R-peak Detector Benchmarking using FieldWiz and Physionet Databases

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Abstract: The R-peak detection in an Electrocardiography (ECG) signal is of great importance for Heart Rate Variability (HRV) studies and feature extraction based on fiducial points. In this paper, a real-time and low-complexity algorithm for R-peak detection is evaluated on single lead ECG signals. The method is divided in a pre-processing and a detection stage. First, the pre-processing is based on a double differentiating step, squaring and moving window integration for QRS complex enhancement. Secondly, the detection stage is based on a finite state machine (FSM) with an adaptive thresholding for R-peak detection. The tested approach was benchmarked in a private *FieldWiz* Database with other commonly used QRS detectors, and later evaluated in the Physionet Databases (mitdb, nstdb, ltstdb and CinC Challenge 2014). The proposed approach resulted in a Sensitivity (Se) of 99.77% and Positive Predictive Value (PPV) of 99.18% in the *FieldWiz* database, comparable with the evaluated state of the art QRS detectors. In the Physionet Databases, the results showed to be highly influenced by the QRS waveform, for MIT-BIH (MITDB) achieving a median PPV of 99.79% and a median Se of 99.52%, with overall PPV of 98.35% and Se of 97.62%. The evaluated method can be implemented in wearable systems for cardiovascular tracking devices in dynamic use cases with good quality ECG signals, achieving comparable results to state of the art detectors.

1 INTRODUCTION

The pervasiveness of wearable devices and the easiness with which the data is collected, transferred and managed has changed numerous industries including health care, sports and lifestyle in general. The healthcare providers, coaches and the end users, ultimately benefit from this additional information in the decision making process. Amongst the physiological signals that can be recorded using wearable devices, the ECG has been widely used in health monitoring, tracking of sports performance, measuring readiness and fatigue, as well as, more recently used in biometric and emotion recognition applications.

The ECG is collected using electrodes, usually placed on the chest, that detect the electrical changes arising from the depolarization and repolarization of the cardiac muscles during each cardiac cycle. From the time-series of a normal ECG, one can distinguish 3 main components, known as the P wave, QRS complex and T wave.

The accurate R-peak detection is critical to extract features from the ECG. The most commonly known feature is the mean Heart Rate (HR), computed from the average time difference of consecutive beats in a selected time window. Other features have been recently getting attention, namely, the Heart Rate Variability (HRV), which derives from the successive time differences between successive heartbeats. A persons' normal HR is susceptible to changes due to intrasubject (e.g. physical or psychological efforts) and intersubject variability (e.g. sex, age or medication). Nonetheless, even if the mean HR is kept constant during a selected time window, the differences between successive heart beats are likely to oscillate around that mean value. The variability of the R-R intervals (i.e. intervals between consecutive R-peaks), known as HRV, is also commonly used as a non-invasive indicator of the autonomic nervous system (ANS).

In spite of the complexity of HRV metrics and their dependency on numerous physiological factors, diseases, lifestyle and acquisition settings, these have been getting increased attention. When studying HRV, fields of interest include emotion recognition (Lane et al., 2009), stress-levels (Zhu et al., 2019),

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training load (Saboul et al., 2016) and, more recently, HRV based training revealed to be a promising tool to achieve increased performance (Javaloyes et al., 2019). Other studies have also addressed the correlation between HRV metrics and emotional stress in the context of sports (Laborde et al., 2011).

A recent review (Buchheit, 2014) stated that contradictory findings with regard to HRV are likely to be related with methodological inconsistencies, unaccounted confounding factors and/or misinterpretation of the results, rather than a limitation of these metrics to inform on the subject physiological status.

In the case of sports and dynamic contexts, R-peak detectors must be: 1) Robust to noise and artefacts; 2) Allow real time monitoring; and 3) Should not be dependable of parameters, subjects or QRS morphologies. Ultimately, the goal of this study is to assess the feasibility of implementing a real-time R-peak detector proposed by the authors. In our approach, the R-peak detection scheme builds upon state-of-the-art techniques, combining the temporal precision of a double derivative pre-processing step, with the numerically efficient and highly sensitive exponential decaying threshold for R-peak detection proposed by (Gutiérrez-Rivas et al., 2015). It comprises:

- A pre-processing stage, consisting of a double differentiating step, squaring, and moving window integration for the QRS complex enhancement (see Figure 1);
- A numerically efficient R-peak detection step, as proposed by (Gutiérrez-Rivas et al., 2015), based on a Finite State Machine (FSM), comprising a dynamic threshold for the detection of the R-peak, encompassing a free parameter Pth (for details see (Gutiérrez-Rivas et al., 2015)). While in the original work the threshold value depended on the amplitudes of all previously detected R peaks, in this work we will restrict this observation window to the previous 20 R-peaks.

The organization of the paper is the following, in Section 2 we present some initial considerations about the QRS detectors. In Section 3 the *FieldWiz* device specifications and preliminary signal quality tests with different electrode settings are presented, together with the *FieldWiz* private database. In Section 4 the private database is used for benchmarking, together with the common ECG databases from Physionet. Lastly, Section 5 encloses the conclusion, discussion and future work.

2 BACKGROUND

Real-time QRS detection was first introduced by Pan and Tompkins (Pan and Tompkins, 1985) in 1985; since then, several algorithms have proposed modifications of this method. These approaches consist of a pre-processing step for QRS enhancement, followed by a decision stage. The enhancement stage usually consists of amplitude based, single or double derivatives, digital filters, wavelet or Hilbert transforms, or a combination of these. Next, the detection step is commonly done using threshold-based and matched filters (Elgendi et al., 2014). Some combinations of these methods are either computationally expensive, hence not suitable for real time applications, or require a learning phase. Thus, some of the most commonly used QRS complex detectors are the original Pan and Tompkins (Pan and Tompkins, 1985), Hamilton (Hamilton, 2002), Christov (Christov, 2004), modified Engelse and Zeelenberg (Lourenço et al., 2012) and Kalidas (Kalidas and Tamil, 2017).

The problems concerning the QRS complex detection arise from the different types of noise that can be present in the ECG signal or from the intersubject physiological variability that results from pathologies e.g. arrhythmia or atrial fibrillation. In the acquisition setting, especially with wearable devices under dynamic conditions, the types of noise include baseline wandering and loss of the electrodes contact due to movement (Acharya et al., 2007). In spite of the recent advances in the field of QRS detection, derivative and digital filters for QRS complex enhancement, combined with an adaptive threshold decision rule, are still the most simple, computationally efficient and reliable detection (Elgendi et al., 2014).

The QRS detection method should be selected based on the signal quality, but also based on the type of study one wants to perform, whether the interest relies in e.g. HR, HRV or R-peak amplitude modulation (RAMP). This is particular important, since most of the QRS detectors have low sensitivity for detecting the R-peak (Porr and Howell, 2019). In this study, from the different detectors tested, only the modified Engelse and Zeelenberg (Lourenço et al., 2012) and stationary wavelet transform based for noise removal (Kalidas and Tamil, 2017) achieved accurate R-peak detection.

Nonetheless, the above-mentioned methods have limitations. For example, Engelse and Zeelenberg (Lourenço et al., 2012) is not robust to noise and dynamic contexts. In the method by Kalidas (Kalidas and Tamil, 2017), the decision step is similar to the decision rule in (Pan and Tompkins, 1985), with the enhancement of the QRS being based on stationary

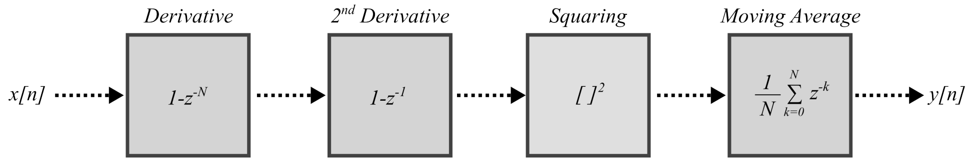

Figure 1: Pre-processing step used in our algorithm. The value N=5 was used in all experimental results.

wavelet transform for noise removal for quasi real-time R-peak detection. Apart from these, in commercial software, the QRS detection is usually extracted using adaptations of the Pan-Tompkins (Tarvainen et al., 2014). The modified Pan-Tompkins with local maximum search is used in most commercial software, where the R-peak is detected once the QRS complex is detected. The latter is the gold standard for HR monitoring in sports.

3 FieldWiz DEVICE

3.1 Specifications

The *FieldWiz* device, shown in Figure 2 a), has a 16-bit ADC converter, the ECG signal is sampled at 250 Hz, stored in memory and extracted a posteriori for analysis. It enables ECG data acquisition under different dynamic conditions (e.g. running and weightlifting), while using alternative setups. The different setups consist in a combination of the *FieldWiz* device with two iterations of the Wiz connected shirt, both depicted in Figure 2 b) and c), as well as the respective electrode placement shown in Figure 2 d).

The electrode pads from the shirt Version 1 are placed on the chest, under the pectoral muscles, while the placement of the shirt Version 2 is done in a lateral position. Improvements from the latter version include the different conductive fabric, the positioning of the electrode pads and the elastic fit. The improved lead placement position shown in Figure 2 d) is known to be important in reducing motion noise and movement artifacts, in particular, under extreme conditions, where artifacts from muscle contractions and movement are a strong source of noise contamination (Francis, 2016).

3.2 Signal Quality Assessment

Initially, experiments were performed using a combination of the *FieldWiz* with both connected shirts described in Section 3.1 in order to assess the ECG quality.

Next, the signal quality was evaluated using an SQI based on simple heuristic fusion described in (Zhao and Zhang, 2018). This method was chosen since it showed good performance in the selected Physionet Databases, and it makes use of common signal quality indexes described in the literature. It adopts four synthesized signal quality indexes: 1) Consistency of the QRS complex detection using different detectors (*qSQI*); 2) Power of the QRS frequency band (*pSQI*); 3) Signal kurtosis (*kSQI*); and 4) Power of the baseline frequency band (*basSQI*).

Based on simple fusion of the four heuristic metrics, each *SQI* (*qSQI*, *pSQI*, *kSQI* and *basSQI*) is evaluated and classified as either '*Optimal*, *Suspicious* or *Unqualified*' with respect to certain pre-computed thresholds. Later, from the classification of each computed *SQI*, the 10 seconds ECG segments were characterized as either *Excellent (E)*, *Barely Acceptable (B)* and *Unacceptable (U)*, explained in (Zhao and Zhang, 2018).

The results for the three signal acquisitions with different experimental settings are shown in Figure 3, consisting of using the electrodes dry, with water, or with electrode gel. From these, the application of water and electrode gel showed comparatively better results when compared to the direct contact of the pads with the skin. Additionally, the use of electrode gel showed consistently saturation of the signal, likely due to the lack of skin/electrode adhesion. As such, the FieldWiz Private Database described next, was created using the pads moisturized prior to use. Similarly, in the context of sports, increased perspiration resulted in higher signal to noise ratio (SNR).

3.3 FieldWiz Private Database

Five recordings (N=5) from four different subjects using the FieldWiz device combined with the Wiz connected shirt (FWv2) and a chest strap (Belt). Labeled as *20200405-TR-FWv2.txt*, 30 min running; *20200413-JM-FWv2.txt*, 60 min running; *20200421-JT-FWv2.txt*, 90 min trail running; *20200505-TR-Belt.txt*, 50 min high intensity interval training (HIIT); *20200508-SS-Belt.txt*: 40 min running. The five recordings accounted for a total of 39817 annotated R-peaks. The acquisitions were made in different days and conditions, taking the following precautions: 1) Applied water to the electrode pads prior to the activity; 2) Using a connected shirt or chest strap of ap-

Figure 2: Experimental acquisition setup. (a) FieldWiz device; (b) Wiz connected Shirt, Version 1; (c) Wiz connected Shirt, Version 2; and d) Electrodes placement for both shirt versions(FieldWiz, 2020).

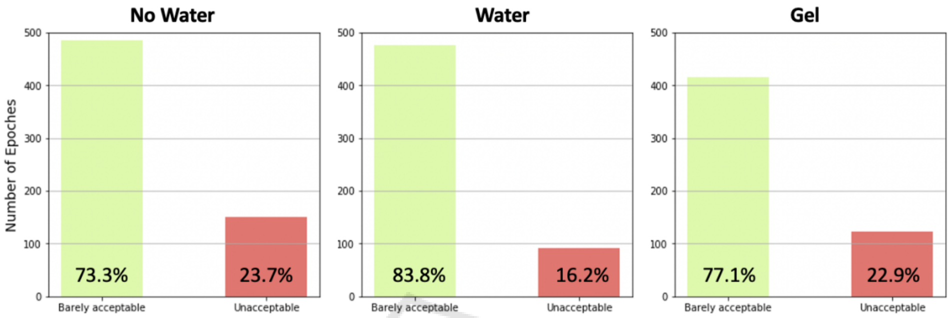

Figure 3: ECG quality assessment. Signal acquired using the *FieldWiz* device and the Wiz connected shirt Version 2, under different settings. a) Without application of water to the electrode pads; b) Moisturizing the pads with water; and c) Applying electrode gel.

propriate size.

The raw ECG was recorded and stored in the device and was later recovered and saved as HDF5 type files. The file format was chosen in order to interface with the signal annotating software *SignalBit* (Lourenço et al., 2014) used for R-peaks annotations; the graphical user interface (GUI) of the annotation tool is shown in Figure 4. Initially, the R-peaks were annotated automatically using the approach by Kalidas (Kalidas and Tamil, 2017) and stored as an HDF5 file. This approach was chosen for its high temporal precision, as described in (Porr and Howell, 2019).

Lastly, the annotations were visually inspected by a cardio-pneumologist technician using the *SignalBit* web-based annotation tool and the automatically generated R-peaks annotations were verified and corrected. The acceptance window of 5 samples, corresponding to 20 ms, in Section 4.1 was chosen, since the automatic detection by Kalidas led to slight imprecision's from the inflexion point of the QRS complex.

The HR estimations using the proposed approach with the selected parameters are shown in Figure 5, directly from the detected R-peaks and using a moving median of 15 samples. In Figure 5 a) and b), the missed R-peaks may occur when the signal quality is poor, which may happen using either the chest strap or the Wiz connected shirt.

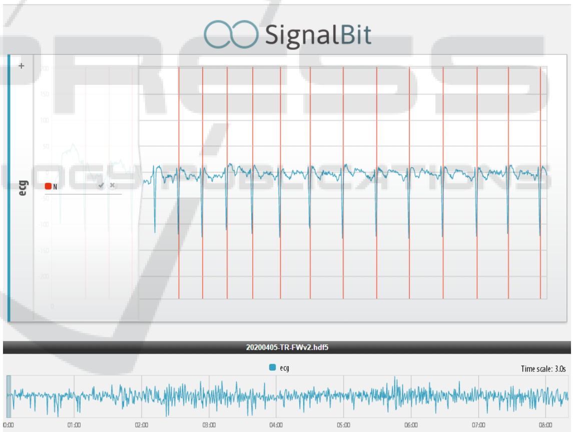

Figure 4: SignalBit web-application environment(Lourenço et al., 2014). Example of raw ECG (blue) and normal sinus rhythm R-peaks (vertical red lines).

4 EXPERIMENTAL RESULTS

4.1 FieldWiz Database Benchmark

In this subsection, the QRS detectors described in Section 2, and the proposed approach were evaluated in the *FieldWiz* Private Database. The Physionet wrapper *WFDB Toolbox* (Silva and Moody, 2014) was used to compare the benchmarked annotations with the detected QRS complexes from the different

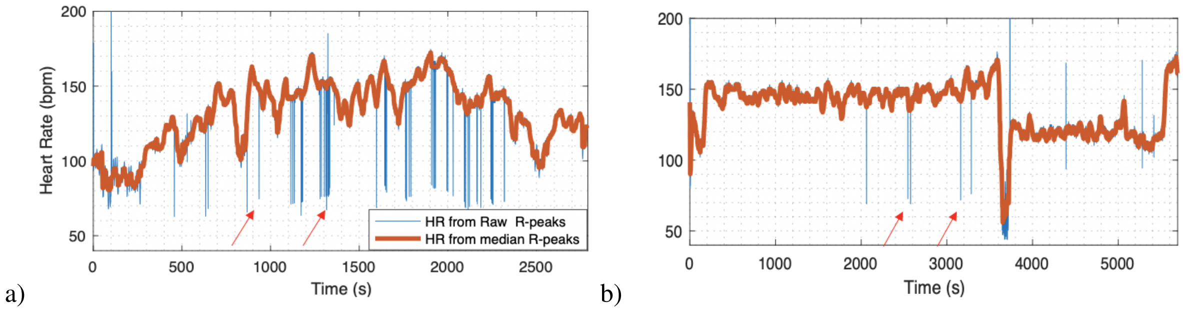

Figure 5: HR estimation from the detected instantaneous R-peaks (blue) and moving median of 15 samples (orange). Missed R-peaks highlighted with the red arrows. a) *Recording: 20200505-TR-Belt* and b) *Recording: 20200421-JT-FWv2*.

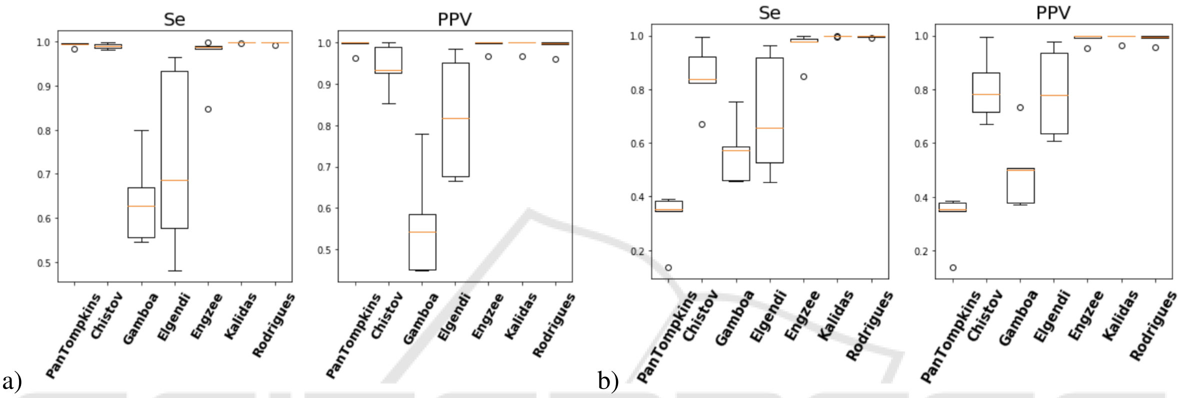

Figure 6: Evaluation of the different QRS detectors: PanTompkins, Christov, Gamboa, Elgendi, Engzee, Kalidas and Rodrigues (proposed approach). Se and PPV using *FieldWiz* dataset for a detection window of a) 100 ms and b) 20 ms.

detectors. First, the acceptance time window of 100 ms was chosen in order to evaluate the different detectors ability to detect QRS complexes in the ECG signals. This was followed by a 20 ms acceptance window, to evaluate the precision of R-peak detection. The results are shown in Figure 6 for the respective 100 ms, Figure 6 a), and 20 ms, Figure 6 b), time windows. The signals with inverted R-wave, as a result of the lead placement, were reverted in order to account for the limitations of Engzee (Lourenço et al., 2012).

From Figure 6 a), when using a wider detection window of 100 ms, any of the methods by PanTompkins, Christov, Kalidas and the proposed method achieved *Se* $> 99\%$, Engzee equal to 96% while Elgendi and Gamboa showed the worst performance at 73% and 64%. The registered *PPV* $> 99\%$ in PanTompkins, Engzee, Kalidas and the proposed approach, Christov with 94% and underperforming are Elgendi and Gamboa at 82% and 56%.

Overall, the results showed that the signal quality using the combination of the FieldWiz and the Wiz connected shirt or chest strap, under the dynamic conditions studied is acceptable for QRS detection using any of the previous methods PanTompkins, Kalidas or the proposed approach with Se and PPV $> 99\%$. In Figure 6 b), considering an acceptance window of 20 ms, the Kalidas and the proposed approach achieved good results, with Se and PPV $> 98\%$, while the PanTompkins, Christov and Gamboa resulted in decreased performance for both Se and PPV.

Ultimately, the method by Kalidas, the proposed approach or a combination of PanTompkins with an additional local search for the inflexion point, would result in reliable R-peak detection. In Figure 5, the HR estimations computed from the instantaneous RR-intervals are shown for different scenarios, weightlifting in a) and run in b). The R-Peaks were detected using the proposed method.

4.2 Physionet Databases Benchmark

The *WFDB Toolbox*(Silva and Moody, 2014) was used to extract the ECG signals and database annotations from MIT-BIH Arrythmia Database (mitdb) (Moody and Mark, 2001), MIT-BIH Noise Stress Test Database (nstdb) (Moody et al., 1984), European ST-T Database (ltstdb) (Taddei et al., 1992) and CinC Challenge 2014 (Goldberger et al., 2000). All non-beat annotations were excluded as detailed in (Moody

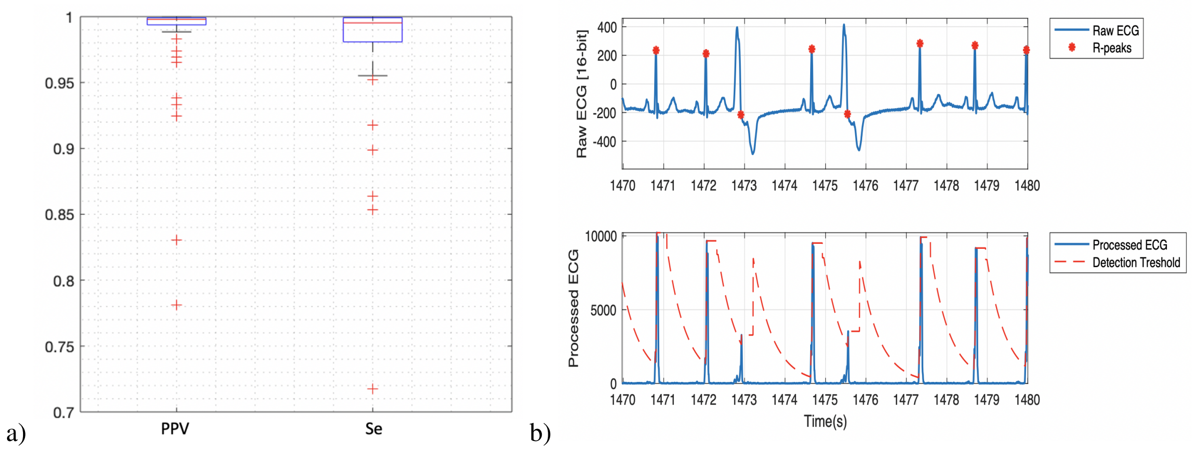

Figure 7: Evaluation of the R-peak detector using MIT-BIH Arrhythmia Database (mitdb). a) PPV and Se boxplot of the 48 records with respective median (red line), 25th and 75th percentile (black lines) and outliers (red '+' symbol). b) Application of the R-peak detector in a 10 seconds ECG segment of *Record ID: 119*. Top: Raw ECG signal (blue) and detected R-peaks (red dots); and Bottom: Processed ECG (blue) and detection threshold (red dashed line).

et al., 2001) and an error margin of 100 ms was considered between the reference and the detected peak.

The ECG morphology is characterized by variability, especially between patients and healthy subjects, which might lead to imprecisions during R-peak detection. A recent review on ten of the most computationally efficient QRS detectors (Liu et al.,) showed that the accuracy of derivative based detectors did not decline significantly on the arrhythmia database. However, when using methods based on double derivatives, each recording should be evaluated individually for clinical applications, since the PPV and Se values might decline drastically for some waveforms, as shown in Figure 7 a).

From the sensitivity analysis, the records with abnormal morphologies revealed to be problematic for the Se and PPV values. Thus, for the Physionet benchmarking, the parameters were chosen to be $N = 5$ and $P_{th} = 3$. The choice of N was based on the slope of the QRS, while P_{th} was chosen from the compromise between PPV and Se in resting conditions.

The results showed to vary widely depending on the QRS morphology; one example of such influence of the ECG waveform in the processed ECG is presented in Figure 7 b). In the case of MIT-BIH (mitdb), PPV (median = 99.79 %, outliers $<$ 95 % Record id: 108, 203, 207, 228, 232) and *Se* (median = 99.52%, outliers $<$ 95 % Record id: 106, 203, 208, 221, 223).

For the remaining databases (challenge 2014, ltstdb, mitdb and nstdb) the results are shown in Table 1 with respective TP, FN, FP, PPV and Se, exhibiting comparable results to state of the art detectors.

5 CONCLUSIONS

In this paper, a modified method for R-peak detection is evaluated. The approach combines a double derivative pre-processing step with a FSM based decision rule. It has low computational load, low memory allocation and it is simple to implement in embedded systems for cardiovascular monitoring during sports. It is robust to baseline wander, abrupt drifts and enhanced T-wave or other low frequency noise. On the other hand, it is sensitive to high frequency noise, atypical ECG waveforms and arrhythmia onsets, thus false detections should be further processed for clinical applications.

Experimental results over the *FieldWiz* database highlight advantages of the proposed approach, including: 1) Robustness to different R-wave polarities; 2) The double derivative step increases R-peak precision in comparison to other FSM approaches (Gutiérrez-Rivas et al., 2015); 3) The Sensitivity of the method is increased for dynamic, fast changing heart rates and R-peak amplitudes.

Limitations of the method include: 1) The choice of the parameter P_{th} was optimized in a private *FieldWiz* database ($N_{Subjects}$ = 5), accounting for HR varying from 60 bpm to 190 bpm, given the use case of the device; 2) Assumption of the individual ECG waveforms to be invariant, as a result, the R-peak is shown to be located in the same position of the ECG waveform for every heart beat cycle; however, in pathological conditions with time varying QRS morphologies, the Se and PPV might be affected, as well as the temporal precision of the R-peak detection; and 3) Lastly, there is a lack of validation of the different

Table 1: Summary of the results obtained (TP, FP, FN, PPV in % and Se in %) using the proposed algorithm in the considered databases. For benchmarking we used Pth = 3 & N = 5 as parameters of the algorithm.

Database	Sampling Rate (Hz)	TP	FP	FN	PPV (%)	Se (%)
Challenge 2014	120-1000	71529	332	884	98.88	99.52
ST-T Database (ltstdb)	250	782483	13712	8082	98.15	98.79
MIT-BIH (mitdb)	360	106590	1758	2904	98.35	97.62
MIT-BIH (nstdb)	360	23957	2907	1633	96.23	98.72

QRS detector methods under highly dynamically activities, as a result of the shortage of publicly available ECG databases with data acquired in such conditions. Furthermore, the confidentiality of the implemented methods in the common commercialized wearable devices raises concerns with respect to the R-peaks detection reliability. This paper explores the use case limitations of the current approaches, and validates an alternative approach that can be used for R-peak detection.

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