Classification of ECG signal with Support Vector Machine Method for Arrhythmia Detection

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Abstract. An electrocardiogram is a potential bioelectric record that occurs as a result of cardiac activity. QRS Detection with zero crossing calculation is one method that can precisely determine peak R of QRS wave as part of arrhythmia detection. In this paper, two experimental scheme (2 minutes duration with different activities: relaxed and typing) were conducted. From the two experiments it were obtained: accuracy, sensitivity, and positive predictivity about 100% each for the first experiment and about 79%, 93%, 83% for the second experiment, respectively. Furthermore, the feature set of MIT-BIH arrhythmia using the support vector machine (SVM) method on the WEKA software is evaluated. By combining the available attributes on the WEKA algorithm, the result is constant since all classes of SVM goes to the normal class with average 88.49% accuracy.

1. Introduction

The electrical activity under normal circumstances starts from an impulse formed by a pacemaker at the Sino Atrial (SA) node. The electrical signals from the SA node flow through both atria, causing the two atria to contract to drain blood into the ventricles. Then this electrical signal flows through the Atrio Ventricular (AV) node and then goes to the bunle of His and splits into two the left and right and ends in Purkinje fibers that activate the ventricular muscle fibers. This causes the two ventricles to contract each other to pump blood throughout the body and produce a pulse. This regular flow of the electricity from the SA node to the AV node causes a regular contraction of the heart muscle known as the sinus beat. Electrocardiograph (ECG) is a device that used to record biological signals formed as a result of the electrical activity of the heart. The ECG is taken by installing electrodes at certain points of the patient's body. The ECG signal has a voltage of up to 3mV and a frequency range of 0.03-100 Hz. The ECG signals have a specific form that can be used as a reference to determine the condition of a person's heart health by a doctor or cardiologist.

The development of medical instrumentation technology based on monitoring systems such as ECG for diagnostic and treatment needs recently tends to switch to wireless technology (ie medical instrumentation that can be used mobile and make patients feel more comfortable) [1-3]. However, some issues related to these demands still need to be developed such as how the tool can be applied...
easily, quickly, accurately and with the best reliability [4]. One of the wireless-based devices in medical telemetry that it is possible to develop is telecardiology which involves the transmission of electrocardiogram signals (ECG) [5-8]. ECG is a diagnostic tool used to measure and record the electrical activity of the heart in detail. Interpretation of the heart recording signal can be used to analyze the presence of cardiac function that has a vital role in life [8]. With built instruments allowing a patient to be able to measure his heart condition at any time, and the resulting data can be sent to the cloud for subsequent access by interested parties.

Reliable algorithm support in the development of wireless technology with real telecardiology capability is very necessary to provide. The most important thing is to ensure the required quality of the developed ECG system. The conventional wireless applications are designed to optimize average throughput. However, the applied ECG monitoring not only require a moderate data rates, but also require a very high level of reliability. The ECG signals are generated by the stimulation of nerve impulses of the heart. The current on the body surface is used to construct a drop voltage from microvolts into milivolt. The typical of the ECG signals consists of P waves, QRS complexes and T waves. The ECG base voltage is known as the isoelectric line measured as part of tracking following the T wave and predates the next P wave. Our aim is to develop an extraction algorithm that can be used to support the designed of the wireless ECG system.

2. Method
To ensure the patient's environmental feasibility in more humane conditions in both physical and physiological health care, monitoring and recording of their physiologically related data is essential [10-12]. To reduce the workload of the medical staff and avoid suddenly accidents, an ECG based wireless is proposed. The conceptual arrangement of a wireless ECG medical instrument is shown in Figure 1. The developed system consists of electrode sensors (to measure the ECG signal), a wireless ECG recorded module (to preprocessed and transmit the ECG signals via Bluetooth), and an android mobile device. Then, an ECG monitoring algorithm include the classifier developed in the android mobile device will continuously monitor the subject heart activities. When the abnormal heart rate is detected by classifier, the classified ECG signals will be sent to the cloud or directly to the physician or family. Based on this mechanism, the cardiac state of the subject can be monitored anywhere in the globe as long as the subject under internet network coverage. The main purpose of ECG wireless development is to develop medical equipment with universal and interoperable interfaces such as transparent to end users, easy to use, easy to reconfigure.

![Figure 1. Smart wireless ECG Scheme.](image-url)
In this study, the ECG data is classified using the Support Vector Machine (SVM) method integrated in the Waikato Environment for Knowledge Analysis (WEKA) software. The WEKA is a software that contains Java-based open source data mining applications. The WEKA consists of a collection of machine learning algorithms that can be used to perform generalizations or formulations from a set of sampling data. The SVM WEKA based on norm least mean square (NLMS) extraction are used to forming training vector, establishing SVM WEKA, training the SVM WEKA and diagnosing Arrhythmia. Figure 2 gives the summarized block diagram of the proposed method.

![Figure 2. The SVM classifier method based NLMS extraction for ECG Arrhythmia diagnosis.](image1)

To evaluate reliability and ensure ease of operation, ECG signals from 24 subjects, aged 24 ± 3 years, were recorded. All subjects are healthy both physically and mentally. Next, each experiment is divided into two session conditions: relax (14 subjects) and type (10 subjects), respectively. Each is equipped with three channel sensors with each location shown in Figure 3 relating to cardiac activity. Once completed, each electrode must be covered with an electrolyte gel to minimize the effect of noise. ECG data were collected from three Ag / AgCl electrodes embedded in a developed wireless ECG system.

![Figure 3. Experiment setup and ECG recorded signals with relax and typing conditions.](image2)
3. Signal Processing

During the experiment, the recorded signal is usually mixed with noise. In order to eliminate these signals a filter algorithm with a certain cut-off frequency design is required. The cut-off frequency is an undesired frequency point where there is a decrease in the gain of 3 dB. In designing a filter, the slope steepness level of the filter can be adjusted in such a way that the output as desired. Filters with frequency design is known as bandpass filter. Band pass filter will pass signal with frequencies in certain range and dampen signal with other frequencies. Above and below the resonant frequency resonance frequency, which has an output voltage of 70.7% of the maximum output voltage is the limits that determine the bandwidth of the filter. Signal extraction is an enabling a designed algorithms and its application for extracting information contained in signals. An adaptive filter with Normalized Least Mean Square (NLMS) algorithm is used reduce noise in the recorded ECG signals while extracting the desired signal characteristics [13-16].

Length of Frequency QRS Complex can reach up to 40 Hz, while P and T waves usually have frequency components up to 10 Hz. By using an integrated filter bandpass with adaptive filter (NLMS), the spectral characteristics of the ECG components in the mean and high-frequency parts will be filtered and attenuated. The filtered signal using the proposed method will then be used to determine the temporal-R location with a linear response. Band Pass Filter with linear response without integration with adaptive filter then R-wave will usually be more difficult to detect. Complex QRS detection is completed when the R-wave temporal location has been found. If using only one ECG channel to detect R-wave, the heart's electrical position needs to be considered (the temporal location is determined by the maximum / minimum combination search). It takes a simple decision logic to decide whether to use the maximum or minimum interval position of the R-wave temporal location search.

Feature extraction on QRS detection experiment uses MIT-BIH Arrhythmia training data with WEKA software. In WEKA pre-processing there are attributes that will be omitted one by one or combined. Some of the used extracted features are: Prev indicates the previous data(Rn-Rn-1), Next indicated the next processed data (Rn + 1 - Rn), Local_Avg: Average before and after designated data as much as W (Width), Avg: Average of all Next in 1 data record, RRIR: Comparison of Next result designated divided Next in front (Nextn / Nextn + 1), 10 RRIR: Comparison of Next to 10 designated results on the next data.

The existing SVM classifier embedded on the WEKA algorithm is used for classification. The SVM is a learning system that uses hypothetical space in the form of linear functions in a high-dimensional feature space, trained with learning algorithms based on optimization theory by applying inductive bias (derived from the theory of statistical learning). With a simple concept, it can be explained as the search for the best hyperplane that serves as a separator of two classes in the input space (i.e., a member of two classes: +1 and -1 and shares an alternate line of discrimination boundaries). Margin is the distance between the hyperplane and the nearest pattern of each class. The closest pattern is called a support vector. The effort to locate the hyperplane is at the heart of the learning process in the SVM.

4. Results and Discussions

The algorithm has been tested on the recorded data from ten healthy volunteers subject aged around 25 ± 3 years old and it functions normally. Figures 4 and 5 show the recorded using developed system (top) and filtered signals using adaptive filter with normalized mean square algorithm (bottom). In normal ECG, the time interval between R-R is 0.6-1s, in case of fast heartbeat the time interval is less 0.6s which is known as sinus tachycardia; in case of slow heartbeat the time interval is more than 1 sec that is known as sinus bradycardia. By referring Figures 4 and 5 we can say that the R-R interval for normal case is between 0.6-1s. All signals from all subject and different distance of wireless ECG recording signals are in the standard form of ECG signals. Compared with the data measured by medical instruments in nursing centers and hospitals, our physiological status monitoring system has
reached the application level. By improving the signal processing ability for filtering, the quality of filtered signal from a farther distance.

Initial stage on detecting subject’s heart condition is developing an algorithm that can be used to detect the QRS position as in Figure 6. The QRS positioning information on each recording signal will make it easier for doctors or family to know their heart conditions. To enhance the accuracy of peak detection related to the QRS position, the signal is preprocessed using an adaptive filter. The R and S points including RR interval were well detected as shown in Figure 7. The obtained results clearly different from the recorded data of relax than typing subjects. If in the previous results with a general filter algorithm the difference is highly significant but with the adaptive filter the peak detection accuracy is only slightly different. Then the proposed filter is sufficiently able to overcome the dynamic interference on the signal recording.

The QRS Detection is the name for a combination of three visible graphical deflections on the ECG signals (usually represented in the center and most visually clear of the search). This corresponds to the depolarization of the right and left ventricular human heart. In adults, it usually lasts 0.06-0.10 seconds; In children and during physical activity, may be shorter. For the results in the first experiment

![Figure 4. Filtered ECG signals from relax subject.](image)

![Figure 5. Filtered ECG signals from typing subject.](image)
the QRS Detection was relaxed against 14 subject all peaks were detected well and had 100% accuracy and sensitivity as shown in Table 1. This perfect result is obtained because the subject at the rilek condition, ECG signal recording process tends not influenced by interference. The results of the experiment on 10 subjects during typing, QRS detection is very diverse. This is caused by the difference in frequency when the subject is typing so that not all results achieve 100% sensitivity and accuracy as shown in Table 2. The SVM uses the existing training data on Arryhtmia's MIT-BIH by using feature sets to be removed and combined so as to obtain stable results for SVM classification in WEKA software, there are Correct and Incorrect indicators on SVM calcification results which show the accuracy of classification. The SVM classification results show that all values pointing to other value and Classifier indicator has a value of 0 which indicate that the accuracy of the feature set having a constant accuracy.

Table 1. The QRS detection results for relax condition.

| No. | File | Desired peak | Detected Peak | Undetected Peak | Undesired peak | TN | TP | FN | FP | Accuracy | Sensitivity | PP |
|-----|------|--------------|---------------|----------------|---------------|----|----|----|----|----------|-------------|----|
| 1   | file1 | 169          | 169           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 2   | file2 | 167          | 167           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 3   | file3 | 156          | 156           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 4   | file4 | 163          | 163           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 5   | file5 | 150          | 150           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 6   | file6 | 190          | 190           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 7   | file7 | 190          | 190           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 8   | file8 | 177          | 177           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 9   | file9 | 166          | 166           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 10  | file10 | 223          | 223           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 11  | file11 | 169          | 169           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 12  | file12 | 176          | 176           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 13  | file13 | 220          | 220           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| 14  | file14 | 152          | 152           | -              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |
| Total |     | 2470         | 2468          | 0              | 0             | 0  | 1  | 0  | 6  | 1        | 1           | 1  |

Table 2. The QRS detection results for typing condition.

| No. | File | Desired Peak | Detected Peak | Undetected Peak | Undesired Peak | TN | TP | FN | FP | Accuracy | Sensitivity | PP |
|-----|------|--------------|---------------|----------------|---------------|----|----|----|----|----------|-------------|----|
| 1   | file1 | 201          | 177           | 4              | 20            | 0  | 1  | 0  | 6  | 0.8806   | 0.977901    | 0.8848 |
| 2   | file2 | 235          | 161           | 19             | 55            | 0  | 1  | 0  | 6  | 0.68511  | 0.894444    | 0.74537 |
| 3   | file3 | 154          | 146           | 1              | 7             | 0  | 1  | 0  | 6  | 0.94805  | 0.993197    | 0.95425 |
| 4   | file4 | 158          | 134           | 7              | 17            | 0  | 1  | 0  | 6  | 0.8481   | 0.950355    | 0.88742 |
| 5   | file5 | 160          | 122           | 15             | 23            | 0  | 1  | 0  | 6  | 0.7625   | 0.890511    | 0.84138 |
| 6   | file6 | 251          | 139           | 24             | 88            | 0  | 1  | 0  | 6  | 0.55378  | 0.852761    | 0.61233 |
| 7   | file7 | 192          | 159           | 4              | 29            | 0  | 1  | 0  | 6  | 0.82813  | 0.97546     | 0.84574 |
| 8   | file8 | 211          | 165           | 11             | 35            | 0  | 1  | 0  | 6  | 0.78199  | 0.9375      | 0.825   |
| 9   | file9 | 161          | 147           | 2              | 12            | 0  | 1  | 0  | 6  | 0.91304  | 0.986577    | 0.92453 |
| 10  | file10 | 186          | 144           | 9              | 33            | 0  | 1  | 0  | 6  | 0.77419  | 0.941176    | 0.81356 |
| Total |     | 1909         | 1494          | 96             | 319           | 0  | 1  | 0  | 6  | 0.79755  | 0.939988    | 0.83481 |
5. Conclusions
In this paper, the developed (i.e., wireless ECG system that consists of mobile physiological examination device and wireless base station) and its application in the experiment is evaluated. One of the crucial steps in the ECG analysis is to accurately detect the different form of P, Q, R and S which represent the entire heart cycle. An application of the adaptive filter with the developed system, the higher quality of the ECG signals is achieved. An improvement of QRS peak detection accuracy supported by adaptive filter about 86% is achieved.
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