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Simple real-time QRS detector with the MaMeMi filter☆

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ABSTRACT

Detection of QRS complexes in ECG signals is required to determine heart rate, and it is an important step in the study of cardiac disorders. ECG signals are usually affected by noise of low and high frequency. To improve the accuracy of QRS detectors several methods have been proposed to filter out the noise and detect the characteristic pattern of QRS complex. Most of the existing methods are at a disadvantage from relatively high computational complexity or high resource needs making them less optimized for its implementation on portable embedded systems, wearable devices or ultra-low power chips. We present a new method to detect the QRS signal in a simple way with minimal computational cost and resource needs using a novel non-linear filter.

1. Introduction

The function of the heart can be detected by sensing the voltage variations that occur on certain parts of the human body surface. An electrocardiograph (ECG) records those voltage changes over time for later analysis. ECG is a fundamental tool used by cardiologist to diagnose cardiac diseases. Moreover, heart rate monitoring has become an extremely popular method to control the evolution of physical training in sports.

The normal sinus rhythm of the heart is characterized by a sequence of some known phases such as P, Q, R, S, T as depicted in Fig. 1. Heart rate is inferred by detecting the QRS complexes and obtaining the period between consecutive R peaks. However, QRS detection is not as simple as it could seem after seeing this ideal situation. ECG signals are usually affected by several noise sources, like muscular contraction and respiration. Moreover, as a consequence of a disease or a temporal alteration, heart beats can have very different characteristic patterns [1]. Real ECG recording databases, like the MIT/BIH ECG database [2], include episodes with all these different phenomena. Such databases allow us to study and design QRS detectors that take them into account. On top of that, by providing simple metrics to compare the performance of different algorithms, they have fostered the research for better and better detection methods.

There are large number of QRS detection proposals [3], and it could seem that the QRS detection problem is already saturated. Nevertheless, with the availability of portable embedded systems, wearable devices, and body area networks there is a renewed interest on analyzing energy efficient algorithms that allow QRS detection with minimal energy consumption so that they can extend battery life of portable equipment [4,6,7] or sports equipment.

In this paper we present a novel algorithm to detect QRS complexes in ECG signals with very low computational complexity. In Section 2 we review some of the methods described in the literature that should be avoided in order to reduce the computational complexity and energy consumption of a QRS detector. Then, Section 3 describes the various processing steps we apply to the signal to detect the heart beats, including the novel MaMeMi filter used to remove the low frequency noise caused by the baseline wander, and the following steps to finally detect the QRS peaks.

Once the method is presented, Section 4 describes the performance obtained by the algorithm when tested against the MIT/BIH ECG database. Section 5 gives more details about the low resource cost of the algorithm implementation. Finally Section 6 presents the conclusions.

2. Computationally costly methods

In this paper we analyze detectors that process digitized ECG data like those present in MIT/BIH. On such data detection is usually a two step process, first a filtering step to remove noise and enhance

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1746-8094/

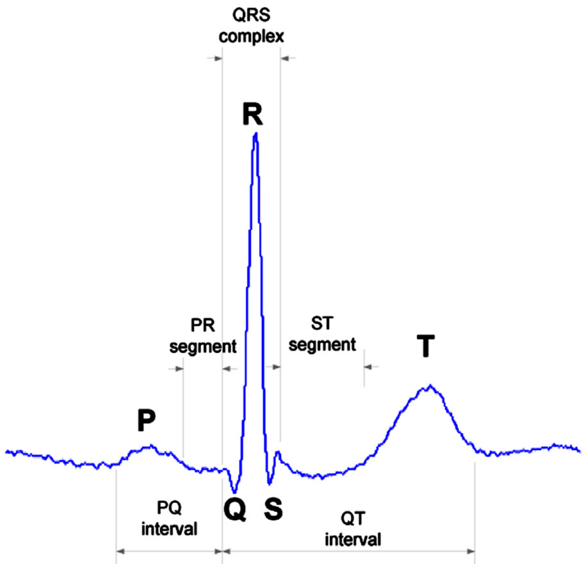

Fig. 1. Example of the parts of ECG (actual fragment of tape 103 from MIT/BIH database).

signal so that QRS complex become clean pulses, and then a second step that analyze the pulses to determine if they are QRS complexes.

The frequency components of the QRS complex range from 10 Hz to 25 Hz. So, most algorithms filter out high and low frequency noise.

Low frequency noise can be removed by different high pass filtering techniques [8–10]. High pass FIR filters for low cutoff frequencies require a large number (let be n) of taps. This kind of filters require n fixed point multipliers and adders that must compute for each sample. This means that at least $2{\cdot}n$ operations are needed for each sample. On the other hand, IIR filters usually need floating point coefficients, hence require floating point multipliers. The downfall of this method is that it takes too much resources in a hardware design or too many clock cycles of a integer microcontroller. Another method to remove the baseline is the subtraction of the median over a window from the signal ([11]). This is an ineffective strategy since the sorting of a signal window must be done for every sample, so for a window of n samples n^2 operations are needed.

For high frequency removal similar problems can arise, although the number of taps is usually lower. A possible technique to remove high frequency noise is the usage of morphological operators as described in [15]. Their principle is simple, but they need to access several values of the input signal for each sample. Common designs combine up to 8 concurrent filters of this kind. So the number of needed operations per sample is not very low.

On the enhancement phase some techniques (used in [12]) include the squaring of the signal. The use of multipliers should be avoided if possible to minimize the resource and energy costs. Other methods (also used in [12]) use the integration of the signal over a window of n samples, which is again requiring n operations for each sample of the signal.

Wavelet transform based methods [13] are also computationally expensive. Hilbert transformation [14], that shows very good results, is also prohibitive since it requires computing FFT over a window for every sample.

3. Proposed design

We propose a novel algorithm to be applied in real-time over ECG signals. Like few similar proposals, it consists of a filtering procedure coupled with enhancement phase, followed by a detection phase resulted after several applied criteria. A diagram of the process is shown in Fig. 2.

The differentiation factor from known methods in proposed one is the use of a new filter to reduce low frequency noise. The detection phase is similar to many other works [3]. The computational cost of most of the algorithms is devoted to the first filtering and enhancement phase. In our case the computational cost is highly reduced, making it very attractive for its application in battery operated devices.

3.1. Low frequency noise suppression

To remove the base wander, we have designed a high pass nonlinear filter. We called it MaMeMi, from maximum mean minimum. The principle is very similar to [11], i.e. subtract a low-pass filtered version of the signal from the original signal to take the higher frequency components. As stated in Section 2, [11] proposes a median filter to get the signal to subtract, which is a computationally costly operation of the order n^2 operations per sample, being n the width of the window used to compute the median. Other works proposed a similar approach using a standard FIR or IIR filter to get the signal subtract. Again this is a computationally costly operation of the order $2{\cdot}n$ per sample, being n the number of taps of the filter. In our case we propose to subtract the mean between the moving maximum and minimum values of the signal. Let $x(t)$ be the discrete time function of the digitized ECG input signal, the filter output $h(t)$ is defined by Eq. (1).

$$h(t) = x(t) - \frac{max^*(t) + min^*(t)}{2} \tag{1}$$

$$max^*(t) = \begin{cases} x(t) & \text{if} \quad t = 0 \\ max^*(t-1) + \sigma \cdot \Delta & \text{if} \quad x(t) > max^*(t-1) \\ max^*(t-1) - \Delta & \text{if} \quad x(t) \le max^*(t-1) \end{cases} \tag{2}$$

$$min^*(t) = \begin{cases} x(t) & \text{if} \quad t = 0 \\ min^*(t-1) - \sigma \cdot \Delta & \text{if} \quad x(t) < min^*(t-1) \\ min^*(t-1) + \Delta & \text{if} \quad x(t) \ge min^*(t-1) \end{cases} \tag{3}$$

In order to obtain the real extrema of $x(t)$ over a window of n samples we would need n comparisons for each sample, and this is precisely the amount of computation that we wanted to avoid. We used pseudo-extrema functions instead that need just one comparison and one operation per sample. We called them max^* and min^*. They are defined in Eqs. (2) and (3) respectively. The principle of operation of the $max^*(t)$ is as follows: we kept a variable with the current maximum, if the value of the input function $x(t)$ is equal or lower than the current maximum, we decreased the current maximum by a factor Δ. If the value of the input function $x(t)$ is higher we then increase the current maximum by a factor $\sigma{\cdot}\Delta$. We interpreted that $max^*(t)$ tries to follow the maximum value of $x(t)$ with some decay over time. The higher the factor σ is, the faster $max^*(t)$ will follow the maximum of $x(t)$. The higher the factor Δ is, the faster the decay will occur. Function $min^*(t)$ is defined similarly. The selection of the best values for σ and Δ is not straightforward since the filter response depends, besides former parameters, on the amplitude of the signals being filtered. The MIT-BIH database was sampled with 11 bit resolution over a range of 10 mV. Heart beats appear as pulses of approximately 1 mV, which become pulses of around 200 units in the digitized signal.

The filter response for sinusoidal signals ranging from 0 to 50 Hz is shown in Fig. 3. To illustrate the different response to different signal amplitudes we show some discrete amplitude values: 10, 19, 55, and 208. Extrema of low amplitude signals are more easily followed and the pseudo-mean is closer to the input signal, so when removing it from the input signal the signal is highly