Implementation of a Robust-Digital QRS-Detection Algorithm for Arrhythmia Monitoring

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***Abstract*—In this project, we implemented a robust digital QRS-detection algorithm based on the method by Lindenberg and Kunt for arrhythmia monitoring. The algorithm was used to detect QRS complexes and extract R peaks. In addition, we introduced improvements to the original algorithm.**

I. Introduction

The analysis of electrocardiogram (ECG) signals is fundamental to diagnosing and monitoring cardiac arrhythmias. Among the key features in ECG signals are QRS complexes, which represent ventricular depolarization and provide critical information about heart rhythm and electrical activity. Accurate detection of QRS complexes is essential for automated arrhythmia detection and other cardiac studies.

This project focuses on the task of heartbeat detection, specifically the detection of QRS complexes, using the algorithm proposed by Lindenberg and Kunt [1]. The algorithm was implemented and tested on datasets from the MIT/BIH Arrhythmia Database [2]–[4] and the Long-Term ST Database [4]–[6]. In addition to implementing and testing the original algorithm, we identify its weaknesses and propose enhancements to address these limitations. These improvements are further tested on the same datasets to evaluate their effectiveness.

II. Methodology

The methodology of this project involved the implementation of a QRS detection algorithm based on the approach described by Lindenberg and Kunt. The algorithm was implemented in MATLAB. In the following, the key steps of the methodology are outlined.

A. Signal Preprocessing

The preprocessing steps, including resampling and converting the files to MAT format for MATLAB, were performed using the WFDB tools [4] before loading the ECG signals and isolating individual channels for subsequent analysis. To ensure consistency, the input signals were standardized using a sampling frequency of 250 Hz, as specified in the original paper.

B. Noise Filtering

To reduce noise and improve signal clarity, a noise-filtering process was applied. This consisted of a dual moving average approach to mitigate low-frequency drifts and high-frequency noise. A short-term moving average emphasized sharp changes in the signal, such as QRS complexes, while a long-term moving average accounted for slow fluctuations. The difference between these averages provided a cleaner signal for subsequent steps.

C. Band-Limited Differentiation

A band-limited differentiator was used to enhance the steep slopes characteristic of QRS complexes. This step involved applying a convolution operation with an impulse response derived from the original algorithm. The result was a differentiated signal highlighting rapid changes, aiding in the detection of QRS complexes.

D. Energy Collection

The differentiated signal was squared to emphasize peaks corresponding to QRS complexes. A moving average integrator was then used to smooth the squared signal, creating an energy profile that facilitated the separation of QRS complexes from noise.

E. Adaptive Classification

An adaptive minimum distance classifier was employed to detect QRS complexes based on the energy profile. Initial estimates for QRS and non-QRS cluster means were calculated from the first two seconds of the signal. The classifier then iteratively updated these cluster means as it processed the signal.

F. Peak Refinement

The final step in the algorithm involved refining the detected QRS locations through a minimax search. This process identified zero crossings in the differentiated signal near the detected QRS indices and isolated segments containing potential R peaks. The precise location of each R peak was determined by finding the maximum value within these segments. Following this refinement, the evaluations were performed.

III. Results

The algorithm was initially tested on the MIT/BIH Arrhythmia Database, which consists of 48 30-minute ECG recordings. The results, summarized in Table I, present the gross and average results using the original algorithm on the MIT-BIH Arrhythmia Database. The table includes sensitivity (the proportion of true positives correctly identified) and positive predictivity (the proportion of positive predictions that are correct).

TABLE I
Summary of Gross and Average Results Using the Original Algorithm on the MIT-BIH Arrhythmia Database

	Sensitivity [%]	Positive Predictivity [%]
Gross	92.33	77.52
Average	92.42	80.38

Additionally, the original algorithm was tested on the Long-Term ST Database (LTSDB), which contains 86 24-hour long ECG recordings. The results for this dataset are summarized in Table II, which provides similar metrics for sensitivity and positive predictivity on the LTSDB recordings.

TABLE II
Summary of Gross and Average Results Using the Original Algorithm on the Long-Term ST Database (LTSDB)

	Sensitivity [%]	Positive Predictivity [%]
Gross	83.70	75.82
Average	83.75	75.40

The evaluation of the original algorithm revealed limitations in its sensitivity and positive predictivity, indicating room for improvement. One of the primary issues was its susceptibility to noise in the ECG signals, which significantly impacted its performance. The algorithm struggled to distinguish between true cardiac events and noise artifacts, leading to reduced accuracy in detecting. This highlights the need for more robust noise-handling techniques to improve its reliability and overall performance.

A. Improvements

To address the limitations of the original algorithm, we implemented several improvements to enhance its performance.

First, we focused on refining the minimax searcher to improve the detection of the R-peaks. The original searcher was modified to better locate the exact R-peaks within a specified window around each detected QRS index. The updated MiniMax searcher performs a more precise search for the R-peak by examining a segment of the ECG signal centered on each QRS index and selecting the maximum value within that window. This refinement reduces the likelihood of missing or incorrectly identifying the R-peaks, ensuring more accurate results.

Additionally, we introduced adaptive thresholding to eliminate false QRS indices that were incorrectly detected due to noise. The adaptive threshold was set as a fraction of the maximum signal amplitude, with a sensitivity adjustment through the threshold fraction parameter. By applying this technique, we filtered out indices where the signal amplitude was below a predefined threshold, thereby removing spurious detections caused by noise or artifacts in the ECG signal.

TABLE III
Summary of Gross and Average Results Using the Improved Algorithm on the MIT-BIH Arrhythmia Database

	Sensitivity [%]	Positive Predictivity [%]
Gross	80.56	97.30
Average	80.11	96.44

TABLE IV
Summary of Gross and Average Results Using the Improved Algorithm on the Long-Term ST Database (LTSDB)

	Sensitivity [%]	Positive Predictivity [%]
Gross	75.00	93.73
Average	75.07	87.95

The results of the improvements made to the algorithm are summarized in Tables III and IV, which present the performance on the MIT-BIH Arrhythmia Database and the Long-Term ST Database (LTSDB), respectively. As shown in these tables, the sensitivity of the improved algorithm did decrease slightly compared to the original. However, the positive predictivity showed a significant improvement.

IV. Discussion

In this project, we implemented and improved a QRS detection algorithm for arrhythmia monitoring based on the method proposed by Lindenberg and Kunt. The original algorithm was tested on the MIT-BIH Arrhythmia Database and the Long-Term ST Database (LTSDB), where it demonstrated satisfactory performance but also revealed limitations in terms of sensitivity and positive predictivity. To address these shortcomings, we introduced two main improvements: refining the minimax searcher for more precise detection of R-peaks and incorporating adaptive thresholding to reduce false QRS detections caused by noise. These changes led to an increase in positive predictivity, which is particularly important for minimizing false positives, a key consideration in clinical applications where reducing false alarms is crucial.

Despite these improvements, the algorithm is still not perfect. While the reduced false positives are beneficial, the drop in sensitivity suggests there is room for further optimization. Future improvements could include exploring

more dynamic thresholding methods that adapt to varying signal conditions or enhancing the minimax searcher by dynamically adjusting the window size based on the characteristics of the detected QRS complex. These additional refinements would likely improve both the sensitivity and reliability of the algorithm, making it more robust for real-world ECG signal analysis.

References

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