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Classification of ECG complexes using self-organizing CMAC

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ABSTRACT

In this study, we apply a self-organizing cerebellar model articulation controller (SOCMAC) network to design an ECG classifier by observing the QRS complex of each heartbeat. The SOCMAC network is an unsupervised learning method, which combines Kohonen's self-organizing map into CMAC. In order to achieve the goal of real-time classification, the data collected are divided into two datasets: the training set for the unsupervised learning of the ECG classifier and the testing set for the real-time classification. In the learning stage, with the help of the proposed performance index, we search for optimal parameters of the network that achieve the best performance. Then the well-trained classifier is used, with the optimal parameters, to classify the testing set. Tested with all the 48 recordings from the MIT/BIH arrhythmia database, the proposed method achieves a classification accuracy of 98.21%, which is comparable to the existing results.

1. Introduction

The electrocardiogram (ECG) is the record of variation of bioelectric potential with respect to time as the human heart beats. Due to the ease of recording ECG in a noninvasive manner, ECG plays an important role in monitoring and diagnosing patients today. Arrhythmia events, any disturbance in the regular rhythmic activity of the heart, are hard to capture, because there is no certainty that they will occur while the patient is being monitored in the hospital. The monitoring of patients' ECG during their day-to-day activities for identifying arrhythmia is therefore necessary. A large amount of data are obtained in the case of monitoring ECG signals of a patient continuously for 24 h. Typically, there could be more than 100,000 heartbeats per channel for analysis. Since visual analysis of such amount of ECG data is time-consuming, many computer-based methods for automatic ECG analysis have been studied for a long time. ECG recognition is a difficult problem even with the aid of a computer, because ECG waveforms differ significantly even for the same beat type taken from the same patient.

Several approaches that automatically classify heartbeats have been proposed in the literature. They include statistical [1,11] and syntactic [2] approaches. In [11], three different features of ECG beats, including third-order cumulant, wavelet entropy, and auto-regressive coefficients, were used to evaluate the performance of Mahalanobis and minimum distance-based statistical classifiers. Artificial neural networks (ANNs) were also employed to exploit their natural ability in pattern recognition tasks for successful classification of ECG beats [3–9]. The multilayer perceptron (MLP) is one of the most popular artificial neural networks used in ECG classification. In [3], the principal characteristics of the ECG signal were extracted by using the principal component analysis technique and then were applied to an MLP for classification. Minami et al. [4] used Fourier transform to extract features of QRS complexes and used an MLP with five input and two output cells to classify the features. Self-organizing maps (SOMs) have also been applied for classifying ECG beats [5,6]. In [5], SOMs were used to design a customized beat classifier and a global beat classifier. Then, the two classifiers were combined together by the mixture-of-experts principle. A

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5×5 SOM was employed for clustering ECG beats into 25 clusters in [6], in which the QRS complexes were represented by the orthogonal Hermite functions. In [7], a multi-channel ART2 neural network was proposed for the classification of two-channel ECG signals. Recently, we have seen a growing number of combined neural network approaches to ECG classification. The neuro-fuzzy network has been used to design the ECG classifier [8,9]. The neuro-fuzzy network is composed of two subnetworks connected in cascade: the fuzzy self-organizing layer performing the pre-classification task and the following MLP working as the final classifier. In [10], the MLPs were used at the first level and the second level for the implementation of the combined neural network. Note that there is a very large literature on the subject of classification of heartbeats, only several of ANN-based approaches are referenced here. A more general overview of this subject can be found in [12] and references there in.

In this paper, a real-time ECG beats classification method is proposed. This method is based on the self-organizing cerebellar model articulation controller (SOCMAC) network [13], which was proposed by our research group. The SOCMAC combines the structure of the cerebellar model articulation controller (CMAC) network into the Kohonen layer of the SOM so that it could perform the function of a SOM and could distribute the learning error into the memory contents of all addressed hypercubes as a CMAC. Therefore, this new type of neural network has the features of both the SOM and the CMAC.

The remainder of this paper is organized as follows. Section 2 briefly describes the ECG data used in this study. The methodology for ECG beat classification and simulation results are shown in Sections 3 and 4, respectively. Finally, Section 5 contains some conclusions.

2. ECG data

Fig. 1 shows a typical ECG beat, where the R wave is the first positive (upward) deflection of the QRS complex. Any disturbance in the regular rhythmic activity of the heart is called arrhythmia. The ECG arrhythmia waveforms differ usually with the amplitude and duration of beats. Especially, important are QRS complex changes. Hence, the QRS complex is a very important signal that is useful in the diagnosis of cardiovascular diseases. In this paper, we use the QRS complex to achieve ECG beat classification.

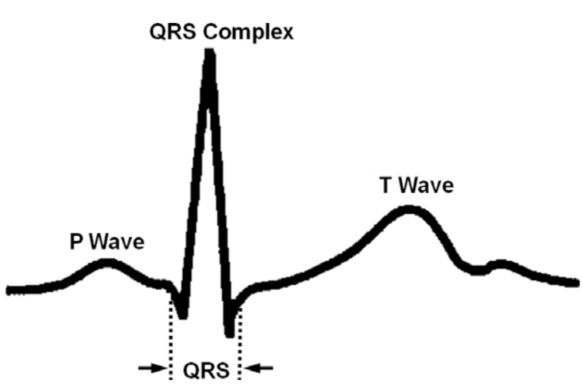

Fig. 1. ECG signal consists of three basic waves: P wave, QRS complex, and T wave.

A common approach used to represent the QRS complex is its morphology with heartbeat interval features. Heartbeat interval features frequently used in the literature include pre-RR-interval, post-RR-interval, and average RR-interval. The pre-RR-interval is defined as the RR-interval between a given heartbeat and the previous heartbeat. The post-RR-interval is the RR-interval between a given heartbeat and the following heartbeat. The average RR-interval is determined by averaging the RR-intervals of the 10 RR-intervals surrounding a heartbeat. By these definitions, we see that the calculation of both the post-RR-interval and the average RR-interval involves the following heartbeats. Therefore, they are not suitable for solving a real-time ECG classification problem when the real-time is strictly defined as 'before the next heartbeat comes'. Here, for achieving real-time classification, we use QRS morphology with only the pre-RR-interval.

In this study, the MIT/BIH arrhythmia database [14], sampled at 360 Hz with 11 bits resolution, was used for the development and evaluation of the proposed ECG classifier, because it contains a wide variety of QRS complex morphologies and different types of noise and artifacts. This database consists of 48 ECG recordings. Each recording is 30 min long and includes two ECG lead signals, denoted lead A and B, respectively. Lead A is the modified limb lead II for 45 recordings and is the chest lead V5 for the other three recordings. Lead B is the lead V1 for 40 recordings and is chosen among the lead II, V2, V4, or V5 for the other eight recordings. All the 48 recordings were used as the data source in our test. To test the robustness of the proposed classifier against noise, we used raw data from lead A (with some beats missing) without using any signal conditioning techniques.

Accompanying each recording in the MIT/BIH database is an annotation file in which the R wave has been annotated and the beat type has been labeled for each ECG beat. Instead of using a QRS detection algorithm, the R wave location provided with the database was used to extract the corresponding QRS complex out from the lead A signal by using a 73-sample window, which is about 200 ms under 360 Hz sampling rate, centered around the R wave. To remove the baseline wander, the mean value was subtracted from each QRS. Then, the input vector to the ECG classifier is of 74 dimensions: 73 for representing the morphology of the baseline corrected QRS and 1 for representing the pre-RR-interval. Note that, for achieving real-time classification, the morphology was not normalized. In many researches, different feature extraction methods have been used to reduce the length of input vector and the computational load of classifier [3–6,11]. However, the performance of ECG classifiers depends both on the extraction method used and the number of terms, functions, or coefficients selected for representing the features [6,11]. In this study, the focus is on the ECG classifier design based on the SOCMAC network, and the discussion on the selection of features is beyond our scope. We simply used the morphology of the QRS complex without feature extraction in this study.