



ADAPTIVE ALGORITHMS FOR REAL-TIME DETECTION OF CARDIAC RHYTHM DISORDERS

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Abstract

Early detection of cardiac rhythm disorders is an important task for telemedicine, remote monitoring, and intelligent medical devices. In particular, real-time processing of cardiac signals, automatic detection of dangerous rhythm changes, and rapid notification in emergency situations significantly increase the practical value of the system. Recent studies show that there are three main challenges in ECG-based automatic arrhythmia detection: distortion of the signal by dynamic noise, inter-patient physiological variability, and resource constraints in edge devices [1]–[4]. This paper proposes an adaptive algorithm for a Holter-based monitoring system operating on the Raspberry Pi platform and automatically sending emergency alerts via GSM technology. The proposed approach includes signal preprocessing, R-peak detection, RR-interval calculation, rhythm evaluation based on adaptive thresholds, two-stage confirmation, and alert transmission for confirmed abnormal events. The aim of the approach is to reduce false alarms, account for individual physiological differences, and ensure resource-efficient real-time operation.



Index Terms— cardiac rhythm disorder, ECG, real-time monitoring, adaptive algorithm, Holter system, GSM alerting, Raspberry Pi, edge computing.

I. INTRODUCTION

Cardiac rhythm disorders are often episodic in nature and may remain undetected during routine short-term examinations. Therefore, continuous monitoring of cardiac activity is clinically important, especially for patients in high-risk groups. Recent reviews indicate that the development of ECG-based automatic arrhythmia detection, wearable monitoring, and edge platforms is driven by the growing demand for systems capable of operating in real time [1], [4].

Although conventional Holter monitoring systems provide long-term recording, in many cases the acquired signals are analyzed only afterwards. This limits the ability to respond immediately in emergency situations. For this reason, the development of real-time systems capable of automatically detecting dangerous rhythm abnormalities and sending alerts is considered an important and relevant research problem [1], [3].

However, the development of such systems is associated with several complex challenges. First, signal quality may deteriorate due to electrode displacement, muscle activity, baseline wander, and other artifacts. Second, because the ECG morphology and RR-interval dynamics of each patient are individual, a single static threshold may not be sufficient for all patients. Third, although complex deep learning models can provide high accuracy, they require considerable computational resources and energy, which makes continuous operation on edge devices more difficult [2]–[4], [6].

In this paper, an adaptive algorithm is proposed for a Holter-based cardiac monitoring system that operates according to the Holter principle and automatically sends emergency notifications via GSM technology. In the proposed system, the



cardiac signal is acquired through a wearable module, processed on a Raspberry Pi-based edge device, and analyzed for R-peak detection and RR-interval evaluation, while abnormal rhythm episodes are identified using adaptive thresholds. If an abnormality is confirmed, the system automatically sends a notification to a physician or the patient's family members through the GSM module.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

Research on the automatic detection of cardiac rhythm disorders covers a broad spectrum of approaches, ranging from classical signal processing techniques to machine learning and deep learning models. Comprehensive reviews report high accuracy levels for AI-based arrhythmia detection; however, they also emphasize that, for practical systems, latency, interpretability, and hardware limitations are equally important considerations [1].

The first major challenge is signal noise. Electrode motion, electromyographic noise caused by muscle contractions, baseline wander, and external electromagnetic interference can significantly distort the ECG signal. Recent reviews show that preprocessing and denoising stages directly determine the reliability of subsequent diagnostic decisions [2].

The second challenge is inter-patient physiological variability. Since each individual has unique ECG morphology and cardiac rhythm characteristics, a general model may lead to errors in some patients. Studies on personalized monitoring indicate that taking individual characteristics into account provides advantages for real-time detection [3].

The third challenge is resource limitation. The complexity of deep learning models makes their deployment on wearable or edge devices more difficult. For this reason, lightweight models, knowledge distillation, and TinyML-based approaches are being actively developed [4], [6].



Based on this analysis, the following problem is formulated in this paper: the development of an adaptive cardiac rhythm detection algorithm that is robust to noise, adaptable to individual characteristics, and capable of operating in real time on an edge platform.

III. PROPOSED SYSTEM AND MATHEMATICAL MODEL

A. System Architecture

The proposed system consists of three main layers: the signal acquisition layer, the edge-processing layer, and the communication/database layer. The signal acquisition layer continuously records the cardiac signal using a wearable ECG sensor. The edge-processing layer is built on the Raspberry Pi platform and performs signal filtering, R-peak detection, RR-interval calculation, adaptive threshold updating, and abnormality confirmation. The communication layer automatically sends alerts through the GSM module when an emergency condition has been confirmed. Studies in edge-IoMT show that such a local-processing-then-transmission architecture is suitable for real-time monitoring [4]. The hardware composition of the proposed monitoring node includes a wearable ECG sensor, a Raspberry Pi-based processing unit, a GSM module, and a user interface for receiving alerts, as shown in Fig. 1.

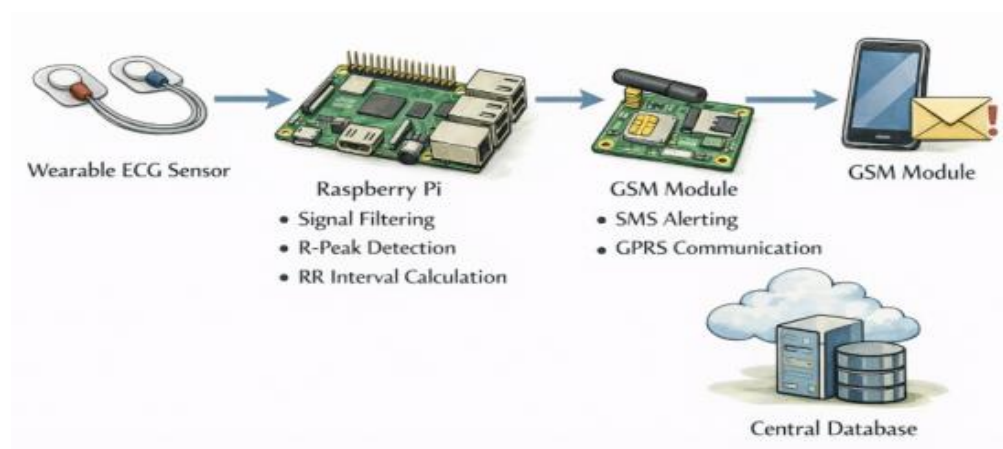


Fig. 1. Hardware configuration of the proposed monitoring node.



As shown in Fig. 1, the signal acquired from the wearable ECG sensor is processed on the Raspberry Pi platform, and confirmed emergency conditions are transmitted to a physician or the patient's family members through the GSM module.

The proposed system is not limited to a single monitoring node. It also supports the integration of multiple distributed monitoring nodes with a central DBMS, which enables remote supervision, event logging, and further clinical analysis. The overall operating architecture of the GSM-based cardiac monitoring system is presented in Fig. 2.

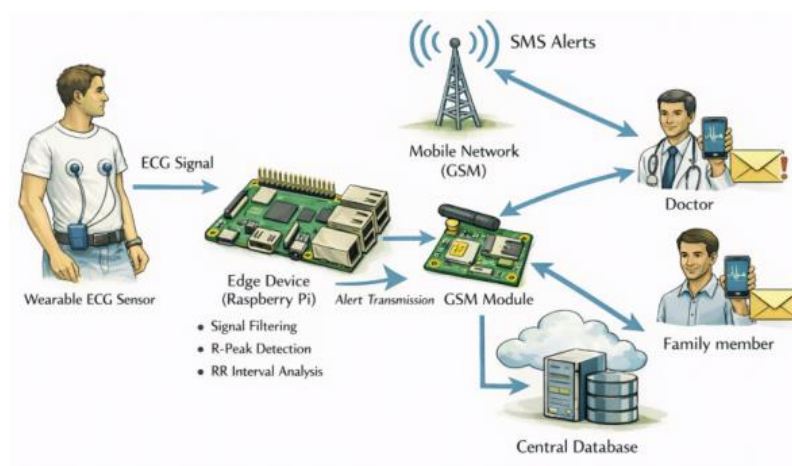


Fig. 2. Overall architecture of the GSM-based cardiac monitoring system.

As shown in Fig. 2, the ECG signal acquired from the wearable sensor is processed on the edge device, detected emergency events are transmitted through the GSM module, and the corresponding records are stored in the central database for remote access by physicians or the patient's family members.

B. Signal Preprocessing

Let the input raw signal be denoted by $x[n]$. The filtered signal is obtained as follows:

$$y[n]=H_BP \{x[n]\} \quad (1)$$



where $H_{BP} \{ \cdot \}$ denotes the band-pass filtering operator.

Next, the signal is normalized as

$$z[n] = \frac{y[n] - \mu_n}{\sigma_n + \varepsilon} \quad (2)$$

where μ_n is the mean value within the current window, σ_n is the standard deviation, and ε is a small positive constant. Studies on denoising and preprocessing methods indicate that this stage is critically important for the reliability of subsequent diagnostic decisions [2].

C. R-Peak Detection and RR-Interval Calculation

A lightweight approach similar to the Pan–Tompkins method is used for R-peak detection. The classical Pan–Tompkins algorithm detects QRS complexes in real time based on slope, amplitude, and width, and reduces false detections through band-pass filtering [5].

If $t_i - t_{i-1}$ denote the occurrence times of two consecutive heartbeats, the RR interval is defined as

$$RR_i = t_i - t_{i-1} \quad (3)$$

The heart rate is then calculated as

$$HR_i = \frac{60}{RR_i} \quad (4)$$

D. Rhythm Evaluation Based on Adaptive Thresholds

The local mean over the last N heartbeats is calculated as

$$\mu_k = \frac{1}{N} \sum_{i=k-N+1}^k RR_i \quad (5)$$

The standard deviation is given by



$$\sigma_k = \sqrt{\frac{1}{N} \sum_{i=k-N+1}^k (RR_i - \mu_k)^2} \quad (6)$$

The adaptive limits are then defined as

$$T_{low,k} = \mu_k - \lambda \sigma_k \quad (7)$$

$$T_{high,k} = \mu_k + \lambda \sigma_k \quad (8)$$

If

$$RR_i < T_{low,k} \quad \text{yoki} \quad RR_i > T_{high,k} \quad (9)$$

the rhythm is considered to deviate from the normal range. Studies on personalized monitoring indicate that adaptation to individual characteristics is beneficial for real-time systems [3].

E. Signal Quality Index

To reduce false alarms, a signal quality index is introduced:

$$SQI_k = \frac{P_{sig}}{P_{sig} + P_{noise}} \quad (10)$$

where P_{sig} is the useful signal power and P_{noise} is the noise power.

F. Two-Stage Confirmation

A single abnormal beat is not considered an emergency event. Over the last M beats, the following quantity is calculated:

$$S_i = \sum_{j=i-M+1}^i A_j \quad (11)$$

If

$$S_i \geq M_{th} \quad \text{va} \quad SQI_k > \tau \quad (12)$$

the event is considered a confirmed emergency condition.



G. Automatic Alert Transmission via GSM

If an emergency condition is confirmed, the system generates an alert packet containing the patient identifier, event type, timestamp, and heart rate information, and transmits it through the SIM900A GSM module. In the proposed monitoring system, signal acquisition, preprocessing, R-peak detection, RR-interval calculation, rhythm evaluation based on adaptive thresholds, and emergency alert transmission are performed in a unified sequential manner, as illustrated in Fig. 3.

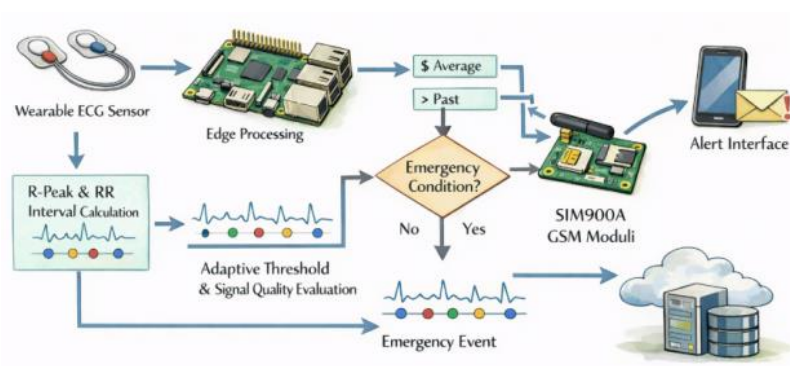


Fig. 3. Operational workflow of the real-time cardiac monitoring system.

As shown in Fig. 3, the signal acquired from the wearable ECG sensor is processed on the edge device, R-peaks and RR intervals are calculated, emergency conditions are identified using adaptive thresholds and signal quality criteria, and confirmed events are transmitted through the GSM module and stored in the database.

The functional behavior of the proposed monitoring system under different operating scenarios is summarized in Table 1.

Scenario	ECG/HR condition	Adaptive detection result	GSM alert	Database logging	Final status



Normal rhythm	RR intervals within adaptive limits	No abnormality detected	No	Yes	Monitoring continued
Short-term noisy segment	Temporary signal distortion, low SQI	Rejected due to low signal quality	No	Yes	False alarm prevented
Tachycardia-like episode	RR intervals below adaptive lower threshold	Abnormality detected	Yes	Yes	Emergency event confirmed
Bradycardia-like episode	RR intervals above adaptive upper threshold	Abnormality detected	Yes	Yes	Emergency event confirmed
Irregular rhythm episode	Unstable RR intervals, repeated deviation	Abnormality detected after confirmation	Yes	Yes	Emergency event confirmed

As shown in Table 1, the proposed system is capable of distinguishing normal cardiac activity, noisy signal segments, and clinically significant abnormal rhythm events, while reducing false alarms through signal quality evaluation and two-stage confirmation.



IV. RESULTS AND DISCUSSION

Preliminary tests of the proposed system demonstrated that the monitoring node can continuously acquire the cardiac signal, process it on the edge device, and transmit alerts through the GSM communication channel when an emergency event is detected. Recent edge-IoMT studies have also confirmed the practical suitability of such an architecture for real-time ECG anomaly detection [4].

The signal processing pipeline included raw ECG filtering, R-peak detection, RR-interval calculation, and adaptive threshold updating. In noisy segments, preprocessing and the use of a signal quality index contributed to reducing false detections [2], as illustrated in Fig. 4.

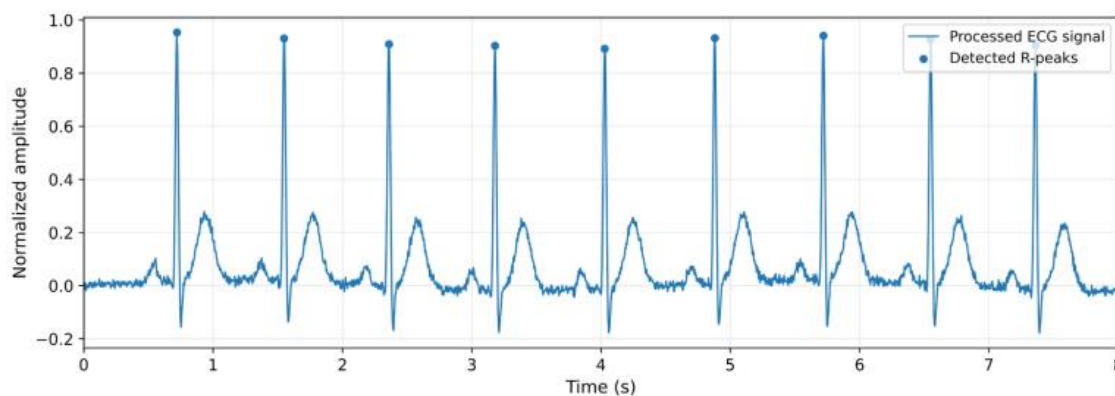


Fig. 4. Sample fragment of the processed ECG signal with detected R-peaks.

As shown in Fig. 4, the proposed algorithm successfully identifies the main diagnostic points of the ECG signal in real time. Peak-detection methods derived from the Pan–Tompkins approach remain a classical basis for this task [5].

The main advantage of the proposed adaptive algorithm is that it evaluates cardiac rhythm not by using static thresholds, but on the basis of current local statistics. As a result, it enables better discrimination between normal heart rate fluctuations and clinically significant deviations.

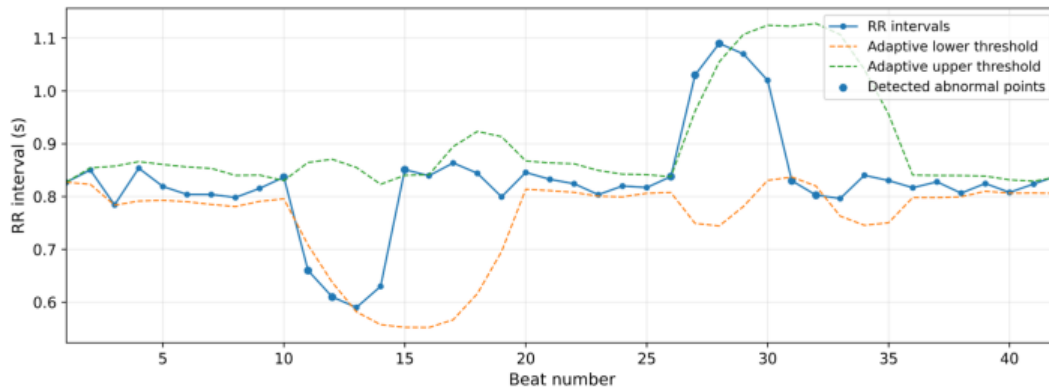


Fig. 5. Sequential variation of RR intervals and the adaptive thresholds constructed on their basis.

Figure 5 shows the sequential variation of RR intervals together with the adaptive thresholds derived from them. As can be seen from the graph, RR values that fall outside the normal range are marked by the system as anomalous points. The use of thresholds adaptable to individual characteristics has been recommended as an effective approach in personalized monitoring platforms [3].

Another important advantage of the proposed method is its suitability for operation on edge platforms. The algorithm does not rely on complex deep neural networks; instead, it is mainly based on filtering, peak detection, sliding-window statistics, and simple logical checks. Therefore, it is suitable for real-time operation on resource-constrained devices such as the Raspberry Pi [4], [6].

At the same time, the proposed system should not be considered a tool for final clinical diagnosis, but rather as an intelligent support system intended to strengthen early warning and remote monitoring. In future work, it would be appropriate to perform quantitative evaluation using standard datasets, including the MIT-BIH Arrhythmia Database [7].

V. CONCLUSION



This paper proposed a Holter-based monitoring system for the real-time detection of cardiac rhythm disorders, operating on an edge device and automatically sending emergency notifications via GSM technology. The system includes the acquisition of wearable ECG signals, signal processing on the Raspberry Pi platform, R-peak detection, RR-interval calculation, rhythm evaluation based on adaptive thresholds, and alert transmission for confirmed abnormal events.

During the study, three main challenges of real-time ECG monitoring systems were analyzed, namely signal distortion caused by dynamic noise, inter-patient physiological variability, and the need to operate on resource-constrained devices. To address these challenges, signal preprocessing, the use of a signal quality index, adaptive statistical thresholds, and a two-stage confirmation mechanism were proposed [2]–[4], [6].

An important advantage of the proposed algorithm is that it does not rely entirely on complex and resource-intensive deep learning models. Instead, it is based on classical signal processing, R-peak detection, sliding-window statistics, and simple decision-making rules. Therefore, the algorithm is suitable for real-time operation on edge platforms such as the Raspberry Pi, while reducing system latency and improving energy efficiency [4]–[6].

In conclusion, the proposed adaptive algorithm represents a promising solution for the real-time detection of cardiac rhythm disorders. It combines practical requirements such as noise robustness, individual adaptability, and resource efficiency, thereby extending the functional capabilities of cardiac monitoring systems. In future studies, it would be appropriate to perform a quantitative evaluation of the system using standard open datasets and real clinical recordings [7].



VI. REFERENCES

[1] A. Ayyub, C. Politis, and M. A. Usman, “A comprehensive review of AI-based detection of arrhythmia using electrocardiogram (ECG),” *Computers in Biology and Medicine*, vol. 196, art. 110594, 2025, doi: 10.1016/j.compbiomed.2025.110594.

[2] Y. Jia, H. Pei, J. Liang, Y. Zhou, Y. Yang, Y. Cui, and M. Xiang, “Preprocessing and denoising techniques for electrocardiography and magnetocardiography: A review,” *Bioengineering*, vol. 11, no. 11, art. 1109, 2024, doi: 10.3390/bioengineering11111109.

[3] S. Raj and K. C. Ray, “A personalized arrhythmia monitoring platform,” *Scientific Reports*, vol. 8, art. 11395, 2018, doi: 10.1038/s41598-018-29690-2.

[4] M. Hizem, L. Bousbia, Y. Ben Dhiab, M. O.-E. Aoueilleyine, and R. Bouallegue, “Reliable ECG anomaly detection on edge devices for Internet of Medical Things applications,” *Sensors*, vol. 25, no. 8, art. 2496, 2025, doi: 10.3390/s25082496.

[5] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm,” *IEEE Transactions on Biomedical Engineering*, vol. 32, no. 3, pp. 230–236, 1985, doi: 10.1109/TBME.1985.325532.

[6] X. An, S. Shi, Q. Wang, Y. Yu, and Q. Liu, “Research on a lightweight arrhythmia classification model based on knowledge distillation for wearable single-lead ECG monitoring systems,” *Sensors*, vol. 24, no. 24, art. 7896, 2024, doi: 10.3390/s24247896.

[7] G. B. Moody and R. G. Mark, MIT-BIH Arrhythmia Database v1.0.0, PhysioNet, 2005. Available: <https://physionet.org/content/mitdb/1.0.0/>



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