QRS complex detection

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Abstract—**In this work, we present an implementation of a QRS complex detection algorithm based on the method proposed by Ding et al. [1]. We focus on optimizing the detection process by avoiding arbitrary parameter values, using a grid search to determine the optimal parameters for filtering across the dataset. The algorithm first preprocesses the ECG signal through baseline removal and peak detection using a Haar-like filter. It then refines peak candidates through adaptive thresholds and a variation ratio test to distinguish true R-wave peaks from noise. We evaluated the performance using sensitivity, positive prediction, and detection error rate metrics. While the algorithm shows promising results, the differences in performance across various parameter settings were minimal, suggesting that the initial detection was already highly accurate. However, our results did not fully match the performance reported by Ding et al., likely due to unspecified parameter values in their work.**

I. Introduction

QRS complex detection is a key area of research in the medical field, with many important uses in healthcare and health monitoring. Detecting the QRS complex—the main feature in an electrocardiogram (ECG) signal—is crucial for tasks like measuring heart rate, identifying irregular heart rhythms, and supporting wearable health devices. Nowadays, heartbeat detectors are found in many everyday gadgets, including smartwatches, fitness trackers, and even some rings.

In this report, we explain how we implemented the QRS detection method proposed by Ding et al. [1] and attempted to further optimize it, mainly by avoiding arbitrary parameter values (for each video) and applying grid search for finding the best-fitting parameters for filtering across the entire dataset.

II. Methodology

Data

We evaluated the implementation on the MIT-BIH arrhytmia dataset [2], composed of 48 half-hour ECG recordings obtained from 47 subjects. The recordings were sampled at 360Hz.

Experiments

As outlined in the introduction, we followed the methodology proposed by Ding et al. [1], which consists of multiple steps.

The first step involved baseline removal. We applied a third-order high-pass Butterworth filter with a cutoff frequency of 0.6 Hz to eliminate low-frequency offsets. This preprocessing step reduced long-term fluctuations, allowing peaks to align more accurately for detection.

The second step focused on peak detection using a Haar-like filter, designed to approximate the shape of an R-wave. Following the specifications in the paper, we constructed and applied the filter to the signal via convolution. The resulting filtered and delayed signal was zero-padded at the beginning to preserve alignment with the labels. This filter generated scores representing the confidence of an R-wave peak at each point. To enhance peak identification and reduce noise sensitivity, we also computed the second-order differences, which quantified the sharpness of signal changes and provided an additional criterion for detecting peaks.

Next step of the first phase was computing the actual scores, which was done by adding weighted second-order difference values to haar-filtered signal values, where the weight constant was 0.55. The goal of this score is to efficiently and accurately sift through potential candidates, prioritizing those with the highest likelihood of being true R-wave peaks.

Lastly, we performed R-wave peak sifting. Instead of using an arbitrary global threshold as described in the paper, we determined the threshold dynamically based on the 80th percentile of the score values. To ensure robustness, we also set a minimum threshold of 0.1. Following this, we enforced an interval constraint to avoid detecting peaks that were too close together (e.g., less than 0.2 seconds apart, corresponding to a heart rate above 300 bpm). This was achieved by identifying the local maxima within each such interval across the recording.

The second phase performs candidate refinement, where additional constraints are used to filter out the peak candidates. The refinement process improves R-wave peak detection by applying adaptive thresholds and a variation ratio test to filter candidates. The adaptive threshold dynamically adjusts based on recent signal strength (using the 5th largest score value from the last 10 seconds) and the regularity of RR intervals, lowering the threshold for expected peaks and raising it for irregular intervals. To handle cases like premature contractions or atrial

fibrillation, the algorithm recalculates intervals or de-emphasizes predictions when necessary. After thresholding, the variation ratio test further validates peaks, distinguishing genuine R-waves from noise. Our implementation enhances this by using a fall-back method where if the 5-th largest score does not exist we use the mean. The result of this filtering is shown on Figure 1.
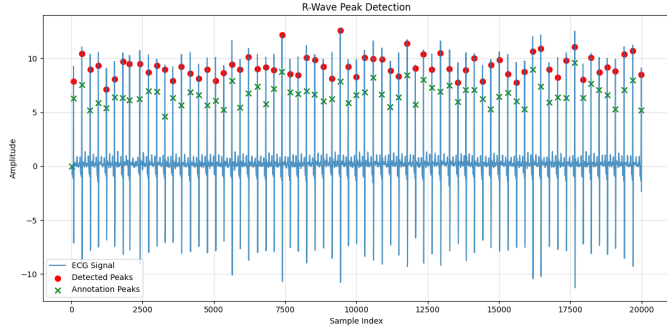

Fig. 1. Refined peak candidates and peak annotations on a sample of a recording.

The final filtering step was applying the variation ratio test, which aims to remove noise-induced peaks in the R-wave detection process without relying on computationally expensive lowpass or bandpass filters. Instead, it uses a simple metric, the variation ratio Ω computed within a region around each candidate peak. The test calculates the ratio between the peak-to-peak variation u_1 and the total variation u_2 in the defined window. True R-wave peaks typically have an Ω 0.5, as u_1 and u_2 are comparable, while noise-induced peaks show much smaller Ω values due to disproportionately high total variation. Peaks with Ω values below a threshold are rejected as noise.

Lastly we applied a grid search to find the best parameters T, $\beta 1$ and $\beta 2$ for the refined peak candidate selection described in the second step, which are used for computing the adaptive threshold.

III. Results and Discussion

We evaluated our implementation using sensitivity (SE), positive prediction (+P) and detection error rate (DER) metrics. When computing the metrics we allowed our predictions to be misaligned with labels by 10 samples. The optimal parameters, their corresponding mean scores and standard deviations are shown in Table I. However, a closer analysis revealed that the differences between parameter values were minimal, which is also clearly visible from Figure 2, indicating that the initial peak detection was already highly accurate. As a result, the sifting process only had a significant impact when the parameters were set too high, potentially degrading the results.

When analysing performance given a certain parameter value set, we noticed that performance fluctuates a lot, also suggested by relatively high standard deviations shown

in Table I, across different recordings, which seemingly corresponds to the recordings with less clear ECG waves.
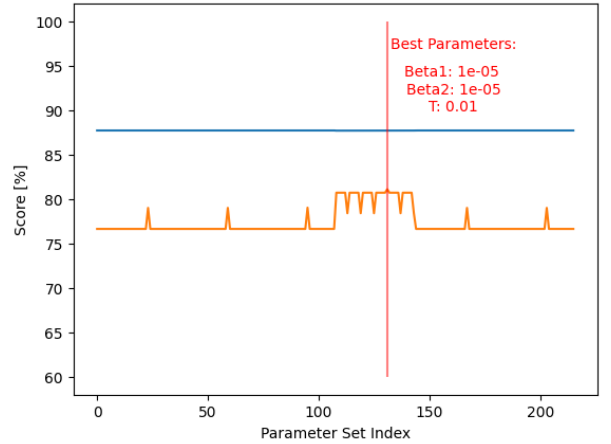

Fig. 2. Parameter value sets vs. mean scores.

The final results are still not comparable to the results reported in the paper, however the values authors used for the parameters are not specified, and the quality of reported results are dubious, since we ran the experiment on the same dataset and used grid search to ensure best parameter values.

TABLE I
Best parameters and corresponding scores.

Parameters	T	$\beta 1$	$\beta 2$
Ours	0.01	0.00001	0.00001
Ding et al.	N/A	N/A	N/A

Results	Mean SE	Mean +P	Mean DER
Ours	0.877±0.21	0.766±0.16	0.460±0.49
Ding et al.	0.999	0.999	0.189

References

[1] J.-J. Ding, C.-W. Huang, Y.-L. Ho, C.-S. Hung, Y.-H. Lin, and Y.-H. Chen, "An efficient selection, scoring, and variation ratio test algorithm for ecg r-wave peak detection," *Experimental and Clinical Cardiology*, vol. 20, pp. 4256–4263, 01 2014.

[2] G. B. Moody and R. G. Mark, "The impact of the mit-bih arrhythmia database," *IEEE Engineering in Medicine and Biology*, vol. 20, no. 3, pp. 45–50, May-June 2001.