Highlighting the Current Issues with Pride Suggestions for Improving the Performance of Real Time Cardiac Health Monitoring

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Abstract. Electrocardiogram (ECG) signal utilized by Clinicians to extract very useful information about the functional status of the heart. Of particular interest systems designed for monitoring people outdoor and detecting abnormalities on the real time. However, there are far from achieving the ideal of being able to perform adequately real time remote cardiac health monitoring in practical life. That is due to problematical challenges. In this paper we discuss all these issues, furthermore our intimations and propositions to relief such concerns are stated.

Keywords: Electrocardiogram, Arrhythmia, and Remote Cardiac Monitoring.

1 Introduction

Electrocardiogram (ECG) is a series of waves and deflections recording the cardiac's (heart) electrical activity sensed by several electrodes, known as leads. ECG signals generated by sensing the current wave sequence related to each cardiac beat. The P wave to represent the Atrial depolarization, QRS complex for ventricular depolarization and T wave for ventricular repolarization. Fig. 1 depicts the basics shape of a healthy ECG heartbeat signal.

ECG signals are very important medical instrument. That can be utilized by Clinicians to extract very useful information about the functional status of the heart. So as to detect heart arrhythmia which is the anomalous heart beat, mapped with different shape in ECG signal noticed by deflection on the P, QRS, and T waves, which acquired by some parameters. That judge against reference ones obtained through the average of normal ECG wave forms sampled from healthy people classified by age, sex, constitution and lifestyle. And then an enormous finding produced [1]. Considering the layout procedures of detecting the heart arrhythmias in real time, which begins with extracting the ECG signals, filtering, specifying the features and descriptors, selecting the training datasets, and end with constructing the classifier model to specify the types of arrhythmia in accurate manner [2].

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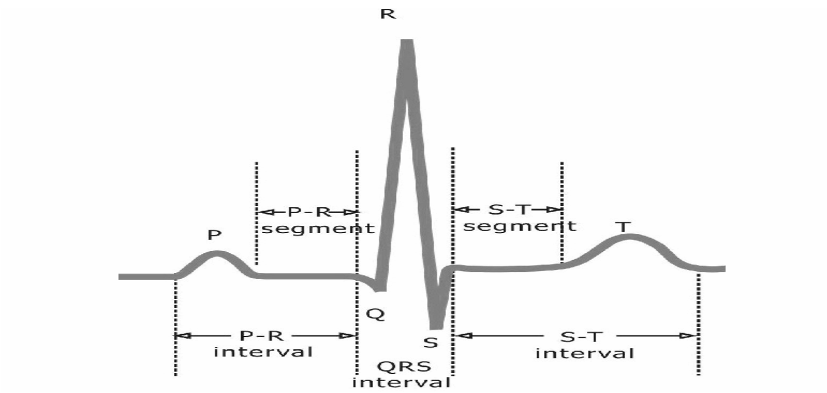

Fig. 1. Shape of a healthy ECG heartbeat signal

We specify a number of convenient challenges that stand in between monitoring the cardiac health in real time in very sufficient way. In this paper we argue these issues in details. In the rest of this paper, we give a brief background of the heart health monitoring problems, addressing the challenges for each step involved in developing real time cardiac health monitoring systems, finally the conclusion and recommendations.

2 Heart Health Monitoring Problems

Wired ECG monitoring in hospital are very crucial for saving people's life. But this kind of monitoring is inadequacy for the coronary cardiac disease's patients, who need following up in home and in the open air, those who need continues monitoring system to save their life. Generally there are three categories of systems for monitoring patients through classifying the ECG signal: 1) classification off-line 2) remote real time classification; and 3) local real time classification. Among the first group of systems, recorded ECG during continues 24 or 48 hours is going to be analyzed later, this type of systems doesn't offer a real time cardiac health monitoring. To overcome this problem, the second group of systems was developed, where remote real time classification is performed. This is can be achieved by sending the ECG data to a monitoring service center, then the ECG analysis can be made. In spite of the advantages, these kinds of systems still present number of disadvantages, such like inefficiency, that due to the high cost for transmitting the ECG data. Beside the difficulties to detect the signals when there is a limitation of networks. Moreover, troubles of compression in relation to reconstructed signal quality and coding delay are noticed. Because of the inherent drawbacks associated with the off-line and the remote real time classification of the ECG, there has been a great deal of interest in the third group of systems, those who provide real time ECG classification through intermediary local computer between the sensor and the control center [3]. It's vital for the automated system to accurately detect and classify ECG signals very fast, to provide a useful means for tracing the heart health in the right time. The effectiveness of such systems is affected by several factors, including the ECG signals, the estimated

ECG's features and descriptors, the dataset used for learning purpose and the classification model which applied. Although the local real time system are superior other systems, but there are still clear challenges, in the following sections we are going to discuss all these challenges.

2.1 The ECG Signal Extraction

The Electrocardiography is a diagnosis tool used by medical doctors to check the status of the heart. In contrast, the ECG can often be normal or nearly normal in patients with undiagnosed coronary artery disease or other forms of heart disease (false negative results.), and many "abnormalities" that appear on the ECG turn out to have no medical significance after a thorough evaluation is done (false positive results) [4].

ECG is recorded by attaching a set of electrodes on the body surface such as chest, neck, arms, and legs. The more the leads the larger the information set of data we can obtain for the heart activities. Early past, physicians used only three sensors (Right Arm RA, Left Arm LA, and Left Leg LL) in a method known as the 3-lead ECG, which suffers from the lack of information about the whole of the heart. The 12-lead ECG is the one of the hottest techniques for monitoring heart activity recording as (I, II, III, aVR, aVL, aVF, V1,V2,V3,V4,V5,V6) leads [5]. This type makes use of four limb electrodes and six chest electrodes in order to provide a comprehensive picture of the electrical activity of the heart from 12 different "viewpoints" around the surface of the body. The particular viewpoint which each lead has of the heart determines the characteristic form of the corresponding ECG signal. As a result, the morphology of the waves which make up the ECG signals for the different leads varies according to the particular lead chosen. Fig. 2 shows a single ECG waveform (heartbeat) from each of the 12 different leads. However, the costs for this enlarged amount of information are higher number of computations, more sophisticated monitoring and breakdown of large data sets, and stringent requirements on the elementary portable hardware platform.

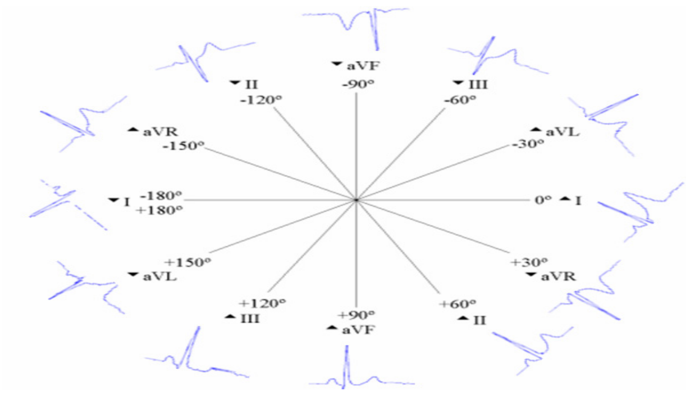

Fig. 2. Selected ECG waveforms from the 12 different leads

Unfortunately most solutions available now are based upon Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database, where each record consists of two leads only [6]. This means, very limited information generated and discovered. As a result, we perceive only some arrhythmias, and monitoring merely the minority of the heart activity. On the other hand, there are 12 leads ECG databases mentioned in the literature just like Physikalisch-Technische Bundesanstalt (PTB), which provided by the National Metrology Institute of Germany. It composes of 16 input channels 14 for ECGs, one for respiration, and one for line voltage. But very little research and work was based on such database.

2.2 ECG Signal Quality

The filtering techniques seek in general, to specify and clarify the ECG wave elements (P, QRS complex, and T). The duration of the P wave is less than 120 milliseconds [7]. The spectral characteristic of a normal P wave is usually considered to be low frequency, below 10–15 Hz. The QRS complex lasts for about 70–110 milliseconds in a normal heartbeat, and has the largest amplitude of the ECG waveforms. Due to its steep slopes, the frequency content of the QRS complex is considerably higher than the other ECG waves, and is mostly concentrated in the interval of 10–40 Hz. The T wave reflects ventricular repolarization and extends about 300 milliseconds after the QRS complex [8]. As a result and due to the clearance of the QRS complex among the other parameters, most techniques detect the QRS complex mainly the R wave and sacrificing by the other parameters like P, T waves. QRS complex facilitates in detecting the RR interval and diagnosing many arrhythmias, such as normal heart beat, premature ventricular contractions, left and right bundled branch blocks, and paced beats. In contrast there are so many arrhythmias which couldn’t be detected without considering the P and T waves [9]. Some arrhythmias, though they may have a different cause, apparent themselves in similar ways on the ECG, taking into account the main two grouping of arrhythmias the Ventricular, that occurs in the ventricles are recognized because of the abnormal QRS-morphology. And the Supraventricular arrhythmias, which occur in the atrium however, can only be predetermined because they have an effect on the ventricular rhythm. For example, prematurity is used as a parameter to detect non-sinus beats, sudden pauses as indicators of atrioventricular conduction disturbances or sinus pauses, and sometimes irregularity as a measure for the presence of atrial fibrillation or flutter. Accordingly, Supraventricular’s abnormalities causing no or only gradual changes in ventricular rhythm are not observed by the current analysis programs, those who are referring only to the QRS complex for tracing the cardiac activity [10]. For that explanation, the way out of this problem would be, of course to analyze the P-wave and other elements of the ECG. Not only but also, measuring the time interval between these elements. Nevertheless, this is technically not feasible in the current remote cardiac health monitoring systems because of signal quality considerations.

2.3 QRS Descriptors

Some of the most descriptors of the QRS complex morphology are developed using pattern recognition techniques [11]. Measuring the diversity between the sequential and frequency characteristics of the QRS complex waveform is also introduced; such like Karhunen-loeve transforms [12], Hermite functions [13], and wavelet transform [14]. Recently, introduced methods of ECG signals adaptive time frequency transform and calculation of the applicable time frequency features pass on the structures of the signals [15]. The most popular approaches are based on pattern recognition techniques using morphological features, it obtained very high accuracy, but there are several disadvantages. First of all, the size of the templates that should be stored in the memory for further matching is very big. Secondly the accuracy relay on the threshold based segmentation techniques to discriminate the component of the ECG signal; these schemes are extremely receptive to the outsized morphological disparity of the ECG not only between different patients or patient cluster but also within the same patient. And finally, the limited numbers of classes of the wave form to descript specific cardiac arrhythmias, which can be extracted using such kind of features. Since there are some methods are using only the morphological descriptors of the QRS complex [16], while others are using the morphological descriptors of the P and T wave [17]. Nonetheless, we cannot use the morphological features of the P, T, and QRS waves to express cardiac patterns that do not have obvious P, T, and QRS complex. For that reason, morphological features are not fitting for describing ventricular fibrillation and some types of tachycardia. Moreover, morphological descriptors are counting a massive number of challenges in relation to computational efforts and time consuming [18]. Such computation is very complex to carry out by wireless sensors, since there are boundaries of power supply and the problem of noise; On the other hand, there are tendencies to detect the abnormality cardiac conditions using features to represent the ECG waveform through the time-frequency [19], by describing the ECG patterns through their frequencies content and time representation. Although it suffers from increasing the number of features assigned to detect different arrhythmias but still it looks much better than other methods, particularly it can be relief to some extent by utilizing the feature subset techniques.

2.4 Training Dataset

Confirming local and global dataset as the main two approaches of training dataset used to learn the classifier model. The local learning set is a customized set to specific patient, and global is built from large database [20] and [21]. The later one is preferable to build a classifier model, while it is static which means the learning process takes place through specific set of data under specific circumstances. Therefore, the model generated will be very accurate in similar situation while it doesn't in different cases. Which means it can be uses to monitor the ECG in hospital not in the open air. On the other hand, in case of the first philosophy there will be a patient adaptable local learning set. In this sense, specific strategies are adopted for local learning in some arrhythmia monitoring. Obviously, the size of the training data is very big and it is satisfy the need of monitoring just specific arrhythmia of specific patient.

The nature of ECG data in real time monitoring applications involves many changes through the time. For example, the different situations and activities of the monitored person are varying along the day, which affecting the heart activities and in usual cases it is not a bad effects but it will be detected by the ECG leads and transferred to the classifier model which is constructed by old training dataset. In case of worse condition when arrhythmias occur, the current classifier model may not detect the abnormalities or it may detect them but afterward [22]. As a result, the model constructed using the old training data no longer need to be adjusted in order to identify with the new concepts. In view of that, developing one classifier model to satisfy all patients in different situation using static training datasets is unsuccessful.

2.5 The Classification Models

Several data mining techniques were used for classifying the ECG data. Such as decision tree [23], support vector machine [24], neural networks [25], nearest neighbor [16], rule base classifier [26], fuzzy adaptive [27], and etc. The judgment upon such techniques bases on accuracy, sensitivity, speed and the reliability of the classifier. Integrating all these factors together, is essential for real time cardiac health monitoring purpose [28] and [29]. Moreover, finding out the most proper classifier model that capable for classifying arrhythmias on real time is very important issue. Even though, it is complicated process. That is due to the fact, each model was designed to detect specific kind of arrhythmias differ from one model to another, diverse arrhythmia database, unlike features extraction techniques, with dissimilarities procedures for preprocessing, and different percentages of training datasets. Although there were some efforts for comparing the performance of different classifiers model by unifying the comparison environment factors [3]. But regrettably, the comparison process takes place through few classification models, few types of arrhythmias, and slapdash to some important concerns; like memory requirement, time consumed and sensitivity. Additionally, the literature has not mentioned any assessments to these models in real life applications, such like evaluating the performance in Personal Digital Assistant (PDA), specifying the gap between the time of occurring the arrhythmia and the moment when it's detected by the model. So far, experimental results appear to indicate that various models are largely equivalent, and there is no evidence that any one model is superior to others. It will be more useful if the evaluation involve extra testing like dealing with noises. For the reason that, such applications in reality affected by so many influences for example, noise caused by surrounding environment or artifacts generated by electrode displacement, changes on the patient's body position or cardio-respiratory interactions.

3 Conclusion and Recommendations

Detecting the heart arrhythmias through ECG monitoring is mature research achievement. Research has been made, encouraging result has been obtained and cardiac health monitoring has reached a certain level of maturity when operating directly or off-line. However there are far from achieving the perfect of being able to perform adequately remote cardiac health monitoring and fulfilling the vision of providing the health care to anyone, anywhere, and any time. There are so many issues facing the current research on the area of real time heart monitoring. The number of ECG leads used to detect the heart signals are so few, limitation on arrhythmias detection quantity and quality, depending mainly upon the R wave and sacrificing by the P and T waves, which can offer better prediction in conjunction with the QRS complex wave. On the other hand, this is technically not feasible in the current remote cardiac health monitoring systems because of signal quality considerations. The computational cost of the QRS complex descriptors is very high and error-prone, which affect negatively the speed, flexibility, and the accuracy of the classifier. Also developing one classifier model to satisfy all patients in different situation using static training datasets is fruitless. Moreover, unfinished evaluations for the current general data mining classification models are listed.

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