Biomedical Signal and Image Processing Lab Assignment 1 - QRS Complex Detection

Maj Bregar
Faculty of Computer and Information Science
Večna pot 113, 1000 Ljubljana
Email: mb95331@student.uni-lj.si

***Abstract*—This report evaluates the Ligtenberg–Kunt QRS detector and introduces lightweight modifications to improve its performance on noisy ECG recordings. Testing on the MIT-BIH and LTST databases shows that the original algorithm struggles with rapid amplitude variations. The report proposes a refractory period, a faster-adapting threshold, and a different 5-point derivative operator, which substantially increase sensitivity and positive predictivity while preserving computational efficiency.**

I. Introduction

QRS detection refers to identifying the precise location of the dominant R-peak to enable reliable ECG analysis. The task of this laboratory assignment was to implement a known QRS detector, evaluate it on the LTST and MIT-BIH databases, and address its weaknesses.

For this purpose we selected the Ligtenberg–Kunt detector as described in [1]. This report outlines its detection pipeline, analyzes its strengths and limitations, and presents improvements together with a comparative evaluation of the original and enhanced algorithms on both ECG databases.

II. Original Algorithm Methods

The Robust-Digital Ligtenberg–Kunt QRS algorithm is a computationally inexpensive detector capable of running online, requiring only current and past local information. Developed in the early 80s, it relies on simple mathematical operations suitable for limited hardware.

The algorithm consists of five sequential processing stages, each transforming the ECG signal into a representation where QRS complexes become progressively easier to identify.

A. Noise Filter

The noise filter removes baseline drift, powerline interference, and transient artifacts using a simple band-pass structure composed of two parallel branches. Each branch contains two cascaded moving-average filters, enabling efficient recursive implementation. The filter output *y(k)* is computed as in (1), where *x(n)* is the input ECG sample and *K* and *L* define the short and long averaging windows.

$$y(k) = \frac{1}{K^2} \sum_{\substack{m=k\\-K+1}}^{k} \sum_{\substack{n=m\\-K+1}}^{m} x(n) - \frac{1}{L^2} \sum_{\substack{m=k\\-L+1}}^{k} \sum_{\substack{n=m\\-L+1}}^{m} x(n) \quad (1)$$

B. Differentiator

The differentiator emphasizes the steep slopes of the filtered QRS complex while suppressing high-frequency noise. Instead of an ideal differentiator, the algorithm uses a band-limited finite-difference operator defined in (2).

$$y(k) = \frac{-x(k+2) - 2\,x(k+1) + 2\,x(k-1) + x(k-2)}{3} \quad (2)$$

C. Energy Collector

The energy collector enhances the prominence of the QRS complex by combining nonlinear amplification with temporal integration. The input differentiated signal is first squared as in (3), emphasizing large-amplitude components, and then passed through a moving-average integrator of length *N*, shown in (4), which accumulates energy over the typical QRS duration.

$$y_a(k) = \big(x(k)\big)^2 \quad (3)$$

$$y(k) = \sum_{n=k-N+1}^{k} y_a(n) \quad (4)$$

D. Adaptive Minimum Distance Classifier

The adaptive minimum-distance classifier determines which detected energy peaks correspond to true QRS complexes. For each sample *k*, a local window $\mathcal{W}_k$ defined in (5) is scanned to locate global maxima according to the peak condition in (6).

$$\mathcal{W}_k = \{\, y(n) \mid n = k-h, \ldots, k+h \,\}, \qquad h = \left\lfloor \frac{W}{2} \right\rfloor \quad (5)$$

$$k \text{ is a peak} \iff \begin{array}{l} y(k) = \max\limits_{n \in \mathcal{W}_k} y(n) \\ \text{and } \big|\{n \in \mathcal{W}_k : y(n) = y(k)\}\big| = 1 \end{array} \quad (6)$$

Each peak intensity $y(k)$ is compared to the current class means μ_{QRS} and $\overline{\mu_{\mathrm{QRS}}}$ and assigned to the closer class, as expressed in (7).

$$\text{peak } k \text{ is QRS} \iff |y(k) - \mu_{\mathrm{QRS}}| < |y(k) - \overline{\mu_{\mathrm{QRS}}}| \quad (7)$$

After classification, the class means are updated using the recursive rules in (8) and (9), allowing the system to track slow morphological changes in QRS amplitude.

$$\mu_{\mathrm{QRS}} := 0.1\, y(k) + 0.9\, \mu_{\mathrm{QRS}} \quad (8)$$

$$\overline{\mu_{\mathrm{QRS}}} := 0.1\, y(k) + 0.9\, \overline{\mu_{\mathrm{QRS}}} \tag{9}$$

The initial class means are computed from the first 2 seconds of the signal, where μ_{QRS} is set to the maximum value and $\overline{\mu_{\mathrm{QRS}}}$ to the minimum.

E. Minimax Searcher

The minimax searcher refines the localization of the R and S points once a QRS complex has been identified by the classifier. For each detected index k, the nearest zero-crossings of the derivative signal $d(x)$ are determined using (10) and (11).

$$c_{\mathrm{L}}(k) = \max \left\{ c \;\middle|\; \begin{array}{l} \mathrm{sign}\big(d(c)\big) \neq \mathrm{sign}\big(d(c-1)\big), \\ c < k \end{array} \right\} \tag{10}$$

$$c_{\mathrm{R}}(k) = \min \left\{ c \;\middle|\; \begin{array}{l} \mathrm{sign}\big(d(c)\big) \neq \mathrm{sign}\big(d(c+1)\big), \\ c > k \end{array} \right\} \tag{11}$$

These zero-crossings define the region in which the R-peaks occur. Within this interval, the R-peak position is obtained by selecting the maximum of the raw signal $x(c)$ as in (12).

$$R(k) = \arg \max_{c_{\mathrm{L}}(k) \leq c \leq c_{\mathrm{R}}(k)} x(c) \tag{12}$$

F. Detector Strengths and Weaknesses

The main strength of the Ligtenberg–Kunt detector is its lightweight implementation, enabling deployment on even the smallest microcontrollers.

Its primary weakness appears in signals where QRS amplitudes change rapidly. The adaptive minimum-distance classifier cannot update its reference values fast enough, causing thresholds to lag behind the true signal. When amplitudes drop, true beats are missed, when amplitudes rise or noise spikes occur, false detections increase. This leads to reduced sensitivity and lower positive predictivity in segments with abrupt or frequent amplitude shifts.

III. Improvements

The simplicity of the original algorithm allows several lightweight modifications that improve noise rejection and threshold adaptability.

To suppress energy waves occurring after the R-peak, we introduce a 200 ms refractory period inspired by the Pan–Tompkins detector [2]. Any peak detected within this interval is ignored, which substantially improves positive predictivity on noisy signals.

A second improvement is a refined thresholding strategy. The class estimates are updated with a slightly higher weight on the current peak value, as shown in (13) and (14).

$$\mu_{\mathrm{QRS}} := 0.125\, y(k) + 0.875\, \mu_{\mathrm{QRS}} \tag{13}$$

$$\overline{\mu_{\mathrm{QRS}}} := 0.125\, y(k) + 0.875\, \overline{\mu_{\mathrm{QRS}}} \tag{14}$$

For classification, we compute a separate adaptive threshold based on the distance between these estimates (15).

$$\mathrm{T} := \overline{\mu_{\mathrm{QRS}}} + 0.15\, (\mu_{\mathrm{QRS}} - \overline{\mu_{\mathrm{QRS}}}) \tag{15}$$

This approach adds no computational cost while allowing the threshold to react more rapidly. The coefficient in (15) controls the trade-off between sensitivity (*Se*) and positive predictivity (*+P*).

Finally, we improve sensitivity by replacing the original derivative with a more accurate 5-point central difference operator, shown in (16).

$$y(k) = \frac{-\,x(k+2) + 8\,x(k+1) - 8\,x(k-1) + x(k-2)}{12} \tag{16}$$

Since this provides a sharper and more stable slope estimate, the minimax search step no longer contributes additional precision and is therefore removed.

IV. Evaluation and Results

We evaluated both the original Ligtenberg–Kunt algorithm and our improved version on the MIT-BIH Arrhythmia Database (*MIT-BIH*) and the Long-Term ST Database (*LTST*). On MIT-BIH, the original method achieved a gross sensitivity of *91.17%* and a positive predictivity of *97.80%*, but its performance dropped sharply on noisy records such as 104, 106, and 228, where sensitivity fell as low as *14.15%* and positive predictivity as low as *59.51%*.

The improved detector is substantially more robust, reaching overall gross scores of *99.67%* (Se) and *99.43%* (+P). A similar improvement is observed on the LTST database, where sensitivity increases from *81.47%* to *98.89%*.

Algorithm Version	**Database**	**Se (%)**	**+P (%)**
Original	MIT-BIH	91.17	97.80
Improved	MIT-BIH	99.67	99.43
Original	LTST	81.47	97.42
Improved	LTST	98.89	97.83

TABLE I: Gross *Se* and *+P* of the original and improved algorithms on both ECG databases.

V. Discussion

This report shows that a simple QRS detector like the Ligtenberg–Kunt algorithm can achieve competitive performance with a few targeted upgrades. Adding a refractory period, a faster-adapting threshold, and an improved derivative operator noticeably increased robustness to noise and signal variability while retaining low computational cost.

Further improvements for this algorithm could include incorporating searchback peak recovery and T-wave discrimination strategies used in more advanced detectors such as Pan–Tompkins. Additional upgrades could draw on established techniques like dual-threshold adaptation, multi-lead fusion for recovering ambiguous beats, and stronger baseline preprocessing to stabilize detection in low-amplitude or noisy segments.

References

[1] A. Ligtenberg and M. Kunt, "A robust-digital qrs-detection algorithm for arrhythmia monitoring," *Computers and Biomedical Research*, vol. 16, no. 3, pp. 273–286, 1983.

[2] J. PAN and W. J. TOMPKINS, "A real-time qrs detection algorithm," *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, vol. 32, no. 3, 1985.