Bulletin of Electrical Engineering and Informatics
Vol. 8, No. 1, March 2019, pp. 261~268
ISSN: 2302-9285, DOI: 10.11591/eei.v8i1.1400

A general framework for improving electrocardiography monitoring system with machine learning

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Article Info

Article history:

Received Oct 28, 2018
Revised Nov 30, 2018
Accepted Dec 26, 2018

Keywords:

Electrocardiography
Framework
Limitations
Machine learning
Medical applications

ABSTRACT

As one of the most important health monitoring systems, electrocardiography (ECG) is used to obtain information about the structure and functions of the human heart for detecting and preventing cardiovascular disease. Given its important role, it is vital that the ECG monitoring system provides relevant and accurate information about the heart. Over the years, numerous attempts were made to design and develop more effective ECG monitoring system. Nonetheless, the literature reveals not only several limitations in conventional ECG monitoring system but also emphasizes on the need to adopt new technology such as machine learning to improve the monitoring system as well as its medical applications. This paper reviews previous works on machine learning to explain its key features, capabilities as well as presents a general framework for improving ECG monitoring system.

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1. INTRODUCTION

Cardiovascular disease has been established as a major threat to human lives and public health. The statistics concerning cardiovascular disease are alarming. It has been reported that the disease kills as many as six million people every year. Most of these deaths resulted from heart attacks. About half of all heart attacks are fatal and a third of the deaths occur before reaching hospitals. Nonetheless, heart disease is potentially avoidable and preventable. The disease has been primarily and extensively diagnosed by using the electrocardiograph (ECG) monitoring system. With its capabilities to detect, monitor and provide useful information about the heart, the ECG monitoring system has been able to reduce the number of premature deaths, improved healthcare services and quality of life as well as lowered healthcare costs [1-7].

Electrocardiograph monitoring system has become the standard procedure for diagnosing the heart since the 1940s. However, the earliest ECG monitoring system was basically developed with electrically primitive analog electronics. Since the first electrocardiography device was introduced, there has been numerous attempts to introduce better systems. Over the years, the ECG system has continued to evolve as well as improve. The advances in new technologies have allowed researchers to design and develop more effective ECG monitoring system. For instance, contemporary ECG monitoring system adopt analog-to-digital converter to convert the signal convey by the system to digital signal that can be manipulated with digital electronics.

Throughout the years, improvement in ECG monitoring system and devices was driven by the advances, capabilities and potentials of new technologies such as pervasive computing, wireless mesh networks, 3D printing, machine learning, cloud computing and big data analytics. These technologies have shape and reshape important aspects of health care and learning. For instance, in health care, machine learning promises a dramatic shift in diagnosis and treatment of heart disease. Rather than wait for troublesome symptoms of the health disease to appear, through machine learning doctors now can continuously monitor the vital signs of patients from a much earlier stage. Despite the capabilities and potentials of machine learning, the literature reveals not only limited research but also not much information on the adoption of machine learning in contemporary ECG monitoring system. This paper attempts to provide some insights into the adoption of machine learning in improving ECG monitoring system. The first part of the paper reviews previous works on ECG monitoring system to highlight its limitations. Following this, the second part examines the literature on machine learning as well as presents a general framework for improving ECG monitoring system.

2. LIMITATIONS OF ECG MONITORING SYSTEM

Electrocardiography (ECG) monitoring system is used to obtain information about the electrical activity of the human heart and to detect cardiovascular disease. The literature indicates that over the years, different types of ECG monitoring system have been developed by using new technologies. The review of the past studies on ECG monitoring system however reveals a great deal of variance in terms of their capabilities and performance. More specifically, the review of the literature reveals several limitations. The limitations as identified in previous research are presented below.

2.1. Lack of learning capabilities

Despite the new technologies and efforts to develop intelligent ECG monitoring system, the review of the literature and past studies indicates that existing system has limited capabilities. For instance, existing ECG monitoring system appears to lack the ability to learn without being programmed. The learning ability of the monitoring system can be improved by making it more responsive and interactive through machine learning. However, the review of past research on ECG indicates very few studies have attempted to adopt this technology. The adoption of machine learning in ECG monitoring system is useful because it can not only help the monitoring system to learn but also be able to provide better detection and prediction of cardiac anomalies [8].

2.2. Limited real time monitoring

Real time monitoring capability of existing ECG monitoring system seems to be not only limited but also not emphasized. Intelligent ECG monitoring system can not only monitor the ECG signal of patients in real time but also detect their different physical activity as well. Equipped with machine learning, the monitoring system can automatically collect information on the physiological as well as physical behavior of patients. Machine learning helps to process, analyze and wirelessly send the information directly to the cardiologist for further evaluation. This will save the time needed to visit and examine patients' vital signs on a regular basis. Furthermore, the monitoring system can be used to gather medical information, monitor patients in remote places, high altitude as well as underwater [9-16].

2.3. Inadequate focus on vital signs

The review of the previous studies on ECG further suggests that existing monitoring system has primarily emphasized on heart rate as the main human vital sign for monitoring cardiovascular disease. However, the literature on heart disease indicates that there are other important vital signs that are also useful for detecting the disease. The other important vital signs included; respiration, body temperature and the blood pressure of the patients. Moreover, several previous studies have also stressed on the need to focus on these vital signs when developing intelligent ECG monitoring system [17, 18].

2.4. Minimal adoption of intelligent sensor

More recently, intelligent sensor is increasingly being recognized as an important technology for improving ECG monitoring system. Findings of research on intelligent sensor have shown that it can make the monitoring system more autonomous, easier to use as well as capable of providing constant monitoring of patients. Despite the various advantages of adopting intelligent sensor technology, the review of past research on ECG appears to indicate that there are not many studies that have focused and exploited the potentials of this technology [19-21].

2.5. Limited ability to detect physical activity

As mentioned earlier, contemporary ECG monitoring system has primarily emphasized on heart rate as the main vital sign for detecting and monitoring heart disease. Given the fact that heart attacks can also occurred in different circumstances (while eating, driving, physical exercising, swimming, etc.), several studies have recommended the need for ECG monitoring system to detect information on physical activity such as walking, running, swimming [22, 23].

As presented above, the review of the literature and past studies on ECG appears to indicate that contemporary ECG system has weaknesses and that they still lack learning capabilities. In view of the limitations of existing ECG devices as identified in previous studies and given the important role of the monitoring system in detecting, preventing, controlling and treating health disease, there is a further need to improve and develop a more capable ECG monitoring system with machine learning. According, the following section explains machine learning and presents a general framework for improving the ECG monitoring system by using the technology.

3. MACHINE LEARNING IN HEALTH CARE

With its various capabilities and potentials, machine learning is fundamentally changing health care. According to [24]–[27], machine learning is replacing the simple estimated score systems that adopt traditional statistics. More recently, machine learning is being used in precision medicine to help physicians to make better predictions. Since analyzing the heartbeat through traditional ECG monitoring system may be prone to human error and is also time consuming, machine learning has been adopted to automate classification of arrhythmia and improve the monitoring system. According to [28, 29], the ECG automatic system for arrhythmia classification involves the following four important sequential steps:

3.1. Preprocessing

Preprocessing as the first step in automated ECG system is involved with the reduction of noise in the ECG signals. Recursive digital filters of the finite impulse response (FIR) is best used for the attenuation of the known frequency bands [30]. Adaptive filter can also be used to remove noise from ECG signals [31], but it does not offer great advantages over the finite impulse response (FIR) digital filters [32].

3.2. Segmentation

Following the preprocessing step, the heartbeat segmentation is concerned with the detection of the R-peak or the QRS complex [33], [34]. In this step, the sensitivity and positive predictivity are used as the two important measures to evaluate the accuracy of the heartbeat segmentation. Over the years, more complex methods such as genetic algorithms [35], wavelet transform [36], filter banks [37], and quad level vector [38] have also been adopted in heartbeat segmentation.

3.3. Feature extraction

The third step in the ECG automatic system for arrhythmia classification involves feature extraction. One of the common features extracted is the RR interval, which is the time between the R-peak of a heartbeat with another heartbeat. A study by [39] has demonstrated the use of normalized RR-interval to improve the classification results. Other feature such as the distances between the fiducial points of a heartbeat (ECG segments) can also be used in feature extraction. In order to determine the fiducial points, an algorithm has been proposed by [40].

3.4. Classification

The fourth step involves classification of the different abnormal heartbeats. As far as classification is concerned, researchers have been using different types of learning algorithms such as support vector machines (SVM), artificial neural networks (ANN), linear discriminant (LD), and reservoir computing with logistic regression (RC). There are however variations proposed for the SVM such as the study by [41] which combined fuzzy theory to refine SVM classification as well as genetic algorithms combined with restricted fuzzy SVM [42]. Having discussed machine learning and its capabilities, the following section presents the general framework for using the technology to improve ECG monitoring system.

4. A GENERAL FRAMEWORK FOR IMPROVING ECG MONITORING SYSTEM

As indicated earlier, machine learning has at least three types of learning capabilities that include; supervised learning, unsupervised learning and reinforcement learning. These learning capabilities can be used to develop the classifier in the ECG monitoring system to enable it to classify arrhythmia (abnormal heartbeat) and different human physical activity. By enabling the ECG monitoring system to recognize as well as classify arrhythmia and physical activity, the system can continuously monitor the abnormal heartbeat of patients and their physical activity at a much earlier stage. This in turn enables preventive measures and more timely interventions. The section below explains briefly the general framework for improving the ECG monitoring system.

4.1. Machine learning and ECG Arrhythmia classification

Using machine learning in the construction and optimization of the classifier for categorizing ECG arrhythmia involves several important steps. The steps include; feature extraction, feature normalization, classifier training, and classifier evaluation [43]. Figure 1 presents the steps in ECG arrhythmia classification.

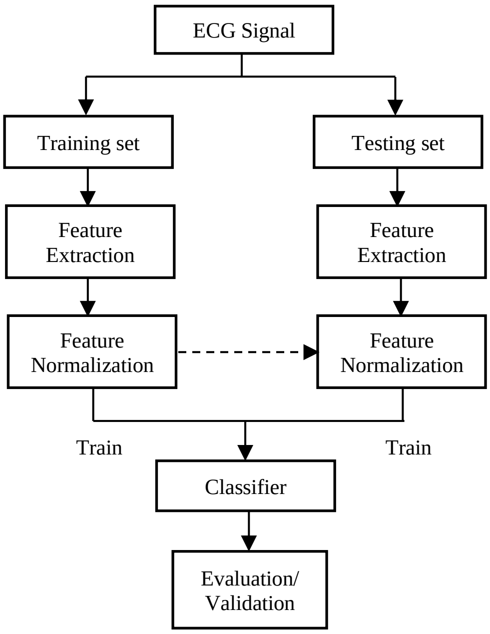

Figure 1. Steps in ECG arrhythmia classification [43]

4.1.1. ECG signal

The data of ECG signals are acquired from the MIT-BIH arrhythmia database [44]. They are used as the training set and the testing set for ECG arrhythmia classification. ECG wave form is the representation of the heartbeat, consisting of five different peaks (P, Q, R, S, T). Their variances, distances and other characteristics can help to identify the properties of the heart-beat [45]. These peaks are represented by their respective values of amplitude and time intervals.

4.1.2. Preprocessing of ECG signal

The raw ECG signals collected by the electrodes can be affected by various artifacts (noises) such as motion, baseline wandering, power-line interference. These artifacts can degrade the accuracy in the ECG classification. Therefore, the denoising or filtering of these artifacts is important to remove the disturbance in the fiducial point of the ECG waveform. Several filtering techniques such as high-pass filter, low-pass filter and adaptive filtering are being used.

4.1.3. Feature extraction

The feature extraction is concerned with the finding of relevant features of ECG data that can influence the accuracy performance of the ECG classification. If all known features are to be considered, it will be a challenge that requires heavy computational resources. Examples of the features are wavelet, RR-interval, R-peak, and QRS amplitude.

4.1.4. Feature selection

Feature selection is concerned with optimizing the features extracted by including only the important attributes or properties of the ECG signal. This is important to ensure that the ECG classification will be more accurate.

4.1.5. Classification

In the classification stage, the ECG signals that represents the heart beats are classified as normal beats or abnormal beats. The different machine learning classifiers used for ECG heartbeats include support vector machine (SVM), artificial neural networks (ANN), and k-nearest neighbor (kNN).

4.1.6. Classifier evaluation

Classifiers selected for the arrhythmia classification are then evaluated by using performance measures such as error rate, sensitivity, specificity, accuracy, and confusion matrix.

4.2. Machine learning and human activity recognition

Similarly, the learning capabilities of machine can also facilitate the ECG monitoring system in terms of recognizing different human activity. In the case of human activity recognition, the adoption of machine learning involves four specific phases. The four phases include; data collection, feature extraction, classification and evaluation [46, 47]. Figure 2 shows the process of human activity recognition (HAR) using machine learning based wearable sensors.

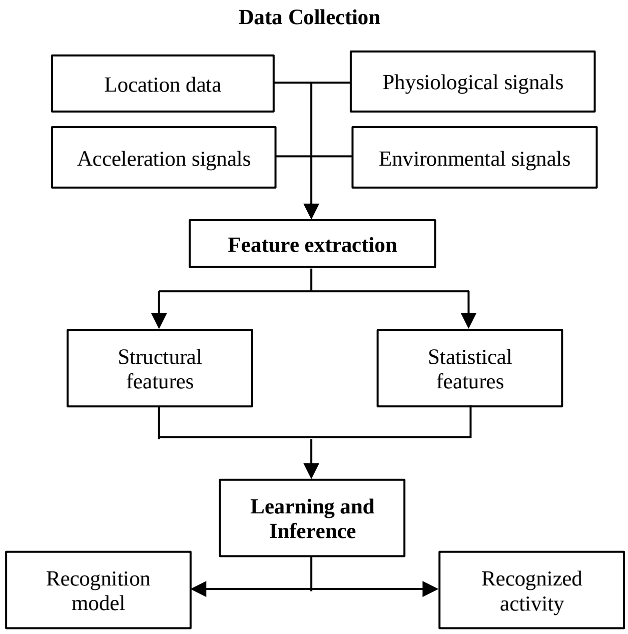

Figure 2. The Process of HAR based on Wearable Sensors [74]

4.2.1. Data collection

In human activity recognition, the first phase involves data collection by measuring the following four types of attributes; location, physiological, environmental, and acceleration. For location data, the global positioning system (GPS) is used to collect real-time navigation data. The physiological signals involve collecting data on human vital signs such as heart rate, respiration, and skin temperature. Environmental sensors are combined with accelerometers and other sensors to provide sufficient data on individual performing physical activities under diverse conditions [48]. The acceleration signal is collected through the triaxial accelerometer to recognize physical activities such as walking, running, or lying.

4.2.2. Feature extraction

In the feature extraction phase, the raw data collected is being processed. Human activity needs to be recognized in a time window basis and not in a sample basis because these activities are performed during long periods of time. Therefore, each time window needs to be applied with feature extraction to filter relevant information and obtain quantitative measures for signal comparison. The two techniques that can be used to extract features from time series data are statistical and structural.

4.2.3. Classification

The classifier needs to be trained with the training set (input set) to classify different types of physical activities. These training set may or may not be labeled. Several important classifiers in human activity recognition are decision trees, Bayesian methods, support vector machine (SVM), C4.5, and artificial neural networks (ANN). The classifier selected needs to be evaluated by using different performance metrics such as accuracy, precision, recall and F-measure.

4.2.4. Evaluation

The selected classifiers for human activity recognition need to be assessed by using different performance metrics that include accuracy, precision, recall and F-measure.

5. CONCLUSION

This paper reviews the limitations of ECG monitoring system as well as presents a general framework for improving the monitoring system with machine learning. Based on the review, the paper identified at least five limitations of past works on ECG monitoring system. The limitations suggest that there is a need to further improve the ability of ECG monitoring system to classify abnormal heartbeat as well as physical activity by adopting the capabilities of machine learning. In addition, the paper surveys various key features and capabilities of machine learning and presents a general framework for using the technology to improve the ECG monitoring system, particularly in terms of detecting different types of heartbeat and physical activity. By being able to recognize different types of heartbeat and physical activity, the ECG monitoring system promises a significant shift in diagnosis and treatment of heart disease.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support provided by Embedded, Networks and Advanced Computing Research Cluster (ENAC) at Universiti Malaysia Perlis, Malaysia.

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