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Fine-tuning ECG Parameters Technique for Precise Abnormalities Detection

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***Abstract*—The number and the types of ECG parameters necessity to detect different arrhythmias with high quality are counting a massive number of challenges in relation to computational efforts. Such computation is very complex to carry out by wireless sensors, since there are boundaries of power supply and problem of noise. Therefore, the current systems cannot detect the abnormalities accurately or detect them but afterward. We proposed a technique to tuning the ECG parameters for achieving better arrhythmias detection in real-time applications. Our proposed methodology selects the features related to the QRS complex plus those related to P or T waves, aiming to design a unique feature set that could be employed to describe specific arrhythmia in very sensitive manner. The performance of the tuning technique has been evaluated using various approaches. The results demonstrate the effectiveness of our proposed technique.**

Keywords-Electrocardiogram (ECG); Arrhythmias; ECG parameters.

I. 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. 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].

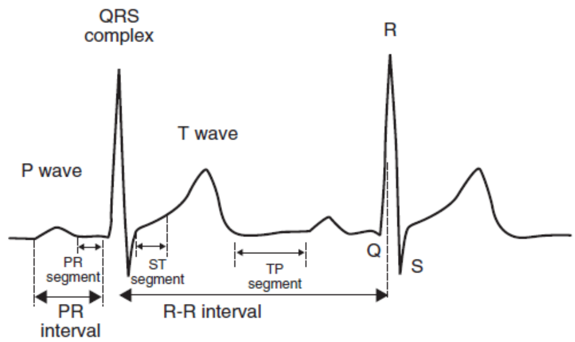

Figure 1. The normal ECG signal

There has been a great deal of interest in the systems which 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 [4].

In this paper we are addressing the necessity of organizing the ECG parameters In favor of detecting different types of arrhythmias, all the ECG parameters must be considered. Such computation is very complex to carry out by a computer with limited resources, although there are great interests in high accuracy to specify the arrhythmias, with high speed to save people life and avoid risks. Therefore, a great attention in the literature is flagging to select a subset of these features in order to detect an arrhythmia accurately.

Our Idea is to select the features related to the *QRS* complex plus those which related to *P* or *T* waves. Our aim is to design a unique feature set that could be employed to describe specific arrhythmia in very sensitive manner and less computation complexity.

In the rest of this paper we will give a brief background of related work, the description of the tuning methods is follow, the experimental works, finally the conclusion.

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II. Related Work

In the following section we will introduce some related work, including the most famous philosophies used to analyses the parameters of the ECG, and incremental learning algorithms utilized to classify arrhythmias.

A. Analysis of the Parameter Computational Problem

Some of the most descriptors of the *QRS* complex morphology are developed using pattern recognition techniques [5]. Measuring the diversity between the sequential and frequency characteristics of the *QRS* complex waveform is also introduced; such like Karhunen-loeve transforms [6], Hermite functions [7], and wavelet transform [8]. 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 [9]. 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 [10], while others are using the morphological descriptors of the *P* and *T* wave [11]. 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 [12]. 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 [13].

Due to the clearance of the *QRS* complex among the other parameters, most techniques uses the *QRS* complex mainly the R wave and ignoring 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 [14]. 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 [15]. In previous work we suggested a nested ensemble technique to solve the problem of ECG parameters that is by manipulating the ECG features to select the proper adequate set (morphological features) to enrich the accuracy [16]. Although the results are promising but the synchronizing of the two components is expensive, which affects the detection of the arrhythmias in real time negatively. Moreover it was static to some extent.

B. Arrhythmias Classification methods

A supervised training technique was used to build a model for classifying the ECG data. The classifier model maps the input features to the required output classes, using adjustable parameters specified during the training process. Automated arrhythmias classification using the ECG features (*P*, *QRS* complex, and *T*) was traditionally performed using supervised and non supervised methods. Several data mining techniques were used for this intention, one of the most famous techniques used to classify the cardiac arrhythmias are utilizing the decision-tree based on different features [17], [18].

Detecting arrhythmias by applying the pattern recognition methods are very well known. Out of which is the Artificial Neural Networks (ANN). The detection process starts by learning the model with different shapes of ECG parameters during the training session, extracting different statistical parameters of these ECG training dataset, and later using these parameters to classify the unseen ECG during the testing session. Several efforts have been made to apply ANNs for the purpose of heart arrhythmias classification and detecting the cardiac abnormalities. Preceding research efforts such as [15] and [19], artificial neural network has compensation of good noise tolerance in addition to its high efficiency when dealing with non-linear problems. But there are so many drawbacks of applying the pattern recognition such as the few numbers of arrhythmias that can be detected due to the limited number of shaped that can be saved in the memory for matching purpose that is beside the computational time which increase rapidly with increasing the number of arrhythmias aimed to be classified, The things that lead to impracticality in real human life. Other methods like support vector machine [20], nearest neighbor [10], rule base classifier [21], and fuzzy adaptive [22] are also introduced in this area. Rodriguez, J. et attempted to drive approach that can build most accurate model for classifying cardiac arrhythmias based on features extraction [23]. He divided the dataset into random groups one for training (66%) and another for validation (33%). He used weka and answertree tool in his experimental. 16 methods were used in the experiments. The judgment upon such techniques bases on the accuracy: the right description of the arrhythmia, effectiveness: the sensitivity to detect the abnormalities on the same time when it take place, efficiency: the speed by which the class of the arrhythmia is going to be specified, and the reliability of the classifier: how far doctors can trust on that model to judge future unseen ECG data. These factors are fluctuating from one to another method.

C. The ECG Parameters Tuning Technique

Our Idea is to select features related to the *QRS* complex plus those which are related to *P* or *T* waves. Our aim is to design a unique feature set that could be employed to describe specific arrhythmia in very sensitive manner.

The tuning processes of these parameters are going to take place through one or two parameters plus the *QRS* depending on the situation. The parameters specifications are change by the arrhythmias detection requirements freely. The exclusivity behind our design is that all the previous works did the tuning of these parameters with equal weight in all arrhythmia types, while it is not true in the practical life. In our design we are going to do sensitive adaptation referring to the necessity of the parameters to detect arrhythmia classes specifically. Consequently much accuracy will be achieve and less computation among other is going to be decorated.

Similar arrhythmias often share a similar features generated by specific parameters. Therefore, it is useful to predict the required parameters to detect specified arrhythmia. The proposed method uses similar arrhythmias collected from the training data. Parameters involvements are measured using the parameter scores $P^c(f)$. The overall parameters lists, which represent the predicted arrhythmia class label, are created from the collected similar cases. The parameter with high Parameter score $P^c(f)$ are grouped together generating the overall parameters list, which indicates the possibilities to assign the arrhythmia class c to the case with specific feature set f (distributed through different parameters included in the overall parameters lists). Accordingly, there will be different parameters list for each arrhythmia, the thing that enhance the accuracy and in the same time reduce the computation efforts. The parameters list of a given cardiac arrhythmia is predicted from similar arrhythmias. They are collected from training data based on general features G^f. The collected cases are used to calculate the parameter scores $P^c(f)$. First, the ten most similar arrhythmias cases are collected for each cardiac arrhythmia *C*. They are collected among the training cases, focusing on the same arrhythmia *C*. parameter selection process are based on the general features G^f:

$$G(C^{parameter}, C^{feature}) = \sum_{f=1}^{n} \log \frac{C^{parameter}}{C^{feature}} \qquad (1)$$

Where $C^{feature}$ and $C^{parameter}$ are the elements to specify the parameters related to specific arrhythmia. $f=1$ to n represent the feature list, which are the general features of the input and training the classifier model to state the arrhythmia's classes. The collected arrhythmias have manually labeled binary maps B^c, which indicates the presence '1' or absence '0' of the feature f to represent the arrhythmia *C*:

$$B^f(C) = \begin{cases} 1 & \text{if handssing(c) = f} \\ 0 & \text{others} \end{cases} \qquad (2)$$

Binary labeled maps B^C are combined to create one general Parameter score P^C for each arrhythmia *C*. As shown in Fig. 2, general parameter score P^C is created through four steps: Gaussian weighted sum B^C, first maximization process O^{1P}, Gaussian weighted average O^{2P}, and final maximization process O^{3P}.

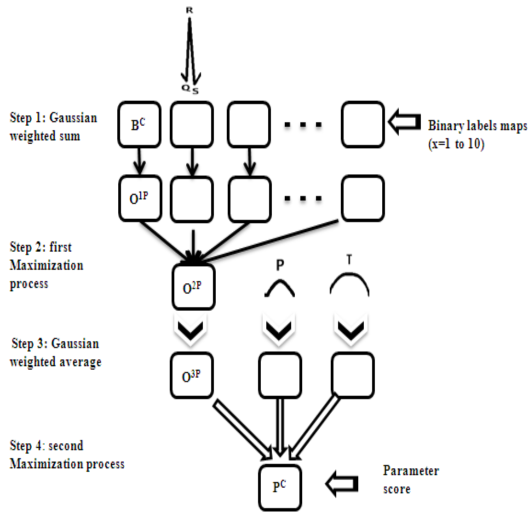

Figure 2. ECG parmeters tuning setps

Step 1:

Ten maps $B^c p_x$ $(x = 1, 2, 3, \ldots, 4)$ for parameter *P* are smoothed out using an isotropic Gaussian function $g\sigma_{sum}$ with a mean of zero and stander deviation of σ_{sum}

$$O_x^{1P}(C) = \sum_{x=1} g^{\sigma} sum(C) B_x^C \qquad (3)$$

It will give the highest values (scores) to the parameter *P*, which can be utilize to specify specific arrhythmia.

Step 2:

The maximum value among the ten outputs $O_x^{1P}(C)$ is taken for any arrhythmia:

$$O_x^{2p}(C) = \max O_x^{1p}(C) \qquad (4)$$

Step 3:

The output O_x^{2P} is smoothed using a Gaussian function whose mean is the focused part *X*:

$$O_x^{3p}(C) = \frac{1}{S} \sum_{x=1}^{4} g^x \sigma_{avg}(C) O_x^{2p}(C) \qquad (5)$$

Where a standard deviation of $g^K\,\sigma_{avg}$ is σ_{avg} and S is the number of features that represents the arrhythmia. It makes the smooth distribution of scores centering on the focused parameter P.

Step 4:

Finally, the P^C calculated from the maximum value among Ox^{3P} of the ten cases for that arrhythmia:

$$P^C(f) = \max O_x^{3p}(C) \qquad (6)$$

Accordingly, the customization for the ECG parameters for any aryhthmia can be achieved.

III. The Experimental Works

A. Invironment

We used a database generated at the University of California, Irvine [24]. It was obtained from Waikato Environment for Knowledge Analysis (WEKA), containing 279 attributes and 452 instances [25]. The classes from 01 to 15 were distributed to describe normal rhythm, Ischemic changes (Coronary Artery Disease), Old Anterior Myocardial Infarction, Old Inferior Myocardial Infarction, Sinus tachycardy, Sinus bradycardy, Ventricular Premature Contraction (PVC), Supraventricular Premature Contraction, Left bundle branch block, Right bundle branch block, degree AtrioVentricular block, degree AV block, degree AV block, Left ventricule hypertrophy, Atrial Fibrillation or Flutter, and Others types of arrhythmias Respectively. The experiments were conducted in WEKA 3.6.1 environment, and carried out by PC with processor Intel core (T M) 2 DUO, speed 2.40 GHz. And RAM 2 GB.

B. Results

We implemented two types of experimental works, the first one to prove the necessity of including the P and T waves in conjunction with the *QRS* complex to evaluate arrhythmias in the right way. And the second work to provide evidence about the value added by our technique regarding the improvement of the classifier's accuracy.

Referring to the first experiment we measure the performance of three different algorithms the OneR, J48 and Naïve Bayes according to the parameter(s) used to classify the arrhythmias. Table 1 summarizes the results for each algorithm.

TABLE I. The Accuracy According To Specific Ecg Parameter

Features	OneR	J48	Naïve Bayes
QRS only	60.4	91.2	76.5
QRS + P	60.4	91.4	77
QRS + T	61.3	91.2	76.7
QRS + P + T	61.1	92.3	77.7

Fig. 3 illustrates the accuracy achieved by each algorithms with different parameter. All of them –except the OneR– their accuracy increase when we include features related to *QRS* complex, P and T, while there was light improvement when *QRS* included with either P or T waves. The result proves that, there is a great need of using all types of features to detect all types of cardiac arrhythmias. *QRS* complex alone, perceive only some arrhythmias and the monitoring process can take place to merely a minority of the heart. On the other hand, we can attain the majority when we utilize the *QRS* with P and T waves.

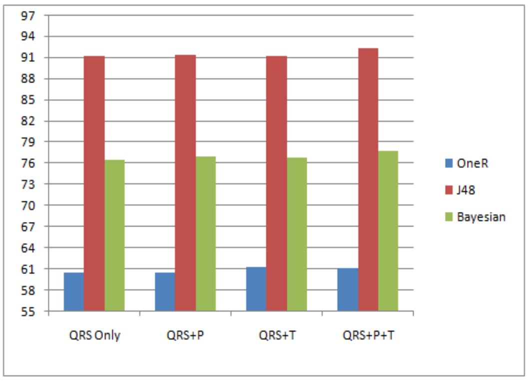

Figure 3. the algorithms performance with different parametes

In the second experiment works we introduced our tuning technique to J48 algorithm and compare its performance before applying the tuning technique, since it scored a high performance when compared with other methods according to the previous experiments.

Fig. 4 shows the superior of the tuning technique in the process of detecting the arrhythmias with high accuracy when compared with the J48 without utilizing the tuning method. It is a clear prove that it can enhance the process of detecting different types of arrhythmia. That simply due to the unique parameters designs to satisfy the detection of each arrhythmia independently. Thus, there could be very efficient cardiac health monitoring to specify the type of the arrhythmia in very accurate mode.

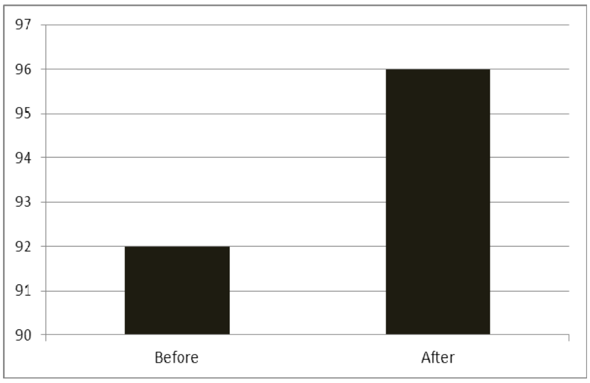

Figure 4. The J48 performance befor and after introducing tuning method

IV. Conclusion

Analyzing the *QRS*, *P*-wave and other elements of the ECG. Not only but also, measuring the time interval between these elements, are required in real time cardiac monitoring. Nevertheless, this is technically not feasible in the current systems because of computation considerations.

The ECG's parameters tuning method suggested for providing the classifier by unique designing of the parameters needed to specify the type of the arrhythmia in very specific manner. Consequently much accuracy achieve and less computation among other is decorated. The performance of the tuning technique has been evaluated using various approaches. The results demonstrate the effectiveness of our proposed technique.

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