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Application of Dynamic Time Warping on Kalman Filtering Framework for Abnormal ECG Filtering

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Abstract.

Existing nonlinear Bayesian filtering frameworks serve as an effective tool for the model-based filtering of noisy ECG recordings. However, since these methods are based on linear phase assumption, for some heart defects where abnormal waves only appear in certain cycles of the ECG, they are unable to simultaneously filter the normal and abnormal ECG segments. In this paper, a new method based on Dynamic Time Warping (DTW), which benefits information of all channels for nonlinear phase state calculation is presented. Results on real and synthetic data show that the new method can be successfully applied for filtering normal and abnormal ECG segments simultaneously.
Keywords: ECG denoising, Kalman filtering, nonlinear Bayesian filtering, linear phase, dynamic time warping.

1 Introduction

The extraction of high-resolution pathological cardiac signals from a multi-channel noisy electrocardiogram (ECG) remains an important problem for the biomedical engineering community. Despite of the rich literature in the field of ECG processing, there are still many clinical applications that lack reliable signal processing tools to extract pathological ECG beats contaminated with background noise. In [1], Bayesian filters such as the Extended Kalman Filter (EKF) and Extended Kalman Smoother (EKS) have been proposed for ECG denoising. The state-space model used for these filters is inspired from [2], which suggests the use of Gaussian mixtures to model realistic synthetic ECGs. The basic idea is to approximate the PQRST waves by the sum of 5 weighted Gaussian shape functions. In [1], the synthetic ECG generator proposed in [2], transferred into polar coordinates from Cartesian coordinates. This modification and some other modifications make it simpler and more straightforward in interpretation [1]. The modified model in its discrete form, with the assumption of a small sampling period of δ is:

$$\begin{cases} \theta_{k+1} = (\theta_k + \omega\delta)\mathrm{mod}(2\pi) \\ z_{k+1} = -\sum\limits_{i\in\{P,Q,R,S,T\}} \delta\dfrac{\alpha_i\omega}{b_i^2}\Delta\theta_{i,k}\exp(-\dfrac{\Delta\theta_{i,k}^2}{2b_i^2}) + z_k + \eta \end{cases} \tag{1}$$

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where θ and z are the state variables in polar coordinates and k denotes the discrete time index. The α_i and b_i correspond to the peak amplitude in millivolts and center parameters of the Gaussian functions used for modeling each of the ECG components. We define $\Delta\theta_{i,k} = (\theta_k - \psi_i)\mathrm{mod}(2\pi)$, in which, ψ_i corresponds to the center of the ith Gaussian function. ω is the angular velocity of the trajectory as it moves around the limit cycle in the $x - y$ plane [1], and η_z is a random additive noise. The system state and process vectors are defined as:

$$\begin{cases} \boldsymbol{x_k} = & [\theta_k, z_k]^T \\ \boldsymbol{w_k} = & [\alpha_P, ..., \alpha_T, b_P, ..., b_T, \psi_P, ..., \psi_T, \omega, \eta_z]^T \end{cases} \tag{2}$$

with $Q_k = E\left\{w_k w_k^T\right\}$ as process noise covariance matrix. The noisy ECG is assumed as observation of the Kalman filter. In addition, by detecting the R-peaks of ECG signal, an additional observation is achieved. In this model it is assumed that the phase values are 'strictly' linear between 0 and 2π in the intermediate samples of two R-peaks. The additional phase observation ϕ and the noisy ECG measurements, s, are related to the state vector as follows:

$$\begin{bmatrix} \phi_k \\ s_k \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \theta_k \\ z_k \end{bmatrix} + \begin{bmatrix} u_k \\ v_k \end{bmatrix} \tag{3}$$

where u_k and v_k are the corresponding observation noises, and the observation noise covariance matrix is given as $R_k = E\left\{[u_k, v_k]^T[u_k, v_k]\right\}$.

In this model a 'strictly' linear phase has been assumed in the state equation of the model. However, it is not always a valid assumption. Application of this model to many of the common ECG abnormalities is rather straightforward, since the model parameters may be simply recalculated and used in the filter model. However, for some heart defects such as the Premature Ventricular Contraction (PVC), where the abnormal wave only appears in certain cycles of the ECG, some modifications in the state equations are necessary to simultaneously filter the normal and abnormal segments. In order to do so, in this paper we intend to modify the phase equation using information of different channels. The rest of the paper is organized as follows: In section 2 equations and theory supporting our proposed method are described. In section 3 results of the proposed method applied on different data and discussion about the results are presented. Finally, our conclusion is stated in section 4.

2 Method

The first modification of the phase state can be adding a random additive noise η_θ to the phase state equation (in this paper we refer to it as 'flexible' linear). Therefore, the phase model would no longer be 'strictly' linear and slight fluctuations around linear phase are allowed. Hence, state equations are:

$$\begin{cases} \theta_{k+1} = (\theta_k + \omega\delta)\mathrm{mod}(2\pi) + \eta_\theta \\ z_{k+1} = -\sum\limits_{i \in \{P,Q,R,S,T\}} \delta \dfrac{\alpha_i \omega}{b_i^2} \Delta\theta_{i,k} \exp(-\dfrac{\Delta\theta_{i,k}^2}{2b_i^2}) + z_k + \eta_z \end{cases} \tag{4}$$

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Although this modification may improve performance of the filter, it still assumes that all beats are almost similar and no beat differs much from the others. Moreover, it only uses information of the current channel to make ECG phase. The second modification, which benefits information of all channels is using Dynamical Time Warping (DTW) [3] for phase state calculation. DTW is a method for measuring similarity between two sequences or matrices, which may vary in time or speed. This method is widely used in speech recognition to recognize a unique word when it is pronounced fast or slowly. In this method an optimal match between two given sequences or matrices with certain restrictions is found [3]. For our problem of interest, a multichannel ECG beat reference $\underline{E}(l) \in \mathbb{R}^M$ is firstly selected and a linear phase is assigned to it, then current multichannel ECG beat $\underline{s}(k) \in \mathbb{R}^M$ and the reference ECG beat are nonlinearly warped to optimize their similarity of their nonlinear variations. Finally, as it is illustrated in Figure 1, the phase observation of the current ECG beat is achieved by aligning linear phase of the reference ECG beat, according to optimal match of the reference and current ECG beats. Computational cost of the method is low and DTW algorithm can be implemented easily. This model of phase state can also be further modified by adding a random additive noise to make it more flexible (in this paper we refer to it as 'flexible' DTW).
Estimation of phase state based on DTW methods is especially valuable when in some beats one or more ECG waves (P, Q, R, S and T) appear sooner or later than normal ones. In those cases, since DTW methods search for optimal match between reference and current beats, premature or delayed occurrence of the ECG waves are compensated in the phase state. Therefore, the EKF filter can better follow premature or delayed ECG waves. Another parameter that may also affect filtering performance is expansion or contraction of each ECG wave in some dissimilar beats. Here again, it is possible to compensate the deviation from linear phase using DTW methods.

3 Results

Figure 2 shows results of proposed methods on a part of the record 116 of the MIT-BIH Arrhythmia Database [4], [5]. This database consists of two-channel ambulatory ECG recordings, in which some beats significantly differ from other beats. Mean ECG has been adopted as reference ECG beat of DTW methods. Mean ECG and other parameters of the method have been calculated according to [1]. As it is seen in Figure 2, the best result is provided by 'flexible' DTW. Although 'flexible-linear' phase provides better results in comparison to 'strict-linear' phase, it is still unable to follow a beat, which is dissimilar to other beats. In order to have better comparison, residual results which are subtraction of the original signal from filtered signals are plotted on the right column of Figure 2. As it is seen, some ECG parts are deteriorated by 'strict' and 'flexible-linear' phases, while, DTW methods are able to follow the signal in these scenarios.

In order to study the performance of the methods in different situations,

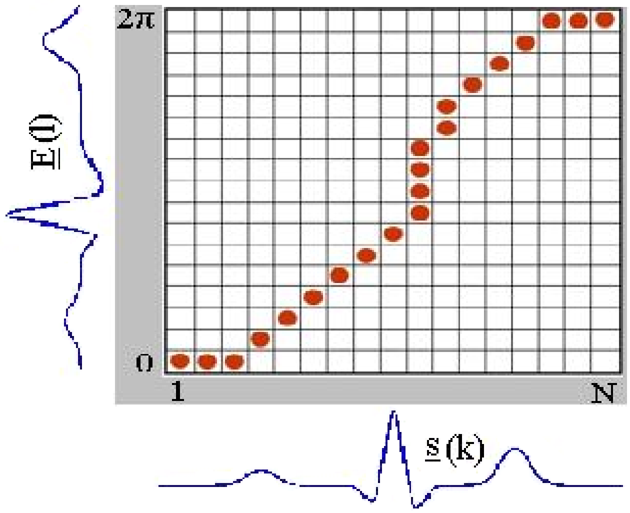

Figure 1: A typical example of DTW method for finding optimal match between reference ECG beat and current ECG beat.

synthetic ECG data have been generated to model these dissimilarities. In (1) ψ_i denotes location of Gaussian functions, so premature and delayed occurrence of the ECG waves can be modeled with varying ψ_i around their values. Expansion and contraction of ECG waves can also be modeled with varying b_i. Figure 3 shows results of different methods for different range of ψ_i variations, where 100% corresponds to 2π. The synthetic data consist of eight channels and input signal to noise ratio (SNR) is equal to 15 dB. For each value of ψ_i variations, fifty trials have been carried out to have statistically reliable results. As it is seen, when ψ_i variations are very low and all beats are very similar, linear methods provide better results, since noise cannot affect them. However, DTW methods are affected by the noise, nevertheless, they did not deteriorate input signals, because their output SNRs are still more than 15 dB. As ψ_i variations become larger, the difference between performance of linear and DTW methods become lower. For variation equal to 0.5%, same performance is achieved and from this point, DTW methods dramatically outperform linear ones.

Similar trials have been carried out for variations of b_i, width of Gaussian functions. As it can be seen in Figure 4, here gain, for low values of b_i variations, linear methods outperform DTW methods. However, as b_i variations become larger, DTW methods significantly outperform linear methods.

Figures 3 and 4 show that adding noise to phase state equation can lead to improve results of DTW methods for large signal distortions. Practically, for very slight variations of ψ_i or b_i, 'flexible' linear method provides the best results, while, for larger values of ψ_i or b_i variations, 'flexible' DTW method outperforms other methods.

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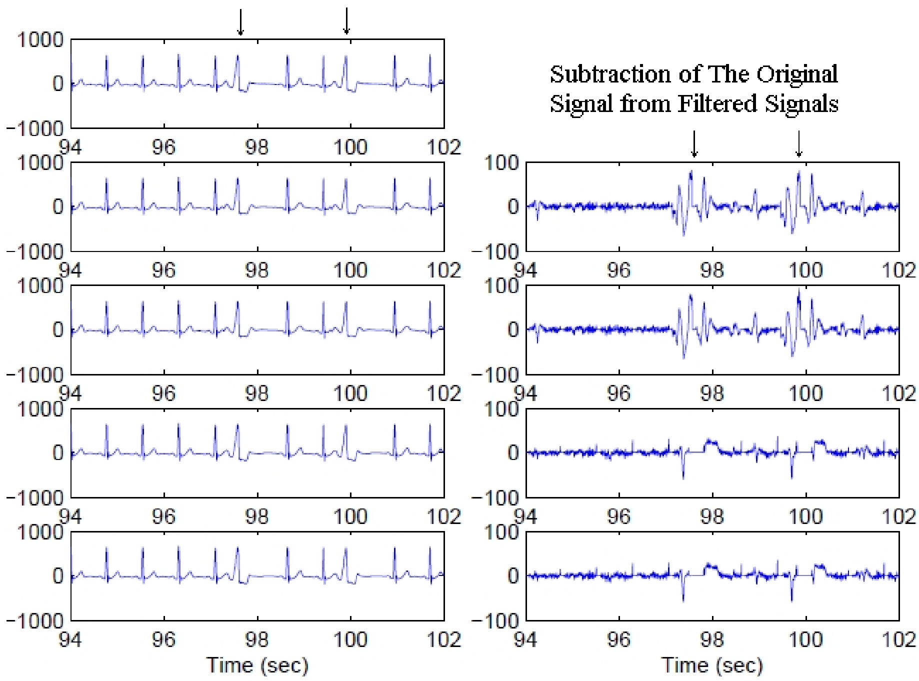

Figure 2: Illustration of proposed method on real data. Left, Up to Down: Original record 116 of the MIT-BIH Arrhythmia Database, 'strict' linear, 'flexible' linear, DTW, 'flexible' DTW outputs. Right, Up to Down: Subtraction of the original ECG from 'strict' linear, 'flexible' linear, DTW, 'flexible' DTW outputs.

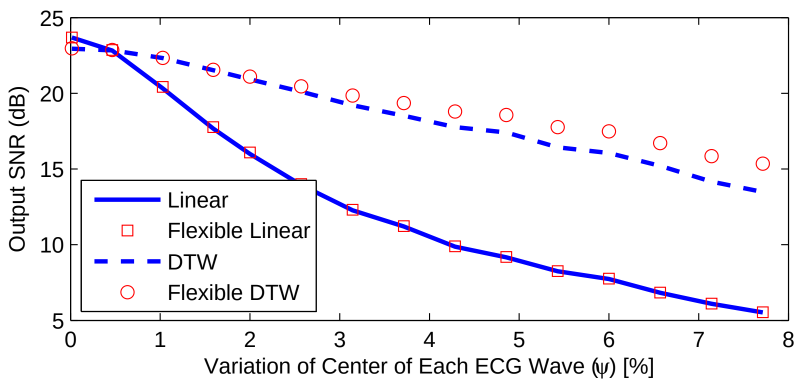

Figure 3: Mean value of EKF output SNR for different range of ψ variations

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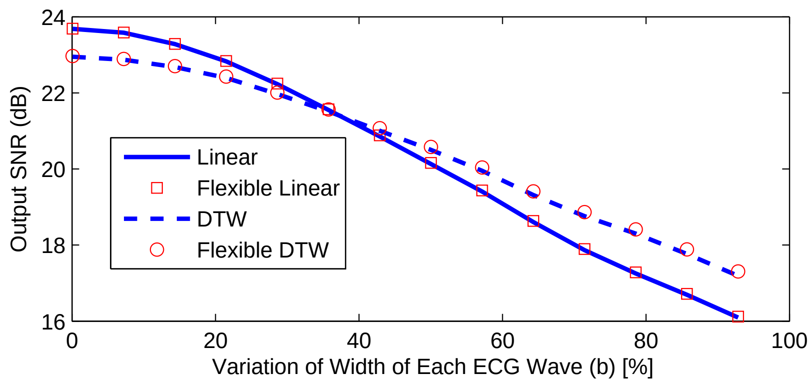

Figure 4: Mean value of EKF output SNR for different range of b variations

4 Conclusion

Different versions of nonlinear Bayesian filtering frameworks have been presented to filter noisy ECG recordings. However, due to the linear phase assumption, they have not been able to filter normal and abnormal ECG segments simultaneously. In this work a new method based on DTW for phase state calculation has been presented. Results on real and synthetic data show that DTW methods provide more reliable phase state when dissimilarity between current beat and other beats is large, because this dissimilarity is compensated in phase state. This method may therefore serve as an effective tool for simultaneously filtering normal and abnormal ECG segments. Moreover, optimal match between reference and current beats, provided by DTW method, may be used in future works as a feature to classify normal and abnormal beats.

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