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Hybrid intelligent system for cardiac arrhythmia classification with Fuzzy K-Nearest Neighbors and neural networks combined with a fuzzy system

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ABSTRACT

In this paper we describe a hybrid intelligent system for classification of cardiac arrhythmias. The hybrid approach was tested with the ECG records of the MIT-BIH Arrhythmia Database. The samples considered for classification contained arrhythmias of the following types: LBBB, RBBB, PVC and Fusion Paced and Normal, as well as the normal heartbeats. The signals of the arrhythmias were segmented and transformed for improving the classification results. Three methods of classification were used: Fuzzy K-Nearest Neighbors, Multi Layer Perceptron with Gradient Descent and momentum Backpropagation, and Multi Layer Perceptron with Scaled Conjugate Gradient Backpropagation. Finally, a Mamdani type fuzzy inference system was used to combine the outputs of the individual classifiers, and a very high classification rate of 98% was achieved.

1. Introduction

An electrocardiogram or ECG represents the electrical activity of the heart, as a waveform graph. An ECG signal contains important information that can help medical diagnosis, reflecting cardiac activity of a patient, if it is normal or failing heart that has certain pathologies. The ECG is the standard tool used in diagnosing heart disease (Health, 2009).

The physicians get those signals easily and noninvasively by adding electrodes to the patient's body. The Holter device is frequently used for ECG recording. Physicians apply the Holter device to the patient when ECG monitoring is required to find the existence of abnormal heartbeats in a one day ECG. A person can register about 100,000 heartbeats in one day (Health, 2009).

The ECG shows each heartbeat as a series of electrical waves. The contractions that pump blood are represented by the P wave, the QRS complex and T wave. The P wave represents activity in the upper chambers of the heart. The QRS complex and T wave represents activity in the lower chambers (Health, 2009) (see Fig. 1).

By arrhythmia we mean any alteration in the activity of the heart rhythm in amplitude, duration or shape of the rhythm. The MIT-BIH Arrhythmia Database is a set of 48 ECG records with 30 min duration each, and each record corresponds to a patient. In this database there are different types of arrhythmias such as: L-Left Bundle Branch Block (LBBB), R-Right Bundle Branch Block (RBBB), A-Atrial Premature Beat, a-aberrated Premature Atrial Beat Premature junctional Nodal J-Beat, Fusion of Ventricular and Normal Beat, I-Ventricular Flutter Wave, J-junctional Nodal Escape Beat, E-Ventricular Escape Beat Supra-ventricular Premature Beat S-, f-Fusion of an Paced Beat Normal and normal heartbeats (MIT-BIH Arrhythmia Database. PhysioBank, 2000).

Many solutions have been proposed to develop automated recognition and classification of ECG. Some processing methods have been applied to the ECG signal: Statistical and Syntatic, MultiLayer Perceptron (MLP), Self-Organizing Maps (SOM), Learning Vector Quantization (LVQ), Linear Discriminant System, Fuzzy or Neuro-Fuzzy Systems, Support Vector Machines (SVM), Bayesian approach, Experts Systems, Markov Models, Hybrid system use a combination of different solutions to improve performance (Acharya, Kumar, & Bhat, 2004; Alzate & Giraldo, 2006; Anuradha, Suresh Kumar & Veera Reddy, 2008; Barbosa, Kleisinger, Valdez, & Monzón, 2001; Belgacem, Chikh, & Bereksi Reguig, 2003; Cepek et al., 2007; Ceylan, Ozbay, & Karlik, 2009; Clifford, Azuaje, & McSharry, 2006; de Chazal & Reilly, 1998; Engin, 2004; Khadra, Al-Fahoum, Al-Nashash, 1997; Maglaveras, Stamkopoulos, Diamantaras, Pappas, & Strintzis, 1998; Nabney, Evans, Tenner, & Gamlyn, 2001; O'Dwyer, de Chazal, & Reilly, 2000; Ozbay, Ceylan, & Karlik, 2006; Patra, Kumar Das, & Pradhan, 2009; Sun & Chan, 2000; Tsipouras & Fotiadis, 2003; Werbos, 1994).

In this paper, we describe a hybrid intelligent system for classifying cardiac arrhythmia classification using three methods: Fuzzy KNN, MLP Gradient Descent with momentum Backpropagation and MLP Scaled Conjugate Gradient Backpropagation, and finally combine these outputs with a Mamdani fuzzy inference system that improves performance by achieving a very high classification rate.

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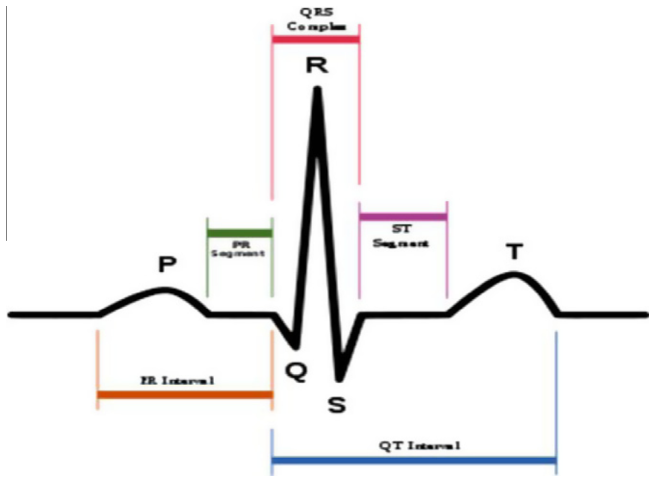

Fig. 1. Normal heartbeat with fiducial points.

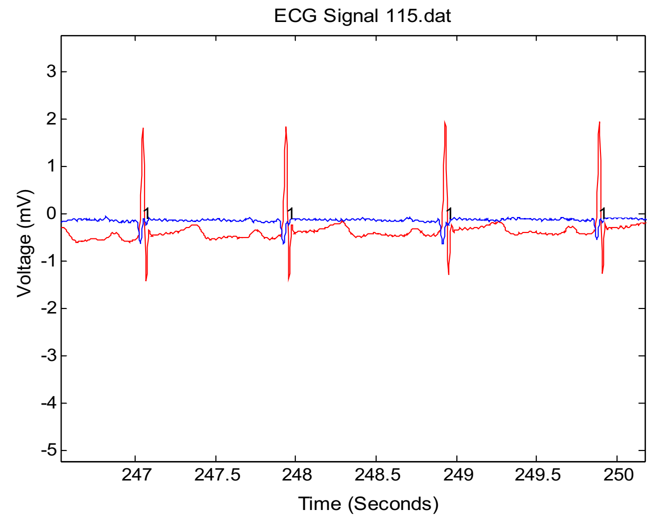

Fig. 3. The red line represents the MLII electrode signal. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2. Problem statement and outline of the proposed method

The problem addressed in this work is the classification of cardiac arrhythmias of the MIT-BIH Arrhythmia Database. The proposed hybrid system learns from a set of samples of arrhythmias: Normal Beat, Left Bundle Brunch Block (LBBB), Right Bundle Brunch Block (RBBB), Premature Ventricular Contraction (PVC), Fusion Paced and Normal Beat. The hybrid system is trained using several samples from each above mentioned class, and during testing it must determine the correct label for a previously unknown sample.

The hybrid intelligent system consists for three classification methods: Fuzzy K Nearest Neighbors, Multi Layer Perceptron with Gradient Descent with momentum Backpropagation and Multi Layer Perceptron with Scaled Conjugate Gradient Backpropagation. Each classifier provides a matrix of memberships or activations in the case of the MLPs, this matrix is called the matrix of integration, and this is the input to the Mamdani fuzzy inference system, which combines the outputs of the three classifiers. The fuzzy system increases the classification rate given by the contribution of each classifier. See the proposed architecture in Fig. 2.

We used the MLII electrode signal of MIT-BIH Arrhythmia Database (see Fig. 3), and for this work five classes were selected: Normal Beat, LBBB, RBBB, PVC, Fusion Paced and Normal Beat. We took 500 samples in total, 100 samples for each above mentioned class. The used records for Normal were 115, 122, and 113, for LBBB 109, 111, 214, for RBBB 118, 124, 212, and for Fusion Paced and Normal class 217.

For the heartbeat segmentation we took the *R* points documented in the database, and for this reason we determine the beginning and the end for each heartbeat. The segmentation was performed manually (see Fig. 4).

A transformation of the signals was proposed, that consists in rearranging the voltage values; we just took the highest larger 70 voltage values and the smaller 70 voltage values per each heartbeat. Having a set of vectors of 140 voltage values, where each vector corresponds to a heartbeat (see Fig. 5 and 6). This transformation provided a simpler signal to be classified.

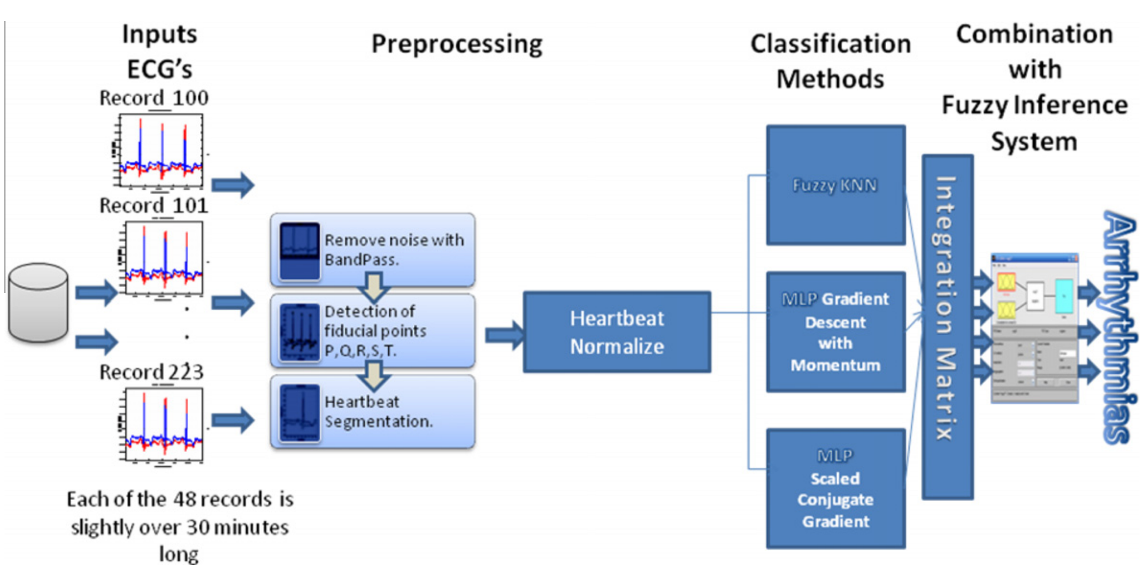

Fig. 2. Architecture of the hybrid system.