2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Deep Learning-Based Data-Point Precise R-Peak Detection in Single-Lead Electrocardiograms

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Abstract— **Low-cost wearables with capability to record electrocardiograms (ECG) are becoming increasingly available. These wearables typically acquire single-lead ECGs that are mainly used for screening of cardiac arrhythmias such as atrial fibrillation. Most arrhythmias are characteruzed by changes in the RR-interval, hence automatic methods to diagnose arrythmia may utilize R-peak detection. Existing R-peak detection methods are fairly accurate but have limited precision. To enable data-point precise detection of R-peaks, we propose a method that uses a fully convolutional dilated neural network. The network is trained and evaluated with manually annotated R-peaks in a heterogeneous set of ECGs that contain a wide range of cardiac rhythms and acquisition noise. 700 randomly chosen ECGs from the PhysioNet/CinC challenge 2017 were used for training (n=500), validation (n=100) and testing (n=100). The network achieves a precision of 0.910, recall of 0.926, and an F1-score of 0.918 on the test set. Our data-point precise R-peak detector may be important step towards fully automatic cardiac arrhythmia detection.**

Clinical relevance— **This method enables data-point precise detection of R-peaks that provides a basis for detection and characterization of arrhythmias.**

I. INTRODUCTION

Low-cost wearables with capability to record electrocardiograms (ECG) are becoming increasingly available. These wearables typically acquire single-lead ECGs [1]. Even though single-lead ECGs do not share the complexity of information as their clinically used twelve-lead counterparts, they can be used to detect cardiac arrhythmias [2]. Cardiac arrhythmias are common, in particular atrial fibrillation, which has an estimated incident rate of 0.5% - 2% worldwide [3]. Although the majority of cardiac arrhythmias are not life threatening, they have been associated with serious cardiovascular diseases, such as stroke [3]. Smart wearables may extend early detection of arrhythmias in the general population [4], but this would require highly accurate automatic detection algorithms.

Existing automatic methods detect and classify different types of cardiac arrhythmias. These methods rely on detection of features from the ECG signal such as the absence of P-waves, or variability in the RR-interval duration [2], which relies on R-peak detection. Common R-peak detection methods are either filtering-based [5]–[9] or wavelet-based [10]. Filtering-based methods use band-pass or moving average filters in combination with thresholds, such as the increase in voltage on the ECG, to determine the location of the peaks, while the wavelet-based methods use the stationary wavelet transform (SWT) to locate the high frequencies related to the QRS-complex. Generally, these methods perform well, but they may lack robustness against noise or pathology.

Recent deep learning (DL) methods have achieved state-of-the-art performance in multiple ECG analysis tasks [11], [12]. They can learn to recognize patterns from raw data, and thereby achieve high robustness. Several DL-methods were specifically designed for R-peak detection. Vijayarangan et al. [13] employed a regression approach using a U-Net-like 1D convolutional neural network (CNN) for R-peak detection in single lead ECGs. The CNN analyzes the raw ECG data and for each data point it predicts the distance to the nearest R-peak. Performance was evaluated using detection threshold. The detection was considered correct if the distance between the automatically detected and reference R-peak was lower than the predefined distance threshold. Setting the threshold to 75 ms, high performance was reported. However, note that the threshold was set high, given the average QRS-complex duration of $<$ 120 ms [14]. Furthermore, Yu et al. [15] proposed an R-peak detection method for 12-lead ECGs. The method employs two 2D CNNs that analyse image representations of ECGs. The first network extracts bounding boxes around QRS-complexes and those are fed into the second network that draws another bounding box closer around the R-peak. Detection was considered successful if the R-peak was within the final bounding box. Conventional and deep learning-based methods detect R-peaks precisely, but their accuracy is limited, which may hamper performance of downstream tasks.

To overcome these shortcomings, we propose a method that uses a fully convolutional dilated CNN for data-point-precise R-peak detection. In ECG acquisition, the device is occasionally mistakenly rotated, which results in the

978-1-7281-1178-0/21/$31.00 ©2021 IEEE

inverse signal polarity. Hence, prior to R-peak detection we propose an optional detection and correction of the ECG polarity. Our method is extensively evaluated using manually annotated data-point-precise R-peaks and compared against other automatic R-peak detection methods.

II. Data

This study included single lead ECGs from the PhysioNet/CinC Challenge 2017 [16]. The ECGs in this dataset were acquired measured using a Kardia Mobile (AliveCor, USA) device. This is a small wearable that can be attached and connected to a smartphone. It acquires single-lead ECGs by creating a circuit with the user's fingertips. The ECGs are sampled with 16-bit resolution at 300 Hz and have a bandwidth of 0.5 to 40 Hz. The ECGs have an arbitrary signal length varying from 9 to 61 seconds. The database contains 8,528 ECGs from individual patients consisting of four classes: 5,076 normal, 758 atrial fibrillation, 2,415 other abnormalities, and 279 ECGs with extensive noise [16]. From this set we randomly selected 500 ECGs for training, 100 for validation, and a hold-out set of 100 ECGs for final testing. The ECGs in each set were equally balanced based on their class. Several ECGs in the dataset were inverted, due to electrode misplacement, i.e. the device was used upside down. To define a reference standard, a researcher with over two years of experience in ECG analysis manually annotated the R-peaks by placing a point on the peak with data-point precision. Normal R-peaks as well as R-peaks present in abnormalities, such as noise or premature ventricular complex, were annotated. Moreover, inversion of the ECG was recorded.

III. Method

We propose an R-peak detection method that uses a CNN that predicts whether the data-point is at the top of the R-peak. Moreover, we provide an option to correct polarity of an acquired ECG through another CNN that can be used as a prior stage to R-peak detection. Both CNNs are designed such that they process ECGs of arbitrary length as the lengths of an ECG can vary from as short as nine seconds to over 60 seconds. Evaluation of the network is performed using precision, recall, and the F1-score.

A. Polarity detection CNN

The polarity CNN takes an ECG as its input and it outputs a binary class that indicates if polarity is inverted. The CNN consists of six 1D convolutional layers with increased numbers of kernels from 16 up to 64, doubling every two layers. Each convolutional layer is alternated with batch normalization, a leaky rectified linear unit, and 2-sized average pooling. The sixth convolutional block ends with a global average pooling layer to handle arbitrary lengths, and the network ends with a fully connected layer and a sigmoid activation function. If this network detects inverted polarity, the ECG is corrected by negating the signal.

B. R-peak detector CNN

The R-peak-detector CNN takes an ECG as its input and it outputs a binary class per data point to indicate if the data-point is at an R-peak. The CNN employs dilated convolutions that enable a large receptive fields with a limited the number of trainable parameters. The architecture consists of nine 1D convolutional layers with increasing numbers of kernels, starting at 16 increasing with a factor two after every two layers. Each convolutional layer is alternated with batch normalization and throughout the network leaky rectified linear units are used for activation. Dilation factors from 2 to 32 are in convolutional layers 3 to 7, following a pyramidal approach with increasing factors of two for each layer. The two final layers use kernel sizes of 1 to mimic fully connected layers. When processing an ECG the network predicts whether a data-point is at the top of an R-peak. The final output is bounded between 0 and 1 by a sigmoid activation function.

C. Training and implementation details

The method was implemented using Python 3.7 and PyTorch 1.8. To correct possible baseline wander, the ECGs were preprocessed with a first order high-pass Butterworth filter with a cutoff frequency of 2 Hz [17]. Networks were trained in 50.000 iterations with mini-batches of 32 instances. Instances were random segments of 2500 data-points (=8.33 s). The networks were optimised using Adam with default parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$, and a learning rate of 10^{-5} for the polarity CNN and 10^{-3} for the R-peak detection CNN. The polarity CNN was optimised with a binary cross-entropy loss, while the R-peak detection CNN was optimised with the mean squared error. Optimal decision thresholds were chosen based on maximum F1-scores on the validation set.

IV. Results and experiments

Evaluation was performed on the 100 hold-out test ECGs with 3,661 manually annotated R-peaks. We have evaluated R-peak detection with and without polarity correction and compared both methods with other R-peak detection methods.

A. R-peak detection with polarity correction

The polarity detection CNN correctly identified all 15 (out of 100) ECGs with inverted polarity. Two ECGs were incorrectly identified as inverted, likely due to large S-deflections that were present in the ECGs. The polarity detection CNN achieved an accuracy of 0.980, a precision of 0.889, a recall of 1.000, and an F1-score of 0.941.

R-peak detection with the polarity detection stage was trained using only correctly oriented ECGs. The method correctly detected 3,389 of the 3,661 R-peaks. False positive (n=272) and false negative errors (n=336) were predominantly observed in ECGs containing noise. The method achieved a precision of 0.910, recall of 0.926, and an F1-score of 0.918.

B. R-peak detection without polarity correction

To evaluate the importance of polarity detection, R-peak detection was trained without prior polarity detection. For this, during training additional data augmentation was applied: ECG recordings were randomly negated to simulate incorrect acquisition, resulting in a R-peak detector that is robust to ECGs with inverted polarity. The method correctly detected 3,305 of the 3,661 R-peaks. False positive errors (n=421) were predominantly close to detected R-peaks, at deep S-deflections, or in ECGs containing noise. False negatives errors (n=356) were mainly R-peaks surrounded by noise, and in rare occasions where the QRS-complex was widened. The method achieved a precision of 0.887, a recall of 0.903, and an F1-score of 0.895.

C. Comparison with other methods

We compared our method with other commonly used R-peak detectors [18]. Figure 1 illustrates detection performance of all evaluated methods. Given that the PhysioNet 2017 dataset contains four classes of ECGs, we show the peak detection performance for each of these classes. Most R-peak detectors do not provide a data-point precise prediction of the R-peak. Therefore, we evaluated the methods using different detection thresholds. Table I lists the performance of each detector. Our proposed data-point precise R-peak detection method outperforms all other methods for every evaluated detection threshold, with and without polarity correction.

V. Discussion and Conclusion

We presented an R-peak detection method that allows robust data-point precise prediction of R-peaks in single-lead ECGs. The method achieves state-of-the-art results and outperforms commonly used R-peak detectors. An optional polarity detection stage, which employs a CNN to detect incorrectly acquired ECGs, may be used to further improve the results.

Errors of our R-peak detection are predominantly caused by false positive predictions in noise-peaks and false positive predictions close to correctly predicted R-peaks. The occasional false negative predictions were mostly present in variations of morphology in QRS-complexes (wider R-peaks) and errors caused by the ECG polarity CNN. By increasing the variability of ECG pathologies in our training set and by improving the polarity CNN we expect that these issues can be addressed.

Polarity detection achieved high accuracy correctly identifying the polarity in 98 out of 100 ECGs. The two failure cases showed R-peaks followed by a deep negative S-deflection and a positive T-top. Likely, the CNN identified the S-deflection as an R-peak, instead of an S-peak. Unlike conventional methods, our deep learning approach is likely to improve in performance when trained with a larger data set that contains more variability in ECG morphologies.

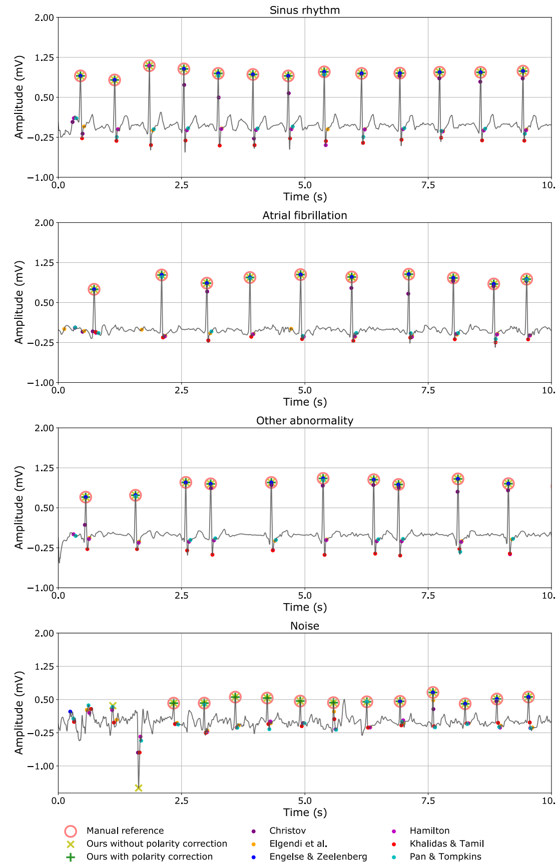

Fig. 1: Peak detection on an ECG for each class for each peak detector.

TABLE I: Results of our proposed R-peak detection with and without a prior polarity correction stage and results of other methods evaluated on the same test set. Performance is evaluated using the F1 score for different detection-thresholds. The highest performances per threshold are indicated with bold font. Note that the method by Kalidas and Tamil [10] did not detect any R-peak with zero tolerance threshold.

	Detection threshold in data-points (1 data-point is 3.33 ms).										
	0	1	2	3	4	5	10	20	30	40	50
Christov [7]	0.129	0.350	0.499	0.583	0.632	0.653	0.708	0.764	0.815	0.836	0.851
Elgendi et al. [9]	0.002	0.012	0.065	0.077	0.079	0.079	0.133	0.399	0.927	0.932	0.940
Engelse & Zeelenberg [8]	0.825	0.825	0.825	0.825	0.825	0.825	0.828	0.840	0.843	0.846	0.849
Hamilton [6]	0.016	0.022	0.023	0.029	0.030	0.031	0.231	0.915	0.944	0.957	0.962
Kalidas & Tamil [10]	0	0.001	0.003	0.011	0.026	0.047	0.883	0.962	0.964	0.967	0.969
Pan & Tompkins [5]	0.006	0.124	0.137	0.137	0.137	0.137	0.194	0.471	0.940	0.955	0.958
Ours w/o polarity corr.	0.895	0.942	0.942	0.942	0.942	0.942	0.969	0.972	0.973	0.973	0.973
Ours with polarity corr.	**0.918**	**0.948**	**0.948**	**0.949**	**0.949**	**0.949**	**0.976**	**0.977**	**0.977**	**0.978**	**0.978**

Our method outperformed common R-peak detectors, especially with strict detection thresholds. This indicates that the strength of our method is its R-peak detection with data-point precision. This feature is especially important in downstream tasks such as arrhythmia detection. For example, during atrial fibrillation the heart rate is often >100 bpm [19] with a highly variable RR-interval of <600 ms, emphasizing the importance of data-point precise detection of R-peaks. Our results show that conventional methods detect R-peaks with less precision, i.e., with thresholds higher than 20 data-points (66.7 ms) that is $>10\%$ of the RR-interval.

Our method may be extended to facilitate such data-point precise measurements of other features in the ECG. As a result it may be a suitable replacement for manual annotation in a variety of clinical and screening tasks. Furthermore, the polarity detection CNN could be trained end-to-end or integrated with the R-peak detection network. Through data-point precise detection of R-peaks, our method may provide a first step towards the development of accurate fully automatic cardiac arrhythmia detection.

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