A Moving Average based Filtering System with its Application to Real-time QRS Detection

Jovan Prodanov (63180376)

Abstract

This report introduces a Moving Average based Filtering System for real-time QRS detection in ECG signals. By combining linear and nonlinear filters, the system enhances the identification of QRS complexes amidst noisy signals. Using data from different databases demonstrates an average precision of 99.54% and sensitivity of 97.91% across 89 records. These results highlight the system's effectiveness in heartbeat detection, crucial for robust heart health monitoring.

1 Introduction

Identifying QRS complexes in ECG signals is vital for heart health analysis. However, noisy signals often make this challenging. This project uses a Moving Average Filter [1], this filter helps clean up the signals, making it easier to spot QRS complexes accurately and in real-time.

This report explains how this filter works and demonstrates its benefits through experiments. The main idea is to enhance the accuracy of detecting heartbeats in noisy conditions, which could greatly improve heart health monitoring.

2 Methods

2.1 Data

This project utilizes datasets from two key resources: the Long Term ST Database [2] and the MIT-BIH Arrhythmia Database [3], using approximately 89 records from these sources (1). The Long Term ST Database aids in evaluating ischaemia detectors and studying myocardial ischaemia dynamics. The MIT-BIH Arrhythmia Database offers crucial insights into arrhythmias. By combining these databases, it is to gain a comprehensive understanding of QRS complexes, enabling the development of accurate detection methods.

2.2 Linear high pass filter

The linear high-pass filter works by subtracting a moving average filter (MAF) output from the input signal. It uses a moving average filter with an odd-sized window of length M to smooth the input signal and isolates high-frequency components by subtracting the smoothed signal from the original.

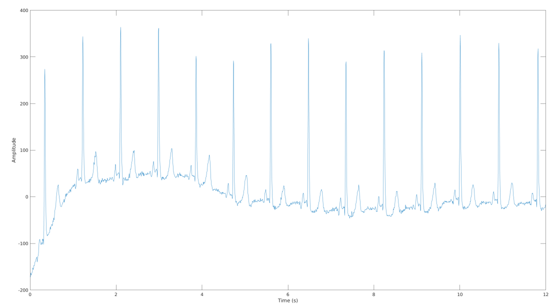

Figure 1: Example signal

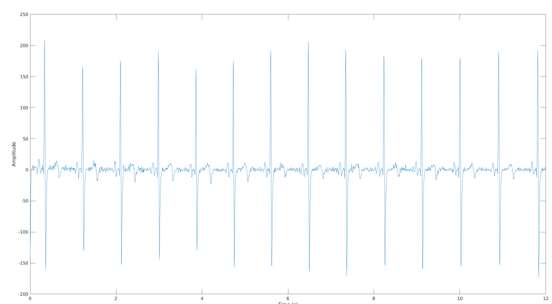

Figure 2: Filtered signal with LHPF (Linear high pass filter)

This method retains high-frequency features, effectively attenuating low-frequency components, enhancing the emphasis on QRS complexes in ECG signals, and suppressing lower frequency noise sources like P or T waves and baseline wander (2). The choice of M significantly impacts the filter's performance, testing was done to figure out the optimal value of M (1).

2.3 Nonlinear low pass filter

The nonlinear low pass filter (NLPF) serves as a crucial component in identifying specific features of a signal while reducing unwanted noise. This filter emphasizes certain features of interest while minimizing undesired noise components.

Given the input signal x and the sampling frequency freq, the window size is calculated as follows:

$$\text{window\_size} = \text{round}\left(\frac{\text{freq}}{200} \times 30\right)$$

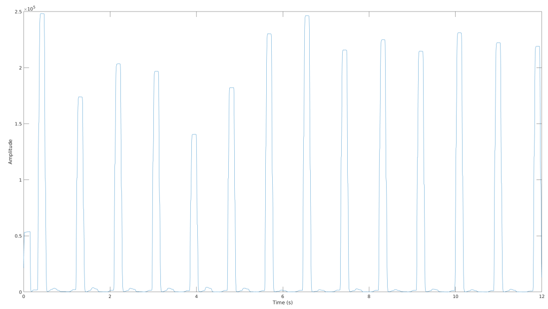

Figure 3: Filtered signal with NLPF (Nonlinear low pass filter)

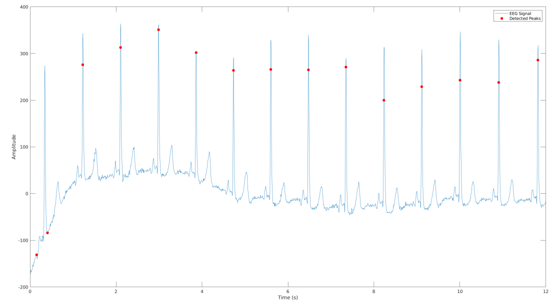

Figure 4: Detected QRS complexes

Using this window size, the algorithm iterates through the signal. For each sample, it squares the value and accumulates the sum of squared values within the defined window. The goal is to capture specific waveform features while suppressing noise components like P or T waves and baseline wander.

The filter highlights peaks related to a specific feature, such as the QRS complex in electrocardiogram (ECG) signals. It achieves this by dynamically adjusting the window size to suit the characteristics of the input signal. The NLPF's nonlinear approach, employing squaring and summation within a moving window, effectively extracts envelope-like features crucial for identifying specific signal components (3).

2.4 Decision

The decision algorithm is the final component in identifying QRS complexes in electrocardiogram (ECG) signals.

The detection algorithm analyzes the output from the NLPF (Nonlinear Low Pass Filter) signal to identify QRS complexes, the key components of heartbeats. It calculates a dynamic threshold based on specific factors like α and γ. This threshold helps pinpoint significant peaks within the signal, representing QRS complexes (4). By comparing each data point against this threshold, the algorithm determines the presence of a QRS complex without explicitly iterating through the signal. When a peak exceeds this adapted threshold, it's recognized as a QRS complex, contributing to the detection output.

Threshold is updated by the formula:

$$\text{Threshold} = \alpha \times \gamma \times \text{PEAK} + (1 - \alpha) \times \text{Threshold}$$

α ranges from 0 to 1, signifying the weight assigned to the new peak in threshold adjustment, while γ typically takes values of 0.15 or 0.2, influencing the threshold calculation.

This adaptive mechanism dynamically adjusts the threshold based on signal peaks and its previous threshold value.

Table 1: Average Sensitivity and Average Precision on records: s20111 s20121 s20151 s20171 202 207 208 220

Settings	**Precision (%) & Sensitivity (%)**
$M = 3, \alpha = 0.05, \gamma = 0.15$	99.50 / 98.49
$M = 5, \alpha = 0.1, \gamma = 0.2$	**99.76 / 98.95**
$M = 5, \alpha = 0.05, \gamma = 0.15$	99.67 / 99.06
$M = 7, \alpha = 0.05, \gamma = 0.15$	99.67 / 99.06

Table 2: Summary of Results

Record	**Precision (%)**	**Sensitivity (%)**
s20111	100.00	99.94
s20121	99.98	99.97
s20151	99.97	99.95
s20171	99.82	99.98
...	...	...
Average of 89 records	99.54	97.91

2.5 Automation

Few scripts were made for the automation of the system, it has the ability to analyse and evaluate multiple ECG records. Using functions such as 'wrann,' 'bxb,' and 'sumstats,' the system conducts evaluations on these records, capturing the results in separate files for easy inspection.

3 Discussion

This system showcases robust performance across two databases, it showcases high precision and sensitivity across numerous ECG records. While certain instances of the results exhibit lower scores, addressing these challenges through algorithmic enhancements and broader dataset can further elevate the system's effectiveness in practical ECG signal analysis and healthcare applications.

References

[1] H.C. Chen and S.W. Chen. "A moving average based filtering system with its application to real-time QRS detection". In: *Computers in Cardiology, 2003*. 2003, pp. 585–588. DOI: 10.1109/CIC.2003.1291223.

[2] Franc Jager et al. "Long-term ST database". In: *Medical & Biological Engineering & Computing* 41.2 (2003), pp. 172–183.

[3] GB Moody and RG Mark. "MIT-BIH Arrhythmia Database". In: *IEEE Eng in Med and Biol* 20.3 (May 2001), pp. 45–50.