient, and to make effective and wise decisions [3].

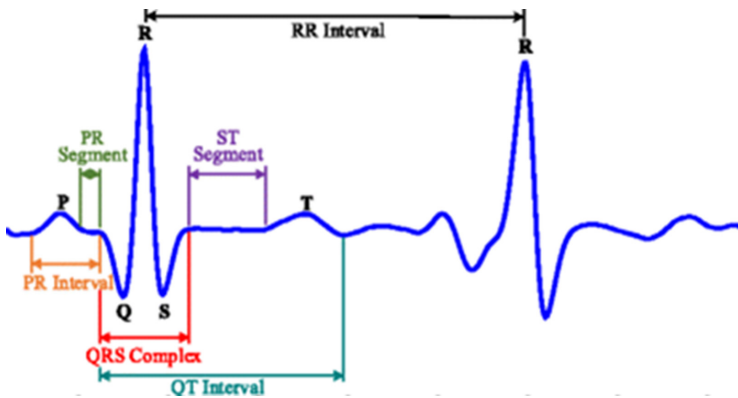


Fig. 1. Heart beat cycle in the ECG waveform [3].

In this work, the performances of Kalman filter and machine learning algorithms based cardiovascular parameter estimation are evaluated and analyzed via simulation. Besides, we propose an algorithm that uses the combination of adaptive Kalman filter and DWT algorithms. Numerical simulation is done to show the performances of the proposed algorithms.

The rest of the paper is organized as follows. In Sect. 2, state of the art and review of related works for cardiovascular signal processing is presented.

The system and signal model is provided in Sect. 3. Performance metrics for cardiovascular parameter estimation is shown in Sect. 4. Simulation results are discussed in Sect. 5 and conclusions are drawn in Sect. 6.

Notations: Vectors and matrices are expressed in lower and upper case boldface letters, respectively. \mathbf{A}^T denotes conjugate transpose of matrix and $\mathbb{E}\{\cdot\}$ is the expectation operator.

2 State of the Art and Review of Related Works

In the past decades, various algorithms with different level of accuracy has been developed and tested for estimating cardiovascular parameters. Stroke volume (SV), cardiac output (CO), and total peripheral resistance (TPR) are some of the parameters that determine the output blood per minute from the heart and give information about the status of patient's heart condition [4].

One of the main problems in ECG signals is the amount of noise which needs noise filtering /denoising to study the characteristics of those parameters. Wavelet is one of the commonly used denoising methods used for ECG signal filtering. In this method, the signal is decomposed in to various bands and each coefficient is processed. Besides, threshold setting and wavelet reconstruction is done to attain the filtered ECG signal [5,6]. This needs an effective thresholding to set the right threshold value that give a better performance. If the ECG signal is too noisy, the wavelet method might not be reliable. Additional signals such as arterial blood pressure (ABP) pulse is used in [7] to study the health condition of the patient in addition to ECG signals. But this adds additional complexity to align the R- peak of ECG signal with ABP pulse, since both are not aligned.

Another recursive denoising method is done by using Kalman filtering. The noise in ECG signals makes it difficult to get a good estimation of time varying cardiovascular state. But, the usage of Kalman denoising, which uses a continual parameter update, enables to attain an estimation of parameters with lower minimum mean square error (MMSE). The extended Kalman filters and adaptive Kalman filters were used for non linear models [8,9]. Empirical mode decomposition (EMD) based adaptive signal processing method has been very essential for non stationary and non linear signal analysis. With the existence of high frequency component in ECG signal, EMD have high probability of filtering the noise but it causes some sort of distortion on the amplitude of the peaks [10,11]. Parameter estimation methods such as Gaussian derivative model [12], autoregressive moving average, Wesseling correlated impedance and other methods were tested [13].

With the classical algorithms, the parameter estimation is mainly based on the shapes of QRS complex, and P and T waves that provide good accuracy for normal ECG signals. However, with the existence of variation in the ECG signal shapes having abnormal rhythms, their performance becomes unreliable. Due to that, data driven approaches including machine-learning models and neural networks have been introduced. Currently, that is more expanded into researches using deep learning algorithms for parameter estimation and classification of

ECG signals. The performance of those algorithms depends on the availability of data besides other factors. That is, with the existence of high amount of training and test data deep learning algorithms are providing good results while other machine learning based algorithms works with better accuracy even with the existence of small amount of data [14, 15].

3 The System and Signal Model

We consider an ECG signal which is contaminated by nose and modeled as [16]

$$\mathbf{y}(n) = \mathbf{x}(n) + \mathbf{v}(n) \quad (1)$$

where the vector $\mathbf{y}(n)$ represents the measured ECG signal, $\mathbf{x}(n)$ is the desired ECG signal, $\mathbf{v}(n)$ is a vector of additive Gaussian noise with $\mathcal{N}(0, \sigma^2)$ due to the sensor and amplifier noise and $n = 0, 1, 2, \dots, N - 1$ when N is the length of the signal. The sources of noise include movements that affects the skin-electrode interface, muscle contractions or electromyographic spikes, respiration, electromagnetic interference and noise from other electronic devices that couple into the device. With the existence of such noise in the ECG signal, studying and characterizing the health condition of the patient makes it very difficult. Due to that there needs an algorithm that is capable of filtering out the noise while extracting the ECG signal. Having that, the estimation and classification of cardiovascular parameters will be effective. Those algorithms have their different techniques and performances as discussed in the subsequent sections.

3.1 Kalman Filtering Algorithm for Cardiovascular Parameter Estimation

Kalman filter is an estimator of optimal state for systems with random noises. It can be used for filtering, smoothing and state prediction of a linear dynamic system depending on the quantity of information available. For that the Kalman filter has two phases: the prediction and correction of the system which allows to estimate the state of a dynamics system of one information, a priori and the actual measurements using the current state of the system, the estimate of the previous state and current measures. Thus the linear representation of the received ECG signal in Eq. (1) can be reformulated as [17, 18]

$$y_k = \mathbf{H}x_k + v_k \quad (2)$$

where \mathbf{H} is the dynamic constant matrix and v_k is the noise with a covariance matrix Q_k .

Let \bar{x}_k be a priori state estimation at step k given the information of the process prior to step k , and \hat{x}_k be a posteriori state estimate at the step k with given measurement y_k . Then, the priori and a posteriori estimation errors can be respectively defined as [17]

$$\begin{aligned}\bar{e}_k &\triangleq x_k - \bar{x}_k \\ \bar{e}_k &\triangleq x_k - \bar{x}_k.\end{aligned}\quad (3)$$

And a priori estimate error and posteriori estimate error covariance is given by [17, 18]

$$\begin{aligned}\bar{P}_k &= \mathbb{E}\{\bar{e}_k \bar{e}_k^T\} \\ \bar{P}_k &= \mathbb{E}\{\bar{e}_k \bar{e}_k^T\}.\end{aligned}\quad (4)$$

Then, the posteriori state estimate is given by [17, 18]

$$\bar{x}_k = \bar{x}_k + K(y_k - \mathbf{H}\bar{x}_k). \quad (5)$$

The difference in the above equation is termed as the measurement residual which shows the discrepancy between actual and predicted state where K is the gain matrix given by

$$K_k = \bar{P}_k \mathbf{H}^T (\mathbf{H} \bar{P}_k \mathbf{H}^T + \mathbf{R})^{-1}. \quad (6)$$

where \mathbf{R} is the covariance matrix. Hence, with Eq. (5) the filtered ECG signal can be achieved [17, 18].

3.2 Machine Learning Algorithm for Cardiovascular Parameter Estimation

Machine learning algorithm is capable to make decisions autonomously without any external support by learning from the data and understanding the patterns that are contained within it. Using that pattern, the machine can perform tasks such as classification and prediction based on the type of algorithm. The three main machine learning algorithms at present includes supervised learning for classification including diagnosis and regression tasks for risk assessment, unsupervised learning for dimensionality reduction and clustering and reinforcement learning for gaming, robot interaction and other applications [19]. The basic building blocks of machine learning algorithms is shown in Fig. 2. The description of each block is outline below.



Fig. 2. Basic steps for ECG signal parameter estimation with machine learning algorithm.

- **Preprocessing:** Due to the existence of noise in the ECG signal, first the signal has to be preprocessed in order to extract its features and perform the estimation task. Filtering is one of the techniques used to preprocess the ECG signal. In this work, we use a second order Butter-worth low pass filter to filter the unwanted signal [20].
- **Feature Extraction:** The task of feature extraction for ECG signal starts from feature selection which includes PQRST wave detection using various algorithms. R-peak detection is essential task while other PQST components can be detected by taking the location of R-peak as a reference and tracking to/from R-peak relative position. The features might be time, amplitude, distance, angle and others that can be useful to characterize the ECG signal and estimation. Wavelet transform approach and time domain analysis is used to detect R-peak and others, respectively as in [20].
- **Parameter Estimation:** At this stage the cardiovascular parameters can be estimated based on the extracted features. Linear regression is one of the most known techniques to estimate cardiovascular parameters. The new sequence of the signal to be estimated with linear regression is given by [21]

$$y'(x) = ax + v. \quad (7)$$

The value of the coefficient a and the value of v that describe the best estimated signal, $y'(j)$ from the real $y(j)$ is given by [21]

$$a = \frac{m \sum_{j=l_1}^{l_2} x(j)y(j) - \sum_{j=l_1}^{l_2} x(j) \sum_{j=l_1}^{l_2} y(j)}{m \sum_{j=l_1}^{l_2} x^2(j) - (\sum_{j=l_1}^{l_2} x(j))^2} \quad (8)$$

$$v = \frac{\sum_{j=l_1}^{l_2} x^2(j) \sum_{j=l_1}^{l_2} y(j) - \sum_{j=l_1}^{l_2} x(j)y(j) \sum_{j=l_1}^{l_2} x(j)}{m \sum_{j=l_1}^{l_2} x^2(j) - (\sum_{j=l_1}^{l_2} x(j))^2}$$

with Butterworth filter $H(f) = \frac{b_1(jf)^n + b_2(jf)^{n-1} + b_{n+1}}{a_1(jf)^n + a_2(jf)^{n-1} + a_{n+1}}$ having filter order n (0, 1, ..., $N-1$) and cut-off frequency $f = 100$ Hz. And $i \in \{w, w+1, \dots, N-w-1\}$ where $l_1 = i - \omega$ and $l_2 = i + \omega$, $m = 2\omega + 1$ with window $\omega = 0.03f_s$ when f_s being the sampling frequency and $j \in \{i - w, i - w + 1, \dots, i + w\}$ [21].

3.3 Proposed Algorithm for Cardiovascular Parameter Estimation

In this section, we propose a new algorithm for cardiovascular parameter estimation by combining adaptive Kalman filtering and discrete Wavelet transform as shown in Fig. 3. In this algorithm, first the noise in the ECG signal is filtered using an adaptive Kalman filter (AKF). AKF predicts the state and error covariance ahead, computes the gain, used the estimate with measurement and then update the error until it gets a minimum defined acceptable error that is the difference of desired signal and the filtered noisy signal.

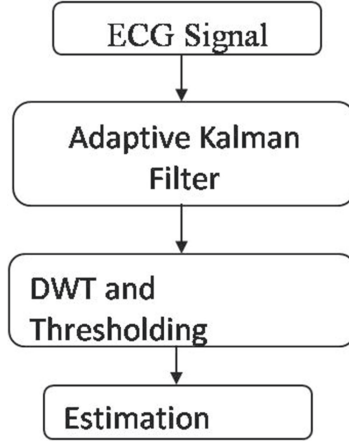


Fig. 3. Block diagram of our algorithm for cardiovascular parameter estimation.

After the noise filtering, the signal is decomposed by Wavelet transform. We use the discrete wavelet transform (DWT) which incorporates low pass filters and high pass filters to reduce the noise that couldn't be filtered with Kalman filter. The DWT signal is given by

$$X[a, b] = \sum_{n=-\alpha}^{\alpha} y(n)\phi_{a,b}(n) \quad (9)$$

where $y(n)$ is the output signal of the Kalman filter to be transformed with n length. And $\phi(n)$ is the window of finite length having a window translation parameter b and dilation/contraction parameter a . The next step is to set the threshold by using hard thresholding approach proposed in [22] to estimate the wavelet coefficients as

$$cD'_j = \begin{cases} cD_j, & |cD_j| \geq t \\ 0, & |cD_j| \leq t \end{cases} \quad (10)$$

where t is obtained by universal threshold selection with a value of $t = \sigma\sqrt{2\log N}$ with the standard deviation of the noise $\sigma = (\text{median}\{|cD_j|/0.6457\})$ where N is the data length, cD_j and cD'_j are wavelet coefficients before and after thresholding [22].

4 Performance Metrics for Cardiovascular Parameter Estimation

To evaluate the performances of cardiovascular parameters estimation algorithms, different parameters are used. Parameters such as True positive Rate (TPR), False Positive Rate (TPR), True positive (TP), False Positive (FP),

False negative (FN), True negative (TN), accuracy, sensitivity and others can be used to check the performance of parameter estimation algorithms. The mathematical expression for accuracy, sensitivity, average FPR and average positive predictive value for N data length is given as follows [7, 25]:

$$\text{Accuracy} = \frac{1}{N} \left(\sum_{i=1}^N \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \times 100\% \right) \quad (11)$$

$$\text{Sensitivity} = \frac{1}{N} \left(\sum_{i=1}^N \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \right) \quad (12)$$

$$\text{FPR} = \frac{1}{N} \left(\sum_{i=1}^N \frac{\text{FP}_i}{\text{FP}_i + \text{TN}_i} \times 100\% \right) \quad (13)$$

$$\text{PPV} = \frac{1}{N} \left(\sum_{i=1}^N \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i} \times 100\% \right). \quad (14)$$

Other performance evaluation parameter is mean absolute deviation (MAD) which gives the average absolute deviation of estimated signal, formulated as [26]

$$\text{MAD} = \frac{1}{N} \sum_{i=1}^N |e(n)|^2 \quad (15)$$

where the error $e(n)$ is the difference between the estimated signal and the original ECG signal. This error can also be used to determine the signal to noise ratio (SNR).

5 Simulation Results and Discussion

5.1 Simulation Parameters

We use the standard ECG signal dataset from a publicly available dataset, MIT-BIH AR dataset [23, 24]. Each ECG signal is sampled at 360 samples per second. The data are used to test the performance of Kalman filter, machine learning and the proposed algorithms for cardiovascular parameter estimation (Table 1).

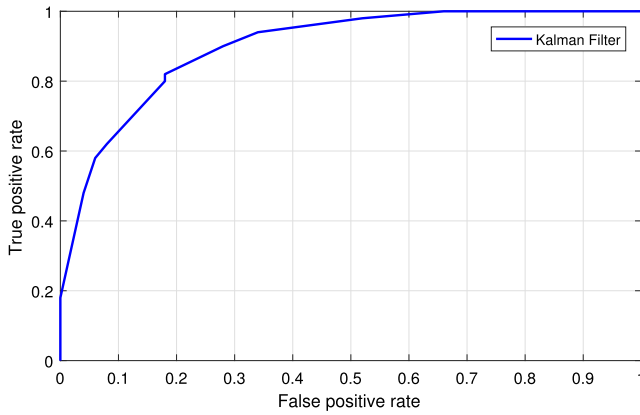
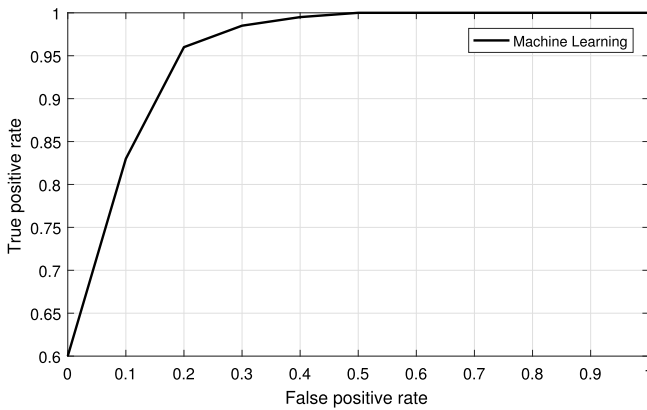
5.2 Simulation Results

We first show the receiver operating characteristics (ROC) curve of Kalman filter based ECG signal denoising algorithm. As shown in Fig. 4, the estimation of ECG signal parameter estimation is higher at high false positive rate values.

Employing Kalman filter can averaged out the noise from the ECG signal and estimate its necessary parameters. We also show the receiver operating characteristics curve of machine learning based ECG signal parameter estimation algorithm in Fig. 5.

Table 1. Simulation parameters used

Type	Parameter	Methods/Value
Butterworth filter	fs	500 Hz [20]
	Filter length	10 [20]
Machine learning	Preprocessing	Butterworth with length10 [20]
	Feature extraction	Wavelet with hard thresholding [22]
	Parameter estimation	Linear regression [21]
DWT	Window length	0.03 fs [21]

**Fig. 4.** Receiver operating characteristics (ROC) curve of Kalman filtering based ECG signal denoising.**Fig. 5.** Receiver operating characteristics (ROC) curve of machine learning based ECG signal parameter estimation method.

The result depicts that by using machine learning algorithm it is possible to achieve an estimation of ECG signal parameter even within a reduced false positive rate. This shows although it has high complexity machine learning algorithms give better performance than classical algorithms.

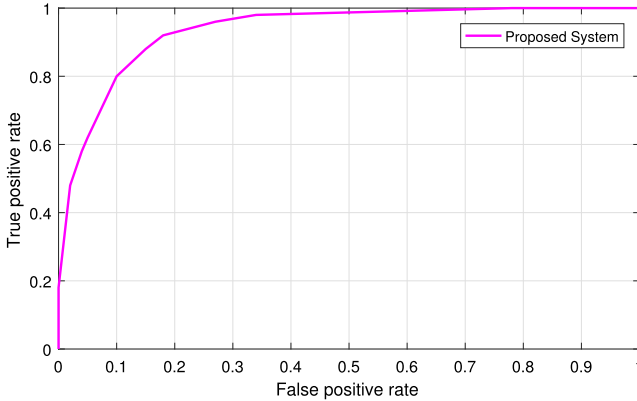


Fig. 6. Receiver operating characteristics (ROC) curve of the proposed algorithm for ECG signal filtering and parameter estimation.

We also plot the receiver operating characteristic curve of our algorithm as shown in Fig. 6. From the ROC curve of the proposed algorithm, it can be seen that a good detection performance can be achieved using classical noise filtering and estimation methods of ECG signal.

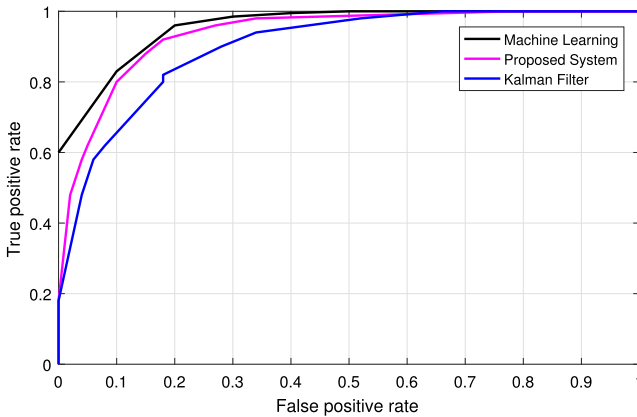


Fig. 7. The ROC for the proposed algorithms.

Finally, we plot the results from the three algorithms together as shown in Fig. 7. The result shows that the proposed classical filtering and prediction

algorithm provides better estimation accuracy than Kalman filtering. This is achieved due to additional usage of DWT blocks in the system. Besides, the proposed method gives nearly the same performance as machine learning algorithm with a lower complexity. Note that due to space limitation, we remove results with other performance metrics stated in Sect. 4 (Table 2).

Table 2. Summary of ROC for the three algorithms

FPR	0	0.1	0.2	0.3	0.4	0.5	0.7	0.8	0.9	1
TPR (Kalman Filter)	0.2	0.64	0.82	0.9	0.96	0.97	0.99	1	1	1
TPR (Machine Learning)	0.6	0.81	0.97	0.98	1	1	1	1	1	1
TPR (AKF with DWT)	0.2	0.8	0.95	0.96	0.97	0.97	1	1	1	1

6 Conclusion

In this work, we analyze the comparative performances of classical method (Kalman filtering) and machine learning algorithms for cardiovascular parameter estimation. We also propose an algorithm which uses joint Kalman filtering and DWT and analyze the performance with numerical simulation. The simulation results show that machine learning algorithm outperforms the classical method (Kalman filtering). However, with the proposed method, a better estimation result is attained compared to classical Kalman filtering. Besides, the result from the proposed algorithm shows that we can achieve a better parameter estimation with classical methods. Hence, this algorithm can be used when there is difficult to find enough training data sets. Investigations of other algorithms like deep neural networks will be the future direction of this work.

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