In Search of an Optimal FIR filter for ECG Delineation

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Abstract

Representative beats (RBs) computed by combining ECG waveforms from multiple cardiac cycles with similar characteristics, are robust to noise and are often used in diagnostic applications for reliable ECG delineation. However, when delineation of individual beats (IBs) is required, the same algorithms need either retraining or denoising of the raw input ECG signals. This study aims to find an optimal finite impulse response (FIR) filter for 12-lead IBs that can reduce the errors of a specific ECG delineation algorithm trained for RBs. The FIR filter was implemented as 1D convolutional layer (same for all leads), no bias term and linear activation function. It was trained by backpropagation, minimizing the increased loss in the original ECG delineation output (P wave, QRS complex and QT interval) caused by larger noises in the training raw data of 12-lead IBs. The loss function included both a binary cross-entropy and an L2 regularization term. Using the PTB-XL and CinC Challenge 2011 databases, the FIR filter was shown to reduce the noise impact on the delineator's output in typical resting or ambulatory ECG monitoring environments.

1. Introduction

Electrocardiogram (ECG) delineation, also known as ECG signal segmentation, refers to the process of identifying and localizing main components of the ECG waveform, including the P-wave, QRS-complex, and T-wave, whose reliable measurement is critical to ECG interpretation [1]. Common noise sources, including baseline-wander, power-line interference, muscle and electrode-motion artifacts can distort the ECG waveform, resulting in erroneously detected, missed, early or late detected components. Noise effects are usually reduced by combining waveforms from multiple cardiac cycles with similar characteristics [2]. The resulting representative beat (RB) is assumed to be a robust representation of cardiac activity, and is therefore often used by algorithms for ECG delineation [3–5]. In contrast, delineation of individual beats (IBs) in noisy raw ECG signals is a more challenging task. Traditional approaches rely on wavelet transforms to decompose ECG signals into frequency bands, then reconstruct only those bands that represent P, QRS and T waves [6–9]. Other studies employ a filter design to enhance specific ECG slopes, and use machine learning techniques to detect representative samples of P, QRS and T waves [10, 11]. Lately, deep neural networks (DNN) with various convolutional encoder-decoder architectures, including residual and recurrent connections, have been proven effective for ECG signal segmentation using raw data of minimal input leads (one or two) [12–14]. Our recent study on 12-lead RBs showed that various DNN architectures [3] perform similar in identifying global PQRST fiducial points common to all ECG leads. Since these models were trained on RBs [3], it is assumed to have reduced noise immunity to noises present in IBs.

This study aims to find an optimal finite impulse response (FIR) filter for 12-lead IBs that can reduce the errors of a specific ECG delineation algorithm trained for RBs. A database-specific FIR filter has been shown to reduce noise impact on the delineator's output in typical resting or ambulatory ECG monitoring environments.

2. ECG databases

Two standard 12-lead ECG databases were used: (i) The PTB-XL database [15], including 21,799 resting 10-s ECG records; (ii) The PhysioNet/Computing in Cardiology Challenge 2011 database (sets A, B) [16] comprising 1,500 10-s records collected by minimally trained volunteers, often affected by noisy leads.

A reference algorithm for ECG delineation (ETM-2.6.5, Schiller AG, Baar, Switzerland [17, 18]) extracted 12-lead IBs with duration of 1.2 s (600 samples at 500 Hz) and generated RBs for each detected IB morphology in the record. ETM-based delineation of RBs provided global fiducial points of the 12-lead PQRST pattern (P-onset, P-offset, QRS-onset, QRS-offset, T-offset).

For this study, ETM provided 223,042 IBs and 20,955 RBs from the PTB-XL database, and 13,926 IBs and 1391 RBs from the CinC Challenge 2011 database.

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3. Methods

The methodological design is illustrated in Figure 1. First, we use a specific ECG delineation DNN model, named convolutional encoder-decoder CED-Net in [3], which was trained to segment a 12-lead RB into three outputs representative of the probabilities of its P wave, QRS complex and QT interval. For this purpose, the DNN training objective minimized a binary cross-entropy (BCE) loss between true labels $\mathrm{x_i} \in \{0,1\}$ (provided by ETM) and predicted labels $0 \leq \hat{\mathrm{x}}_\mathrm{i} \leq 1$, using a number of N=512 samples belonging to the RB:

$$BCE = -\frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}}(\mathrm{x_i}.\log(\hat{\mathrm{x}}_\mathrm{i}) + (1-\mathrm{x_i}).\log(1-\hat{\mathrm{x}}_\mathrm{i})).$$

Second, the pretrained CED-Net model is applied for delineating the raw ECG data in IBs, noisier than RBs. To reduce the noise, an FIR filter is implemented as one-dimensional convolutional layer with one filter (same for all leads), no bias term, and a linear activation function:

$$\mathrm{y[t]} = \sum_{\mathrm{n=-44}}^{44}\mathrm{h[n].x[t-n]},$$

where x[t], y[t] are input and output samples at time t; h[n] represents the 89 coefficients of a non-causal FIR filter with valid padding, which aligned the IB length (600 samples) to the original CED-Net input (512 samples).

The goal is to train the FIR filter such that it removes as much noise as possible while keeping the ECG signal consistent with the original segmentation objective. Therefore, the original ECG delineation CED-Net model is preserved unchanged (frozen) and its main training objective remains the same. Here, only the convolutional layer is trained through backpropagation, minimizing the increased loss in the CED-Net delineation output caused by larger noises in the training raw data of 12-lead IBs. However, since CED-Net had already some inherent resilience to noise, the incentive for the convolutional layer to remove such noise turned out to be relatively low.

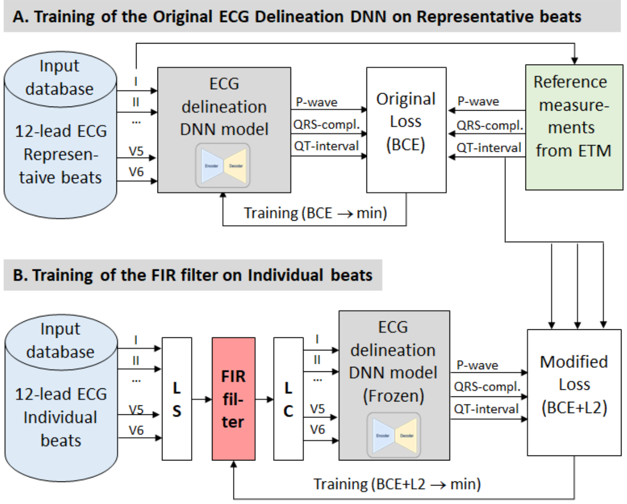

Figure 1. Training concept of the original ECG delineation and FIR filter. LS: Lead splitting, LC: Lead concatenation; BCE: Binary cross entropy, L2: L2 norm.

In order to introduce a specific incentive to remove as much noise as possible, we used Parseval's theorem. For an FIR filter with impulse response $h[n]$ and frequency response $H(\omega)$, Parseval's theorem states [19]:

$$\sum_{n=-\infty}^{\infty}|h[n]|^2 = \frac{1}{2\pi}\int_{-\pi}^{\pi}|H(\omega)|^2 d\omega.$$

We made no assumptions about the frequency content of the noise but we were interested in a filter that removes as many frequency components as possible. One way to formulate this is to require $\int_{-\pi}^{\pi}|H(\omega)|^2 d\omega$ to be minimal. According to the Parseval's theorem, this is equivalent to minimizing the FIR filter's impulse response's L2 norm, which was added as a term to the modified loss:

$$\text{Modified Loss} = \text{BCE} + \lambda\sum_{n=-\infty}^{\infty} h[n]^2,$$

where the absolute value of the L2 norm was omitted because the convolutional layer works only with real numbers. By increasing the weight λ of L2 regularization term, the resulting FIR filter becomes more aggressive at the price of a reduced delineation performance.

4. Results

Setting λ to provide L2 norm with about 30% weight to the modified loss, we trained two FIR filters with IBs from the PTB-XL and CinC Challenge 2011 databases. The filters effectively reduced the input noise and improved the DNN delineation output (Figure 2). Their impulse and frequency responses, the frequency content of input ECG signals, as well as the CED-Net delineation performances are studied in Figures 3,4.

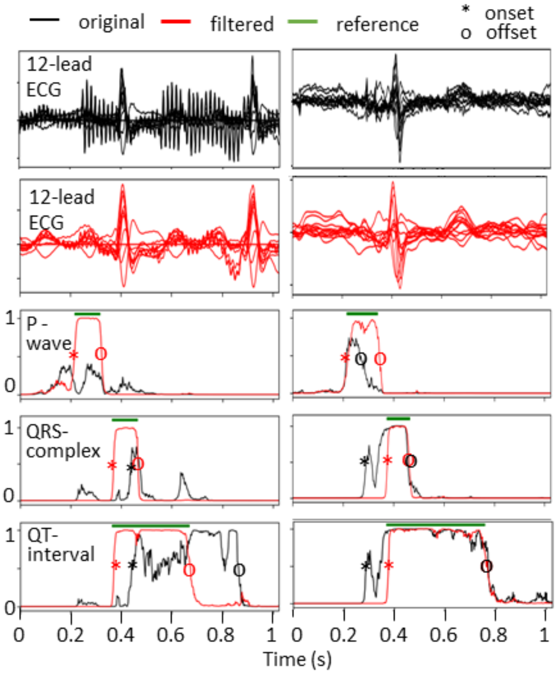

Figure 2. Two examples of 12-lead IBs with and without FIR filter application, and the CED-Net delineation output for the P-wave, QRS-complex and QT-interval.

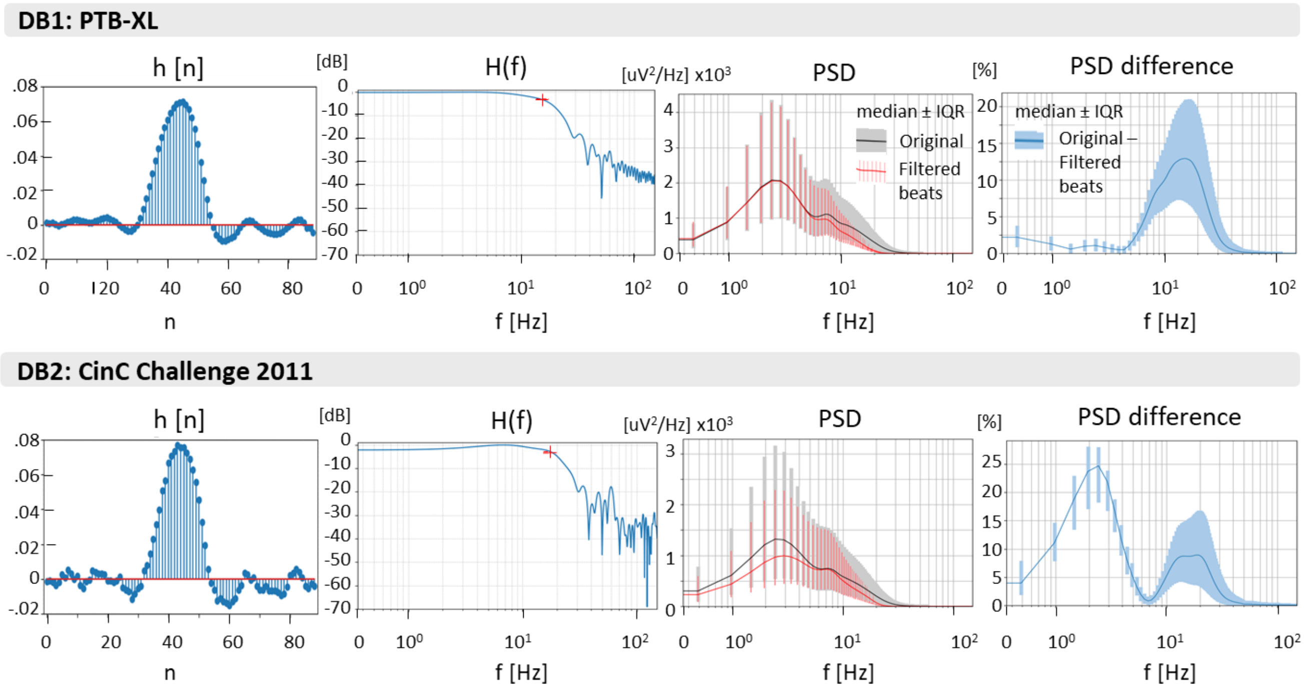

Figure 3. Characteristics of two FIR filters optimized for delineation of 12-lead individual beats in PTB-XL and CinC Challenge 2011 databases. h[n]: impulse response; H(f): frequency response with marked cut-off at -3dB (red +); PSD: Power spectral density of individual beats (original and filtered): Summary from all 12 ECG leads; PSD difference: subtraction of the PSD of filtered beats from the PSD of original beats, normalized to the maximum PSD value of original beats. PSD statistical distributions for all beats in the databases are depicted as median ± interquartile range.

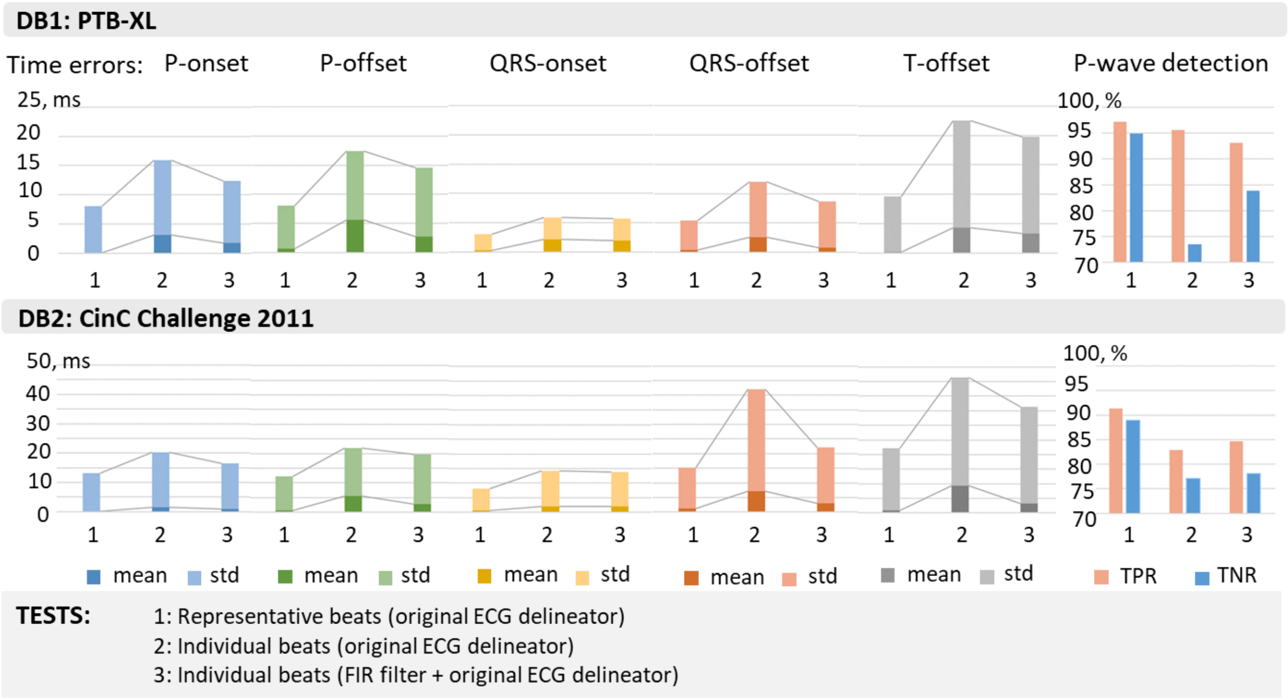

Figure 4. Performance of the original DNN model for delineation of 12-lead ECG beats, including five time errors (stacked bars for the range of abs(mean) + standard deviation) and P-wave detection (TPR: True Positive Rate, TNR: True Negative Rate) in three test conditions: (1) without filter on representative beats, (2) without filter on individual beats, (3) with an FIR filter on individual beats, optimized for PTB-XL and CinC Challenge 2011 databases.

5. Discussion and conclusions

Using IBs from PTB-XL and CinC Challenge 2011 databases, we trained two FIR filters for optimal ECG delineation in the presence of noise from resting and ambulatory ECG monitoring. Despite differences in noise content, the trained impulse and frequency responses of both filters behaved similarly (Figure 3), acting as low-pass filters with a cutoff (-3dB) at 15–17 Hz and a notch at 50 Hz. Additionally, the filter trained with the noisy CinC Challenge 2011 database showed high-pass characteristics. Spectral differences between original and filtered beats (Figure 3) reveal suppression of frequencies 10–30 Hz and removal of low-frequency components around 2.5 Hz in the noisy database, improving ECG delineation despite these frequencies are part of the diagnostic bandwidth. This effect can be seen in Figure 2, where the examples show power-line and high-frequency noise removal, some smoothing of the QRS waveforms, and enhancement of the P and T-waves. This results in more definitive delineation outputs that correspond to the reference timing of P-wave, QRS-complex, QT-interval.

The results in Figure 4 show that the original ECG delineation algorithm, trained on RBs, presented reduced performance when applied to IBs. Although PTB-XL is a resting database and IBs are expected to be less affected by noise, the time errors TE (mean±standard deviation) increased by 12.9 ms (T-offset), 9.4 ms (P-offset), 7.9 ms (P-onset), 6.6 ms (QRS-offset), 2.8 ms (QRS-onset). The P-wave detection performance also decreased by 2% (true positive rate, TPR=97.2% vs. 95.6%) and 21.4% (true negative rate, TNR=94.9% vs. 73.5%). After applying the FIR filter, TE decreased by 3.6 ms (P-onset, 1.8±10.6 ms), 3 ms (P-offset, 2.7±11.8 ms), 0.15 ms (QRS-onset, 2.0±3.8ms), 3.4 ms (QRS-offset, 0.77±7.9 ms), 2.8 ms (T-offset, 3.3±16.4 ms); P-wave TNR increased by 10.4% (83.9%) at the cost of slight TPR drop by 2.5% (93.1%).

The observations about performance trends are similar with the noisy CinC Challenge 2011 database, although TE are about twice larger; TPR, TNR for the P-wave are reduced by about 7%. In conclusion, database-specific filtering can improve delineation of individual beats.

Acknowledgments

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