Anomaly detection of ECG with Reinforcement Learning

Kim Johyeon
College of Artificial Intelligence
Sungkyunkwan University)
Seoul, Korea
nangddi2@g.skku.edu

Park Su Yeon
College of Artificial Intelligence
Sungkyunkwan University)
Seoul, Korea
yeonlife17@gmail.com

***Abstract*—Heart diseases such as arrhythmia have been pointed out as a major cause of death worldwide. Therefore, monitoring electrocardiogram (ECG) data can effectively manage risk. However, the existing arrhythmia diagnosis method requires a lot of labor and time for cardiologists and is inconvenient to patients because of many electrodes. In order to solve these inconveniences and continuously analyze the patient's ECG data, we aimed to detect abnormal signals using reinforcement learning in a wearable device such as a smart watch. Due to data limitations, the data of 4 patients were used in the MIT-BIH dataset instead of the actual smart watch data, and the model was learned through the distribution of normal data. Normal data was predicted using the Q-table learning method, and denoising and smoothing were performed using Wavelet Transformation and Savitzky-Golay filter. The best MAPE was about 0.156 and the RMSE was about 0.066. If it exceeds a specific threshold (2.5xStandardDeviation) based on the distance between the predicted data and the actual data, it is detected as abnormal. Through this project, we present the possibility of utilizing reinforcement learning in wearable devices.**

***Index Terms*—Reinforcement Learning, ECG, Wavelet Decomposition, Savitzky-Golay Filter**

I. INTRODUCTION

The electrocardiogram(ECG) data can determine if someone has arrhythmia which means the heart has an abnormal heart rate or irregular rhythm. It causes a variety of serious problems, ranging from complications such as angina, heart valve disease, and myocardial infarction to sudden death [20]. To diagnose arrhythmia, cardiologists examine patients' electrocardiograms for 24 hours according to Holter monitoring and diagnostic practices [21]. This requires a lot of time and labor for a cardiologist, and puts a lot of electrodes on patients for ECG measurements, which causes discomfort.

Therefore, instead of attaching electrodes all day long, attempts are being made to use smart watches or small wearable devices to collecting heartbeat information and continuously analyze ECG data [22]. Along with the development and prevalence of wearable devices, these studies will help manage the potential risks of patients easily and conveniently. Although most ECG data analysis shows good performance through deep learning models, training the models requires a significant amount of time and resources.

In [2], they used deep reinforcement learning to analyze ECG and used age parameter for learning. In [3] they also used deep reinforcement learning combining it with Support Vector Machine(SVM), and it took 6 days to use 11 subjects. In [4], a deep CNN reinforcement learning model was used.

In the case of small mobile devices and smart watches that collect ECG data, training time and memory capacity must be considered, so this project proposes a Q-table learning method to learn and predict normal heartbeat patterns. In addition, Wavelet Transformation and Savitzky-Golay filter were used to denoise and smooth signals.

II. BACKGROUND

A. Challenges in Anomaly Detection for ECG

ECG signals are crucial for automated prediction systems, yet they often present challenges due to their overwhelming nature, noise, and complexity. In essence, this underscores the necessity for multiple pre-processing stages to adequately condition ECG signals for utilization in any predictive model [4]. For instance, denoising and sampling, heartbeat detection, segmentation, and feature extraction, are vital pre-processing methods in Arrhythmia prediction system.

Plus, according to the development of sensor technology, ECG monitoring device became small and wire-free wearable that allow patients to perform everyday activities with minimal disturbance. Most of ECG monitoring devices typically did not implement on board anomaly detection and heartbeat-classification functionalities. In real-time monitoring system, integrating anomaly-detection capabilities directly on a low power wearable device is considered as a challenge [23].

B. Current Approaches and Technologies

In recent years, advancements in sensor technologies, machine learning, and signal processing have opened new avenues for improving anomaly detection in ECGs. Pattern recognition and machine learning algorithms, including supervised and unsupervised techniques, offer the potential to analyze complex patterns in ECG data and identify deviations from normal operating conditions. Recently, deep neural networks have shown very good performance in ECG data prediction. Unfortunately, the computational requirements of

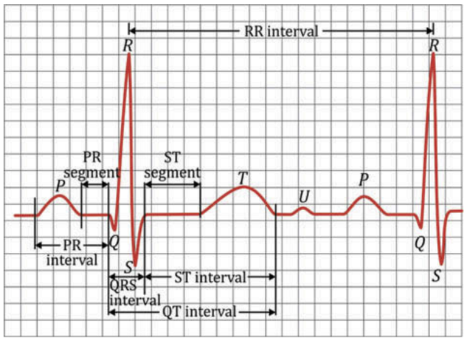

Fig. 1. ECG PQRST Sequence for one Cycle, Source [7]

deep neural networks are not compatible with the limited resources available on most wearable device [24].

C. PQRST wave

The ECG signal is composed of a repetitive waveform known as the PQRST complex. The P wave originates from the action potential initiated by the sinoatrial node (SA node) located in the upper right atrium. This action potential propagates outward from the right atrium, generating an equivalent electric dipole pointing towards the lower left side of the heart, resulting in the appearance of a positive P wave on the ECG.

The Q wave represents the depolarization wave traveling between the atria and ventricles through the atrioventricular (AV) node. The rapid conduction through the His-Purkinje network activates the lower part of the ventricles, producing an equivalent depolarization dipole directed towards the negative lead, observed as a short-lived, large-amplitude negative Q wave on the ECG.

The R wave signifies the major ventricular depolarization. The AV node-mediated depolarization through the His-Purkinje network activates the upper ventricles, resulting in an equivalent dipole directed towards the positive lead and presenting as a prominent positive R wave on the ECG.

The PQ segment, also known as the PR segment, appears as a flat line on the ECG and represents the time during which electrical activity passes through the AV node en route to the ventricles. It is located between the end of the P wave and the beginning of the Q wave.

The RR interval, defined as the duration between the peaks of two subsequent R waves, typically represents the cardiac cycle duration. The S wave represents the activation of the lower part of the ventricles, appearing as a negative waveform on the ECG, and the segment between the R wave and S wave characterizes the ventricular base.

The T wave indicates ventricular repolarization, reflecting the return of myocardial cells to their resting state. The outward propagation of repolarization generates a negative equivalent dipole directed towards the negative lead, resulting in a positive T wave on the ECG [2].

In summary, the PQRST complex in the ECG waveform corresponds to different phases of cardiac electrical activity, providing valuable information about the heart's functioning.

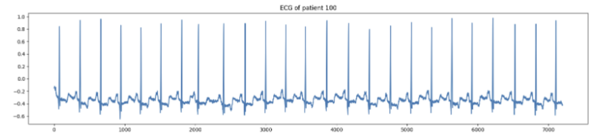

Fig. 2. Sample ECG data for Patient 100

Abnormalities occur when the height, frequency, or distortion does not conform to this pattern. In other words, these disparities from the normal PQRST can be classified as anomalies. It is also crucial to detect distinct patterns of heart anomalies different from random noise and outliers.

D. Objective of the Project

The primary objective of this project is to investigate the application of Reinforcement Learning techniques in enhancing anomaly detection within ECG systems. By leveraging RL, we aim to develop a model that can adapt to automatic alerting system, learn from historical data, and identify anomalies in real-time, thereby improving the overall safety and performance of ECG data.

III. Method Designed

We train a dataset through a reinforcement learning model to predict future values and find the difference between the actual and predicted values. If this difference exceeds a threshold (2.5x standard deviation), we mark it as an anomaly, or arrhythmia. Heart rhythm abnormalities tend to follow a pattern. Because they have a frequency, they are different from normal noise or outliers. Anomalies were manually generated for system testing.

A. Dataset

The dataset is a beginner-friendly version of the MIT-BIH Arrhythma Database [1], which contains 48 electrocardiograms (EKGs) from 47 patients that were at Beth Israel Deaconess Medical Center in Boston, MA in 1975-1979. There are 48 CSVs, each of which is a 30-minute echocardiogram (EKG) from a single patient record 201 and 202 are from the same patient). Data was collected at 360 Hz, meaning that 360 rows is equal to 1 second of time.

In Fig. 2., sample ECG data for patient 100 is presented. Data from 5 patients(patient 100, patient 101, patient 103, patient 114, patient 115) were used for verification, and only data representing a normal pattern for about 20 seconds were sampled so that they could learn quickly and in real-time from a smart watch. Data for 16 seconds (6,000 steps) was used to train the model, and data for the remaining 4 seconds (1,200 steps) was used to test the learned model. The threshold for outliers was also calculated from the data for 16 seconds.

B. Wavelet Decomposition

It is easier to remove noise in the frequency domain than in the time domain, so we use wavelet decomposition to convert

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \varphi^{*} \frac{(t-b)}{a} dt$$

a: Scale (dilation) parameter, b: Location of wavelet,
φ: *Wavelet function*, x: Signal

Fig. 3. Continuous Wavelet Transform

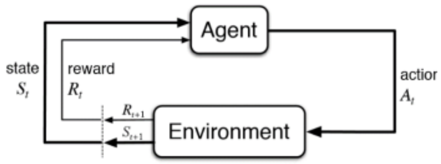

Fig. 4. Reinforcement Learning Architecture

the original data in the time domain to the frequency domain. The formula is as follows:

First, we remove the noise from the original signal, and then we remove the noise from the predicted signal.

C. Reinforcement Learning

Reinforcement Learning is a branch of machine learning that focuses on training intelligent agents to make sequential decisions by interacting with an environment. The fundamental concept behind RL is learning through trial and error, where the agent learns to perform actions that lead to favorable outcomes and avoids actions that result in negative consequences. This learning process is guided by a reward signal, which provides feedback to the agent on the desirability of its actions.

We used the epsilon-greedy policy with the epsilon 0.3. Reward was defined to be the inverse of the distance between a predicted and actual action. Thus award would be high if the distance is close and low if the distance is far. We also used Q-Table whose Q-Values are determined by Bellman Equation. A Q-table determines the next best action given the current state.

To test the learning, we calculated the Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). MAPE means the distance between the actual and the prediction. RMSE means the average difference between predicted values and actual values, providing an estimation of how well a predictive model can predict the target values (accuracy).

$$Q(s,a) = \sum_{s',r} p(s',r|s,a)[r + \gamma \max_{a'} Q(s',a')]]$$

immediate reward reward for taking action action a in state s

discount γ *is the discount factor*

$Q(s,a)$ *is the Q - value for state s and action a*

$p(s',r|s,a)$ *is the probability to s' and with r when a & s*

' is the next state, a' is the next action

Fig. 5. Bellman Equation

$$Anomaly\ if\ |\text{predicted} - \text{actual}| > (2.5 \times \sigma)$$

Fig. 6. Anomaly Detection Equation

$$y_i = \sum_{j=-n}^{n} c_j \cdot x_{i+j}$$

y_i: *estimated smoothed value at i*

x_{i+y}: *data in the moving window*

n: $\frac{1}{2}$ *width of moving window*

c_j: *coefficient of polynomial fit*

Fig. 7. Savitzky-Golay Filter Equation

D. Anomaly Detection

Create a reinforcement learning model that learns the normal distribution of ECG data to detect anomalies. We determined whether the distance between the actual and predicted values exceeded a certain threshold. We set the threshold to 2.5 times of standard deviation. If the distance is greater than this, an anomaly is present.

E. Savitzky-Golay Filter

The Savitzky-Golay Filter is used in signal processing to remove noise while preserving important features of the time series. It works with polynomials and windows to determine where and how to put the smoothed values. To perform a forecasting task, we removed the noise with wavelet decomposition, and then a Savitzky-Golay filter is used to perform the final smoothing of the forecast.

IV. Results

In this project, reinforcement learning is used to predict normal ECG and detect outliers by calculating the distance from the actual value. This proves it is possible to learn the time series forecasting model with reinforcement learning and produce good results even through 16 seconds data. Since ECG data has the nature of repeating certain patterns, it could be learned with only 16 seconds, which was suitable for application to smart watches or mobile devices. In addition, it showed advantages in terms of memory capacity and processing speed because it did not use deep neural network.

ECG data of five patients (patient 100, patient 101, patient 103, patient 114, and patient 115) from the MIT-BIH dataset were all processed and learned in the same way.

To process ECG signals, noise was first removed using Wavelet Decomposition, and the wave domain was switched back to the time domain. After that, the second peak data appearing in ECG data is set as the starting point of 0 seconds.

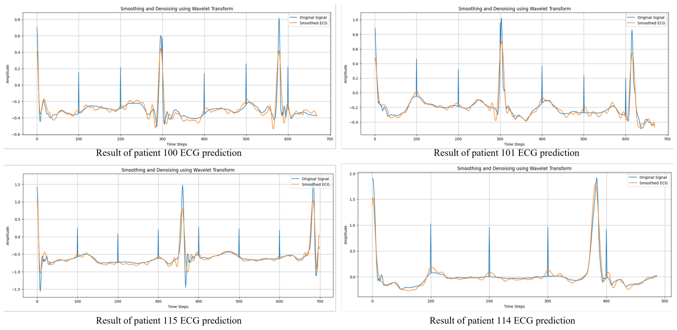

Fig. 8. Results of 4 patients ECG (100, 101, 114, 115)

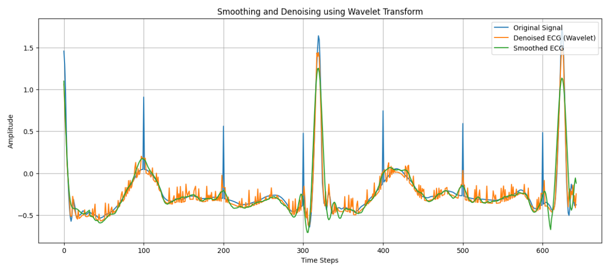

Fig. 9. Result of patient 103 ECG with denoised and smoothed graph

The processed data is learned by the Q-table learning model in consideration of the spike, and the reward is calculated through the distance between the actual and predicted values. The shorter the distance, the more reward is given, and the longer the penalty is given. To calculate the reward, the inverse of the distance is used. The predicted value also needs to be processed for denoise and passes through the Savitzky-Golay filter for smoothing. ECG prediction results are evaluated through MAPE and RMSE, and the results can be confirmed in Fig. 8., Fig.9. and Table 1. MAPE and RMSE are measured by predicted values and anomaly-free original data to assess their effectiveness in predicting normal data in the absence of anomalies.

Among the several experiments, the best result was data on patient 100, which showed about 0.1539 for MAPE and 0.0664 for RMSE. This indicates that the results predicted by the model are performing well.

Next, 4 seconds of data to test abnormality detection is also predicted through the model. It also uses Wavelet Decomposition for denoising and passes through Savitzky-Golay Filter to smooth signals. Since this result predicts a normal ECG signal, if an abnormality is indicated in the actual ECG, the distance between them will be large. To detect this, the standard deviation of 16 seconds multiplied by 2.5 is used as the threshold.

Accuracy was used to evaluate abnormality detection, and some were classified as false positive compared to the actual anomalies detected, so it will be meaningful if research to improve it proceeds in the future. Detailed results on this can be found in Table. 1.

TABLE I
TIME SERIES PREDICTION AND ANOMALY DETECTION EVALUATION

Table	**Evaluation Results**		
Patient ID	***Accuracy***	***MAPE***	***RMSE***
patient 100	83.3	0.1566	0.6691
patient 101	66.6	0.2415	0.0666
patient 103	100.0	0.5965	0.1104
patient 114	100.0	4.8566	0.0774
patient 115	85.7	0.1217	0.1295

V. CONCLUSION

The goal of this project was to detect outliers in ECG data collected from wearable devices. For evaluation, the MIT-BIH dataset was used and learning was performed using 16-second data of 5 patients normal ECG data. Abnormal detection was performed using a smoothed predicted value through a Q-table learning model using a normal ECG signal with noise removed through wavelet decomposition. This methods are simple to apply to mobile devices, easy to use, and lightweight.

Results demonstrated the goal could be accomplished, and the applicability of reinforcement learning could be proved also. However, there was a limitation that several arrhythmia classes could not be classified. Plus, it would be more meaningful if there was a comparative experiment on memory size and performances of the deep Q-learning model and the Q-table learning model.

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