ECG fiducial point extraction using switching Kalman filter

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ABSTRACT

In this paper, we propose a novel method for extracting fiducial points (FPs) of the beats in electro-cardiogram (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 modeled with Gaussian functions and ECG baselines are modeled 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 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. 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. 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.

1. 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). Up to now, different methods have been used for detecting the QRS complex. See [1] for a review. These methods are based on mathematical functions, filtering approaches (digital filters [2], adaptive filters [3]), classification methods (neural network approaches [4], support vector machine (SVM) [5], fuzzy C-means algorithm [6]), wavelet transform [7] and empirical mode decomposition (EMD) [8]. Low pass differentiation (LPD) [9], hidden Markov models (HMM) [10–14], partially collapsed Gibbs sampler (PCGS) [15], wavelet transform [16–18], correlation analysis [19,20] and extended Kalman filter (EKF) [21–24] are also used for ECG FP extraction.

FP extraction has been used as a preprocessing step in several applications such as detection of fragmented QRS complex [25],

mobile health care applications [26], "Selvester QRS scoring" system [27], ischemia detection [28], ECG-based subject identification system [29] and biometric recognition based on fusion of ECG and EEG signals [30,31].

Switching state space models are defined as the combination of HMMs and state space models [32]. When the model is linear and additive Gaussian noise exists, the switching state space models are known as "Switching Kalman Filter" (SKF) [33,34]. In the SKF, at each time instance, the states are estimated by several Kalman filters (KFs). Furthermore, a hidden discrete state variable called *switch* is considered whose status changes over the time according to a Markov model. The switch indicates the KF which estimates the states better than others.

SKF is used for several applications such as figure tracking [35], acoustic segmentation [36], contour tracking in clutter [37], modeling and detecting motor cortical activity [38], prediction and tracking an adaptive meteorological sensing network [39], tracking and event detection at traffic intersections [40], ECG ventricular beat classification [41] and finally for apnea bradycardia detection from ECG signals [42].

Although the methods based on dynamic models (EKF) [24] and sequential methods (HMM) [14] have been used for ECG FP extrac-

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tion, the methods based on SKF (which is combination of KF and HMM methods) have not been used for this application yet. The goal of this paper is showing the ability of SKF-based methods for ECG FP extraction.

In [21–24], methods based on EKF have been proposed. The main limitation of such methods is their sensitivity to the initial location of the Gaussian functions as well as initial parameters of EKF, that must be defined by the user. Conversely, one of the advantages of the proposed SKF model is that it is not sensitive to the initial location of Gaussian functions and initial parameters of SKF.

According to McSharry's model [43], ECG waves (P-wave, QRS complex and T-wave) are modeled with Gaussian functions. Baselines and segments between ECG waves are modeled 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 [17], PCGS [15] and EKF-based method (EKF17) [22]. We also have a comparison with our previously proposed methods (linear and nonlinear EKF25 [23,24]). Validation and comparison are done over Physionet QT database [44,45].

The paper is organized as follows: ECG dynamical model and details of SKF approach for ECG FP extraction are described in Section 2. Section 3 presents the experimental results, and finally Section 4 concludes the paper.

2. Methods

In this section, we first present the ECG model we used and then we fully describe the proposed SKF method.

2.1. ECG Kalman filtering framework

McSharry et al. [43] have proposed a synthetic ECG generator which is based on a nonlinear dynamic model. Sameni et al. [46] transformed it into polar coordinates from Cartesian coordinates and proposed an EKF-based framework which has two state variables and two corresponding observations. The discrete state-equations of this model are as follows:

$$\begin{cases} \varphi_{k+1} = (\varphi_k + \omega_k \delta) \quad mod(2\pi) \\ z_{k+1} = -\sum_i \delta \dfrac{\alpha_{ik}\omega_k}{b_{ik}^2} \Delta\theta_{ik} \exp\left(-\dfrac{\Delta\theta_{ik}^2}{2b_{ik}^2}\right) + z_k + \eta_k \end{cases} \quad (1)$$

where k denotes the discrete time, φ_k is the phase of ECG and ω_k is the beat-to-beat angular frequency of the RR interval. In this model, z_k is a state variable which is the sum of 5 Gaussian functions ($i \in \{P, Q, R, S, T\}$) and represents estimated amplitude of ECG. Each Gaussian function is defined with three parameters: α_{ik}, b_{ik} and θ_{ik}, which correspond to the amplitude, width and location of the Gaussian functions and $\Delta\theta_{ik} = (\varphi_k - \theta_{ik}) mod(2\pi)$; δ is the sampling period and η_k models the inaccuracies of the dynamic model.

2.2. Proposed dynamic model

For an ECG beat, we can define seven segments: B_1, P, PQ (B_2), QRS, ST (B_3), T and B_4 which are shown in Fig. 1. In the proposed model, we consider separate states for P-wave, QRS complex and T-wave which are modeled with Gaussian functions. We also assign a state defined with a first order AR model to each baseline (B_1, B_2, B_3 and B_4). Similar to previous EKF-based models, we also consider the phase of ECG as a state. Hence, a model with 8 states
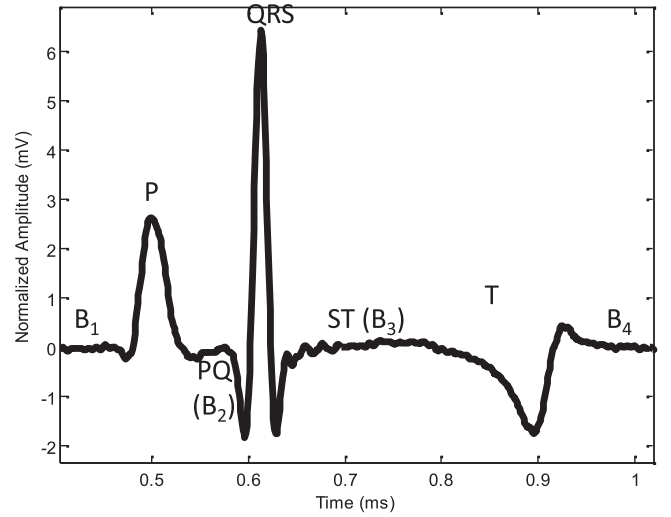

Fig. 1. Segments of a single ECG beat.

is generated. In fact, although segments B_1 and B_4 are almost similar, since we find the fiducial points for each beat separately, we consider two separate segments B_1 and B_4. Discrete state and observation equations of this model are defined in (2) and (3), respectively. We use "C" to denote the QRS complex. In (2), for simplicity we consider that the coefficients of AR models are equal to one ($a_{B_1} = a_{B_2} = a_{B_3} = a_{B_4} = 1$) but in general, other values smaller and very close to 1 can be examined.

$$\begin{cases} \varphi_{k+1} = (\varphi_k + \omega_k\delta) \quad mod(2\pi) \\ B_{1,k+1} = a_{B_1}B_{1,k} + \eta_{B_{1,k}} \\ P_{k+1} = -\dfrac{\delta\alpha_{P,k}\omega_k}{b_{P,k}^2} \Delta\theta_{P,k} \exp\left(-\dfrac{\Delta\theta_{P,k}^2}{2b_{P,k}^2}\right) + P_k + \eta_{P_k} \\ B_{2,k+1} = a_{B_2}B_{2,k} + \eta_{B_{2,k}} \\ C_{k+1} = -\displaystyle\sum_{i\in\{Q,R,S\}} \delta\dfrac{\alpha_{ik}\omega_k}{b_{ik}^2} \Delta\theta_{ik} \exp\left(-\dfrac{\Delta\theta_{ik}^2}{2b_{ik}^2}\right) + C_k + \eta_{C_k} \\ B_{3,k+1} = a_{B_3}B_{3,k} + \eta_{B_{3,k}} \\ T_{k+1} = -\dfrac{\delta\alpha_{T,k}\omega_k}{b_{T,k}^2} \Delta\theta_{T,k} \exp\left(-\dfrac{\Delta\theta_{T,k}^2}{2b_{T,k}^2}\right) + T_k + \eta_{T_k} \\ B_{4,k+1} = a_{B_4}B_{4,k} + \eta_{B_{4,k}} \end{cases} \quad (2)$$

$$\begin{cases} \Phi_k = \varphi_k + v_{1k} \\ z_k = B_{1,k} + P_k + B_{2,k} + C_k + B_{3,k} + T_k + B_{4,k} + v_{2k} \end{cases} \quad (3)$$

In (2), the first state is the phase of the ECG. States 3, 5 and 7 are distinct ECG waveforms. The ECG baselines are considered as the 2nd, 4th, 6th and 8th state variables. The system state and process noise vectors are defined as:

$$\begin{aligned} \underline{x}_k &= [\varphi_k, B_{1,k}, P_k, B_{2,k}, C_k, B_{3,k}, T_k, B_{4,k}]^T \\ \underline{w}_k &= [\alpha_{i_k}, b_{i_k}, \theta_{i_k}, \omega_k, \eta_{j_k}]^T \\ i &\in \{P, Q, R, S, T\}, \quad j \in \{B_1, P, B_2, C, B_3, T, B_4\}. \end{aligned} \quad (4)$$

In (3), the first observation is a linearly approximated phase of ECG beat, and z_k is the recorded ECG which can be considered as the sum of $B_{1,k}$, P_k, $B_{2,k}$, C_k, $B_{3,k}$, T_k and $B_{4,k}$ states in the model. Observation and measurement noise vectors are defined, respectively, as: $\underline{y}_k = [\Phi_k, z_k]^T$ and $\underline{v}_k = [v_{1k}, v_{2k}]^T$.