



Classification of Arrhythmia Through ECG Signals Using Windowing Technique

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Abstraction: The classification of arrhythmias through electrocardiogram (ECG) signals using the windowing technique involves breaking down continuous ECG data into smaller, manageable segments (windows) for more precise analysis and detection of abnormal heart rhythms. This approach enables the identification of arrhythmias by extracting relevant features from segmented windows, allowing for accurate classification using a support vector machine.

Keywords: Electrocardiogram (ECG), Classification, Arrhythmia, Band Pass Filter

1. Introduction

Arrhythmias, or irregular heartbeats, are a significant medical concern as they can lead to serious complications such as stroke, heart failure, and sudden cardiac arrest. Early detection and accurate classification of arrhythmias are critical for timely intervention and effective treatment. One of the most used diagnostic tools for monitoring and analyzing the heart's electrical activity is the Electrocardiogram (ECG). The ECG records the electrical signals generated by the heart, providing valuable information about its rhythm and electrical activity. If the heart rate is too high, that is, above 100 beats per minute, then this situation is called tachycardia, and if the heart rate is too low, that is, below 60 beats per minute, then it is called bradycardia [8].

According to the World Health Organization (WHO,2021), cardiovascular diseases (CVDs) are the leading global cause of death, taking an estimated 17.9 million lives each year, with more than 75% occurring in low- and middle-income countries (LMICs) [5].

ECG analysis is an effective way of evaluating heart health. Therefore, the identification and classification of ECG signals are essential to cardiovascular diseases. Not only for early prevention but also necessary for timely detection and proper treatment. It is of considerable significance to study the classification of related ECG signals [7]. Heart diseases are major threats to global health. Electrocardiogram (ECG), a non-invasive diagnostic tool for heart diseases, is widely used in clinical practice, putting a heavy burden on cardiologists [6].

Figure 1 describes the construction of an ECG signal, which is important for interpreting the results of the test.

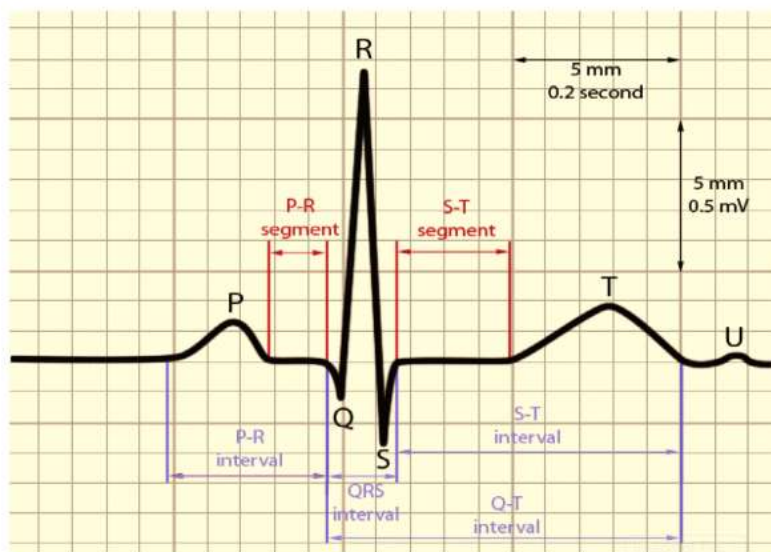


Figure 1. The Construction of ECG Signal.

An electrocardiogram (ECG) consists of five waves: P, Q, R, S, and T. The P wave indicates atrial contraction, and the T wave indicates ventricular repolarization. The QRS complex, which is a key component of an ECG, is composed of Q, R, and S waves. The QRS complex represents the electrical activity of ventricular depolarization as it spreads through the ventricles. The T wave, which follows the QRS complex, is an indicator of ventricular repolarization. In clinics around the world, there are more than 300 million clinical ECG records. ECG is the most essential, helpful, prudent routine assessment approach [1].

Electrocardiogram (ECG) monitoring shows the electrical activity of the heart, which is recorded as an electrocardiographic signal. This signal can be used to identify abnormal heart rhythms and other heart-related conditions, contributing significantly to the prediction of heart diseases [4].

Electrocardiography is a technique of recording the bioelectric currents generated by the heart. The graphical display of this recording is called an electrocardiogram (ECG), and it provides useful information about the functional status of the heart. Analysis of ECG is of great importance in the classification of cardiac anomalies. In a clinical setting, such as in intensive care units, it is essential for automated systems accurately to detect and classify electrocardiographic signals. The correct performance of these systems depends on several important factors, including the quality of the ECG signal, the applied classification rule, and the learning and testing datasets used. The ECG is characterized by a recurrent wave sequence of P, QRS and T waves associated with each beat. The QRS complex is the most striking waveform, caused by ventricular depolarization of the human heart. Once the positions of the QRS complexes are found, the locations of other components of ECG, such as P and T waves and ST segments, are found relative to the position of QRS, to analyses the complete cardiac period [2].

2. Methodology

Data collection: The data collection process for arrhythmia classification typically involves obtaining ECG CSE datasets from various sources, either through clinical setups or publicly available datasets.

Data preprocessing: Filtering, feature extraction, model development & evaluation.

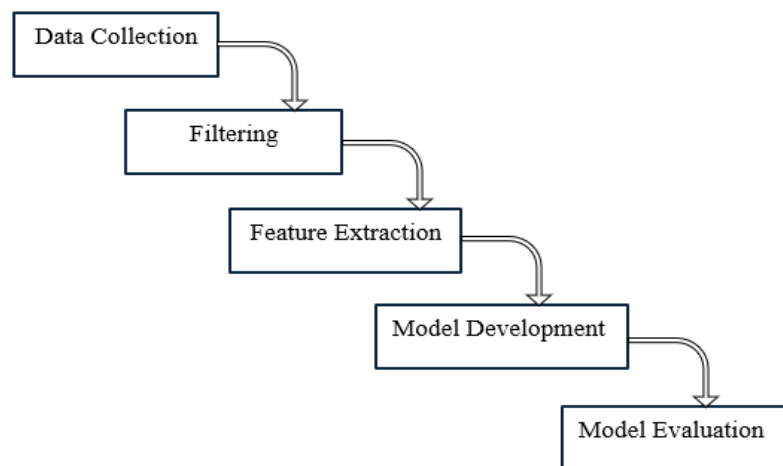


Figure 2. Steps of classification of arrhythmia

❖ **Filtering:** In threshold detection the filtered ECG signal improves the reliability of detection. In the preprocessing, the ECG with this Kaiser Window band pass filter improves the signal-to noise ratio and increases the overall detection sensitivity. This technique reduces the number of false positives caused by the muscle noise, 60 Hz interference, baseline wander, and T wave interference, where the cut off frequency is about 0.5-40 Hz and the order is 7. After filtering, the signal is differentiated to provide the QRS complex slope information. After differentiation, the signal is squared point by point [9].

❖ **Feature Extraction:** Each heartbeat consists of five parts: P, Q, R, S, T. Each of them has specific meanings. The processing steps required of a state-of-the-art computerized ECG arrhythmia monitoring system are pre-processing, QRS Complex Detection, Beat-by Beat ECG Signal Classification and Morphology Feature Extraction, On-line Diagnosis [10].

- Load ECG database files case by case.
- Implement FIR bandpass filter with Kaiser Window for removing noise.
- We apply the threshold condition to detect and mark the R-wave.
- Now between two consecutive R-peak time intervals we will find the P wave by applying the threshold condition.
- Now between two consecutive R-peak time intervals we will find the T wave by applying threshold conditions.

QRS Detection:

An adaptive filter designs itself based on the characteristics of the input signal to the filter and a signal that represents the desired behaviour of the filter on its input.

The signal pass band of the QRS complex is different for different subjects and even for different beats of the same subject

The noise and QRS complex pass bands overlap. A matched filter can maximize the signal to- noise ratio for detection of a known signal in noise. However, the design of an optimal matched filter requires knowledge of both the signal and the correlation statistics of the noise. The non-stationary nature of the signal and noise in an ECG represents an obstacle in application of matched filtering to QRS detection [10].

Algorithm:

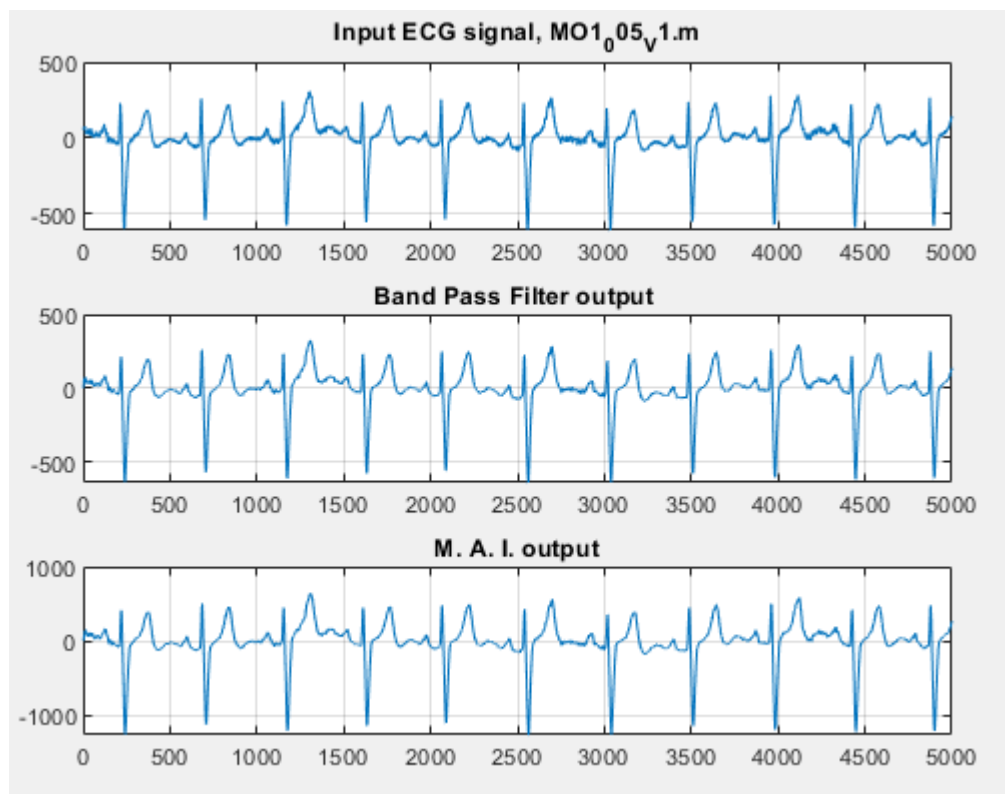
Pre-processing: Remove noise, segment, normalize, and resample the ECG signal.

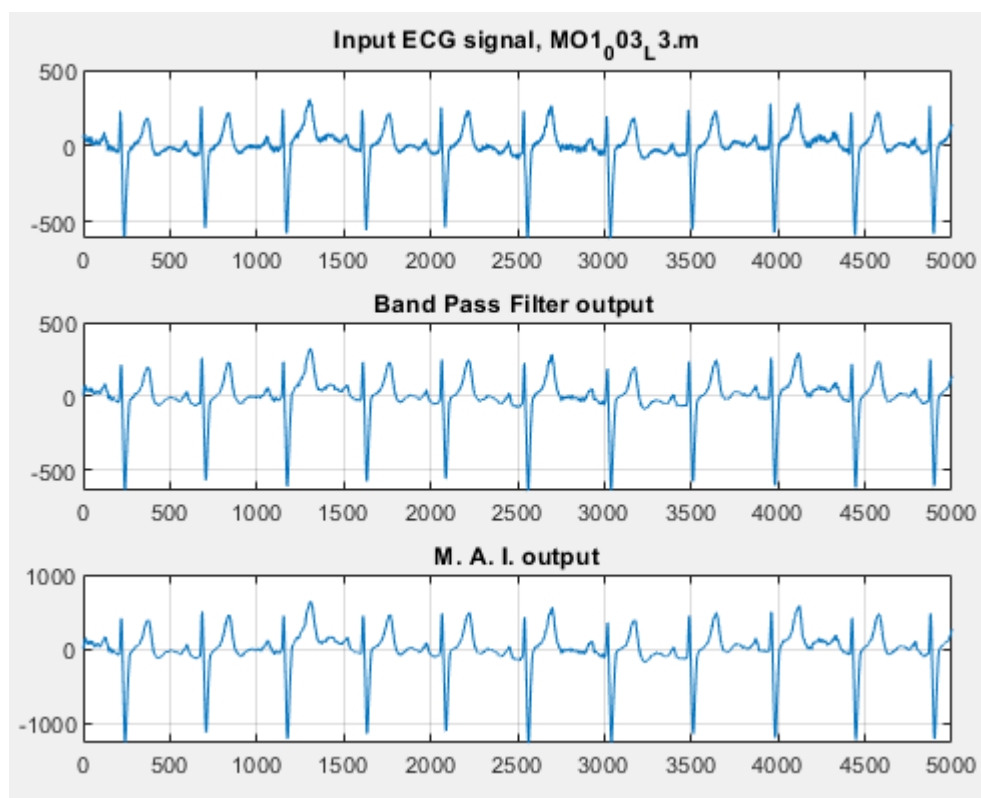
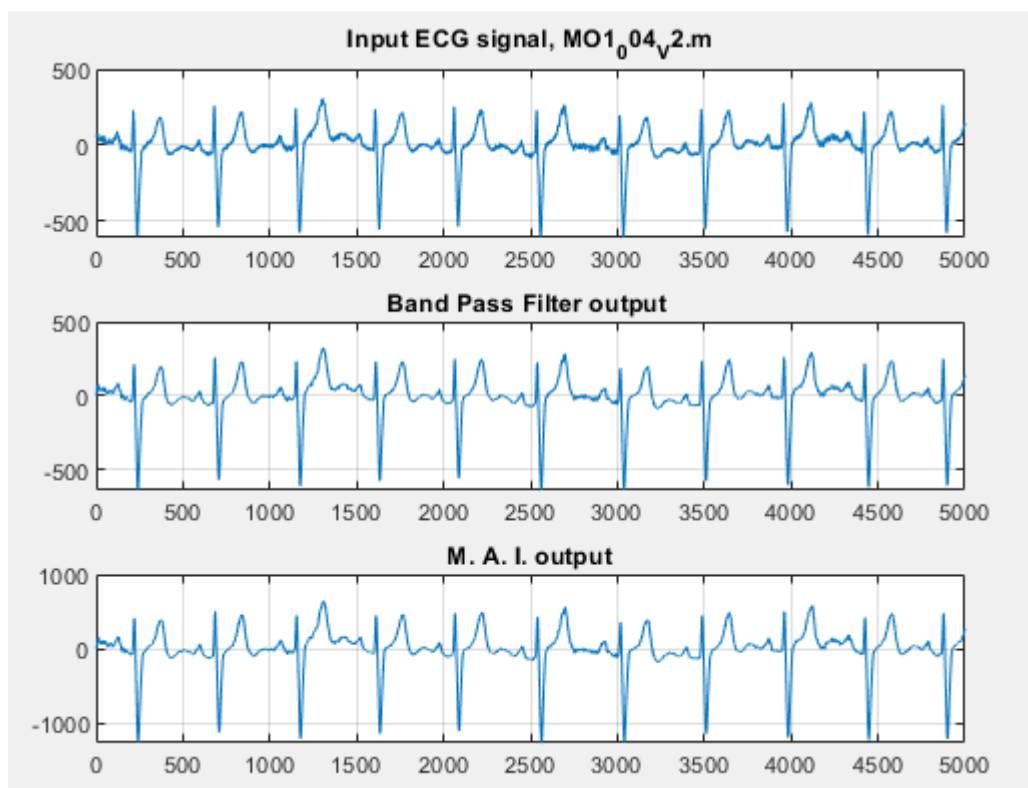
Feature Extraction: Extract time-domain, frequency-domain, and statistical features from the ECG signal.

Labeling: Label the data with arrhythmia classes.

3. Result

The algorithm is tested on standard CSE ECG database, having multi-lead ECG signal recordings for 58 cases. Each digital record constitutes a 10 second recording containing 5000 samples taken at a rate of 500samples/sec. This algorithm reliably detects QRS complexes using slope, amplitude and width information. A Kaiser Window band pass filter preprocesses the signal to reduce interference, permitting the use of low amplitude thresholds to get high detection sensitivity. The algorithm periodically adapts each threshold and RR interval limit automatically. This adaptive approach provides for accurate use on ECG signals having many diverse signal characteristics, QRS morphologies and heart rate changes.





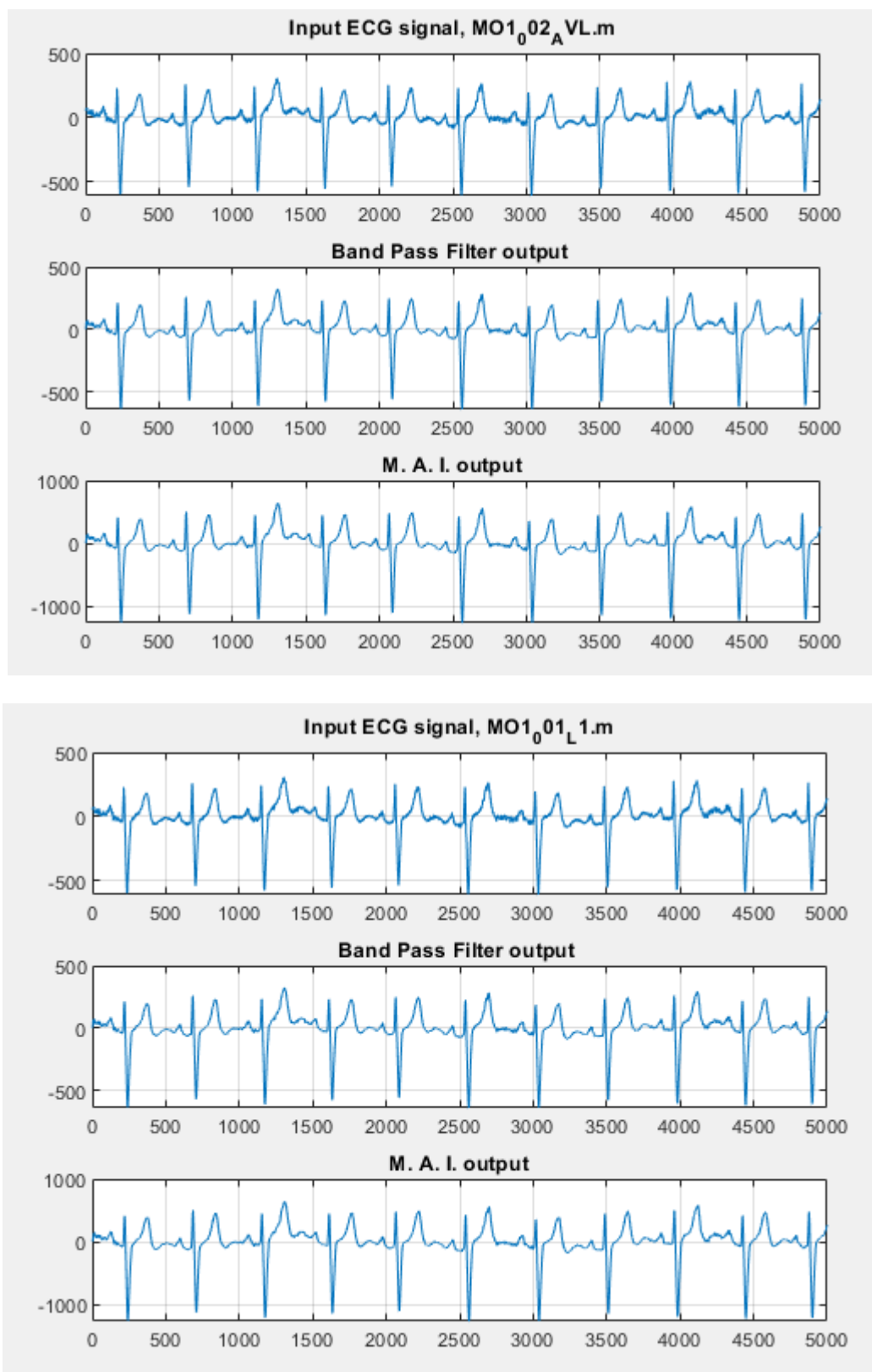


Figure 3. Input, Band Pass Filter & M.A.I. Output

4. Conclusion

The windowing technique is a powerful method for classifying arrhythmias from ECG signals. By segmenting the signal into smaller windows and extracting key features, it improves the accuracy and efficiency of arrhythmia detection, offering potential for real-time, automated clinical applications.

5. References

1. Shikha Dhyani, Adesh Kumar, Sushabhan Choudhury, Analysis of ECG-based arrhythmia detection system using machine learning, Elsevier B. V. Publication, 17 April 2023, 2215-0161, doi: 10.1016/j.mex.2023.102195.
2. S. S. MEHTA, N. S. LINGAYAT, Detection of QRS complexes in electrocardiogram using support vector machine, Journal of Medical Engineering & Technology, Vol. 32, No. 3, May/June 2008, 206 – 215, doi: 10.1080/03091900701507183.
3. Shoaib Sattar, Rafia Mumtaz, Mamoon Qadir, Sadaf Mumtaz, Muhammad Ajmal Khan, Timo De Waele, Ingrid Moerman, Adnan Shahid, Cardiac Arrhythmia Classification Using Advanced Deep Learning Techniques on Digitized ECG Datasets, Sensors 2024 Apr, 2484. doi: 10.3390/s24082484.
4. Bach-Tung Pham, Phuong Thi Le, Tzu-Chiang Tai, Yi-Chiung Hsu, Yung-Hui Li, Jia-Ching Wang, Electrocardiogram Heartbeat Classification for Arrhythmias and Myocardial Infarction, Sensors (Basel). 2023 Mar; 23(6): 2993. doi: 10.3390/s23062993.
5. Cesar N. Silva, Arrhythmia Classification Using MATLAB® Classification Learner App, Science and Technology Publications, Volume 4, pages 220-225, 2023. doi: 10.5220/0011666300003414.
6. Jintai Chen, Kuanlun Liao, Kun Wei, Haochao Ying, Danny Z. Chen, JianWu, ME-GAN: Learning Panoptic Electrocardio Representations for Multi-view ECG Synthesis Conditioned on Heart Diseases, PMLR 162, 2022.
7. Mengze Wu¹, Yongdi Lu², Wenli Yang³ and Shen Yuong Wong^{2*}, A Study on Arrhythmia via ECG Signal Classification Using the Convolutional Neural Network, Frontiers in Computational Neuroscience, 2021 Jan. doi: 10.3389/fncom.2020.564015.
8. M A Firyulina, I L Kashirina, Classification of cardiac arrhythmia using machine learning techniques, IOP Publishing, 2020, DOI 10.1088/1742-6596/1479/1/012086.
9. Nilesh Parihar and Dr. V. S. Chouhan, De-noising Of QRS Complex Using Windowing Technique, IJGTI 1, 2012.
10. Nilesh Parihar, ANALYSIS OF ECG WAVE USING PERCEPTRON NEURAL NETWORK, Int. J. Adv. Res. 12(09), 970-974, 2024, DOI 10.21474/IJAR01/19529.