Analysis of electrocardiographic (ECG) signals: Report on Detecting heart beats with QRS complex detection (1.a)

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I. Abstract

This report covers development and evaluation of an R-peak detection algorithm employed in the role of electrocardiographic (ECG) signals analysis. This method has two stages: preprocessing using exponential weight mean-variance (EWMV) and detection stage employing finite state machine (FSM). Because this method doesn't require manual parameter tuning, exhibits high accuracies and has low complexity and resource consumption, this makes it a viable option for wearable ECG devices.

II. Introduction

In an electrocardiographic (ECG) analysis, the essential signal is a QRS-complex, where the R-peak has the highest amplitude. Detection of this R-peak serves as a basis for detecting heart function and diagnosing cardiac conditions.

The algorithm's implementation in this report is based on the article from Tien et al. [1]. Two optimizations were tested: first was averaging the ECG signals' channels and the second was made using a Butterworth filter. Each algorithm was evaluated on two databases: Long Term ST Database (LTSTdb) [2] and MIT-BIH Arrhythmia Database (MITdb) [3].

III. Methods

Heartbeat detection algorithm consists of two stages.

A. Preprocessing stage

Here, the main goal is to emphasize the QRS-complex area and to level out contributions which come from other signals. Thus, exponential weight mean (μ) and exponential weight variance (var) are calculated using equations (1-3). By using exponential weighting, we don't need to store windows which reduces computation time.

$$\mathrm{var}[n] = (1-\alpha)[\mathrm{var}[n-1] + \alpha\big(x[n] - \mu[n-1]\big)^2] \quad (1)$$

$$\mu[n] = (1-\alpha)x[n] + \alpha\mu[n-1] \quad (2)$$

$$\alpha = 1 - \frac{2}{N-1} \quad (3)$$

B. Detection stage

The detection stage is a finite state machine (FSM) which consists of three states:

1. State: This is a time period equal to $QRS_{int} + RR_{min}$. Where $RR_{min} = 200$ms and $QRS_{int} = 60$ms. In this time period, the maximum amplitude of the signal and it's position is saved. The t_h is equal to the magnitude of the maximum amplitude of the R-peak.

2. State: The duration of the second state depends on the location of the R-peak position in the first state. The t_h is equal to the magnitude of the maximum amplitude of the R-peak for the duration of the second state but for the last point, when it is equal to the mean value of the amplitudes of the R-peaks already found.

3. State: In this state, the t_h is reducing exponentially (4). When the signal $(var) > t_h$, the state ends and returns to first state.

$$t_h[n] = t_h[n-1]\exp -P_{th}/f_s \quad (4)$$

Where $P_{th} = -\frac{ln(0.1)}{0.4}$ and f_s is sampling frequency.

IV. Results

A. Detection results

In the Fig. 1 an example of the algorithm's detection of R-peaks and the detected threshold on the first few heartbeats in a sample *s20011* from the LTSTdb is shown.

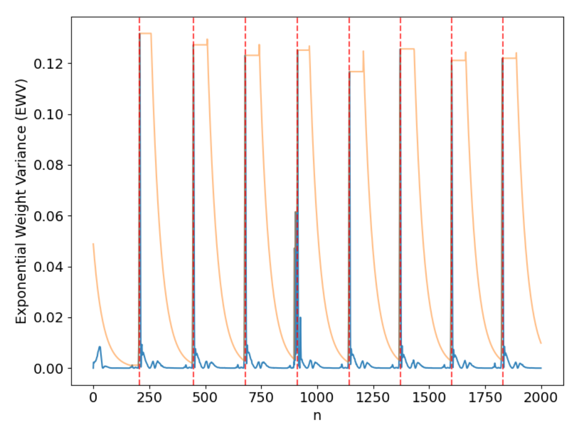

Fig. 1. R-peak detection (dashed) on the EWMV processed signal (blue) and threshold (orange).

B. Performance results

In this section, three variants of results are presented: algorithm using the first channel of the ECG signal (Table I), algorithm using the averaged ECG signal of both channels (Table II) and an algorithm with optimization - an applied Butterworth filter on the ECG signal (first channel) (Table III).

Database	Se %	+P %
MITdb	99.29	98.98
LTSTdb	99.51	98.57

TABLE I
Performance (gross) metrics of the algorithm

Database	Se %	+P %
MITdb	98.26	97.86
LTSTdb	99.48	99.29

TABLE II
Performance (gross) metrics of the algorithm using an averaged ECG signal

Database	Se %	+P %
MITdb	99.31	99.15
LTSTdb	99.55	98.67

TABLE III
Performance (gross) metrics (algorithm + butterworth filter)

All three tables show high performance metrics. The highest performing algorithm is the third with applied Butterworth filter, but the improvement is small as the first algorithm is already very high performing.

C. Discussion

The results presented in the tables give the performance of three different variants of the ECG signal processing algorithm. In summary, the first algorithm performs well but the optimization using the Butterworth filter gives the best overall performance, particularly for the MITdb dataset. Notedly, the performance was still not improved significantly. Averaging the channels shows mixed results. This likely implicates that the benefits of this approach vary depending on the the ECG signals and how they were obtained.

The advantages of this finite state machine algorithm is simplicity and low computational complexity while still achieving high performance metrics. This makes it well-suited for wearable devices. The weakness of this algorithm could be in the noise detection, because while it adapts thresholds to the ECG signal, it could struggle with very high noise.

References

[1] D. Tien, P. N. T. Ma, T. Nam, V. T. Ta, and T. Thi Thao Nguyen, "A low-complexity r-peak detection based on exponential weight mean-variance for wearable ecg devices," 10 2023, pp. 415–420.

[2] F. Jager, A. Taddei, G. B. Moody, M. Emdin, G. Antolic, R. Dorn, A. Smrdel, C. Marchesi, and R. G. Mark, "Long-term st database: a reference for the development and evaluation of automated ischaemia detectors and for the study of the dynamics of myocardial ischaemia," *Medical & Biological Engineering & Computing*, vol. 41, no. 2, pp. 172–183, 2003.

[3] G. B. Moody and R. G. Mark, "The impact of the mit-bih arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, May-Jun 2001.