519.23:612.171.1

NEW APPROACH TO ECG'S FEATURES RECOGNITION INVOLVING NEURAL NETWORK

A.Babloyantz

International Solvay Institutes for Physics and Chemistry, C.P. 231,
Boulevard du Triomphe, B-1050 Brussels, Belgium

V.V.Ivanov

International Solvay Institutes for Physics and Chemistry, C.P. 231,
Boulevard du Triomphe, B-1050 Brussels, Belgium

Laboratory of Information Technologies, Joint Institute for Nuclear Research,
141980, Dubna, Russia

P.V.Zrelov

Laboratory of Information Technologies, Joint Institute for Nuclear Research,
141980, Dubna, Russia

A new approach for the detection of slight changes in the form of the ECG signal is proposed. It is based on the approximation of raw ECG data inside each RR-interval by the expansion in polynomials of special type and on the classification of samples represented by sets of expansion coefficients using a layered feed-forward neural network. The transformation applied provides significantly simpler data structure, stability to noise and to other accidental factors. A by-product of the method is the compression of ECG data with factor 5.

Предложен новый подход для определения незначительных изменений формы сигнала электрокардиограммы (ЭКГ). Метод основан на аппроксимации данных ЭКГ внутри каждого RR-интервала с помощью полиномиального разложения специального вида и последующей классификации выборок, представляемых коэффициентами этого разложения, с использованием прямоточной нейронной сети. Используемое преобразование обеспечивает значительно более простую структуру данных, устойчивость к шуму и другим случайным факторам. Дополнительным результатом применения метода является сжатие объема данных ЭКГ в 5 раз.

INTRODUCTION

In the recent years there has been some interest in the application of artificial neural networks to the analysis of electrocardiograms. Investigation of these problems follows several directions:

- compression of raw electrocardiogram (ECG) data to be stored without loosing any significant features of the ECG signal [1];
- detection of QRS-complexes with the help of a neural network, providing their location and the determination of heart rate [2];
- the automated classification of ECG patterns [3,4,5].

The aim of this paper is to identify slight changes in the form of the ECG signal applying a multilayer perceptron (MLP). In our approach the input into neural network are not raw ECG data, but specially transformed data, which provides significantly simpler structure of analyzed samples, stability to noise and to some other accidental factors.

1. TRANSFORMATION OF ECG DATA

An essential drawback of neural network applications to the analysis of ECG's features is connected with the supplying to the network input of amplitudes of directly measured electrical activity. Depending on digitization frequency the number of such measurements inside the inter-beat interval may exceed $250 \div 500$, and the network with such number of inputs is not easy to process. Moreover, it is not clear what features of ECG can be recognized by the neural network, as, in this case, inessential details, like noise, will be also memorized. In addition, because of the heart rate variability (HRV), the duration of ECG cycles, even for healthy individuals, is not constant. Therefore, each interval may include different number of measurements, and this does not permit one to use neural network with the fixed number of input nodes.

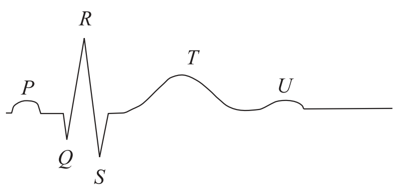

Fig. 1. Schematic representation of one ECG cycle

On the other hand, each cycle of the heart activity represents the combination of few waves (P-wave, QRS-complex, T-wave and sometimes U-wave) separated by flat intervals. Figure 1 gives the schematic representation of one ECG cycle, starting from the P-wave onset[1]. Thus, principal features can be described using less amount of information, and, hence, the input data to be analyzed by a neural network can be significantly decreased. Mathematically this means the transition into the space with smaller dimensionality where ECG features can be recognized more clearly.

The compression of ECG data can be achieved by different methods (see, for instance, [7]). In the simplest case such methods imply an expansion in the Fourier set of trigonometric functions. The high quality of the function approximation can be achieved applying orthogonal polynomials forming the so-called Chebyshev systems. In particular, Chebyshev polynomials of the first and the second kind are widely used[2], due to their simplicity. But, in practical applications, when the function is given in fixed number of points, the problem of the expansion coefficients evaluation arises.

As the ECG is represented by measurements taken in equal time intervals, then the expansion in a system of polynomials orthogonal on a set of uniformly spaced points $P_{k,n}(x),\ k = 0, 1, 2, ..., m \leq n$ (see, for instance, [7]) seems to be the adequate approach for the ECG signal approximation.

These polynomials are related by the following recurrent equation:

$$\left(x - \frac{n}{2}\right) P_{m,n}(x) + \frac{(m+1)(n-m)}{2(2m+1)} P_{m+1,n}(x) +$$

[1]The polarity of each wave depends on a concrete ECG channel (lead).

[2]In [6] Chebyshev polynomials were applied for the compression of cardiological data. The procedure envisage the division of ECG on small subintervals where only three expansion coefficients provide the mean-squared error $\leq 1\%$ and the compression factor $6 \div 12$.

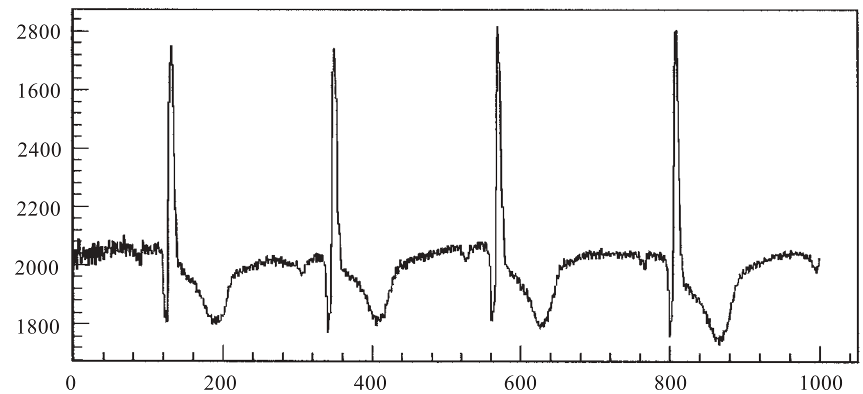

Fig. 2. ECG of healthy individual

$$+\frac{m(n+m+1)}{2(2m+1)}P_{m-1,n}(x)=0, \qquad 1\le m\le n, \tag{1}$$
$$P_{0,n}(x)=1, \quad P_{1,n}(x)=1-\frac{2x}{n}.$$

The generalized polynomial $P_m(x)$ constructed as a linear combination of polynomials (1):

$$P_m(x)=c_0P_{0,n}(x)+c_1P_{1,n}(x)+\ldots+c_mP_{m,n}(x), \tag{2}$$

with coefficients

$$c_i=\frac{(2i+1)n^{(i)}}{(i+n+1)^{(i+1)}}\sum_{k=0}^{n}f(k)P_{i,n}(k), \quad i=0,1,2,\ldots m, \tag{3}$$

where

$$n^{(i)}=n(n-1)\ldots(n-i+1),$$

provides the best approximation of the ECG signal $f(x)$ in sense of the method of least squares [7].

The processing of raw ECG data has been performed by sequential analysis of inter-beat intervals specified by peaks dominating in the QRS-complexes[1]. These peaks were detected by the threshold technique. The number of points inside RR-intervals (see Fig. 2) varied from 215 to 240. Figure 3 shows the result for one of intervals presented in Fig. 2. In order to show full R-peak, all intervals, represented in figures, were slightly shifted toward Q-peaks. Figure 3,*a* shows the original data, whereas, Fig. 3,*b* is the result of the polynomial approximation (2). The number of expansion coefficients in (2) was $m=44$, which corresponds to the compression factor of about 5.

[1]The QRS-complex morphology depends on the concrete ECG channel. For channel presented in Fig. 2 the R-peak dominates in the QRS-complex.

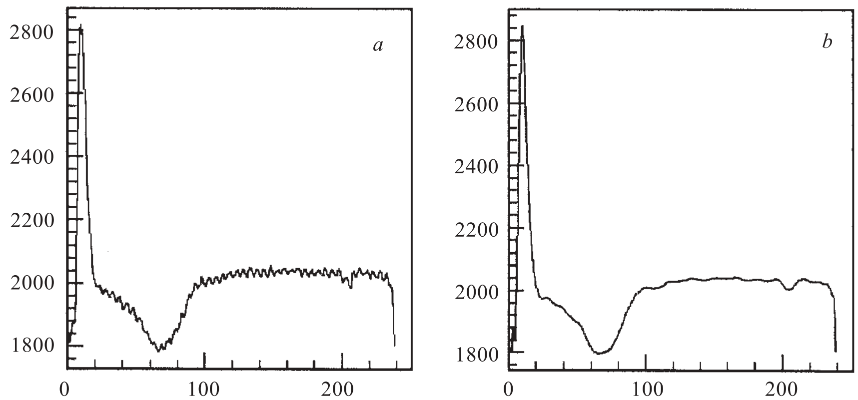

Fig. 3. *a*) One inter-beat interval of raw ECG, *b*) approximation (2) of the same interval

As a result of the above expansion the principal features of the RR-interval can be described using significantly less amount of information. Moreover, for higher recording frequency the number of these coefficients will not change significantly with the increasing of the number of points inside the RR-interval.

2. RECOGNITION OF ECG FEATURES BY MLP

The MLP simulator from the JETNET 3.0 package [8] was used for the pattern recognition. The network had 44 input neurons corresponding to the number of expansion coefficients, the hidden layer with varying number of neurons, and one output neuron indicating, whether or not there was a normal ECG pattern in the presented input. All neurons had the identical transfer function $y = \tanh(x)$.

The neural network was trained to recognize samples represented by the expansion coefficients corresponding to RR-intervals of the normal ECG and the ECG with some abnormality. An artificial pathological pattern was produced from the normal one by changing the polarity of P-wave (see Fig. 4). Gaussian noise was added to the normal and to the pathological patterns. The value of the standard deviation σ was ranged from 10 to 40[1].

The set of *normal* and *abnormal* simulated patterns were applied alternately for the neural network training. When all training patterns had been processed once, one learning epoch was finishing and another was starting. The correction of the weights was performed after each epoch applying Manhatten algorithm (see details in [8]).

After training, the performance of the neural network was evaluated using a new set of simulated patterns. The rate of correctly recognized samples was used as a measure of the neural network performance. The recognition rate achieved for the testing set with $\sigma = 20$ was equal to 100 % and 91 % for the case with $\sigma = 40$. Figure 5 represents intervals with simulated noise (two upper plots correspond to $\sigma = 20$, two lower plots — to $\sigma = 40$). Left plots show the normal ECG, wherever right plots depict the pathological signal. Figure 6

[1] In units of original scale (see Fig. 2).

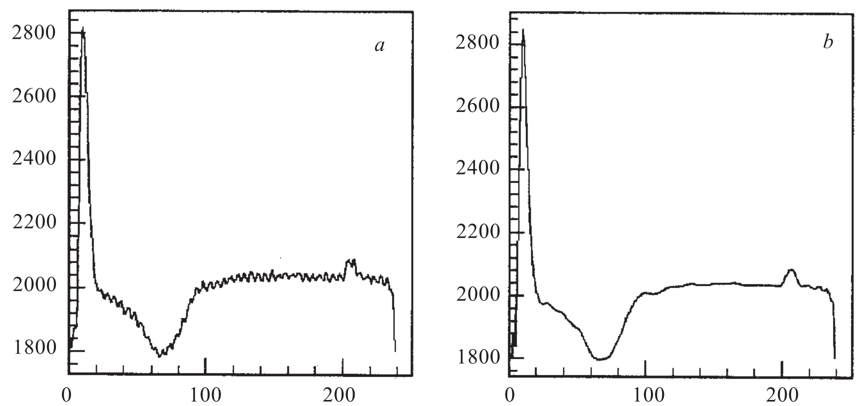

Fig. 4. *a*) Pathological pattern obtained by a slight modification of original signal (see text), *b*) approximation (2) of the same pattern

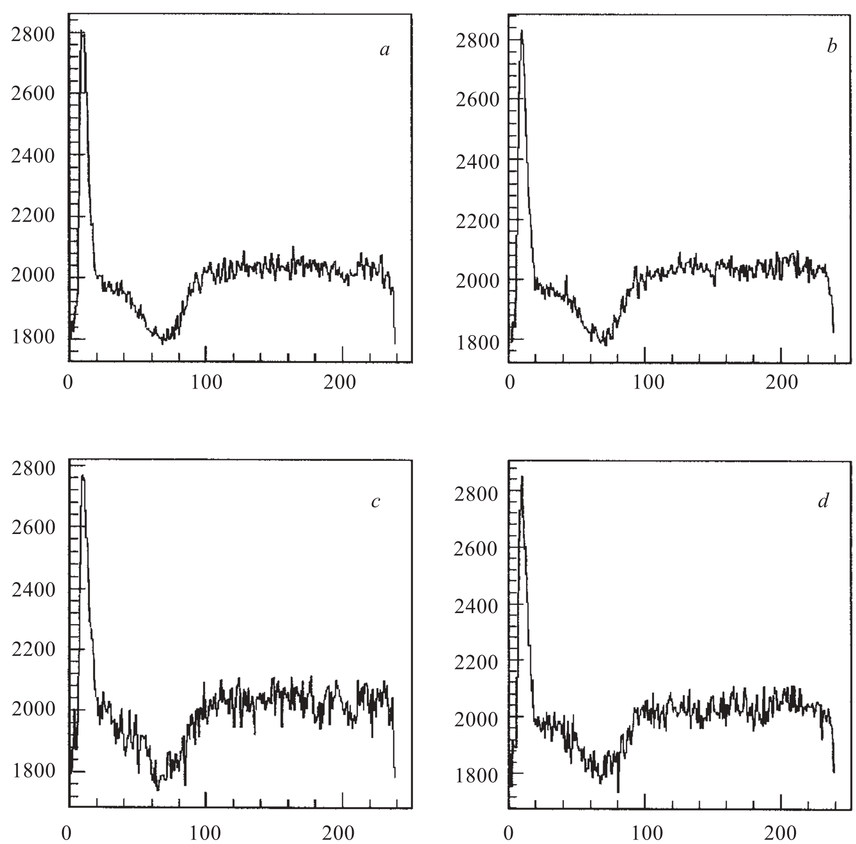

Fig. 5. Typical intervals subjected to the classification: left and right plots respectively represent data of normal and pathological ECGs: *a*) and *b*) correspond to $\sigma = 20$, *c*) and *d*) correspond to $\sigma = 40$

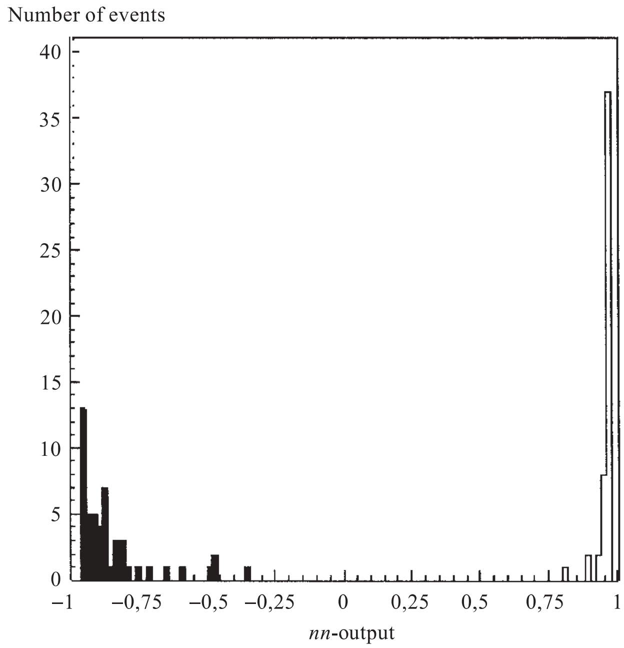

Fig. 6. Distribution of output signals from the neural network classifying noisy patterns with $\sigma = 20$. Threshold value is 0. Contribution of normal ECG patterns is presented by black histogram

shows the distribution of output signals of the neural network resulting from the processing of 100 patterns for $\sigma = 20$. Those events which are greater than the threshold correspond to the ECG patterns with pathology, below the threshold are the events corresponding to normal ECG patterns (singled out by black).

3. ROBUSTNESS OF THE METHOD

The fact that our approach is able to recognize with a high accuracy the ECG signals augmented with a considerable amount of Gaussian noise demonstrates the stability of the method to possible fluctuations and noise.

The robustness of the method even in the presence of variability in the RR-interval duration follows from the assumption that for normal ECG such fluctuations do not change significantly the topological features of ECG waves, such as different relations in amplitudes or in their durations. In this connection, the variability can be considered as some deformation, such as the extension or compression in time of waves forming one heart beat, and which cannot significantly affect the expansion coefficients.

CONCLUSION

In our work we developed a new approach for the recognition of slight changes in the form of the ECG signal. It is based on the approximation of raw ECG data, inside the inter-beat interval, by the polynomial expansion of special type. After the approximation, the set of expansion coefficients is presented to the MLP neural network for the recognition. Such transformation provides significantly simpler data structure, stability to noise and to some other accidental factors.

The method has been tested on model data, produced on the basis of real ECG data and generalizing the features of normal ECG and the ECG with some abnormality. We demonstrated that our approach permits one to recognize, in conditions of considerable noise, a normal ECG signal from slightly modified ECG one, which may arise in some cardiac pathologies.

Thus, we believe that our method can be useful for the diagnosis of barely noticeable pathologies from the visual examination of ECGs. A by-product of the method is the compression of raw data: its reduction with the compression factor 5.

Acknowledgements. The authors are grateful to Dr. S.B.Marasanov for interesting discussions and useful comments.

This work was partially supported by the Commission of the European Community within the framework of the EU–RUSSIA Collaboration under the ESPRIT Project CTIAC-21042.

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Received on January 22, 2001.