Zero frequency resonator based extraction of R–peaks in ECG signals

RaviShankar Prasad
exptoipiplusone@gmail.com

Gürkan Yilmaz
CSEM
Neuchatel, Switzerland
gurkan.yilmaz@csem.ch

Mathew Magimai.–Doss
Idiap Research Institute
Martigny, Switzerland
mathew@idiap.ch

***Abstract*—The electrocardiogram (ECG) signal has widely been used for cardiac health assessment, monitoring and diagnosis of pathological conditions. ECG signals are majorly characterized by the location of R–peaks, which appear as sudden discontinuities in the signal. Popular methods to identify the R–peak in QRS rely on adaptive thresholding a filtered or transformed ECG signal. Pertaining to its behavior, this paper presents a new approach to extraction of R–peak in ECG. The proposed method is based on zero frequency filtering (ZFF) of signals, a method proposed to extract the impulse–like excitation in speech signals. The method uses a sharp decaying resonator centered at 0 Hz is used to filter ECG. After a block–wise removal of the trend imparted by the ZFF, locations of the R–peaks are obtained at the positive–to–negative zero crossing locations of the filtered signal. The novelty of the method lies in the fact that it doesn't rely heavily on transforms or adaptive thresholding to derive R–peak locations. We validate the proposed method on the publicly available MIT–BIH Arrhythmia ECG signal database. Our investigations show that the proposed method yields a performance competitive to the state–of–the–art methods.**

***Index Terms*—R–peak identification, zero frequency filtering, trend removal, ECG.**

I. Introduction

Electrocardiography is a popular measure to sense the cardiac health and activity [1], [2]. ECG signals are captured in a non-invasive way using electrodes placed over the skin, and represent the pattern of depolarizing (*P–wave* and *QRS complex*) and re–polarizing (*T–wave*) of heart during each heartbeat. QRS complex is a high gradient transient region which is mostly used to characterize the cardiac functionality. The R–peak in QRS complex appears as a prominent singularity in the contour, which is used towards QRS identification [3].

R–peak identification methods are mostly categorized as time–domain (TD), frequency domain (FD), or more recently using neural networks (NN), owing to their way of localization the discontinuity. The TD– and FD–based methods accentuate the high gradient singular behavior using signal processing methods, such as computing derivative, high–pass filtering, and computing Hilbert envelope, etc. Early work on R–peak identification focused on TD processing of ECG and subjecting thresholds over signal derivative [4], [5]. Signal derivatives, however also resulted in amplification of artifacts, and hence dynamic thresholding and filtering were introduced to filter spurious peaks. Consequently, bandpass filtering, high– and low–pass filtering, notch filtering, median filtering, mostly within a range 0.1–120 Hz were introduced to improve the R–peak identification [6]–[12]. More recently, adaptive filtering methods based on least mean square (LMS) method and its variants have been effective in improving identification accuracy while maintaining low computational complexity [13]–[15].

FD–based methods on the other hand utilize multiscale decomposition of ECG using wavelets to emphasize singular characteristics in ECG. The filtered signals obtained at subsequent detail levels are then subjected to fixed thresholds to localize R–peak [16]–[18]. Wavelets have also been utilized to smooth the irregularities within the detail coefficients obtained from the multi–resolution analysis of ECG, to suppress spurious peaks [19], [20]. Similar work introduces optimal filter design, and implementing bi–orthogonal wavelets for fast R–peak detection in wearable devices [21]–[23]. NN–based approaches have also gained popularity to identify R–peaks, however, more approaches focus on ECG classification based on characteristic morphologies, and abnormality in cardiac pattern [24], [25].

In general, almost all popular methods have reported high ($\sim 100\%$) sensitivity and accuracy towards the task of R–peak identification, while their results primarily depend on using thresholds on filtered signals [10]. The present paper proposes a new method for R–peak identification in ECG, motivated from zero frequency filtering (ZFF), a signal processing method proven effective to identify the excitation components in speech signals [26]. The proposed method exploits the fact that the singular behavior of R–peak in ECG also reflects in its spectral response all frequencies, including 0 Hz. The proposed method filters the preprocessed ECG using a heavily decaying resonator centered at 0 Hz, and after a block mean removal operation, the R–peaks can easily be identified at positive–to–negative zero crossings of the resultant signal. The novelty of the proposed method lies in the fact that it does not depend on thresholding for localizing R–peaks. This paper leverages the ability of ZFF to identify discontinuities, and localizing these based on change of the phase of filtered signal.

The paper is organized as follows: Section II gives a background on the ZFF method. Section III presents the proposed method for the detection of QRS complex. Section IV presents the experimental studies and analysis of errors made in R–peak location detection. Finally, Section VI concludes the paper.

II. Background on zero frequency filtering

The ZFF method was originally proposed to identify the instants of significant excitation in speech signals. Speech is understood as a resultant of an impulse–like excitation, serving as a source, acting on a vocal–tract system component. It is difficult to derive these components from the resultant speech as the characteristics of either of these components are not explicitly known. The ZFF method builds on the understanding that the spectral characteristics of a temporal discontinuity (or impulse behavior) are evenly spread across all bands, including very low frequencies such as in the vicinity of 0 Hz. As the contribution of other elements in the production system is minimal at such low frequencies, the ZFF method filters the signal with a digital resonator centered at 0 Hz, also known as the zero frequency resonator (ZFR), to yield the excitation characteristics. The zero frequency filter is implemented as a cascade of two resonators, each centered at 0 Hz, with a resulting impulse response given by

$$h[n] = s[n] + 2h[n-1] - h[n-2], \tag{1}$$

and the equivalent transfer function is given by,

$$H(z) = \frac{1}{1 - 2z^{-1} + z^{-2}}, \tag{2}$$

where $s[n]$ is the input to the resonator.

The magnitude response of this cascade of resonators exhibits an approximate roll–off of 24 dB per octave, significantly reducing the influence of other components in the spectrum. The signal when filtered using the resonator, which is implemented as an integrator, exhibits a growing trend. The trend is removed using a block mean removal operation given by

$$t(x) = x[n] - \frac{1}{2K+1} \sum_{k=n-K}^{n+K} x[k], \tag{3}$$

where $x[n] = s[n] * h[n]$ is output of the ZFR. The trend removal operation is performed corresponding to each resonator, and hence is done twice in this case. The resultant signal $y[n] = t(t(x))$ reflects the contribution of the impulse–like discontinuity at the positive–to–negative zero crossing points (Z_{PNZ}), depending on impulse polarity. For speech signals, the excitation components exhibit impulses with a negative polarity, and hence their locations are identified at negative–to–positive zero crossing points.An ideal duration of the choice of the trend removal window $(2K+1)$ is maintained between 1.5 and 2.5 times an estimated average fundamental period of the impulses, to identify their locations at Z_{PNZ} in $y[n]$, given by,

$$i \in Z_{PNZ} \,|\{(y[i+1] \cdot y[i]) < 0 \wedge y[i+1] < 0\}, \tag{4}$$

and is identified as the set of locations of impulse or discontinuity in the signal $s[n]$. As explained in the following section, the proposed method derived using the ZFF method, can efficiently extract the R–peak locations in the ECG.

III. Proposed method

The R–peak appears as a discontinuity in the ECG, and this leads to the hypothesis that locations of these transient–like instances can accurately be identified using the ZFF method. This is further complemented by the fact that the QRS complex is a pseudo–periodic phenomena, and hence an approximation of the beat frequency can be utilized as the trend removal window duration in ZFF to extract R–peak location.

Fig. 1 shows an example to illustrate identification of R–peaks in ECG using the proposed method. Fig. 1(a) shows a segment S_1 of the ECG signal obtained from the MIT–BIH database along with the manually annotated R–peaks (- -) locations. Fig. 1(b) shows the processed signal S_{12}, obtained by multiplying S_1 with its derivative S_2, along with annotations. Deriving the signal S_{12} accentuates the singular behavior of the R–peaks. It can be observed that enhancement of R–peaks during the processing step yields a pseudo–periodic signal with positive polarity impulse–like behavior. Fig. 1(c) shows the ZFF signal Y obtained from S_{12}. The Z_{PNZ} locations in Y (- -) can be seen appearing in correspondence to the annotated locations (- -).

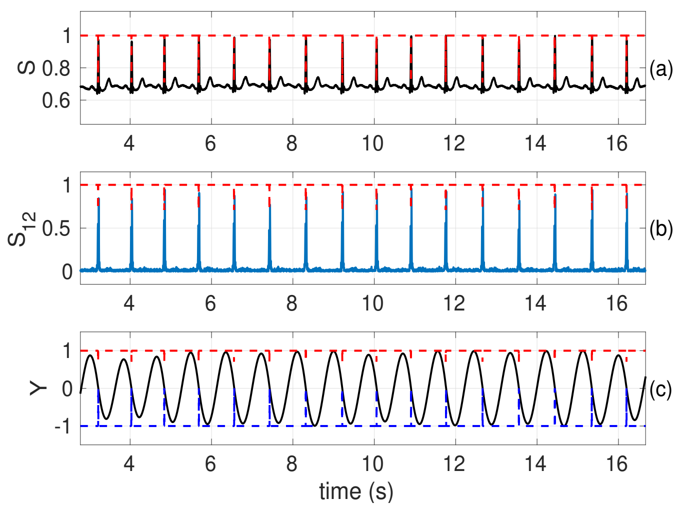

Fig. 1. (a) ECG signal S_1 and (b) S_{12}, with R–peak annotation (−−), (c) ZFF signal Y with Z_{PNZ} (−−) and annotation (−−).

The ZFF method is easy to implement, with filtering and trend–removal being two major computational steps. The resonator characteristics significantly mitigate the effect of interference across spectrum, and capture the periodic impulse–like instances in the signal. For normal cardiac activity, the proposed method does not explicitly depend on other hyper–parameters and loosely relies on the estimate of periodicity of the QRS complex, and hence can be deemed threshold–free. However, for segments in ECG with R–peaks appearing at arrhythmic intervals, the proposed method may occasionally give a false positive within the trend removal duration. To overcome this shortcoming, we propose a dynamic threshold, derived using the slope of ZFF signal at the Z_{PNZ} locations, to validate Z_{PNZ} locations as correct R–peaks. The slope value is used to weigh the running mean computed over S_{12}, which then results in significantly large values at the true positive locations. More precisely, the algorithm to derive R–peaks is given by steps 1–5 in Alg. 1. For cases of arrhythmic episodes in ECG, steps 6–9 can be implemented to avoid false positives and improve accuracy.

Algorithm 1 Algorithm to extract R–peaks in ECG using ZFR

1: First, pre–emphasize the ECG signal (S) to suppress the effect of low frequency noise and biases, and to sharpen the gradient at the R–peak, resulting in S_1.
2: Compute the gradient of S_1, as S_2, and derive the product signal $S_{12} = S_1 \times S_2$.5, and also obtain an estimate of average R–R interval by computing auto correlation of S_{12}.
3: Filter S_{12} through the ZFR, H (in Eqn. 2), to yield signal $X = S_{12} * H$.
4: Apply trend removal as per Eqn. 3 on X by setting K in the range of $[1.5 - 2]$ times the average R–R interval information to obtain ZFF signal Y.
5: Obtain the set of R–peak locations Z_{PNZ} by identifying the PNZ locations in the ZFF signal Y, as per Eqn. 4.
6: Obtain the slope E of Y at locations in Z_{PNZ}.
7: Compute a running mean S_R of S_{12}, using 20 samples window, and weight S_R at Z_{PNZ} with values in E.
8: Convolve S_R with Gaussian window of duration 60 ms.
9: Remove the locations $k \in Z_{PNZ} \mid S_R(k) \leq \delta$; ($\delta = \frac{median\{E\}}{3}$) to eliminate the possible false positives.

IV. Experiments and results

In this section, we present the experimental setup and protocols, evaluation measures, and the results obtained over publicly available benchmarking dataset.

A. Database and experimental protocols

Evaluation of the proposed algorithm for the task of identification of the QRS complex is performed over ECG signals from MIT–BIH database. The database contains clean and noisy signals, with cases of inverted QRS complexes and has regularly been used for evaluation of different methods proposed for R–peak detection. The MIT–BIH Arrhythmia database comprises of 48 half–hour excerpts of two–channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory [27]. The ECG signals are obtained along with different noise sources and non–sinus beats. The recordings are acquired at a sampling rate of 360 Hz, with 11–bit resolution over a 10 mV range. The records were annotated by cardiologists for each beat for all 48 records in the database. Based on the average heart rate of 60–80 beats per minute across all the records, we chose to set the trend removal duration parameter $> 2K + 1$, i.e. 850 samples (2.35 s) for our analysis on these databases (step 4, Algo. 1). Results obtained from the proposed method are compared with TD, FD, NN, and hybrid (HD), methods presented in the literature. Several TD– and FD–based methods employ computation of the Hilbert envelope (HE) of the differenced ECG signal S_2 for highlighting the R–peak behavior. The proposed method is hence evaluated on HE computed upon S_{12}, to compare its efficacy for identifying impulse–like behavior in signals.

B. Evaluation measures

We use two standard performance measures to evaluate the proposed algorithm, namely sensitivity (S_e) and positive predictivity ($+P$). These measures are computed from the true positive (TP), the false positive (FP) and the false negative (FN) counts as follows:

$$S_e(\%) = \frac{TP}{TP + FN} \times 100; \quad +P(\%) = \frac{TP}{TP + FP} \times 100. \tag{5}$$

An R–peak is considered detected correctly if the predicted location falls within a tolerance duration of 60 ms ($\sim$ 20 samples for MIT–BIH) of the annotated beat location. The TP count refers to the number of R–peaks properly detected. FN refers to the number of undetected R–peaks, and FP count refers to false alarms i.e. number of false R–peak locations given by the method.

TABLE I
Performance of different methods on the MIT–BIH database. BPF: bandpass filtering, WT: wavelet transform, Δ : derivative, SWT: Stationary WT

Method	S_e	$+P$
TD		
BPF + Δ [6]	99.78	99.87
Hamming self–convolutional FIR window [11]	99.93	99.95
BPF, Teager energy, and Shannon energy [12]	99.90	99.93
Complete Ensemble Empirical Mode Decomposition (CEEMD) [28]	99.96	99.89
FD		
WT and moving average [29]	99.68	97.24
SWT and adaptive thresholding [16]	99.88	99.84
SWT and Teager energy [18]	99.94	99.97
WT and coefficient multiplication [30]	99.64	99.82
SWT and adaptive thresholding [31]	99.65	99.66
ND		
CNN + RNN [25]	99.91	99.90
HD		
BPF and R–CNN [24]	99.24	99.9
PROPOSED		
Zero frequency filtering (ZFF)	99.68	99.85
ZFF + Hilbert envelope	99.64	99.85

C. Results

Tab. I gives the results obtained for records in the MIT–BIH database. The table also presents a contrast of our results with different methods pertaning to TD–, FD–, NN–, and HD–based methods in the literature. The table also presents results obtained with Hilbert envelope over S_{12}, which appear similar to results obtained using ZFF, This reinstates the efficacy of the method to capture the singular behavior within gradient of ECG. A comparison in the table shows that the proposed method performs consistent with other methods. Given a high positive predictivity, the method does not produce many false positives. The experiments validate the central hypothesis of the proposed method, i.e. the singular characteristics of R–peaks in the ECG signal can analogously be captured by applying ZFF method.

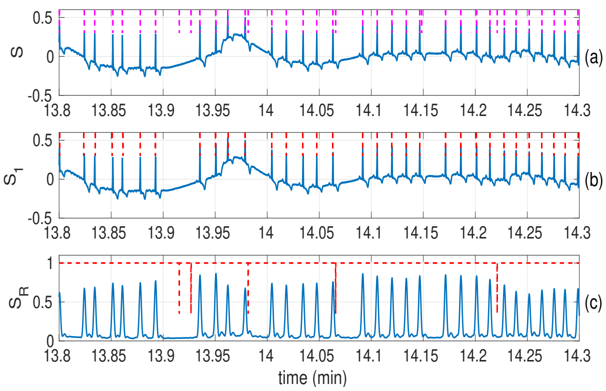

Fig. 2. (a) ECG (Record #219) S with annotation (–). (b) ECG with R–peaks from ZFF(–). (c) S_R with false positives locations (–).

V. Analysis

The section provides analysis of performance of the method in case of arrhythmic beats. The section also gives analysis of performance on ECG data collected from a wearable sensor.

A. *Eliminating false positives in arrhythmia*

As stated in [32], there are arrhythmic records in MIT–BIH database leading to R–peaks occurring at irregular intervals. Implementation of the trend removal over ZFR output X imposes a Z_{PNZ} location across each window duration of $2K + 1$ samples, resulting in erroneous predictions for arrhythmic beats. A way to handle such cases is to use a dynamic threshold derived on S_R, as explained in steps 6–9 in Alg. 1. Fig. 2 shows one such example of record in MIT–BIH database with arrhythmia. The record also contains few spurious annotations where R–peak is absent. The proposed method identifies the false positives based on δ suggested in step 9 in Alg. 1. Figs. 2(a) and 2(b) show the ECG signal with annotated R–peaks (–), and the R–peak locations identified using the proposed method (–), respectively. Fig. 2(c) shows a few locations (–) where the false positives are identified in annotations using the S_R signal. Neither the ECG signal, nor the S_R signal exhibit a R–peak behavior, contrary to the annotations at these locations. The signal doesn't exhibit significant energy content at these locations, similar to sharp peaks at locations corresponding to other R–peaks. The figures show that using a threshold δ over a running mean of gradient weighted ECG signal S_R, the spurious R–peak locations can be eliminated.

B. *Analysis on a wearable sensor*

The study further analyzed the proposed method on ECG collected through wearable sensor SENSE [33]. SENSE is composed of two cooperative sensors, equipped with dry stainless steel electrodes. The ECG acquisition is band–limited between 0.67 Hz and 40 Hz with a $f_s = 321.25$ Hz. The data from 3 participants wearing SENSE and conversing with each other in an office room is collected for about 11 minutes in sitting position, resulting in an overall signal duration 34 minutes. SENSE provides an estimate of R–R interval which is compared with the R–R intervals obtained using the proposed method.

For the sake of completeness, we compared the R–R peak interval duration obtained (i) from the ground truth, (ii) by SENSE based on correlation analysis, and (iii) from R–peak locations yielded by the proposed method. SENSE does not give R–peak locations, hence we create a ground truth for comparison. To reduce the annotation time, we first ran the proposed method to get an hypothesis for R–peak locations. We examined those hypothesized locations and manually annotated the correct R–peak location. Figs. 3(a1)–(c1) present the difference in R–R interval duration obtained from (iii) and (i) (red), for the three participants, respectively. It can be observed that the difference with respect to the ground truth is mostly clustered around 0, indicating a precise estimate. The figures also gives the histogram of difference between (ii) and (i) (blue), showing a larger difference, for all three participants. It is worth noting that SENSE originally has been developed as an aid for sports activity, where there is a trade–off between very precise estimate of R–R peak interval and computation cost.

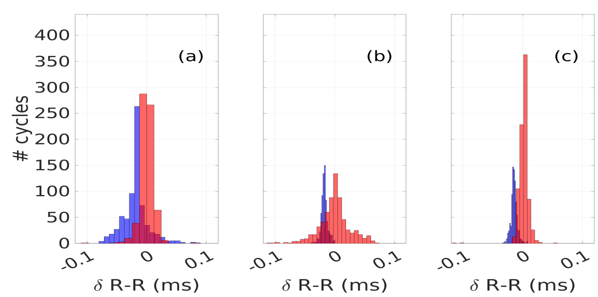

Fig. 3. Comparison of the ground truth R–R duration (in s), with that given by SENSE (blue), and obtained using the proposed method (red), for participants 1, 2, and 3 (a, b, and c), respectively.

VI. Conclusion

The paper proposes a novel method to detect R–peaks by exploiting their singular behavior in ECG. Location of these peaks are obtained at the positive–to–negative zero crossing instants within the signal filtered through the ZFR. The proposed method depends majorly on two hyperparameters: trend removal window duration, and a dynamic threshold based on the strength of the hypothesized R–peaks. These hyperparameters can be set on the fly with basic statistical operations (correlation and median identification) on the data. Hence, the proposed method appears low in computational complexity, and hence is expected to be faster. This however can be investigated across different data and platforms.

ACKNOWLEDGMENT

This work was partially funded by the Swiss National Science Foundation through the project Towards Integrated processing of Physiological and Speech signals (TIPS), grant no. 200021_188754. This work was carried out by the first author during his postdoctoral research at the Idiap Research Institute, Martigny, Switzerland. The authors would like to thank Dr. Olivier Chételat and Dr. Mathieu Lemay from CSEM for their constructive feedback.

REFERENCES

[1] Essam H Houssein, Moataz Kilany, and Aboul Ella Hassanien. Ecg signals classification: a review. *International Journal of Intelligent Engineering Informatics*, 5(4):376–396, 2017.

[2] wenliang zhu, Xiaohe Chen, Yan Wang, and Lirong Wang. Arrhythmia recognition and classification using ecg morphology and segment feature analysis. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 16(1):131–138, 2019.

[3] R Rodríguez, A Mexicano, J Bila, S Cervantes, and R Ponce. Feature extraction of electrocardiogram signals by applying adaptive threshold and principal component analysis. *Journal of applied research and technology*, 13(2):261–269, 2015.

[4] Jiapu Pan and Willis J Tompkins. A real-time QRS detection algorithm. *IEEE Trans. Biomed. Eng*, 32(3):230–236, 1985.

[5] J Fraden and MR Neuman. QRS wave detection. *Medical and Biological Engineering and computing*, 18(2):125–132, 1980.

[6] Mohamed Elgendi. Fast QRS detection with an optimized knowledge-based method: Evaluation on 11 standard ECG databases. *PloS one*, 8(9):e73557, 2013.

[7] Felipe I Donoso, Rosa L Figueroa, Eduardo A Lecannelier, Esteban J Pino, and Alejandro J Rojas. Atrial activity selection for atrial fibrillation ECG recordings. *Computers in biology and medicine*, 43(10):1628–1636, 2013.

[8] Zhancheng Zhang, Jun Dong, Xiaoqing Luo, Kup-Sze Choi, and Xiaojun Wu. Heartbeat classification using disease-specific feature selection. *Computers in Biology and Medicine*, 46:79–89, 2014.

[9] Qiao Li, Cadathur Rajagopalan, and Gari D Clifford. A machine learning approach to multi-level ecg signal quality classification. *Computer methods and programs in biomedicine*, 117(3):435–447, 2014.

[10] Jinkwon Kim and Hangsik Shin. Simple and robust realtime QRS detection algorithm based on spatiotemporal characteristic of the QRS complex. *PloS one*, 11(3):e0150144, 2016.

[11] Amandeep Kaur, Alpana Agarwal, Ravinder Agarwal, and Sanjay Kumar. A novel approach to ecg r-peak detection. *Arabian Journal for Science and Engineering*, 44(8):6679–6691, 2019.

[12] Hamed Beyramienanlou. A robust method to reliable cardiac qrs complex detection based on shannon energy and teager energy operator. *Circuits, Systems, and Signal Processing*, pages 1–13, 2020.

[13] Chacko John Deepu and Yong Lian. A joint qrs detection and data compression scheme for wearable sensors. *IEEE Transactions on Biomedical Engineering*, 62(1):165–175, 2014.

[14] Shweta Jain, Mitul Kumar Ahirwal, Anil Kumar, Varun Bajaj, and GK Singh. QRS detection using adaptive filters: A comparative study. *ISA transactions*, 66:362–375, 2017.

[15] C Venkatesan, P Karthigaikumar, Anand Paul, S Satheeskumaran, and RJIA Kumar. Ecg signal preprocessing and svm classifier-based abnormality detection in remote healthcare applications. *IEEE Access*, 6:9767–9773, 2018.

[16] Vignesh Kalidas and Lakshman Tamil. Real-time qrs detector using stationary wavelet transform for automated ecg analysis. In *2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE)*, pages 457–461. IEEE, 2017.

[17] Mounaim Aqil, Atman Jbari, and Abdennasser Bourouhou. Adaptive ECG wavelet analysis for R-peaks detection. In *2016 International Conference on Electrical and Information Technologies (ICEIT)*, pages 164–167, 2016.

[18] Lahcen El Bouny, Mohammed Khalil, and Abdellah Adib. A wavelet denoising and teager energy operator-based method for automatic qrs complex detection in ecg signal. *Circuits, Systems, and Signal Processing*, 39(10):4943–4979, 2020.

[19] Pooja Sabherwal, Monika Agrawal, and Latika Singh. Automatic detection of the r peaks in single-lead ecg signal. *Circuits, Systems, and Signal Processing*, 36(11):4637–4652, 2017.

[20] Yaprak Eminaga, Adem Coskun, and Izzet Kale. Hybrid IIR/FIR wavelet filter banks for ECG signal denoising. In *IEEE Biomedical Circuits and Systems Conference (BioCAS)*, pages 1–4, 2018.

[21] Yao Zou, Jun Han, Xinqian Weng, and Xiaoyang Zeng. An ultra-low power QRS complex detection algorithm based on down-sampling wavelet transform. *IEEE Signal Processing Letters*, 20(5):515–518, 2013.

[22] Deepak Berwal, Yogendera Kumar, et al. High performance qrs complex detector for wearable ecg systems using multi scaled product with booth multiplier and soft threshold algorithm. In *2015 International Conference on Signal Processing and Communication (ICSC)*, pages 204–209. IEEE, 2015.

[23] Ashish Kumar, Manjeet Kumar, and Rama Komaragiri. Design of a biorthogonal wavelet transform based r-peak detection and data compression scheme for implantable cardiac pacemaker systems. *Journal of medical systems*, 42(6):1–12, 2018.

[24] Hao Yang, Maolin Huang, Zhipeng Cai, Yingjia Yao, and Chengyu Liu. A faster r cnn-based real-time qrs detector. In *2019 Computing in Cardiology (CinC)*, pages Page–1. IEEE, 2019.

[25] Wenjie Cai and Danqin Hu. Qrs complex detection using novel deep learning neural networks. *IEEE Access*, 8:97082–97089, 2020.

[26] K Sri Rama Murty and B Yegnanarayana. Epoch extraction from speech signals. *IEEE Transactions on Audio, Speech, and Language Processing*, 16(8):1602–1613, 2008.

[27] George B Moody and Roger G Mark. The impact of the MIT-BIH arrhythmia database. *IEEE Engineering in Medicine and Biology Magazine*, 20(3):45–50, 2001.

[28] Md Billal Hossain, Syed Khairul Bashar, Allan J Walkey, David D McManus, and Ki H Chon. An accurate qrs complex and p wave detection in ecg signals using complete ensemble empirical mode decomposition with adaptive noise approach. *IEEE Access*, 7:128869–128880, 2019.

[29] SA Chouakri, Fethi Bereksi-Reguig, and Abdelmalik Taleb-Ahmed. QRS complex detection based on multi wavelet packet decomposition. *Applied Mathematics and Computation*, 217(23):9508–9525, 2011.

[30] Zahia Zidelmal, Ahmed Amirou, Mourad Adnane, and Adel Belouchrani. QRS detection based on wavelet coefficients. *Computer methods and programs in biomedicine*, 107(3):490–496, 2012.

[31] Diptangshu Pandit, Li Zhang, Chengyu Liu, Samiran Chattopadhyay, Nauman Aslam, and Chee Peng Lim. A lightweight qrs detector for single lead ecg signals using a max-min difference algorithm. *Computer methods and programs in biomedicine*, 144:61–75, 2017.

[32] M Sabarimalai Manikandan and KP Soman. A novel method for detecting r-peaks in electrocardiogram (ecg) signal. *Biomedical Signal Processing and Control*, 7(2):118–128, 2012.

[33] Gürkan Yilmaz, Pierre Starkov, Mathilde Crettaz, Josias Wacker, and Olivier Chételat. A low-cost USB-compatible electronic stethoscope unit for multi-channel lung sound acquisition. In Jorge Henriques, Nuno Neves, and Paulo de Carvalho, editors, *XV Mediterranean Conference on Medical and Biological Engineering and Computing – MEDICON 2019*, pages 1299–1303, Cham, 2020.