Spectral and Higher-Order Statistical Analysis of the ECG: Application to the Study of Ischemia in Rabbit Isolated Hearts

Marina Ronzhina[1], Tomas Potocnak[1], Oto Janousek[1], Jana Kolarova[1], Marie Novakova[2], Ivo Provaznik[1]

[1]Department of Biomedical Engineering, Brno University of Technology, Brno, Czech Republic
[2]Department of Physiology, Faculty of Medicine, Masaryk University, Brno, Czech Republic

Abstract

There are many different approaches for heart beat classification. Probably the main task is extraction of relevant features from the beat. The present paper is focused on the study of ECG cross spectral coherence and higher-order cumulants and their ability to classify normal and ischemic cardiac beats. Using these parameters as the input for neural network classifier allows achieving classification error only 4%. Thus, they can be successfully used to solve this task.

1. Introduction

There are many different methods for ischemia manifestation studying. The most common of them are based on the monitoring of ECG morphology parameters, such as QRS, P and T wave duration, wave's slope velocities, magnitudes of negative and positive peaks, angles of maximal and minimal amplitude vectors, QT length, ST length, etc. [e.g. 1-4]. Values of these parameters can be further used for automatic classification of ischemic/non-ischemic cardiac beats which are usually represented by PQRST [1,3-5] or QRS complexes [2,5]. However, such approach is highly dependent on accuracy of ECG delineation. This is closely related to detection of ECG waves (P, Q, R, S, and, T wave). Detection of these structures is particularly difficult and time consuming in data recorded during long-term animal experiments with ischemia because of rapid changes in ECG morphology.

Representation of cardiac beats in terms of their spectral or statistical parameters can also be used to recognize some pathological states of patient. Many authors use wavelet transform [e.g. 6,7] and higher-order statistics to extract ECG features [e.g. 8-10]. These approaches require only R peak detection (manually or automatically) to select cardiac beats from ECG in comparison to methods described above and allow successful studying of electrical activity of the heart in experiments with ischemia.

2. Methods

2.1. ECG recording

The experiments were performed in accordance with the guidelines for animal treatment approved by local authorities and conformed to the EU law. Eight New Zealand rabbits underwent general anesthesia with i.m. injection of xylazin and ketamin. The heart was then rapidly excised, the aorta cannulated and the heart was placed in a bath, filled with Krebs-Henseleit solution (1.25mM Ca^{2+}, 37°C). It was retrogradely perfused on Langendorf apparatus in the mode of constant perfusion pressure (85mmHg) [11].

The orthogonal ECGs recorded by touch-less method using two pairs (*x* and *y* leads) of Ag-AgCl disc electrodes [11-12] according to the experimental protocol with control and ischemia periods (both 15 minutes long) were used in this study. Global ischemia was induced by stopping flow of the solution into the heart. The sampling frequency of 2 kHz was used in this study. It is sufficient for the correct detection of R waves. The proposed methods were realized in Matlab 7.5 (The MathWorks, Inc.).

2.2. Data preprocessing

The parts with some artefacts or noise were rejected from analysis.

Before spectral and statistical parameters calculating low-frequency baseline wander was suppressed in ECGs with Lynn's filter with cut-off frequency of 0.5 Hz. R waves were then detected with the detector based on the wavelet transform. Some results of ECG filtering and R waves detecting are shown in Fig.1.

The QRS-T (510 samples or 0.255s length) segments were selected from ECGs for further analysis, 59 samples before and 450 samples after R wave (see Fig.2). Mean values of RR interval were 681 and 1283 samples (or

0.34s and 0.64s) for control and ischemic phases, respectively. It ensured that no P waves from adjacent waves from adjacent beats were included in analysed QRS-T segments. Total number of cardiac beats selected from all signals was 8000 (500 beats for each phase and each animal).

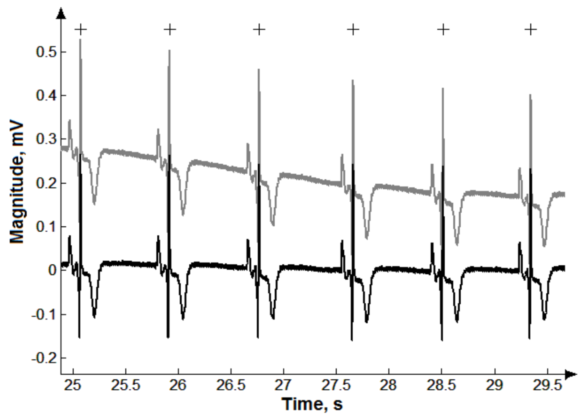

Figure 1. Non-filtered (grey) and filtered (black) ECG from x lead with detected R waves (indicated by '+').

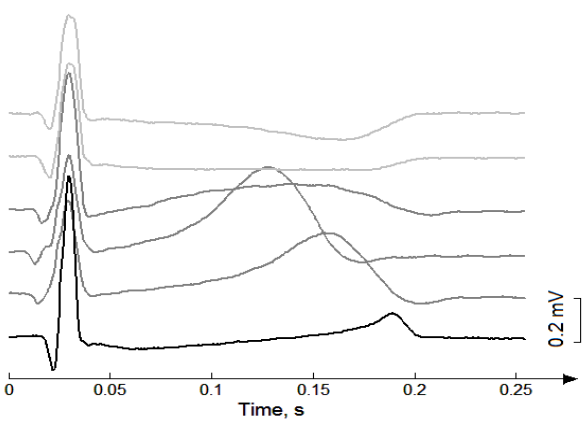

Figure 2. Examples of beats selected from the same ECG (x lead) in control (black) and ischemia (grey and light grey) phase.

2.3. Spectral parameters of ECG

The similarity between pairs of different leads or different parts of ECG from the same lead can be estimated by means of the cross spectral coherence (CSC). The CSCs were estimated for cardiac beats selected from x and y leads for control and ischemic phases as:

$$C_{xy} = \frac{\left|P_{xy}^{2}\right|}{P_x P_y}, \tag{1}$$

where P_{xy} is the cross power spectrum calculated for x and y lead ECG, and P_x and P_y are the power spectra estimated from x and y leads ECG, respectively. P_x and P_y were calculated via Welch method with Hamming window (100 samples long) and 50% overlap. 10 values evenly distributed within CSC vector (range 0-100 Hz) were then chosen for analysis of the beats.

2.4. Higher-order statistical parameters of ECG

ECG can be also described in terms of its higher statistics parameters, such as the second-, third- and fourth-order cumulants which allow to reduce the variation of beats among the same group (e.g. ischemic/non-ischemic), time- and amplitude shift of the signals, and the effect of Gaussian noise [13]. For zero-mean statistical process $x(n)$ (the cardiac beat), these parameters can be defined using its moments [14]:

$$C_{2x}(t_1) = m_{2x}(t_1), \tag{2}$$

$$C_{3x}(t_1, t_2) = m_{3x}(t_1, t_2), \tag{3}$$

where C_{2x}, C_{3x} are the 2nd-, and the 3rd-order cumulants of $x(n)$, t_1, and t_2 are the time lags, and m_{2x} and m_{3x} are the higher-order moments calculated from $x(n)$ as:

$$m_{2x}(t_1) = E\{x(n)x(n+t_1)\}, \tag{5}$$

$$m_{3x}(t_1, t_2) = E\{x(n)x(n+t_1)x(n+t_2)\}, \tag{6}$$

where E is the expectation operator.

All beats were decimated by a factor 5. Thus, each beat was represented by 102 samples. The values of the 2nd-order and also the 3rd-order cumulants from normalized diagonal slices (by setting $t_i = t$, $i = 1,\ldots,j-1$, for jth-order cumulant [14]) calculated from x lead beats were chosen for further analysis. Each cardiac beat was thus represented by 10 values of cumulants distributed evenly within all length of the beat.

2.5. Classification using multilayer neural network

Artificial neural networks (ANNs) are parallel adaptive systems suitable for solving of non-linear classification problems. Multilayer backpropagation neural networks (BPNNs) are supervised systems which require not only input but also output ('desired') vectors for training. Output of ANN is generated using special function - transfer function, such as log-sigmoid, linear, and hard-limit function. During training process, parameters of BPNN (i.e. weights and biases) change to minimize performance function which can be represented by mean squared error (MSE). Trained BPNN is then validated by using a new data. This classification approach is very often used to classify the cardiac beats [e.g. 7, 15, etc.].

In this study, the normalized (to the range -1..+1) beats from control and ischemic phases of experiments are distinguished using BPNN with 30 inputs (ten values for C_{xy}, C_{2x}, and C_{3x}), one hidden-layer (10 neurons with log-sigmoid transfer function) and 1 output neuron (with log-sigmoid transfer function). Topology of designed BPNN is shown in Fig.3.

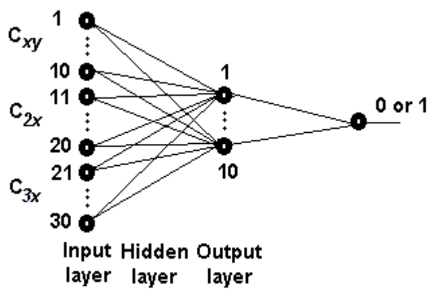

Figure 3. Network topology.

80% out of total number of beats were used to train BPNN with gradient descent learning method; other beats were used to test BPNN after training. In target vector, control and ischemic beats were represented by '0' and '1', respectively.

3. Results

CSCs computed from x and y leads for control and ischemic phase are shown in Fig.4 and Fig.5, respectively. Significant changes in CSCs calculated for different phases of experiment, especially in the region 5-50 Hz, can be observed. The maximum of coherence in this region shifts towards the higher frequencies (up to approx. 100 Hz) during ischemia whereas values of CSC remain almost invariable for control phase.

The examples of the 2nd- and the 3rd-order cumulants for beats from control and ischemic phase are shown in Fig. 6. The changes in beat morphology are reflected in the shape of its cumulants. Moreover, higher-order cumulants have lesser variance in comparison with original beats.

The above properties of the values of CSC and cumulants make them suitable for using as classification features.

In present work, classification ability of these three different beats parameters is validated using ANN model. The proposed BPNN classifier allows to distinguish between the beats from control and ischemic phase with the total testing error 4% (calculated for test inputs in test phase). The course of network performance is shown in Fig.7. It is clear that 330 epochs (denoted by grey circle) are sufficient to achieve required performance (MSE=0.01).

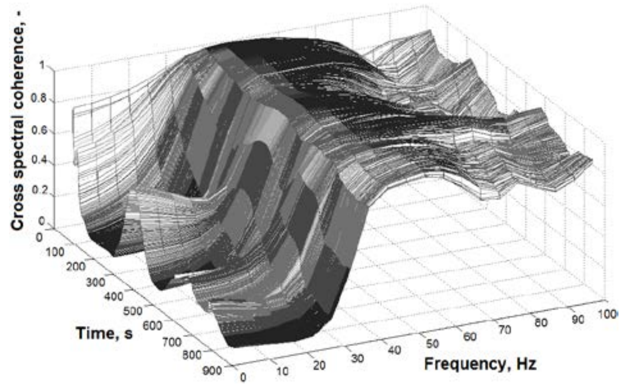

Figure 4. Cross spectral coherence (in range of 0-100 Hz) of chosen beats from control phase calculated for x and y leads.

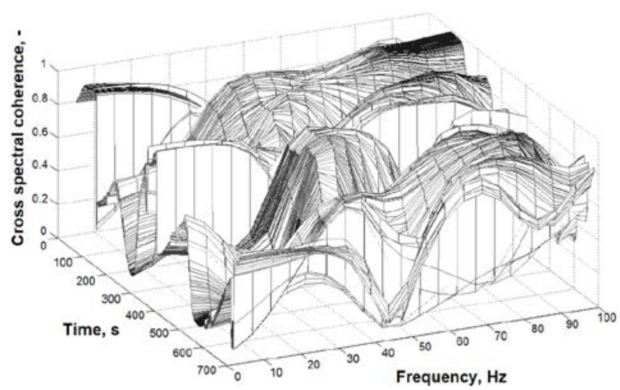

Figure 5. Cross spectral coherence (in range of 0-100 Hz) of chosen beats from ischemic phase calculated for x and y leads.

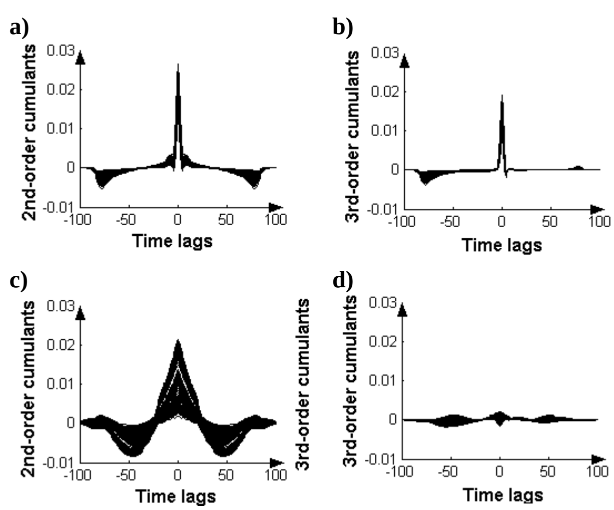

Figure 6. Higher order cumulants calculated for the beats from control (a and b) and ischemic phase (c and d).

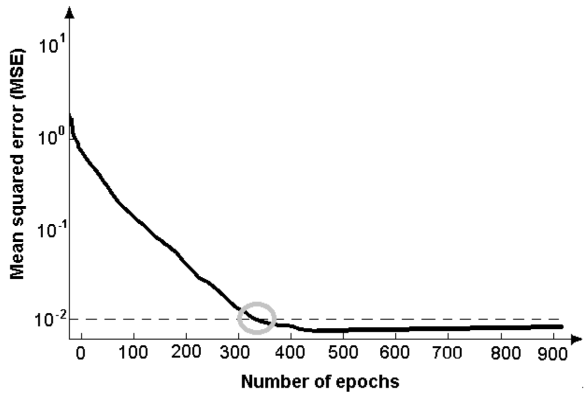

Figure 7. Network performance.

4. Conclusions

Cardiac beats classification is very difficult task. There are plenty of various methods for extraction of features from ECG and further classification into different groups.

The present study shows that the values of cross spectral coherence and higher-order cumulants calculated from QRS-T segments of ECG can be successfully used to classify normal and ischemic cardiac beats. The proposed method uses data recorded with only two pairs of ECG electrodes. Moreover, it does not require total delineation of the signal which is time consuming and often problematical task. Using these parameters as the input for neural network classifier allows achieving classification error only 4%. These results can be used in future studies aimed at classification of the beats recorded during experiments with repeated ischemia.

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References

[1] Chazal P, O'Dwyer M, Reilly RB. Automatic classification of heartbeats using ECG morphology and heartbeat interval features. IEEE Transactions on Biomedical Engineering 2004;51:1196-1206.

[2] Christov I, Gómez-Herrero G, Krasteva V, Jekova I, Gotchev A, Egiazarian K. Comparative study of morphological and time-frequency ECG descriptors for heartbeat classification. Medical Engineering and Physics 2006;28:876-887.

[3] Doquire G, de Lannoy G, François D, Verleysen M. Feature selection for interpatient supervised heart beat classification. Computational Intelligence and Neuroscience 2011;1-9.

[4] Zeng XD, Chao S, Wong F. Ensemble learning on heartbeat type classification. Proceedings of 2011 ICSSE 2011:320-325.

[5] Darwich A, Fokapu O. The effect of pathologic cardiac events on the spectral content of ECG. Proceedings of the 29th Annual International Conference of the IEEE EMBS 2007:674-677.

[6] Minhas FA, Arif M. Robust electrocardiogram (ECG) beat classification using discrete wavelet transform. Physiological Measurement 2008;29:555-570.

[7] Sahab AR, Mehrzad Gilmanek Y. An automatic diagnostic machine for ECG arrhythmias classification based on wavelet transformation and neural networks. International Journal of Circuits, Systems and Signal Processing 2011;5:255-262.

[8] Engin M, Fedakar M, Engin EZ, Korürek M. Feature measurements of ECG beats based on statistical classifiers. Measurement 2007;40:904-912.

[9] Martis RJ, Acharya UR, Ray AK, Chakraborty C. Application of higher order cumulants to ECG signals for the cardiac health diagnosis. 33rd Annual International Conference of the IEEE EMBS 2011;1697-1700.

[10] Park KS, Cho BH, Lee DH, Song SH, Lee JS, Chee YJ, Kim IY, Kim SI. Hierarchical support vector machine based heartbeat classification using higher order statistics and hermite basis function. Computers in Cardiology 2008;35:229-232.

[11] Nováková M, Moudr J, Bravený P. A modified perfusion system for pharmacological studies in isolated hearts. In: Analysis of Biomedical Signals and Images. Brno: Vutium Press, 2000;162-164.

[12] Kolářová J, Fialová K, Janoušek O, Nováková M, Provazník I. Experimental methods for simultaneous measurement of action potentials and electrograms in isolated heart. Physiological Research 2010;59:S71-S80.

[13] Karimifard S, Ahmadian Alireza. A robust method for diagnosis of morphological arrhytmias based on Hermitian model of higher-order statistics. Biomedical Engineering OnLine 2011;10:1-18.

[14] Mendel JM. Tutorial on higher-order statistics (spectra) in signal processing and system theory: theoretical results and some applications. Proceedings of the IEEE 1991;79:278-305.

[15] Ayub S, Saini JP. ECG classification and abnormality detection using cascade forward neural network. International Journal of Engineering, Science and Technology 2011;3:41-46.

Address for correspondence:

Marina Ronzhina
Department of Biomedical Engineering
Faculty of Electrical Engineering and Communication
Kolejní 4
612 00, Brno
Czech Republic
ronzhina@feec.vutbr.cz