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Analysis Heartbeat Segmentation with Smoothing Filtering Technique

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ABSTRACT

Cardiovascular diseases remain a significant cause of mortality globally, necessitating accurate methods for analyzing cardiac signals for clinical applications such as arrhythmia detection and cardiac disease diagnosis. Heartbeat segmentation is a critical step in delineating different phases of the cardiac cycle, essential for understanding cardiac activity. However, traditional segmentation methods encounter challenges due to noise and artifacts in raw signals, which can compromise accuracy. Smoothing filtering techniques have emerged as a solution to enhance signal quality before segmentation. Among these techniques, the Savitzky-Golay (S-G) filter stands out for its ability to preserve signal characteristics effectively. This study systematically explores the integration of smoothing filters with segmentation algorithms to enhance the accuracy of cardiac signal segmentation, particularly in ambulatory monitoring settings with varying levels of noise and artifacts. Utilizing ECG signals from the MIT-BIH Arrhythmia Database, the study investigates the impact of smoothing filtering on segmentation performance across different signal-to-noise ratios (SNRs). The results demonstrate that smoothing filtering significantly improves segmentation accuracy, particularly at lower SNRs, by mitigating noise-induced inaccuracies. These findings underscore the critical role of smoothing filtering in improving the reliability of cardiac signal analysis, ultimately contributing to enhanced patient care and outcomes in cardiovascular medicine.

1. Introduction

Cardiovascular diseases remain a leading cause of mortality worldwide, necessitating accurate and efficient methods for analyzing cardiac signals to various clinical applications such as arrhythmia detection, heart rate variability analysis, and cardiac disease diagnosis [1,2]. Among the key tasks in cardiac signal processing is heartbeat segmentation, a critical step in delineating the different phases of the cardiac cycle.

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Heartbeat segmentation refers to the process of dividing a cardiac signal in an electrocardiogram (ECG) into constituent parts or segments. These segments represent different phases of the cardiac cycle including the P wave, QRS complex along with T waves as shown in Figure 1. QRS complex and R-peaks have an important role in almost all automated ECG analysis segmentation algorithms as stated by Peng *et al.,* [3]. Based on the identified QRS complex and R-wave, the rest of the segments can be detected.

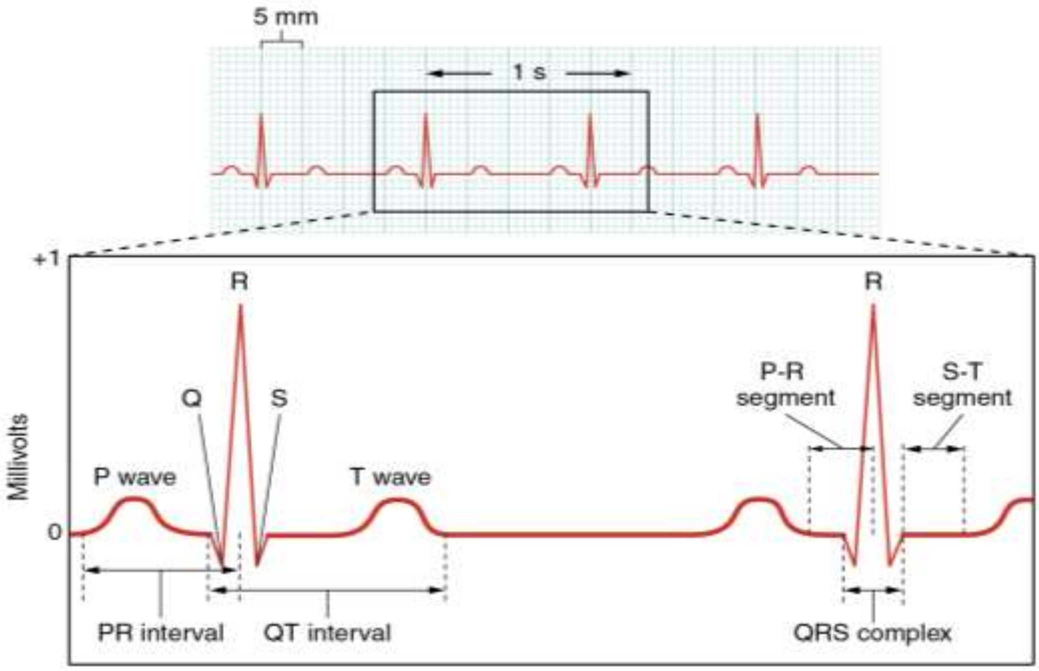

Fig. 1. Heartbeat segmentation and main features in ECG signal [4]

Analysis of heartbeat segmentation components is crucial for accurate analysis and diagnosis of cardiac activity. Traditional segmentation methods often encounter challenges due to the presence of noise and artifacts in the raw cardiac signal, which can compromise the accuracy of segmentation results leading to incorrect diagnoses and treatment decisions [5-8].

In response to these challenges, researchers have turned to smoothing filtering techniques as a processing step to enhance the quality of cardiac signals before segmentation [9,10]. Based on Chinomos *et al.,* [10] smoothing filters are adept at reducing noise and baseline wander while preserving the essential features of the signal, making them particularly well-suited for improving the segmentation process. However, some of the smoothing techniques are not very effective and some of them destroy the characteristics of signal during filtering process.

A Savitzky-Golay (S-G) is one of the techniques which can smoothen out the signal without destroying its original properties [11,12]. Typically, the technique used linear least squares for data smoothing, which helps to obtain high signal-to-noise ratio and retains the original shape of the signal. The principle behind S-G filter is to obtain the appropriate Polynomial degree fitting order and frame size properties since the performance of filter mostly depends on them.

The objective of this study is to explore a systematic methodology for applying smoothing filters with segmentation algorithms, thereby facilitating more robust and accurate segmentation of cardiac signals. Through this research, the aim is to address the following key questions: How do the smoothing filtering techniques affect the performance and accuracy of existing segmentation algorithms in ambulatory cardiac monitoring, particularly in the presence of varying level of noise and artifacts? By addressing this question, valuable insights into the role of smoothing filtering techniques in enhancing heartbeat segmentation can be explored, ultimately contributing to improved cardiac signal analysis and patient care.

2. Material and Methods
2.1 Materials

The ECG signal from MIT-BIH Arrhythmia Database [13,14] were used in this study. This database is chosen because of the signal recorded in a supervised clinical environment using a Holter monitor contain noise and artefacts that can serving as a realistic data to assess the performance of smoothing technique. In this study, the ECG signal was produced based on records 100 from the MIT-BIH Arrhythmia Database (Records 100) with (10, 5, 0, -5, -10 and −15) dB signal-to-noise ratio (SNR) motion artifact noise. The ECG signal with SNR using a scheme by Apandi *et al.,* [15,16] used to determine the relationship between the intensity of noises and beat segmentation performance. The noise recording contained typical artefacts in an ambulatory signal such the motion artefact collected from physically active volunteers with standard ECG recorders and equipment.

2.2 Methods

In this study, the methodology used to analyze the heartbeat segmentation is shown in Figure 2. Three main stages will be implemented in this study (1) data preprocessing; (2) smoothing filtering and (3) heartbeat segmentation. Firstly, the raw ECG signal was collected as data in this study. Then the raw ECG signal will be pre-processed and smoothened to increase the precision of data. Finally, the QRS complex will be extracted in ECG signal to obtain the segmentation of heartbeat.

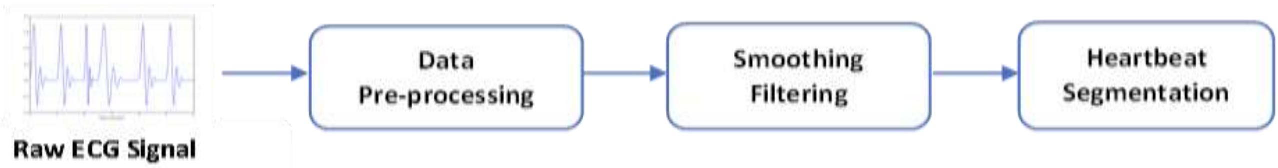

Fig. 2. The heartbeat segmentation method

2.1.1 Data preprocessing

In this stage, the pre-processing was conducted to filter the background noises in raw ECG signal. The band-pass filtering technique [17] is used to reduce the influence of high-frequency and low-frequency noises, thus suppress the P and T waves that do not contribute to identify QRS complex in ECG signal. The band-pass filtering technique offers good transition-band characteristics at low coefficient orders, making it efficient to implement. The band-pass filter with the passband of 8-20Hz is used in this study to remove the baseline wander, a 50 Hz powerline interference and reduced the amplitude of T-waves. The technique was designed using the cascaded low-pass and high-pass filters.

2.1.2 Smoothing the signal using Savitzky-Golay Polynomial Smoothing filtering technique

Savitzky-Golay (S-G) is a type of digital smoothing filter that uses polynomial regression to fit a smooth curve to the data. The filter [9,10] is generally used to smoothen the signal to increase the precision of the data without distorting the signal tendency. It uses the convolution process by fitting the data point with low degree polynomial by the method of linear least square. A S-G filter performs better in some applications than the standard averaging FIR filters [9], which tend to filter high-frequency content along with the noise.

S-G filter is applied to a series of digital data point. The subsets of consecutive data points are fitted using a low order polynomial with linear least square method and convolution of all the polynomials is then obtained [18,19]. The data having a set of $n\{x_j, y_j\}$ point, where $j = 1,2 \ldots n$ and x is and independent variable whereas y is an observed value, can be represented with a set of m convolution coefficients, $C1$, and given as in Eq. (1),

$$Y_j = \sum_{j=(m-1)/2}^{j=(m-1)/2} C_i y_{j+1} \frac{m+1}{2} \leq j \leq n - \frac{m-1}{2} \tag{1}$$

Implementation of S-G filter typically requires three inputs: the ECG signal (x), the order of the polynomial (k) and its frame size (f) [15]. The best fit values of k and f for a signal are generally estimated using trial and error method. Alternatively, the values can also be obtained using prior experience or previously estimated values for a particular level of SNR for the given signal. In this study, the values for order of polynomial are 10 and frame size is 31 is used as it has been tested successfully on noisy signal [12].

2.1.3 Heartbeat segmentation

Heartbeat segmentation process refers to the extraction of the higher peak in QRS complex to obtain heartbeat segments. In this study, the Pan Tomkins algorithm [14,17] technique is used to segment the signal. After the smoothing process, the signal was then differentiated to highlight the sharp slopes of the QRS complex. To further emphasize the QRS complex, the signal was then squared to obtain positive values. The final processing step involved a moving window integration with an average window of 150 ms. This window was chosen to match the width of the widest possible segmentation. QRS peaks of at least 300 ms apart were identified in the pre-processed signal and classified as segments depending on the adaptive threshold. Figure 3 shows the implementation of each stage in this study. The smoothing filtering technique increased the precision of the data and enhanced the higher slopes of peak in the noisy signal.

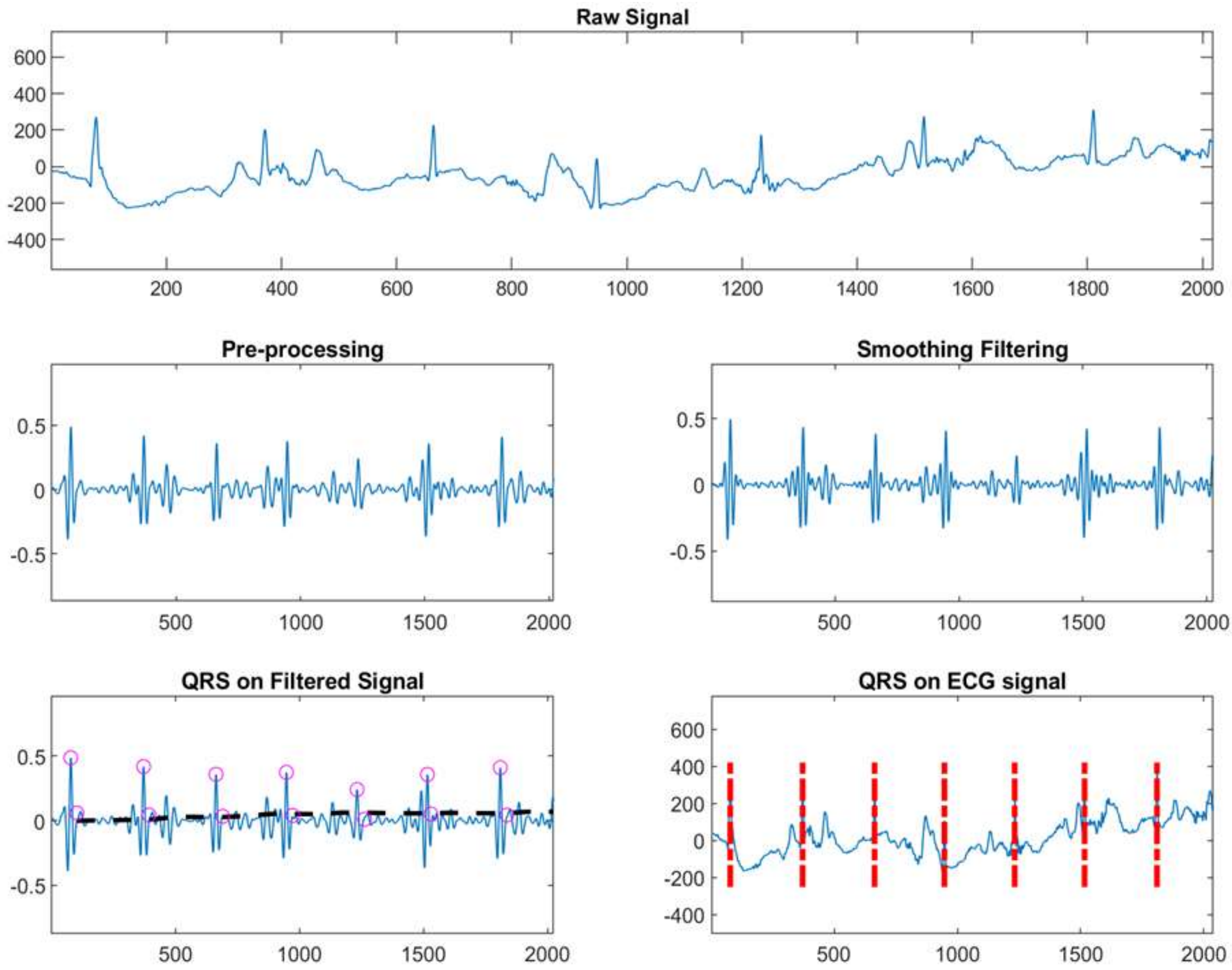

Fig. 3. The implementation of heartbeat segmentation

3. Results and Discussion

To validate the heartbeat segmentation performance, each detected QRS peak was categorized as true positive (TP), false positive (FP) or false negative (FN). TP denotes the total number of QRS peaks detected as the QRS complex, FP denotes the total number of non-QRS peaks or noises detected as the QRS complex and FN represents the total number of QRS complexes that was not detected. Two evaluation metrics which were sensitivity (SE) and positive predictivity (PP) were calculated using Equation (2) and (3), respectively [19,20]. The SE denotes the percentage of true beats that are correctly detected by the algorithm, whereas the PP denotes the percentage of detected true beats. These two metrics were calculated using the total number of TP, FN and FP.

$$\mathrm{SE} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100\% \tag{2}$$

$$\mathrm{PP} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \times 100\% \tag{3}$$

Table 1 and Figure 4 shown the result between heartbeat segmentation with and without smoothing filtering technique across different signal-to-noise ratios (SNRs). SNR levels ranging from 10 to -15 dB were evaluated. Based on the results, at higher SNR (10 dB), both methods achieve perfect performance, indicating no significant difference. At SNR 5 dB, both methods performed similarly in terms of SE, but smoothing slightly improved PP. At SNR 0 dB, smoothing significantly improved SE and PP compared to segmentation without smoothing. Smoothing notably improved SE and PP compared to segmentation without smoothing at SNR -5, -10 and -15 dB.

Table 1
Result of Segmentation with and without Smoothing Filtering

Records 100	PT with Smoothing		PT without Smoothing	
SNR	SE (%)	PP (%)	SE (%)	PP (%)
SNR 10	100	100	100	100
SNR 5	100	100	100	99.21
SNR 0	100	95.42	99.12	77.88
SNR -5	98.2	73.61	93	57.67
SNR -10	90.06	55.72	78.62	46.32
SNR -15	74.92	44.20	59.13	36.59
Average	93.86	78.16	88.31	69.61

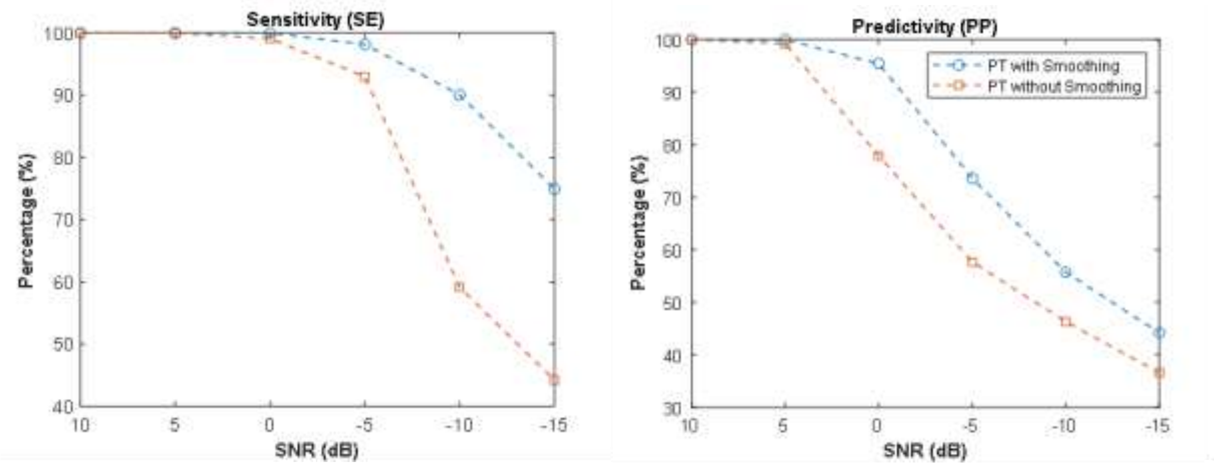

Fig. 4. Analysis result of segmentation with and without smoothing filtering

The result shows that the smoothing filtering technique generally enhances heartbeat segmentation performance, especially at lower SNR levels, improving both sensitivity and positive predictive value. However, at lower SNRs, smoothing filtering generally improves both sensitivity (SE) and positive predictive value (PP) compared to segmentation without smoothing. Specifically, at SNR 0 dB and below, smoothing consistently enhances SE and PP, with notable improvements observed even at SNR -15 dB. These findings underscore the beneficial impact of smoothing filtering in improving the accuracy of heartbeat segmentation, particularly in noisy environments, by enhancing both detection sensitivity and positive predictive value.

Based on analysis results in Figure 4, a clear trend of improved performance with the implementation of smoothing filtering, especially evident as the SNR decreases. At SNR 0 dB and beyond, the technique significantly boosts both SE and PP, indicating a more accurate detection of heartbeat events and a reduction in false positives. Even at SNRs as low as -15 dB, where noise levels are high, smoothing filtering continues to provide substantial enhancements in SE and PP compared to segmentation without smoothing.

These results highlight the robustness and effectiveness of the S-G smoothing filtering technique with order of polynomial 10 and frame size is 31 in mitigating the adverse effects of noise and improving the reliability of heartbeat segmentation, thereby contributing to more accurate cardiac monitoring and analysis in challenging ambulatory settings.

4. Conclusions

The findings of the analysis underscore the critical role of smoothing filtering in enhancing the accuracy of heartbeat segmentation, particularly in the context of ambulatory cardiac monitoring where noise levels can be substantial. The observed improvements in sensitivity (SE) and positive predictive value (PP) across a range of signal-to-noise ratios (SNRs) demonstrate the efficacy of this technique in mitigating the adverse effects of noise and artifacts on segmentation performance. The consistent enhancements provided by smoothing filtering, even at lower SNRs, suggest its utility in real-world scenarios where noise contamination is inevitable.

These results have significant implications for the development of robust cardiac monitoring systems capable of accurately detecting and analysing heartbeat events in noisy ambulatory environments. Incorporating smoothing filtering into segmentation algorithms can lead to more reliable and clinically relevant assessments of cardiac function, ultimately improving patient care and outcomes. Further research could explore optimization strategies for smoothing parameters and investigate its integration with other noise reduction techniques to achieve better performance improvements in ambulatory cardiac monitoring applications.

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