Embedded QRS Detection for Noisy ECG Sensor Data Using a Matched Filter and Directed Graph Search

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Abstract

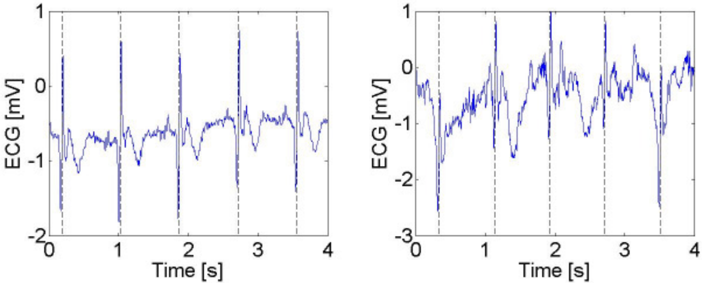
In a lot of medical as well as sports applications, the precise recognition of heart beat (HB) events in electrocardiogram (ECG) sensor signals is mandatory to facilitate subsequent diagnosis and analysis of the data. However, especially in the presence of motion, e.g. in sports or sleep monitoring, the signal-to-noise ratio of such signals can become very low. This paper discusses the accurate detection of the QRS complexes corresponding to heart beats in this noisy environment. The noise cannot be completely eliminated by traditional bandpass filtering because the signal bandwidth often has considerable overlap with the bandwidth of the artifact.
We describe a novel method using a simple Matched Filter (MF) and subsequent directed graph search to accurately detect the QRS complexes in the ECG signal. When using the MF, a clean QRS template is correlated with the noisy signal. This procedure is optimal in the case of white noise. However, false detection of QRS complexes can occur because of the extraneous peaks added by motion artifacts. To circumvent this, we additionally perform a directed graph search, eliminating these extraneous peaks. The method can easily be implemented on the restricted hardware environment of customary embedded microprocessors. We demonstrate the effectiveness of our method by application to real ECG sensor data.

1 Introduction

Accurate QRS complex [1] detection in a mobile environment offers new opportunities for analysis and monitoring applications, e.g. in sports or homecare. We will show a reliable method for this detection that is implementable on mobile hardware, i.e. does not pose too many computational requirements.

2 Materials and Methods

Figure 1 shows two ECG example signals. While the heart beats can clearly be identified in Fig. 1(a), the presence of motion artifacts as exemplified in Fig. 1(b) severely complicates the recognition. Still, humans can identify the QRS complexes corresponding to heart beats. The most straightforward approach first selects likely events in the signal, then removes those



(a) Typical, undisturbed ECG signal.

(b) ECG signal in the presence of motion artifacts.

Fig. 1: ECG example signals. The dashed lines represent beat locations as identified by medical expert annotators [2].

event time points that can not represent HB because they would signify unnatural beat times.

Our proposed recognition procedure closely follows the human approach. We first detect likely heart beat events by applying a Matched Filter (MF) [3]. MFs are an established concept used in information transmission where the waveform of the original signal is known, see Figure 2. The coefficients of the filter are the time-reversed values of the sought signal. It can be shown that the MF maximizes the output SNR.

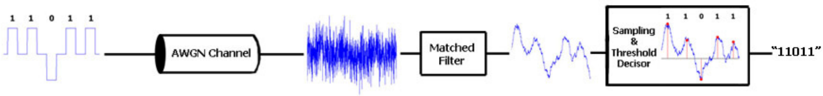


Fig. 2: MF application. Source: http://en.wikipedia.org/wiki/Matched_Filter.

In our case, the original waveform is also known from clear reference signals. We thus build a waveform prototype by averaging over $N = 100$ QRS complexes. The application of the MF to the noisy signal then gives us likely

HB time points, which is illustrated in Figure 3. The output shows some incorrect detected events that are due to the motion artifacts.
To remove these, we perform a graph search, eliminating these extraneous peaks. We interpret all peaks as vertices of a directed graph with weights, and iteratively add the most likely vertices. The algorithm is depicted in Figure 4 and works as follows: First, the mean distance d_m of the currently

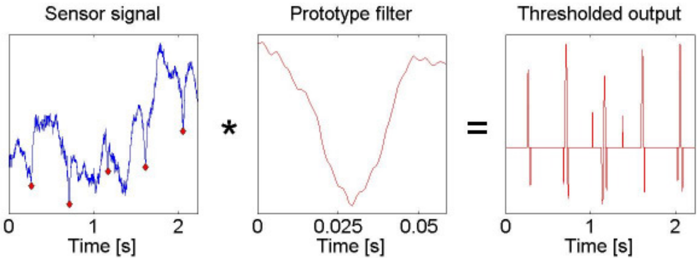


Fig. 3: Application of the MF prototype filter to the noisy signal. Correct heart beat locations are marked with diamonds in the leftmost plot.

examined $k = 5$ vertices is calculated and propagated to the next candidate heart beat locations, see Fig. 4, left. The next vertex is then set by taking the one that leads to the lowest distance of the current subset, which is depicted in Fig. 4, right. This process is then iterated. In the case that no likely candidate can be found, a maximum of one vertex at a time is inserted.

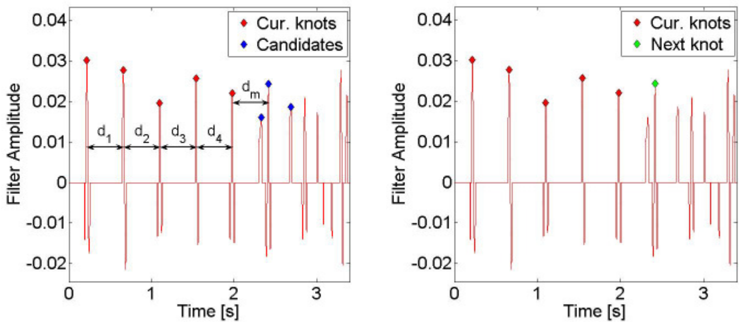


Fig. 4: Candidate search (left) and establishment of next vertex (right).

3 Experiments

We conducted our experiments using the MIT-BIH Noise Stress Test Database which is part of the PhysioBank signal archives [2]. In this database, half hour records of electrode motion artifacts have been added to clean half hour ECG recordings. Artifacts from electrode motion are considered the most troublesome, since they can mimic ectopic beats and cannot be removed easily by simple filters. By adding the noise in a controlled way, the SNR of the generated signal is known. The process is further described in [4]. The correct beat locations are known from the clean signal and have been annotated by experts. Two different subjects *S1* and *S2* are contained in the database with different SNR of noise added to the clean signal.

The performance of our algorithm is summarized in Table 1. For the different subjects, the half hour recordings were examined for decreasing SNRs. The percentages shown are those HB that do not differ more than t_{max}=0.01 s from the annotated time HB time points. Our algorithm proved to work reliably at all investigated levels of noise. The small number of misdetections can easily be smoothed out by a simple lowpass filter.

Subject	Nr. HB	SNR=24dB	SNR=18dB	SNR=12dB	SNR=6dB
S1	2166	99,6%	99,6%	99,4%	98,4%
S2	1543	99,7%	99,7%	99,6%	98,4%

Tab. 1: Summary of the algorithm performance for different SNRs.

All our algorithm components can easily be implemented on a microprocessor for mobile use. Matched Filters have already successfully implemented on such devices [5], the graph search and an additional lowpass filter do not demand too much computational power either.

4 Conclusions

We presented an algorithm for the detection of heart beats in ECG signals that exhibit artifacts due to the presence of motion. We first applied a MF to identify likely events in the signal; to remove erroneous HB we additionally performed a directed graph search. All presented algorithm components can be implemented on a microprocessor for mobile usage. We demonstrated the effectiveness of our method by application to real ECG sensor data and substantiated that our method works reliable. Even when the SNR decreases to 6dB, well over 98% of HB are detected correctly.

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