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Switching Kalman filter based ECG signal processing for Fiducial points

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ABSTRACT: This is the method for extracting fiducial points (FPs) of the beats in electrocardiogram (ECG) signals using switching Kalman filter (SKF). In this method, according to McSharry's model, ECG waveforms (P-wave, QRS complex and T-wave) are modelled with Gaussian functions and ECG baselines are modelled with first order auto regressive models.

In the proposed method, a discrete state variable called "switch" is considered that affects only the observation equations. We denote a mode as a specific observation equation and switch changes between 7 modes and correspond to different segments of an ECG beat. At each time instant, the probability of each mode is calculated and compared among two consecutive modes and a path is estimated, which shows the relation of each part of the ECG signal to the mode with the maximum probability. ECG FPs is found from the estimated path.

For performance evaluation, the Physionet QT database is used and the proposed method is compared with methods based on wavelet transform, partially collapsed Gibbs sampler (PCGS) and extended Kalman filter. It is observed that for our proposed method, the mean error and the root mean square error across all FPs are 2 ms (i.e. less than one sample) and 14 ms, respectively. These errors are significantly smaller than those obtained using other methods. The proposed method achieves lesser RMSE and smaller variability with respect to others.

KEY WORDS: Fiducial Point, Kalman Filter,

I.INTRODUCTION

An electrocardiogram (ECG) describes the electrical activity of the heart. Onset, offset and peak location of ECG waves are known as fiducial points (fps).

Detection of the fiducial points (fps) in an ECG signal reveals the abnormality function of the heart. Hence it is important to detect the fiducial point in an ECG signal.

The aim of the proposed work is to show the ability of SKF-based methods for ECG FP extraction. And the results show that our proposed method is very accurate, sensitive, and robust to noise, making it a suitable to real applications on automatic health care systems.

An electrocardiogram (ECG) describes the electrical activity of the heart. Onset, offset and peak location of ECG waves are known as fiducial points (FPs).

Till now, different methods have been used for detecting the QRS complex.

These methods are based on mathematical functions, filtering approaches, classification methods.

Low pass differentiation (LPD), hidden Markov models (HMM), partially collapsed Gibbs sampler (PCGS). Wavelet transform , correlation analysis and extended Kalman filter (EKF) are also used for ECG FP extraction.

II. SIGNIFICANCE OF THE SYSTEM

It is observed that in our proposed method, the mean error and the root mean square error across all FPs are 2 ms (i.e. less than one sample) and 14 ms respectively.

These errors are significantly smaller than those obtained using other methods. The proposed method achieves lesser RMSE and smaller variability with respect to others.

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III. LITERATURE SURVEY

Estimation of state variable in a system is quite important. One of the estimation algorithms is Kalman filter. Kalman Filter (KF) is an algorithm that combines models and measurements. The latest measurement data is an important part of the KF algorithm because the latest data will correct the prediction results, so the estimation results are always close to the actual conditions.

Kalman filter was applied in many problems, such as estimation of river water levels, estimation of some environmental problems, estimation of heat distribution, and many others.

It is used in areas as diverse as aeronautics, signal processing, and futures trading. At its core, it propagates a state characterized by a Gaussian distribution using linear transition functions in an optimal way. Since it is optimal, it has remained relatively unchanged since it was first introduced, but has received many extensions to apply it to more than just linear Gaussian systems.KalmanFiltering so popular because of

- good results in practice due to optimality and structure
- Convenient form for online real time processing.
- Easy to formulate and implement given a basic understanding.
- Measurement equations need not be inverted.

In 1960, R.E. Kalman published his famous paper describing a recursive solution to the discrete-data linear filtering problem. Since that time, due in large part to advances in digital computing; the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation.

A very "friendly" introduction to the general idea of the Kalman filter can be found in Chapter 1 of [Maybeck79], while a more complete introductory discussion can be found in [Sorenson70], which also contains some interesting historical narrative. More extensive references include [Gelb74; Grewal93; Maybeck79; Lewis86; Brown92; Jacobs93].

The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error.

The filter is very powerful in several aspects: it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modelled system is unknown.

The process of finding the "best estimate" from noisy data amounts to "filtering out" the noise. However a Kalman filter also doesn't just clean up the data measurements, but also projects these measurements onto the state estimate. Given only the mean and standard deviation of noise, the Kalman filter is the best linear estimator. Non-linear estimators may be better. If all noise is Gaussian, the Kalman filter minimises the mean square error of the estimated parameters.

IV. METHODOLOGY

Block Diagram:

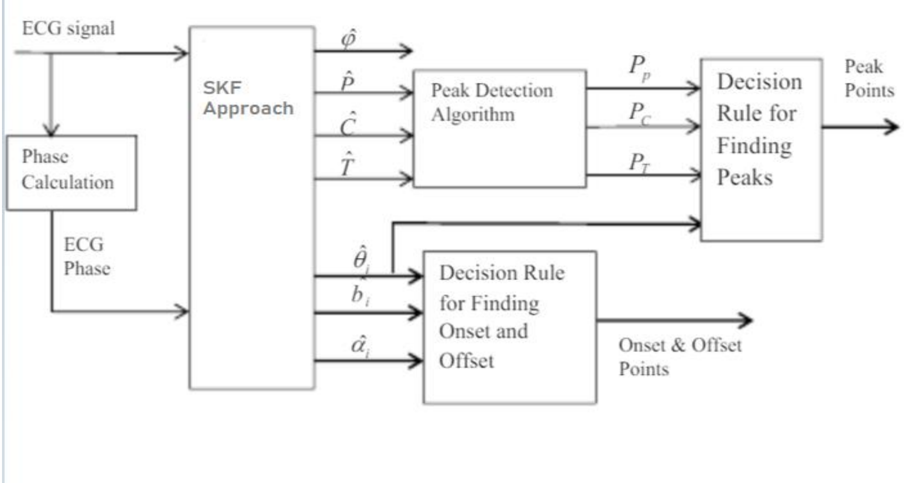

Figure 1.1

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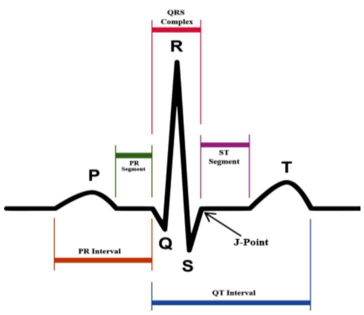
Here in this block diagram, ECG Signal is generated and phase calculation is done in the next step. Such Phase is called as ECG phase. It is further sent to Switching Kalman Filter Approach where the main algorithm lies. From there onwards Peak Detection Algorithm and Decision Rule for Finding Onset and Offset is done.
A decision is taken in the Decision rule for Finding Peaks is done and from there required peak points are generated. And similarly Decision Rule for Finding Onset and Offset plays the equal significant role for the determination of Onset and Offset Points.
According to McSharry's model, ECG waves (P-wave, QRS complex and T-wave) are modelled with Gaussian functions. Baselines and segments between ECG waves are modelled with first order auto regressive (AR) models.
In this SKF approach, a discrete switch affects only the observation equations and switches between 7 different values related to the 3 waves and the 4 baseline segments. The performance of the proposed method is compared with previously published methods, including Wavelet, PCGS and EKF-based method.
We also have a comparison with our previously proposed methods (linear and nonlinear). Validation and comparison are done over Physionet QT database.

To detect all the peaks that an adult human heart performs in one minute, it would only take 2.5 s. So this process directly leads to low computational costs.In brief, we consider 25 parameters of ECG signal as states of an EKF and we will find peak, onset and offset of all characteristic waves (QRS complex, p and t waves) of ECG signal. For validation of our method, we will use QT database (QTDB).

Flow Chart:

PQRS Waveform: Figure 1.2



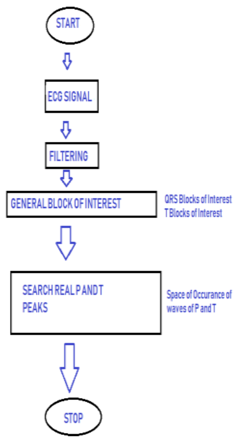


Figure 1.3

The proposal to find the onset and offset of waves from the estimated path is as follows:
• P on: the point in which the path transits from levels 1 to 2
• P off: the point in which the path transits from levels 2 to 3
• QRS on: the point in which the path transits from levels 3 to 4
• QRS off: the point in which the path transits from levels 4 to 5
• Ton: the point in which the path transits from levels 5 to 6
• Toff: the point in which the path transits from levels 6 to 7 Since the peaks can be positive or negative, peak position of waves (P peak, R peak, T peak) are defined as the maximum of absolute value of signal between onset and offset.

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ECG Based Heart Beat:

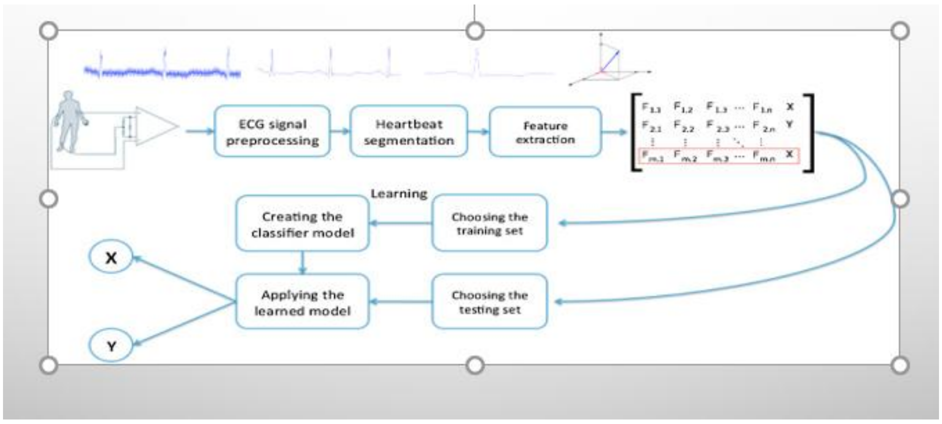
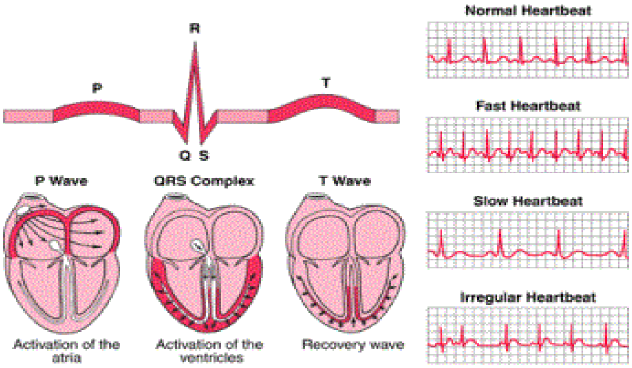


Figure 1.4

ECG Reading the waves:



- **Figure 1.5**

- An electrocardiogram (ECG) represents the electrical current moving through the heart during a heartbeat. The current's movement is divided into parts, and each part is given an alphabetic designation in the ECG.

- Each heartbeat begins with an impulse from the heart's pacemaker (sinus or sinoatrial node).
- This impulse activates the upper chambers of the heart (atria). The p wave represents activation of the atria.
- Next, the electrical current flows down to the lower chambers of the heart (ventricles). the QRS complex represents activation of the ventricles.
- The electrical current then spreads back over the ventricles in the opposite direction. This activity is called the recovery wave, which is represented by the t wave.
- Many kinds of abnormalities can often be seen on an ECG. They include
  - a previous heart attack (myocardial infarction),
  - an abnormal heart rhythm (arrhythmia),
  - an inadequate supply of blood and oxygen to the heart (ischemia), and
  - Excessive thickening (hypertrophy) of the heart's muscular walls.
- Certain abnormalities seen on an ecg can also suggest bulges (aneurysms) that develop in weak areas of the heart's walls. aneurysms may result from a heart attack.

- If the rhythm is abnormal (too fast, too slow, or irregular), the ECG may also indicate where in the heart the abnormal rhythm starts. Such information helps doctors begin to determine the cause and the most appropriate treatment.

V. EXPERIMENTAL RESULTS

Data and evaluation metrics:

To evaluate the performance of the proposed method in extracting ECG fiducial points, we need ECG recordings annotated by physicians.
Thus, we use records of Arrhythmia, Normal Sinus Rhythm, ST Change and Supraventricular databases which are annotated in the Physionet QT database (32 records). The records are sampled at 250 Hz (4 ms between 2 successive samples) and each of them has 30–50 annotated beats.
Totally we use 975 annotated beats for evaluation of the performance of the methods. We use 2-fold cross validation for each record and the initial parameters of SKF model are found from train data.
For quantitative evaluation of a FP extraction method, we calculate the estimation error defined as time differences between estimated points by proposed method and cardiologist annotations (considered as ground truth).
Quantitative results are reported using common metrics: mean (m), standard deviation (sd) and root mean square error (RMSE), defined as follows:

$$RMSE = \sqrt{MSE} = \sqrt{1/N \sum_{i=1}^{N} (e_i)^2} = \sqrt{(m^2 + sd^2)}$$

N is the length of error vector and where ei = yˆi − yi is denoted as the i^{th} element of the estimation error vector yi and yˆi are the ith cardiologist annotation and estimated point, respectively. m, sd and RMSE are given in ms. Since RMSE considers mean and standard deviation of error, it is a more relevant parameter for comparing methods.
Simulink:

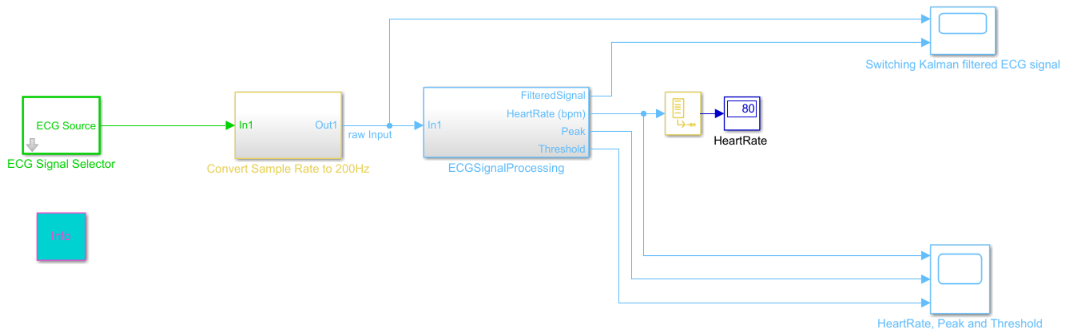


Figure 1.6

Enter the value of BPM (Beat per minute) 72
Enter the value of Duration in second 2
Enter the value of peak of the wave 1
Heart rate, peak and threshold waveforms:

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PQRS Waveform with 72 bpm:

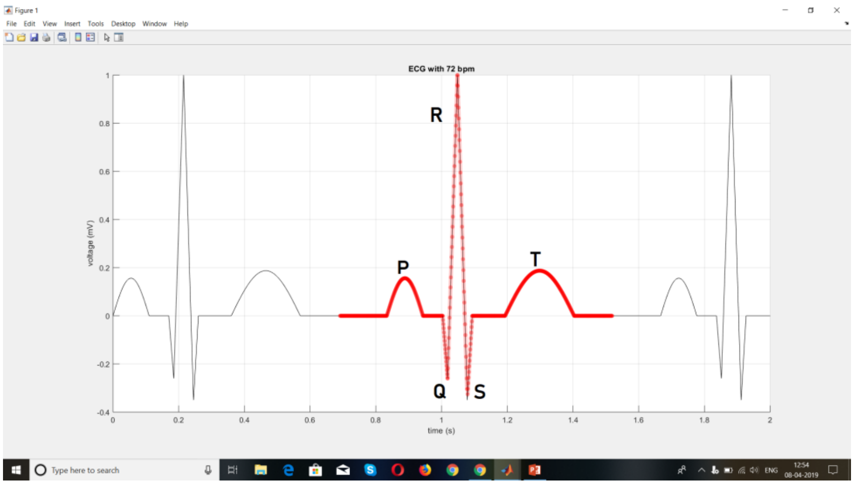

Figure 1.7

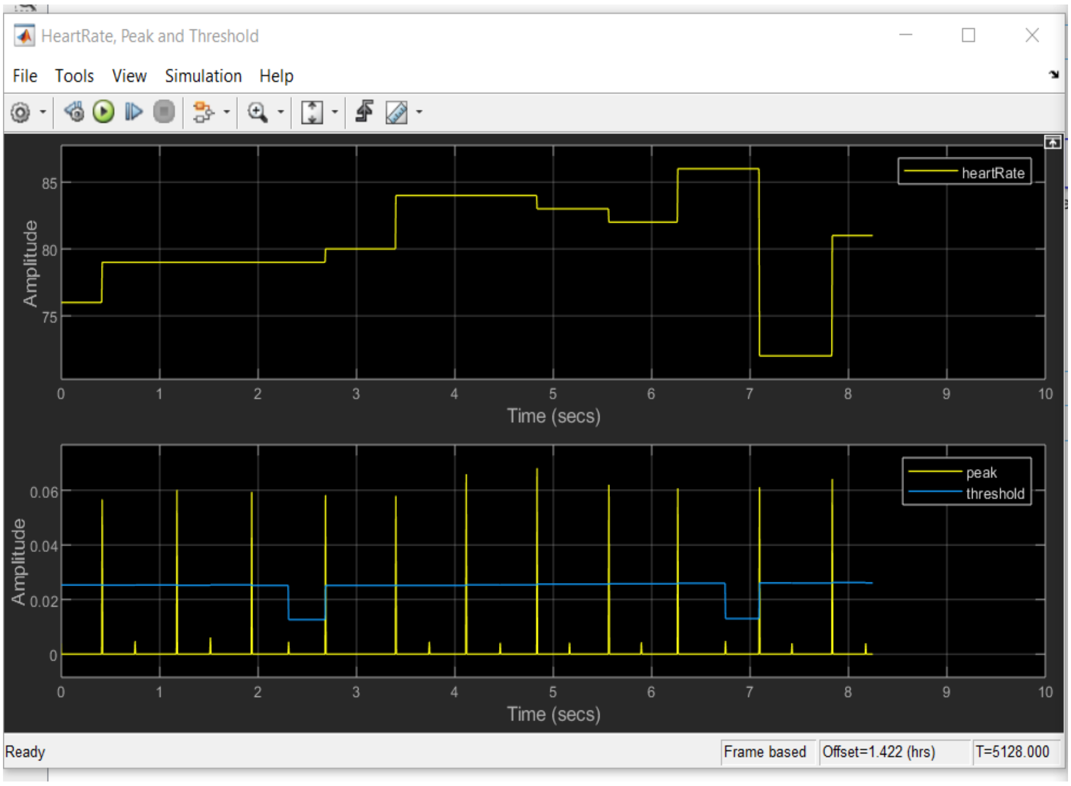

Figure 1.8

This Waveform displays the values of Heart rate, Peak and Threshold values.

Switching Kalman Filtered ECG Signal:

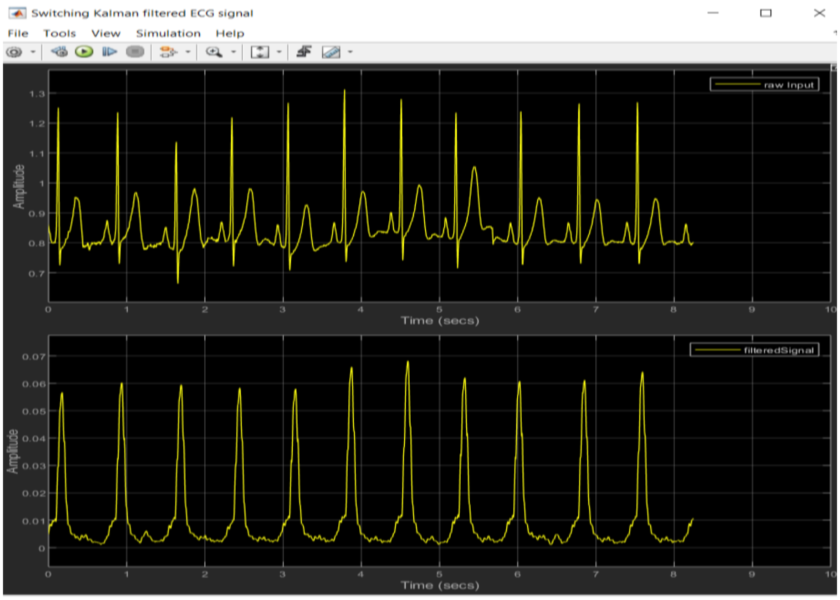

Figure 1.9

Here the both generated, Raw Signal and the Kalman Filtered signal is displayed in the above picture.

VI.CONCLUSION AND FUTURE WORK

For performance evaluation, the Physionet QT database is used and In this method, ECG waveforms (P-wave, QRS complex and T-wave) are modelled and We denote a mode as a specific observation equation and switch changes between 7 modes and corresponds to different segments of an ECG beat. At each time instant, the probability of each mode is calculated and compared among two consecutive modes and a path is estimated, which shows the relation of each part of the ECG signal to the mode with the maximum probability. ECG FPs are found from the estimated path.
The work done proves the ability of Kalman Filtering based analysis of ECG signal for fast detection of cardiac abnormalities. Moreover the potential of ECG in cardiac analysis is also represented. Depending on this status, the future research direction in this field can be indicated as below:

ECG pre-processing and feature extraction: In almost all reported works time plane features and amplitude information are used for further application. A further study can be carried out to consider the variation in instantaneous frequency or correlation coefficient etc. as the parameter for classification and other related applications. Moreover, the outcome of fusing these parameters with existing sets can be examined. ECG classification**:** Apart from the arrhythmic beats used in this work, several other kinds of arrhythmia are possible to occur. Classification systems for them can also be developed. Moreover, other cardiac abnormalities can be considered along with the present ones to generate a robust ECG classifier. For example, effort can be given to identify the location of Myocardial Infarction.

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