A New Neural Network System for Arrhythmias Classification

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ABSTRACT
A new neural network system for classification of the cardiac rhythm is presented in this paper. The system is composed of two neural network classifiers: a morphological classifier cascaded to a timing classifier. While the morphological classifier classify the P and QRS complexes into normal and/or abnormal beats, the timing classifier takes as inputs the information of the morphological classifier and the duration of the PP, PR and RR intervals and output the following arrhythmias: sinus tachycardia, sinus bradycardia, sinus arrhythmia, atrial extrasystoles, atrial tachycardia, atrial fibrillation, atrial flutter, ventricular tachycardia, ventricular extrasystoles, ventricular flutter and supraventricular tachycardia in addition to the normal sinus rhythm.

I. INTRODUCTION

ECG’s are a standard tool used to diagnose heart disease. A typical cycle of an ECG is shown in Fig.1. To interpret an ECG, Physicians first locate P-waves, QRS-complexes, T-complexes and U-waves. Physicians then interpret the shapes (morphology) of these waves and complexes; in addition they calculate the heights and interval of each wave, such as RR interval, PP interval, PR interval, QT interval, and ST segment (see Fig. 1).

An ECG is said normal if all the above parameters are normal.
In the case of cardiac rhythm diseases, physicians define the following classes: sinus, atrial, ventricular and jonctional rhythms diseases [1].
• Sinus rhythm diseases are characterised by QRS complexes and P waves with normal morphology but RR, PP and PR intervals have values different from the normal ones leading to the following arrhythmias: sinus tachycardia, sinus bradycardia and sinus arrhythmia.

• Atrial rhythms diseases are characterised by a P wave of abnormal morphology and a normal QRS complex. In addition temporal characteristics (PP, RR and PR duration) allow the distinction between different abnormalities such as: atrial extrasystoles, atrial tachycardia, atrial flutter and atrial fibrillation.

• Ventricular rhythm diseases are defined by QRS complexes of abnormal morphology and a normal P wave. But there is no relation between these waves. In addition knowledge of PP, PR and RR intervals allow the differentiation between: ventricular extrasystoles, ventricular tachycardia ventricular flutter and ventricular fibrillation.

• Some abnormalities affecting the P and QRS waves such as the supraventricular tachycardia.

From the above constatations, implementation of a correct automatic arrhythmia classifier must take into account morphological variations of P and QRS complexes and timing variations of RR, PP and PR intervals.

Traditionally, the task of classification is to assign an input pattern (like a cardiac signal) represented by a future vector to one of many prespecified classes. A lot of work has been done to solve the problem of ECG's classification.

Classical approaches for ECG classification use timing classifiers implemented using a decision tree and which use temporal criteria and amplitudes to distinguish between normal and abnormal rhythms [2]. Others use pattern recognition such as the syntactic approach in which the ECG pattern is described by a set of primitives[3] and the statistical approach in which Bayes theorem is used[2]. Experts systems[4] and fuzzy logic theory have also been used in ECG classification[5]. However, none of these methods has well succeeded in solving classification problems. This is mainly because ECG signals vary in time and morphology in the same time and/ or for different patients, and models used are non linear models.

The advances of neural networks have created a new impetus for automatic classification [6]. Essentially, in biomedical, the benefit of neural networks comes from their ability to use non-linear models, to learn and generalize from examples without knowledge of rules, to learn patterns with response to newly input patterns and to classify.

Recently, multi-network systems have been used for arrhythmias classification [7],[8].

In [7] an hybrid classifier composed of a timing decision based tree classifier and a morphological neural network classifier. While the timing classifier is used to classify some arrhythmias the morphological neural network classifier is used to recognize variation of the morphology in a typical TV 1:1. However, variation of morphology is not only specified for the TV 1:1 but for most arrhythmias.

In [8] two cascaded neural networks have been used to classify eight categories: sinus rhythm; sinus tachycardia; atrial fibrillation slow; atrial fibrillation fast; narrow complexes tachycardia; slow wide complex rhythm and ventricular fibrillation. However, an important number of temporal characteristics related to only the QRS complex has been used. Distinction between wide and narrow complexes
has been made successfully but a disease like the atrial fibillation for example which is described by an abnormal P wave and PP interval cannot be described only by the temporal future characteristics as chosen by the author.

We have developed a new approach for arrhythmia classification by neural networks. The difference of our classifier from the other neural networks classifiers we have learnt [7], [8], is that our neural network classifier try to imitate the physician's reasoning in the sense that it takes into account the morphology of P and QRS complexes and which uses duration of PP, RR and PR intervals.

Section II describes the network architecture. Section III describes the algorithms used. In section IV examples of different arrhythmias are applied to the classifier. Finally, a brief discussion and conclusion on this work are presented.

II. NETWORK ARCHITECTURE
The system is composed of two stages cascaded neural network classifiers (Fig. 2.). The first one is a morphological classifier which is used to distinguish between normal and abnormal QRS and P waves; the second one is a temporal classifier. The morphological neural network classifier takes as input two vectors which represent the P and QRS waves respectively.

To recognize a morphology, each wave is sampled into twenty samples, which are used as input to the morphological classifier and which outputs one of the four classes (P\textsubscript{normal}, QRS\textsubscript{normal}), (P\textsubscript{abnormal}, QRS\textsubscript{normal}), (P\textsubscript{normal}, QRS\textsubscript{abnormal}) and (P\textsubscript{abnormal}, QRS\textsubscript{abnormal}).

The results of the first classifier in combination with the temporal futures RR, PP and PR intervals are used as input to the second neural network timing classifier which outputs the following 12 categories: normal sinus rhythm (NS), sinus tachycardia (ST), sinus bradycardia (SB), sinus arrhythmia (SA), atrial extrasystoles (AE), atrial tachycardia (AT), atrial fibrillation (AF), atrial flutter (AFL), ventricular extrasystoles (VE), ventricular tachycardia (VT), ventricular fibrillation (VF) and supraventricular tachycardia (ST).

For a given signal, the timing classifier outputs a classification after each set (P, QRS, PP, PR and RR).
III. NETWORKS TRAINING

The two networks use the three layer back-propagation algorithm with generalized delta rule [9]. Two sub networks are used to classify P and QRS waves separately. Each network has three layers: an input layer connected to the P or QRS samples via a delay line, an output layer whose number of units is equal to the number of classes of the patterns (in our case two classes for each wave) and a hidden layer which performs a non linear transformation by its non linear units. Results of the two networks are combined to form one of the above four classes. The P and QRS are trained for each type of derivation.

For a given derivation, to construct a training set for the morphological classifier four normal QRS complexes, four normal P waves, four abnormal QRS and four abnormal P complexes are selected. Normal P and QRS complexes are trained to have an output of 1.0 while abnormal rhythms have 0.0. Training is done in batch mode [9]. In all of the training examples, the global error condition is less than $1 \times 10^{-4}$.

The timing classifier has an input of five neurones a hidden layer of ten neurones and an output layer of fifteen neurones. However, due to the number of output neurones to be classified, the network is divided to four sub-networks: the first network is trained to classify sinus rhythm diseases, the second network is trained to classify atrial rhythm diseases, the third network is trained to classify ventricular rhythm diseases and the last one is trained to classify supraventricular rhythm diseases. For all the sub-networks training is done on line or per example [9] and the mean squared error condition is less than $1 \times 10^{-4}$.

IV. EVALUATION

Due to the lack of a local or standard arrhythmia database at our level, we have selected some electrocardiographs signals of 1000 msec and scanned them via a PC. Then we sampled the QRS and P waves manually after each 4msec.

For instance, we selected the following eight files: normal sinus rhythm, sinus tachycardia, sinus bradycardia, atrial extrasystol, atrial tachycardia, atrial fibrillation, ventricular extrasystol and ventricular tachycardia for testing of the system.

In most cases the morphological classifier distinguished correctly normal P and QRS complexes from abnormal P and QRS complexes. However in some cases a normal P hidden in a T wave or RS segment was recognised as abnormal and then the timing classifier failed automatically in classifying the signal.

V. DISCUSSION AND CONCLUSION

We have proposed a new system of arrhythmia classification based on a morphological and a timing neural network classifier.

The focus of our work is to show that an automatic arrhythmia classifier capable of classifying a large number of arrhythmia's can be successfully built; the idea is to first decompose the problem of classification into smaller ones, construct small classifiers and then combine them to form a complete classifier.

The success of our system depends on how well the P and QRS complexes are detected.
In practice, QRS complex is well detected but detection of P wave is difficult due to low amplitude variable morphology and variable time location of the P wave. This is the first implementation of the system and there is much work to do. Our next objective is to test of the system with a standard database, to compare with other training algorithms and finally implement the system in VLSI.

REFERENCES