Summary

A reliable detection of the R-peak in an electrocardiogram (ECG) is fundamental for heart rate (HR) estimation, heart rate variability (HRV) analysis, biometric recognition techniques and additional ECG waveform based analysis.

However, challenges arise when identifying the R-peak from ECG signals collected under dynamic conditions using wearable devices. In this paper, the performance of six commonly used QRS detectors is evaluated in a private ECG database acquired using the *Fieldwiz* device. The database comprises five recordings acquired under dynamic conditions: trail running and weightlifting. A novel R-peak detection algorithm is presented for single lead ECG signals, divided in a pre-processing stage and a detection stage based on a finite state machine (FSM). The detection threshold is dynamically updated, making it suitable for R-peak detection under fast heart rate (HR) and R-wave amplitude changes.

The R-peaks from the raw ECG signals were annotated, and the proposed method benchmarked against common QRS detectors. The combined acquisition setup and presented approach resulted in Sensitivity (Se) of 99.77% and Positive Predictive Value of (PPV) of 99.18%, comparable to evaluated state of the art real time QRS detectors.

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A Low-Complexity R-peak Detection Algorithm with Adaptive Thresholding for Wearable Devices

1) Introduction

> ECG applications:

Heart Rate (HR) monitoring, Heart Rate Variability (HRV) analysis and biometric identification.

HRV as an indicator for training load[1], overall physical and mental stress[2]. HR and HRV (HR(V)) monitoring is recommend to be used in every athlete's training[3]. However, it can not inform on all aspects of fatigue, emotion or psychophysiological state. Ultimately, the role of in-game stress, emotional state and readiness is still an active research topic[3].

> Applications:

HR(V) can be used in both individual and collective sports. HR should me measured weekly during rest and exercise and HRV metrics are still limited during rest and provide an indirect measure of the autonomic nervous system.

> Challenges:

Gold standard HR measurements are taken using chest straps, these are more uncomfortable when compared with regular wearable vests. **How reliable are wearable shirts for HR monitoring?**

In the context of sports, there is a shortage of available and annotated datasets of raw ECG signals acquired under dynamic conditions. **How do different QRS detectors behave under dynamic conditions?**

> Goals:

Create private database with ECG acquired under dynamic conditions using *FieldWiz* and Wearable T-shirt.

Evaluate the reliability of common QRS detection methods. Propose new real-time R-peak detection method.

2) Methodology

> Data acquisition:

5 recordings (39817 annotated R-peaks)
Running and Weightlifting training
250 Hz sampling rate; 16-bit resolution

> R-Peak detection:

Pre-Processing, Fig 1.
Detection Stage, Fig 2.

ECG Pre-processing (4 steps):

$$y_1[n] = x[n] - x[n-N] \quad (1)$$

$$y_2[n] = y_1[n] - y_1[n-1] \quad (2)$$

$$y_3[n] = (y_2[n])^2 \quad (3)$$

$$y[n] = \frac{1}{N}\sum_{k=0}^{N} y_3[n-k] \quad (4)$$

Fig 1. *x[n]* raw ECG signal. 1-2) First and second derivatives with *N* = 5; 3) Squaring; 4) Moving integration.

Detection Stage (3 states):

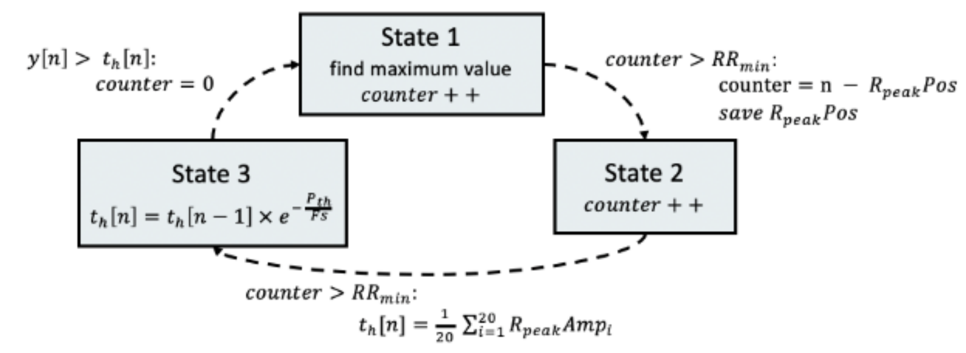

Fig 2. Representation of the Finite State Machine. RR_{min} - *refractory period of the heart;* t_h *– detection threshold;* F_s *– sampling frequency;* P_{th} *– exponential decay and* $R_{peak}Amp$ *– amplitude of the R-peak.*

3) Results

> Parameter optimization:

N – free parameter used in pre-processing
P_{th} - free parameter for exponential decay used in detection threshold

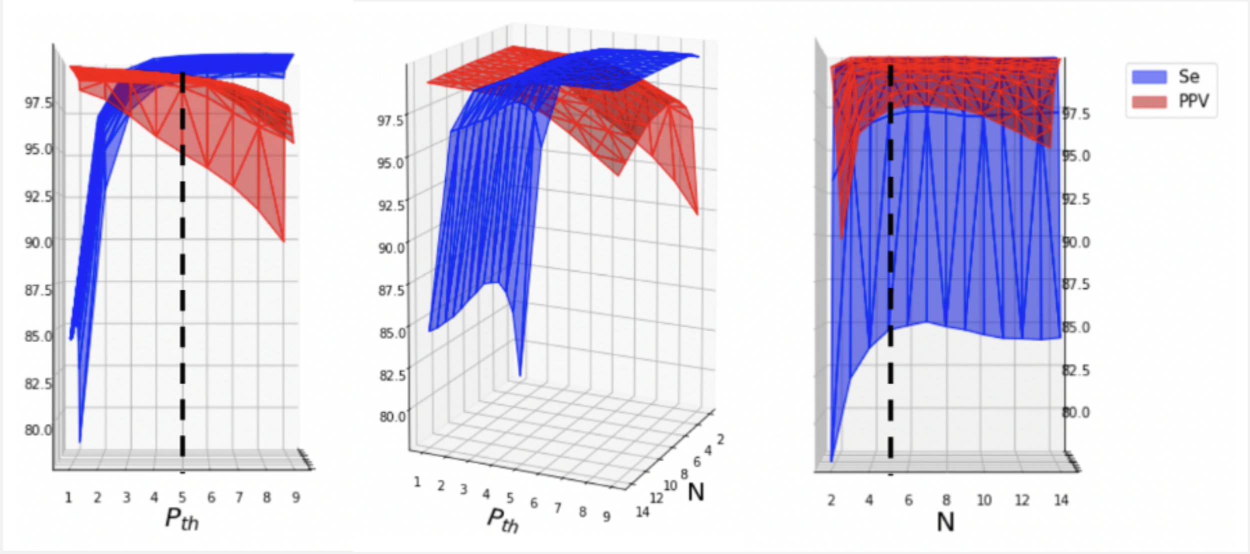

Fig. 4: Parameter optimization (P_{th} and *N*), Sensitivity (*Se*, blue) and Positive Predictive Value (*PPV*, red) planes. a) Se and *PPV* with varying P_{th}; b) Transverse plane and c) Se and *PPV* with varying *N*. The selected values of P_{th} = 5 and *N* = 5 are represented by the black dashed line.

↑ P_{th} → ↑ *Se* and ↓ *PP*
↓ P_{th} → ↓ *Se* and ↑ *PPV*
➡ $P_{th} \in [3,5]$, $N \in [4,8]$ ➡ Se and PPV > 98 %

> Benchmarking:

QRS detections: Pan and Tompkins, Christov, Gamboa, Elgendi, Engzee, Kalidas and proposed approach with P_{th} = 5 and *N* = 5.

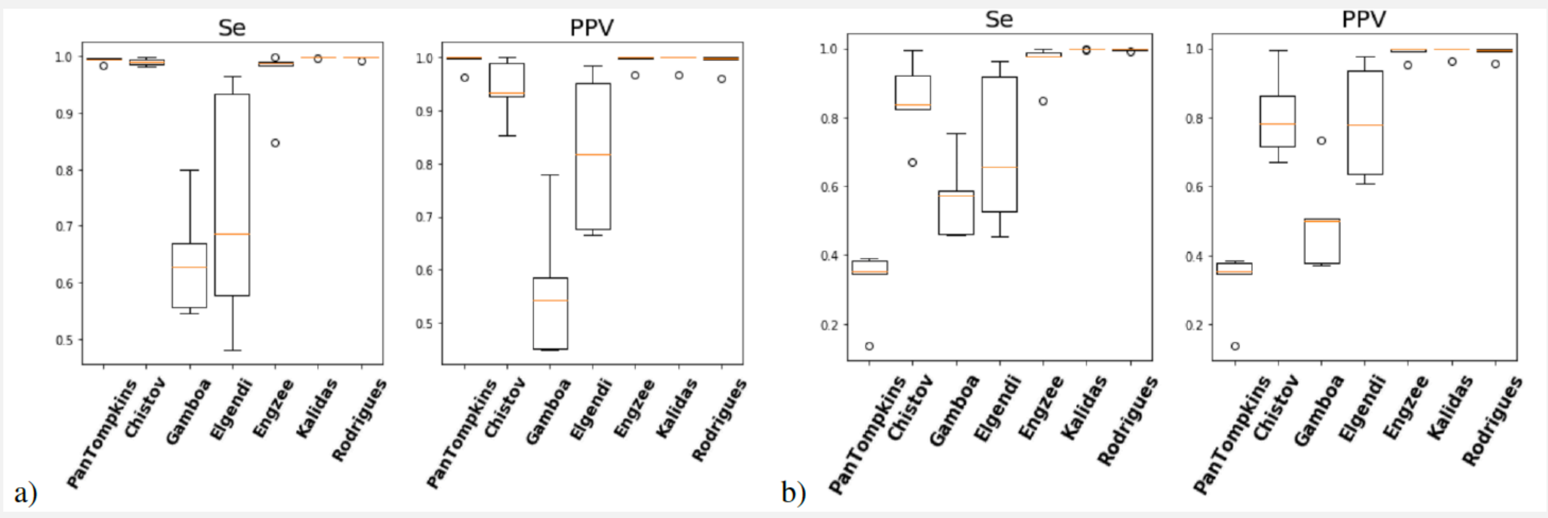

Fig. 5: Evaluation of the different QRS detectors: PanTompkins, Christov, Gamboa, Elgendi, Engzee, Kalidas and proposed approach. Sensitivity (Se) and Positive Predictivity Value (PPV) using the FieldWiz private dataset. Using a detection window of a) 100 *ms* and b) 20 *ms*.

4) Conclusions

Table 1) R-peak detections Sensitivity (Se) and Positive Predictive Value (PPV) and respective means (μ) and standard deviations (δ) of the different QRS detectors (Pan and Tompkins, Christov, Gamboa, Elgendi, Engzee, Kalidas and the proposed approach). TABLE a) using a detection window of 100 *ms* to the annotated R-peaks and TABLE b) detection window of 20 *ms*.

(a) Detection window of 25 samples (100 *ms*).

Method	Se (μ)	Se (δ)	PPV (μ)	PPV (δ)
PanTompkins	99.34	0.43	99.04	1.50
Chistov	99.07	0.61	93.95	5.20
Gamboa	63.98	9.21	56.23	12.02
Elgendi	72.88	19.16	81.82	13.21
Engzee	96.16	5.72	99.25	1.29
Kalidas	99.90	0.11	99.27	1.37
Rodrigues	99.77	0.23	99.18	1.52

(b) Detection window of 5 samples (20 *ms*).

Method	Se (μ)	Se (δ)	PPV (μ)	PPV (δ)
PanTompkins	32.23	9.43	32.04	9.19
Chistov	84.96	10.93	80.53	11.44
Gamboa	56.53	10.87	49.83	13.12
Elgendi	70.29	20.50	78.71	15.10
Engzee	95.71	5.543	98.80	1.75
Kalidas	99.85	0.12	99.23	1.37
Rodrigues	99.64	0.28	99.06	1.60

> Pre-processing based on double derivative increased R-peak temporal precision when compared to single derivative. Increased sensitivity was achieved with exponential decaying threshold. Suitable for dynamic settings and fast changing heart rate and R-peak amplitudes.

> Parameter optimization was performed in a dataset of N = 5 with HR in the range between 60 and 190 bpm, building upon the future use cases of the device. Lower heart rates (e.g. 40 bpm), may lead to increased False Positives (FP) and higher rates (e.g. 200 bpm), may result in False Negatives (FN), hence further evaluation of the method using a larger database should be done.

> Combination of the FieldWiz and Wiz shirt achieved Se and PPV > 99%, when using QRS detection using PanTompkins, Kalidas or the proposed approach using 100 ms acceptance window. Detection window of 20 ms achieved Se and PPV > 99% for Kalidas and proposed approach.

References

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