A Feasibility Study of Complete Neural Net Based Classification of Signal Averaged High – Resolution ECGs

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Abstract

Classification of signal averaged ECGs is divided into two phases: (a) QRS–onset and QRS–offset determination and (b) categorization based on three derived features: QRS duration (QRSd), root mean square of the terminal 40ms of the QRS (RMS) and the terminal low amplitude signal of the QRS below 40μV (LAS). Purpose of this feasibility study was the neural realization of each of these phases and the comparison of the different approaches. Both steps were realized with the neural network and the standard approach. Four combinations of the methods are possible. These were tested on 95 high–resolution signal averaged ECG recordings from 51 healthy volunteers and 44 patients with coronary artery disease. Using a neural network in the classification phase increased the sensitivity of the whole process by approximately 30% compared to the standard method without the need to visually correct the QRS–onset and –offsets. These initial results are very positive but need to be substantiated with further patient data.

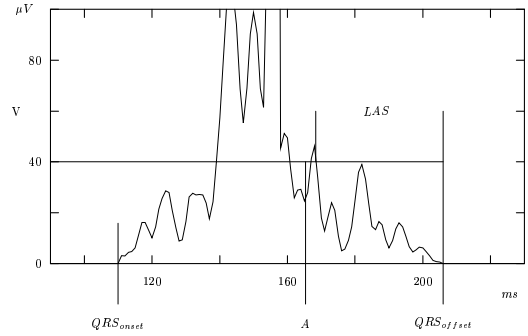
1. Introduction

High-resolution electrocardiography is used for the detection of fractionated micropotentials, which serve as a noninvasive marker for an arrhythmogenic substrate and for an increased risk for malignant ventricular tachyarrhythmias. Ventricular late potential analysis (VLP) is herein the generally accepted noninvasive method to identify patients with an increased risk for reentrant ventricular tachycardias and for risk stratification after myocardial infarction [1, 2, 3]. Techniques commonly applied in this purely time–domain based analysis are signal-averaging, high-pass filtering and late potential analysis of the terminal part of the QRS complex. The assessment of VLP's depends on three empirically defined limits of the total duration of the QRS and the duration and amplitude of the terminal low–amplitude portion of the QRS complex [4, 5].

In this study we investigated the neural realization of the time domain based analysis. As the process of decision making is separated into two phases: (a) feature extraction and (b) categorization these two phases were modeled with two different multilayer perceptron neural networks. This results in four different combinations of the standard and neural approaches. These are compared.

2. Notation

A formalized description of the three features used for time domain analysis of signal averaged ECGs is as follows:



- QRSd (QRS duration):

$$QRSD := QRS_{offset} - QRS_{onset}$$

- RMS (Time A: $A := QRS_{offset} - 40ms$):

$$RMS := \sqrt{\frac{1}{QRS_{offset} - A} \sum_{i=A}^{QRS_{offset}} V_i^2}$$

- LAS (Duration of the low amplitude signal below 40μV):

$$LAS := QRS_{offset} - argmax\{i \mid V_i \geq 40\mu V\}$$

3. Subject data

We compared a group of 51 healthy subjects (group A) with 44 cardiac patients at a high risk for malignant ventricular arrhythmias (group B, VT patients). All healthy

volunteers (mean age 24.0±4.1 years) had a normal resting ECG and a normal echocardiogram, and no cardiac symptoms or coronary risk factors. The patients with a high–risk for malignant ventricular arrhythmias (mean age 61.2±8.9 years) were selected from our electrophysiologic database. Inclusion criteria were the presence of coronary artery disease, a previous myocardial infarction, a history of at least one symptomatic arrhythmia, and inducible sustained ventricular tachycardia ($>$ 30 seconds) at electrophysiologic testing. Patients with bundle branch block or atrial fibrillation were excluded. All patients of group B underwent coronary angiography and programmed right ventricular stimulation due to clinical indications. Stimulation was done from the right apex and the right outflow tract. The stimulation protocol included up to 3 extrastimuli during sinus rhythm and at baseline pacing with a cycle length of 500 ms, and a maximum of 2 extrastimuli at baseline pacing with cycle lengths of 430 ms, 370 ms, and 330 ms. Group B consisted of 10 patients with single vessel disease, 17 patients with double vessel disease, and 17 patients with triple vessel coronary artery disease. Nineteen patients had a previous posterior infarction, 14 patients had a previous anterior infarction, and 11 patients had both a previous anterior and a previous posterior infarction. Mean left ventricular ejection fraction was 44.0%±14.9%. Forty-one patients had a documented episode of spontaneous, sustained ventricular tachycardia or ventricular fibrillation. Out of the remaining three patients, 1 patient had syncopes and non–sustained ventricular tachycardias on Holter monitoring, and 2 patients had syncopes of presumed cardiac origin.

4. Methods

4.1. ECG recordings

High–resolution signal averaged electrocardiograms were recorded during sinus rhythm from bipolar orthogonal X, Y, Z leads. Before ECG recording antiarrhythmic drugs were stopped for at least four half–lives. The skin was carefully prepared and recordings were done with the subjects in reclining position in a Faraday cage. Sampling rate was 2000 Hz, A/D resolution was 16 bit, and an analog bandpass filter of 0.05-300 Hz was used (anti–aliasing). The ECG's were recorded with the Predictor system (Corasonix Inc., Oklahoma, USA). The three leads were combined into a vectormagnitude signal $V = \sqrt{X^2 + Y^2 + Z^2}$ and bidirectionally filtered with a 4–pole Butterworth filter (40–250 Hz).

4.2. Overview

An overview of the evaluation process is given in Fig. 1. From the signal averaged ECG estimated and visually corrected QRS–onset and –offset points are used as target values for the training of the feature extraction multilayer perceptron. This neural net is trained to predict these points from the bidirectional filtered ECG. From these points the features QRSd, LAS and RMS are calculated. These serve as the input to the next stage. The standard approach of obtaining these values consists of inspecting and if necessary correcting an estimation given by a conventional signal processing algorithm, in this case the Predictor© system, see [5]. The difficulty with this approach lies in finding the QRS–offset.

The next stage consists of categorization of the ECGs based upon the three extracted features. This is done by another multilayer perceptron network trained to predict the correct group status, see Section 2. The same is done with empirically found and defined limits of QRSd, LAS and RMS [5]. More formally, the standard method classifies into VLP positive if 2 of 3 criteria are met: QRSd $>$ 114ms, RMS $<$ 20μV, LAS $>$ 38ms. Evaluation of this categorization is against group status.

4.3. Multilayer perceptron

It has been proved that multilayer perceptron (MLP) networks built of 3 layers of artificial neurons are capable of approximating any continuous function. Together with the backpropagation algorithm for weight adaptation MLP's are powerful schemes for function approximation and categorization [6].

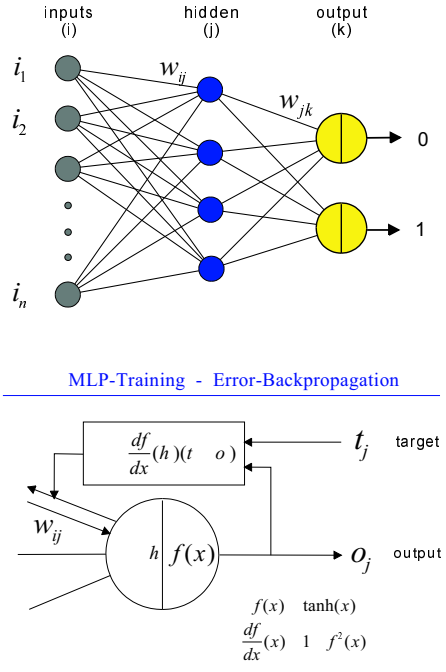


Figure 2. Multilayer perceptron net and backpropagation.

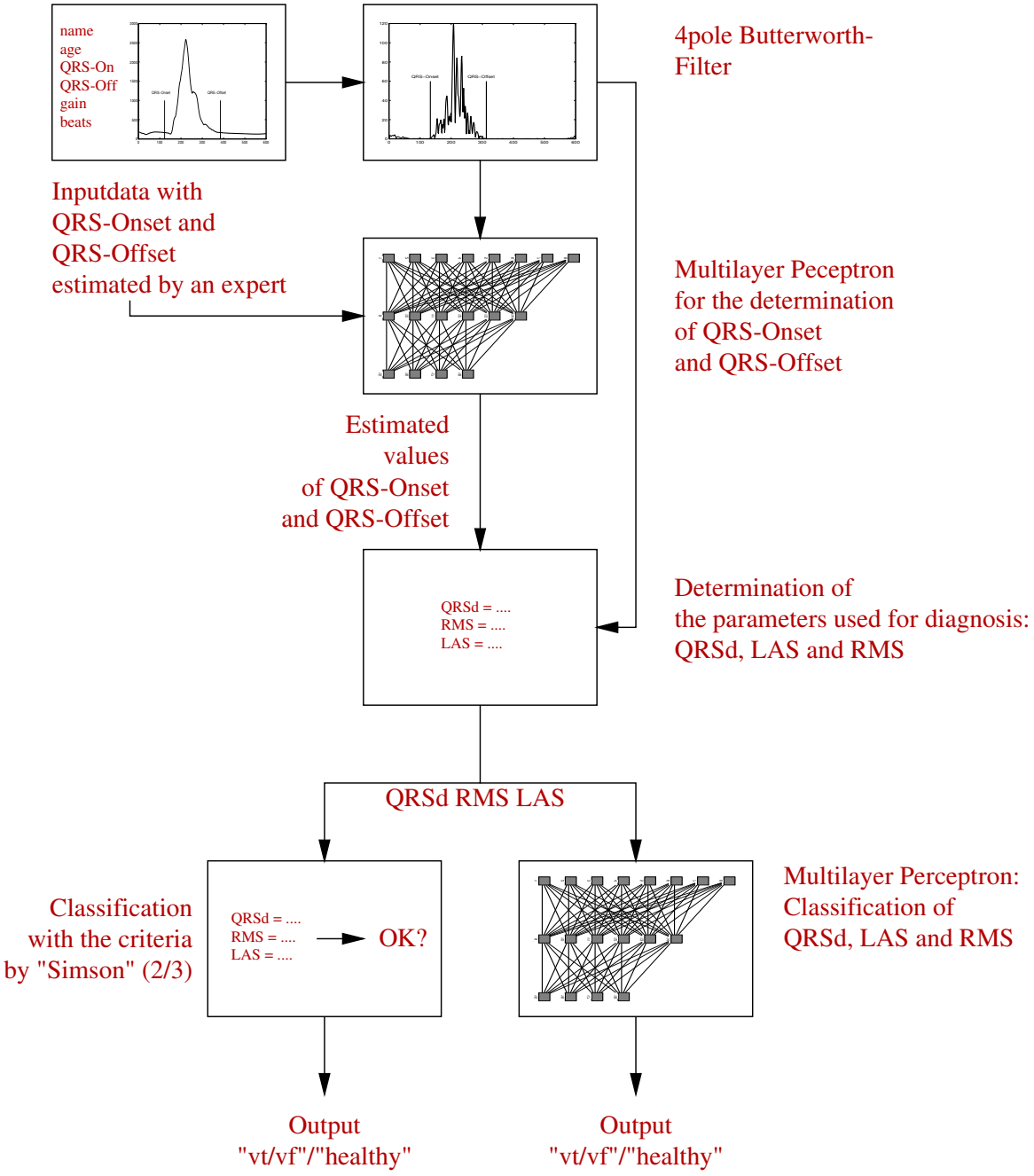


Figure 1. Overview of the decision process incorporating neural and standard methods.

4.4. Training of QRS–onset and –offset

The training of the feature extracting MLP was done by sliding an empirically determined window of 16ms, i.e. 32 inputs, over the bidirectionally filtered QRS complex. The target value was either a "1" if the QRS–onset or –offset was inside the window or a "0" if it was outside. This results in a balanced training set: ratio of "1" to "0" target values is 2.8. The onsets and offsets were visually determined. The best performing net was of size 32–8–1. All neurons had a Fermi transfer function.

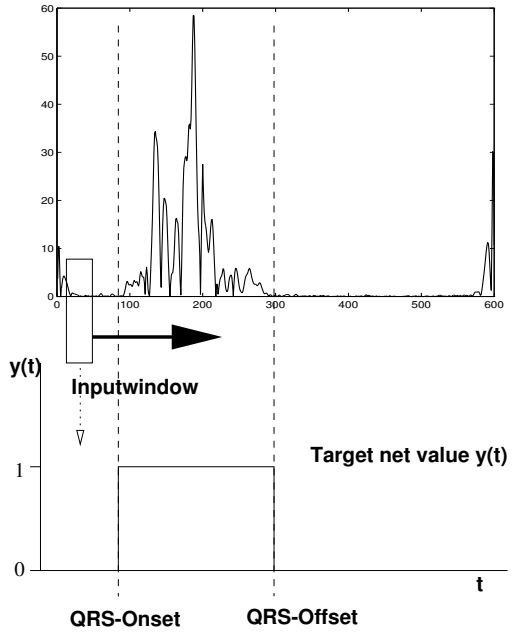


Figure 3. Training of the QRS–onset and –offset. MLP input: 32 sample points within the input window. MLP target: value of the characteristic function $y(t)$.

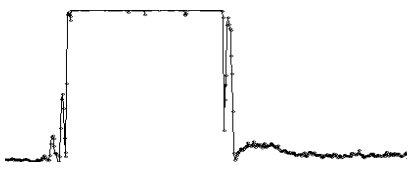


Figure 4. Sample net output for the QRS–onset, QRS–offset training.

4.5. MLP training with calculated features

For each QRS complex the three features QRSd, RMS and LAS (see Section 2) were calculated. QRS–onset and –offset were either estimated by an expert or by the feature extraction MLP network (previous subsection). MLP networks (3 input neurons, 8 hidden neurons and 1 output neuron) were trained to predict the patient's group status.

5. Results and conclusion

The classification process of signal averaged ECGs is separated into two phases: (a) feature extraction and (b) categorization according to the found feature values. These steps were realized both with the neural network (MLP) and the standard approach (STD). Four combinations of the methods are possible. Combinations involving a neural network were evaluated applying a 5–fold cross-validation:

	Acc	Sens	Spec	PPV	NPV
STD & STD	0.789	0.409	0.960	0.928	0.731
MLP & STD	0.754	0.513	0.906	0.918	0.696
STD & MLP	0.851	0.736	0.949	0.925	0.806
MLP & MLP	**0.846**	**0.745**	**0.933**	**0.906**	**0.809**

This feasibility study gives very positive initial results on using a neural network for the classification of signal averaged ECGs. Furthermore the feature extracting MLP makes the system independent of a correction of QRS–onset and –offset.

References

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