Ultra-High Frequency ECG Deep-Learning Beat Detector Delivering QRS Onsets and Offsets

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Abstract

Background: *QRS duration is a common measure linked to conduction abnormalities in heart ventricles.*

Aim: *We propose a QRS detector, further able to locate QRS onset and offset in one inference step.*

Method: *A 3-second window from 12 leads of UHF ECG signal (5 kHz) is standardized and processed with the UNet network. The output is an array of QRS probabilities, further processed with probability and distance criterion, allowing us to determine duration and final location of QRSs.*

Results: *The model was trained on 2,250 ECG recordings from the FNUSA-ICRC hospital (Brno, Czechia). The model was tested on 5 different datasets: FNUSA, a dataset from FNKV hospital (Prague, Czechia), and three public datasets (Cipa, Strict LBBB, LUDB). Regarding QRS duration, results showed a mean absolute error of 13.99 ± 4.29 ms between annotated durations and the output of the proposed model. A QRS detection F-score was 0.98 ± 0.01.*

Conclusion: *Our results indicate high QRS detection performance on both spontaneous and paced UHF ECG data. We also showed that QRS detection and duration could be combined in one deep learning algorithm.*

1. Introduction

QRS duration (QRSd) describes the time difference between the start (QRS onset) and end (QRS offset) of ventricular depolarization. A healthy, young population usually has low QRSd, around 70-80 ms, while patients with conduction diseases have QRSd higher than 110 ms. Since the QRSd can be easily read from printed ECG, it is an essential metric for cardiologists.

Our former work showed a deep-learning method for detecting QRS complexes in ultra-high-frequency (UHF-ECG) data [1] as a future enhancement to VDI-vision software [2]. Here, we further extended the previous model to deliver QRS onsets and offsets, allowing QRS detection and measurement of QRS duration in one inference step.

2. Data

In this study, we use two private and three public datasets. The method was trained and validated on the data (N=3,018) from FNUSA hospital (Brno, Czechia), containing 12-lead UHF-ECG signals sampled at 5,000 Hz from 78 healthy and 942 CRT subjects (before and after implantation). The dataset contains recordings with both spontaneous and paced QRSs. A total of 2,250 ECG recordings acquired from 780 subjects were used as a training set; other 768 ECG records (450 spontaneous and 318 paced) acquired from 240 subjects were used as a validation set.

The QRS annotation marks were automatically generated by the previous QRS detector (UHF-Solver software by ISI of the CAS, Brno, Czechia). The duration of the QRS complexes was obtained from an automatic detector based on wavelet transform [3]. This detector was the most accurate in the challenge LBBB Initiative of the ISCE 2018 meeting [4], where a reduced subset of MADIT-CRT data [5] was used.

For cross-database tests, we selected four independent datasets: FNKV (by FNKV hospital, Prague, Czechia), sampled at 5,000 Hz, contains 298 recordings (278 stimulated, 20 spontaneous). FNKV subjects were mostly treated by His bundle or Parahisian stimulation. Annotation marks for QRS complex position were manually prepared using SignalPlant software [6]. We also selected Cipa [7], LUDB [8], Strict LBBB [4] datasets. These datasets contain only records with spontaneous rhythm. The boundaries of the QRS complexes were determined by certified cardiologists by manual inspection of each ECG recording.

The desired output of the network was constructed from QRS annotation marks and QRS duration annotations. Thus, for each recording, we built a rectangular signal representing ongoing ventricular depolarization: samples between QRS onset and offset were set to 1, and all the other samples remained at zero.

Table 1. Datasets for validation (FNUSA) and cross-database tests (FNKV, Cipa, Strict LBBB, LUDB).

Database	Sampling frequency [Hz]	Rhythm	Recordings
FNUSA	5,000	Spont.	450
		Paced	318
FNKV	5,000	Spont.	20
		Paced	278
CIPA	1,000	Spont.	5,749
Strict LBBB	1,000	Spont.	602
LUDB	500	Spont.	200

3. Method

For QRS onset and offset detection, we selected a deep learning model with the Unet architecture [9]. The neural network processes a 12-lead ECG signal with an input window of 3 seconds, meaning the input array size is 12x15,000 (12 leads x 5,000 Hz times 3 seconds).

The output of the network has the same length as the input. For each sample, we receive the probabilities of QRS complex occurrences. The output array has a size of 2x15,000, which represents the probability of QRS/background from which the QRS onset and offset can be further obtained.

3.1. Preprocessing

The model is intended to be used with UHF-ECG data. Therefore, each signal was first resampled to a frequency of 5,000 Hz (if sampling differed) and then standardized using a z-score.

3.2. Neural network architecture

Compared to our previous UNet network architecture for UHF-ECG [1], we use 1D convolutional layers with different hyperparameters (kernel size = 12, stride = 6;5). After each convolutional layer, a 1D batch normalization layer followed by a ReLU activation function and max pooling layer was used. The output of the network is passed through a softmax activation function to produce final QRS probabilities.

3.3. Model training

The model has been trained for 40 epochs, using Adam optimization with a learning rate of 0.0001. A weighted cross-entropy loss function was used due to imbalanced output classes. We used a graphic-processing unit (GPU) with “Compute Unified Device Architecture” (CUDA) for training (GeForce RTX 2080 Ti).

3.4. Postprocessing

The output of the network is an array of QRS probabilities. To obtain the final QRS positions and thus their durations, the output must be post-processed. Segments of the output signal are considered QRS if their probability is higher than 0.7 and their duration is at least 50 ms (empirically determined on a validation FNUSA dataset). If two consecutive QRS complexes have a distance of less than 60 ms, they are combined into a single QRS complex segment. The initial and final 100 ms of the utilized 3s signal segment are not included in the final QRS duration and detection result calculations.

4. Results

The performance of the model on the validation dataset (FNUSA) and the test datasets is summarized in Table 2. Results for the datasets containing spontaneous (Spont.) and paced data are reported separately.

To verify the ability of the model to estimate QRS duration, mean absolute error (MAE), mean error (ME) between annotation and model output and standard deviation of the mean error (STD) were used. We validated the results of QRS detection using the F-score.

Table 2. Results of QRS duration estimation (MAE, ME, STD) and QRS detection (F-score).

Data	Rhythm	MAE [ms]	ME [ms]	STD [ms]	F-score
FNUSA	Spont	8.64	6.22	11.15	99.42
	Paced	20.65	-13.41	12.17	97.59
FNKV	Spont	14.57	-7.51	15.28	98.53
	Paced	19.52	5.65	18.78	97.39
CIPA	Spont	9.40	-7.93	8.04	-
S. LBBB	Spont	12.37	0.28	16.42	-
LUDB	Spont	12.78	0.04	11.46	98.31

Results for QRS duration for the FNKV dataset are reported only for QRS complexes belonging to the major morphological group because annotations were not generated for other groups.

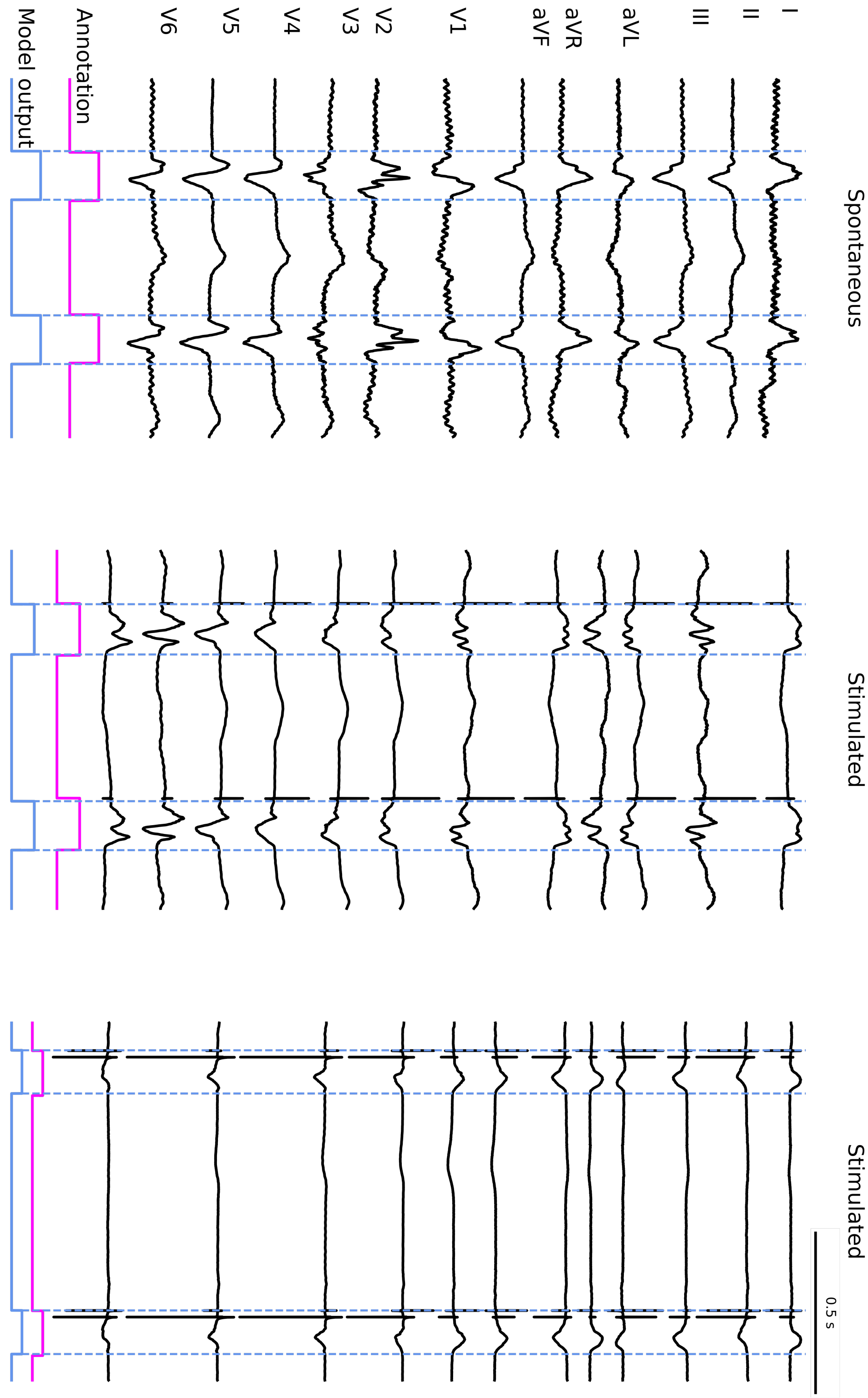

Figure 1. Three examples of network input and output; spontaneous ECG (top) and two different types (middle, bottom) of stimulated ECG. Black curves refer to ECG signals, blue rectangular curves refer to model output and magenta curves refer to annotation marks.

QRS complex detection achieves an average test F-score of 0.98 ± 0.01; QRS duration achieves an average MAE of 13.99 ± 4.29 ms between the annotated durations and the output of the algorithm. We could not test QRS detection performance on CIPA and Strict LBBB datasets since they contain only a single averaged shape.

5. Discussion

The results of the proposed deep learning model for QRS detection were compared with our previous work on a test database from FNKV [1]. The new model performs slightly better (F-score of 98.53% for spontaneous and 97.39% for paced QRSs) than our previous solution for QRS detection (F-score of 97.30% for spontaneous and 97.25% for paced QRSs). The difference from the previous architecture is in the size of the kernels of the convolutional layers. More importantly, it differs in the size of the annotation "rectangle," which forms a signal that a model is trained to produce (Fig1, blue signal). These rectangles are no longer of a fixed duration of 10 ms; their size corresponds to the QRS duration of the associated ECG recording.

Regarding the QRS duration, we obtained an average MAE of 13.99 ± 4.29 ms across all datasets. The results of our model on the Strict LBBB database (12.78 ± 11.46 ms) were compared with a publicly available wavelet transform-based algorithm (9.80 ± 7.8 ms) [3]. Our model shows worse performance on Strict LBBB data. However, the presented algorithm was trained on the FNUSA dataset, and Strict LBBB data were used as an unseen, cross-database test. This contrasts with the compared algorithm [3], which used a public part of Strict LBBB data for training and, furthermore, it reports QRS duration performance on the same - training - data.

6. Conclusion

In this study, we presented a deep learning algorithm for QRS detection, focusing on its onset and offset and thus delivering the QRS duration in a single inference step. Furthermore, our results showed that although we brought new functionality to the QRS detector, we also improved its detection F-score. The presented model will be considered for implementation in future versions of VDI-vision software [2] for real-time UHF-ECG analysis.

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