A Comparison of Graph- and AI-based R-peak Detection on Long-Term (Continuous) Electrocardiogram Recordings

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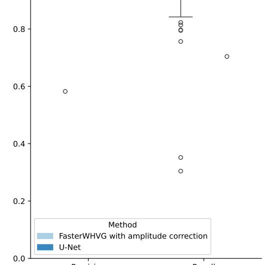
Background: Detecting QRS in long-duration electrocardiogram (ECG) recordings is essential for evaluating heart rate variability and identifying cardiac conditions. However, continuous ECG signals from wearable devices can contain amplitude fluctuations, due to motion artifacts and electrode displacement, strongly affecting the performance of QRS detection. **Objectives:** To address these challenges, we conducted a comparative evaluation of two QRS detection algorithms: FastWHVG, a graph-based algorithm using weighted horizontal visibility graphs, with amplitude correction and U-Net, a convolutional encoder–decoder deep learning architecture for ECG segmentation. **Methods:** This study utilized a dataset comprising 98 multiday recordings from an ongoing clinical cohort, acquired using a commercially available single-lead wearable device (Vivalink, CA, USA) with a sampling rate of 128 Hz and 1μV amplitude resolution. Median duration of the recordings was 4.96 days for a total duration of 486 days. The FastWHVG amplitude correction was addressed by disregarding signal values exceeding ± 5 mV. The U-Net algorithm was trained on 40 recordings from the dataset, and both algorithms were evaluated on the remaining 58 recordings (276 days). **Results:** FastWHVG achieved median precision of 0.98 [IQR: 0.97, 1.00] and recall of 0.93 [IQR: 0.90, 0.97], whereas the U-Net reached median precision of 0.99 [IQR: 0.99, 0.99] and recall of 0.98 [IQR: 0.97, 0.99]. The results showed improved recall of U-Net with statistical significance $p < 0.05$ assessed using Wilcoxon rank test, whereas improved precision without statistical significance. **Conclusion:** U-Net, trained and tested on partitions of the same dataset, reflects within-dataset generalization but may be sensitive to sampling rate and device differences. FastWHVG is training-independent and computationally cheaper but remains affected by large amplitude oscillations that degrade performance even after correction.



Precision and Recall for FastWHVG with amplitude correction and U-Net