ZESZYTY NAUKOWE POLITECHNIKI ŚLĄSKIEJ 1993

Seria: AUTOMATYKA z. 108 Nr kol. 1150

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APPLICATION OF A THREE-LAYER FEEDFORWARD NEURAL NETWORK FOR CLASSIFING ELECTROMEDICAL SIGNALS

Summary. An attempt to use a simulated neural network structure as a biomedical signal classifier is described in this paper. The input patterns are portions of digitized ECG recordings. The neural network is a two- or three-layer feedforward structure of sigmoidal elements. The generalized delta rule is used as a learining algorithm. The network, trained in a constant number of 300 rounds, can reach very high performance, close to 100% for training set and about 96% for testing set disjoint with the training set. The network also proves to be very robust when classifying patterns corrupted by simulated muscle noise. However, the negative effect of large storage capacity of the network can be observed when many hidden units are employed.

ZASTOSOWANIE TRÓJWARSTWOWYCH SIECI NEUROPODOBNYCH BEZ SPRZĘŻEŃ ZWROTNYCH DO KLASYFIKACJI SYGNAŁÓW ELEKTROMEDYCZNYCH

Streszczenie. W artykule przedstawiono próbę wykorzystania dwu- i trójwarstwowych sieci neuropodobnych bez sprzężeń zwrotnych do klasyfikacji sygnałów EKG. Przeprowadzono badanie wpływu liczby jednostek ukrytych na jakość klasyfikacji oraz badanie odporności sieci na zakłócenia sygnału wejściowego.

Input patterns

As one of the most important non-invasive diagnostic methods of modern medicine, electrocardiography allows not only early detection of cardiac diseases, but also support for diagnosis of many other disorders, like electrolytic imbalance. Diagnosing cardiac disorders, especially dangerous nowadays, becomes a medical task of very high priority.

A typical ECG signal recording contains several specific points that carry the most important information, appearing on a base line (isoline), that corresponds to zero electric activity of the heart muscle. The most interesting, from diagnostic point of view, is the so-called QRS complex, which corresponds to depolarization of the ventricular muscle of the heart. The QRS complex is preceded by the P wave that corresponds to depolarization of the auricular muscle; after it comes the ST line, corresponding to slow depolarization of the ventricular muscle, and the T wave that is generated during the phase of fast repolarization of the ventricular muscle. Correct interpretation of the QRS complex is essential for detecting most cardiac disorders, however, P and T waves also carry important information. In the case described below, the whole PQRST complex was classified. Recognized patterns were divided into two classes:

a) "auricular" PQRST complexes that are characteristic for ECG recordings of healthy patients (see Fig. 1a).
b) "ventricular" PQRST complexes (which are, due to some disorder, generated in the ventricular area of the heart muscle). When such complexes are found in an ECG recording, it may indicate arhythmia: QRS complexes in this case are usually broader (more than 120 ms) than auricular complexes; furthermore, the T wave and ST line displacement is opposite to the largest-amplitude wave of the QRS complex. (see Fig.1b).

These two classes were also called "correct" and "incorrect". The purpose of the experiment was to find out whether a two-output neural-like structure can learn to respond correctly when a pattern containing a PQRST complex belonging to a certain class is presented at the inputs. As the input patterns we used unprocessed ECG recordings, containing several thousands of samples, that were made with an electrocardiograph supplied with a 12-bit ADC running with sampling frequency of 250 Hz. These samples were collected into files of signed integers and stored on floppy disks.

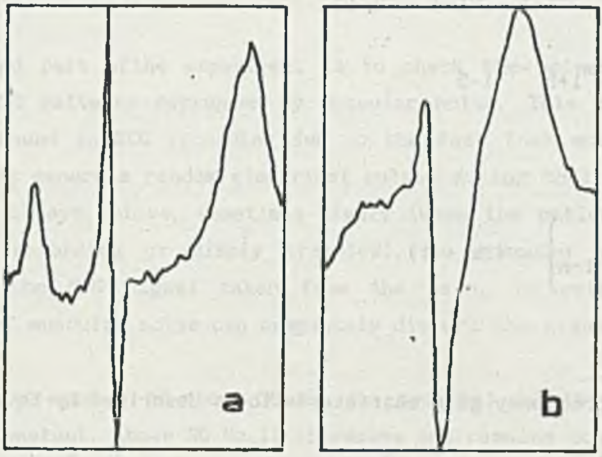

Fig. 1. Typical examples of auricular (a) and ventricular (b) PQRST complexes

Rys. 1. Typowe przykłady zatokowych (a) i komorowych (b) zespołów PQRST

Preprocessing

Due to the fact that a typical recording contains tens of PQRST complexes, we first have had to extract single patterns from a continuous set of samples. The reason to do it is that attempt to build a shift-invariant network, capable of detecting the beginning of a very PQRST complex by "sliding" its inputs through the signal record lies behind the computational power (and memory capacity) of the computers that we have used (such networks usually involve high redundancy due to the fact of duplicating its fragments that learn to recognize the same parts of a pattern but differently shifted). Instead, we have decided to use preprocessing of the ECG signal using a digital filter to detect R waves and "cutting out" several samples around it. To find the R wave, we have applied a "fiducial point" detector, being essentially a cascade of simple digital filters described by Equations 1..6 [14].

$$y_i = 1/4(x_{i-1} + 2x_i + x_{i+1}) \qquad (1)$$

$$y_i = 1/8(x_{i+2} + 2(x_{i+1} + x_i + x_{i-1}) + x_{i-2}) \qquad (2)$$

$$y_i = x_{i+12} - x_{i+4} + x_{i-4} - x_{i-12} \tag{3}$$

$$y_i = 2x_i - x_{i+5} - x_{i-5} \tag{4}$$

$$y_i = x_i^2 \tag{5}$$

$$y_i = \left[\sum_{n=-k}^{k} x_{i-n}\right] / (2k + 1) \tag{6}$$

The complete frequency gain characteristic is described by Equation 7:

$$K(\Theta) = \cos^2(\theta/2)\cos(\theta)\cos^2(\theta/2)\sin(4\theta)\cos(8\theta)\sin^2(2.5\theta) \tag{7}$$

where $\theta = 2\pi f/f_{sampl}$

Due to the fact that the detector had a fixed frequency characteristic, position of the fiducial point varied for different morphologies of the ECG signal (because of their slightly various spectra). This problem can be solved by centering each pattern to closest maximum of the QRS complex. However, it is not necessary, because patterns belonging to the same class will always have approximately the same shift; it is not "important" for the network that the patterns be all similar in general, only within classes.

After finding the fiducial point, the PQRST complex is to be classified as an "auricular" or "ventricular" by a human expert. This is done because we have used a supervised learning algorithm, so every teaching pattern should have its class description. The expert's task is also to determine the baseline level (usually found 66 msec before the fiducial point; this value is used as default but could be changed), used later in the experiment. Because of the limited size of the network, we have decided to take every second sample from the original recording. This has not impaired the essential features (shape) of a pattern but has made the teaching and recognizing time shorter. A complete pattern has contained 75 samples of the ECG signal, with the fiducial point placed at the 26th sample, a number specifying the isoline level and the class description.

Muscular noise simulation

The second part ofthe experiment is to check the network's ability to recognize ECG patterns corrupted by muscular noise. This kind of noise is frequently found in ECG recording due to the fact that motor units of the chest muscles generate random electrical pulses during their activity. These muscles are always active, sometimes highly (when the patient is subject to stress ECG recording or simply trembles), so muscular noise is always present in the ECG signal taken from the skin. In extreme conditions, amplitudes of muscular noise can completely distort the signal (SNR = 0 dB or less).

Up to the frequency of about 30 Hz, the spectral density of muscle noise is roughly constant. Above 30 Hz it increases and remains constant again. The larger the patient's effort, the more the spectrum is shifted towards lower frequencies. Unfortunately, spectrum of the muscular noise overlaps the diagnostically significant area of the ECG signal spectrum. Thus, it cannot be simply filtered (e.g. electrically) without losing part of the information contained in the signal. A typical way of eliminating muscular noise is averaging a number of evolutions centered around a fiducial point [14]. It is an effective method of eliminating muscular noise, however, it requires implementation of special algorithms and also preclassification of input signal (averaging an evolution of a different morphology would significantly distort the result).

Muscular noise can be modeled by a random white noise of Gaussian amplitude distribution. This model can be accepted because electrodes for ECG recordings have relatively large area comparing to the dimensions of a single motor unit, so they sum random potentials from many units at the same time, giving in result a Gaussian distribution. Such a model has been used in the second part of the experiment. To generate a noise simulation series we have used a Box-Mueller generator, in which mean value is 0 and variance is calculated directly from given signal-to-noise ratio. The Box-Mueller generator has used uniform-distribution random numbers generated by a Random function within the program.

Network architecture

The network used in the experiment has been relatively simple; it has had an input layer 75 units wide, a hidden layer from 2 to 12 units wide (a two-layer model without hidden units has been also examined) and two outputs corresponding to the classes 'auricular' and 'ventricular'. The architecture of the network has admitted neither feedback nor cross-connections (directly from input to output). Neither the strength nor sign of the connection has been limited, however, the output of any unit is limited to the interval (0,1) due to the characteristics of the sigmoidal model:

$$o_i = [1 + \exp(-net_i)]^{-1} \tag{8}$$

where $net_i = \sum_j w_{ij}\, o_j$ is the weighted sum of the inputs.

All the units are of the same type (uniform network).

To achieve initial conditions 'closest to the nature' (no a priori information in system) and avoid favoring any particular type of input, initial state of the network is generated randomly by filling the connectivity matrices with random numbers varying from -0,5 to 0,5.

Learning scheme

Before attempting any pattern recognition, a network must learn sample patterns for a certain period of time. In this experiment we have used a supervised training algorithm called delta rule. It involves following operations:

```
for each training pattern do
begin
   feed pattern values to inputs;
   propagate activation through network;
   calculate outputs;
   compare outputs with desired values and calculate output error;
   modify each weight, propogating the error back through the network;
end
```

Three main formulas that stand for the basis of the general delta rule are described in Equations (9 - 11).

$$\delta_i^{(N)} = (t_i - o_i) \cdot f_i[F_i'(net_i^{(N)})] \cdot F_i'(net_i^{(N)}), \tag{9}$$

$$\delta_i^{(n)} = f_i' \, [F_i(net_i^{(n)})] \cdot F_i'(net_i^{(n)}) \cdot \sum_k \delta_k^{(n+1)} \, w_{ki}^{(n+1)} \quad , \tag{10}$$

$$\Delta w_{ij}^{(n)} = \eta \, \delta_i^{(n+1)} \cdot o_j^{(n)} \tag{11}$$

where:

t_i is the target value for PE_i,

o_i is the current output of PE_i,

net_i is the weighted sum of PE_i inputs,

w_{ki} is the weight from PE_i to PE_k,

F_i is the output function of PE_i (defined in (8)),

f_i is the activation function of PE_i (identity),

η is the learning rate,

index (n) means n-th layer.

Notice that there is no explicitly given error for hidden units: it must be calculated by backpropagating the error from subsequent layer (the algorithm is thus recursive).

In the case of two-layer structure, since there is no hidden layer, the learning algorithm involves the classical delta rule [16]:

$$\Delta w_{ij} = \eta \cdot (t_i - o_i) \cdot F_i' \, (net_i) \cdot o_j \tag{12}$$

After preprocessing, we have obtained 475 files containing PQRST complex patterns; among these are about 30% 'ventricular' cases and about 70% 'auricular' cases. From this set we have randondy selected 300 patterns to produce a training set (proven that there are representatives of all possible morphologies included), while the rest has been used for testing. Such a large number of training patterns should have guaranteed that the patterns will be generalized, not memorized individually; there is an empirical rule that says that proper generalization takes place when the number of training patterns is roughly equal or larger than the number of modifiable connections (however, it's a very general rule). During the learning process, patterns have been repeatedly presented to the inputs and weights have been modified, according to the delta rule algorithm. Each cycle of presentation of all the patterns has been called a teaching round. We have used a constant number of 300 rounds, and, to observe the network's behavior dynamically, we have saved its image (i.e. connectivity materices) every 10 rounds.

Testing the networks

After training, we have performed three kinds of tests on the networks. First, we have checked their ability to classify patterns belonging to the training set, then we have tested the networks on the set of remaining 175 patterns which are not included in the training set, finally we have tested the quality of recognition of noise - corrupted patterns. This test has been performed on 50 patterns selected randomly from these that were recognized correctly. To avoid the effect of strong influence of the noise to the input pattern (at very low signal-to-noise ratio, shape of the pattern depends more on the stochastic noise process than on the signal itself), we have performed the tests 10 times for each pattern with different noise realization.

As it was said before, we have been recording the network state (connectivity matrices) during the training session every 10 rounds and then we have checked the network performance for all the matrices by repeating the recognition task. Recognition results for the training set are shown at Fig.2. and for the testing set at Fig.3. Summary of the results is contained in table 1.

It can be easily noted that the number of 300 teaching rounds is much too large for achieving good results, for the performance close to 100% is reached after 30 rounds. This may be explained by the fact that, even though there are 300 training patterns (a number comparable to the number of weights), there are only two classes; the representatives of each class are quite similar to each other. This probably has caused the situation when many similar training patterns are forcing the same output pattern. In fact, one training round, consisting of about 200 presentations of patterns belonging to one class, must be more effective than a round having for instance 20 presentations, and the teaching process is therefore strongly convergent. Furthermore, no important deterioration of recognition quality has been observed during tests on the second set of patterns, disjoint with the training set.

Table 1

Quality of recognition of undisturbed patterns (results given in percent scale)

Training rounds	Number of hidden units					
	0	2	4	6	9	12
10^1	98,33	98,67	99,00	99,33	99,33	99,33
100^1	99,67	99,67	99,67	99,67	99,67	99,67
200^1	99,67	99,67	99,67	99,67	99,67	99,67
300^1	99,67	99,67	99,67	99,67	99,67	99,67
10^2	98,29	98,29	98,86	98,86	98,86	98,86
100^2	98,29	98,29	98,29	98,29	98,29	98,29
200^2	97,71	98,29	97,71	98,29	98,29	98,29
300^2	97,71	98,29	97,71	98,29	98,29	98,29

1) test results for training set (300 patterns)

2) test results for testing set (175 patterns)

In the second part of the experiment we have performed some tests to check the networks's performance on noisy patterns. The results are summarized in Table 2 and shown on Fig. 4.

Table 2

Quality of recognition of noise-contaminated patterns (results given in percent scale).

Signal to noise ratio	Number of hidden units					
	0	2	4	6	9	12
40 dB	100,0	100,0	100,0	100,0	100,0	100,0
20 dB	100,0	100,0	100,0	100,0	100,0	100,0
10 dB	100,0	99,80	99,80	100,0	99,80	99,80
5 dB	99,20	98,60	98,60	99,60	99,40	99,40
0 dB	96,80	96,80	95,40	96,20	96,80	95,20
- 5 dB	83,60	85,40	84,60	81,60	83,80	85,80
-10 dB	68,20	64,40	63,20	66,40	63,60	62,80

It can be noted that, at signal-to-noise ratios higher than +10 dB, the performance of the neural classifier is very close to 100%. It strongly decreases at SNR lower than 0 dB, when the image becomes difficult to recognize even for a human expert. The signal-to-noise ratio of -10 dB was the worst value tested. The noise is so strong that it is impossible for a human to recognize the pattern. The network reached more than 60% of correct recognitions, indicating that it is also a limit of its capabilities (however, the percentage of correct recognitioons is still larger than a half). As a rule, misclassifications are repeating for certain test patterns, indicating that some patterns are more liable to classification errors (errors depended on the signal features).

This test shows also another interesting feature: whenever classification errors occur, simpler networks (i.e. those having less hidden units) tend to perform generally better than those having more hidden units (for instance, at - 10 dB SNR the best results are obtained for the two-layer structure, while the worst - for the structure with 12 hidden units). Such a phenomenon can be explained by a fact that more hidden units means more 'degrees of freedom', which in consequence allow the network to develop more 'strict' class representations, while less or no hidden units allows only 'approximate' or 'fuzzy' representations. A pattern that is distant from both classes may be then classified by a 'large' network as an error (both outputs close to 0), however, one of the outputs will be larger and will be chosen to indicate the class. 'Constrained' networks cannot develop so strict classification boundaries, so they may work better. It may lead to conclusion that increasing the number of hidden units not always improves the classification (it should be remembered however, that the task itself deos not require a large network).

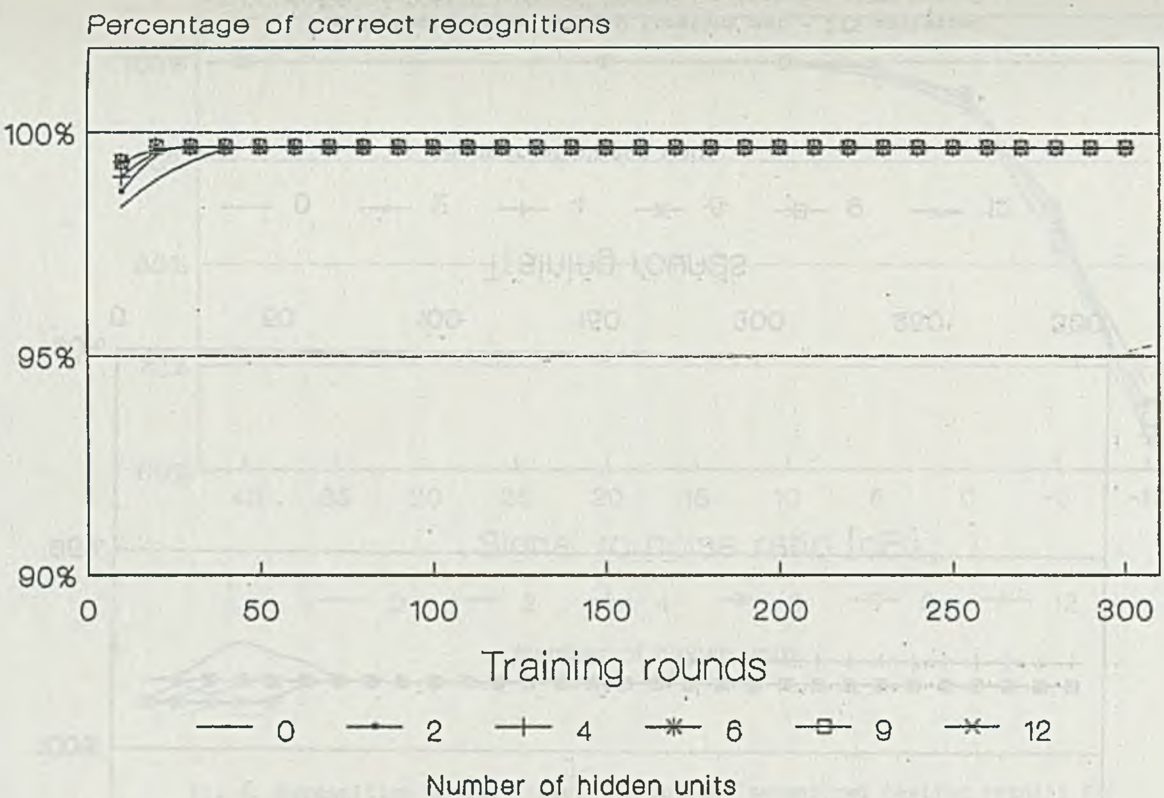

Fig.2. Recognition quality (training set - 300 patterns)

Rys.2. Jakość rozpoznania (zestaw uczący - 300 obrazów)

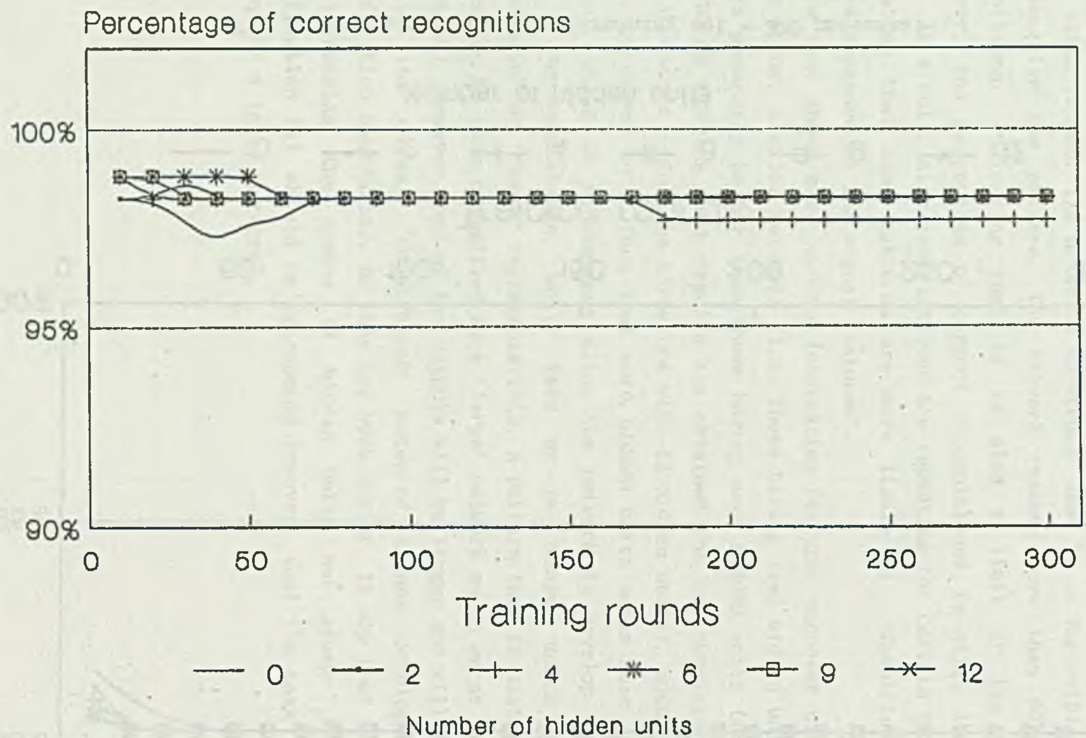

Fig. 3. Recognition quality (testing set - 175 patterns)

Rys. 3. Jakość rozpoznania (zestaw testujący - 175 obrazów)

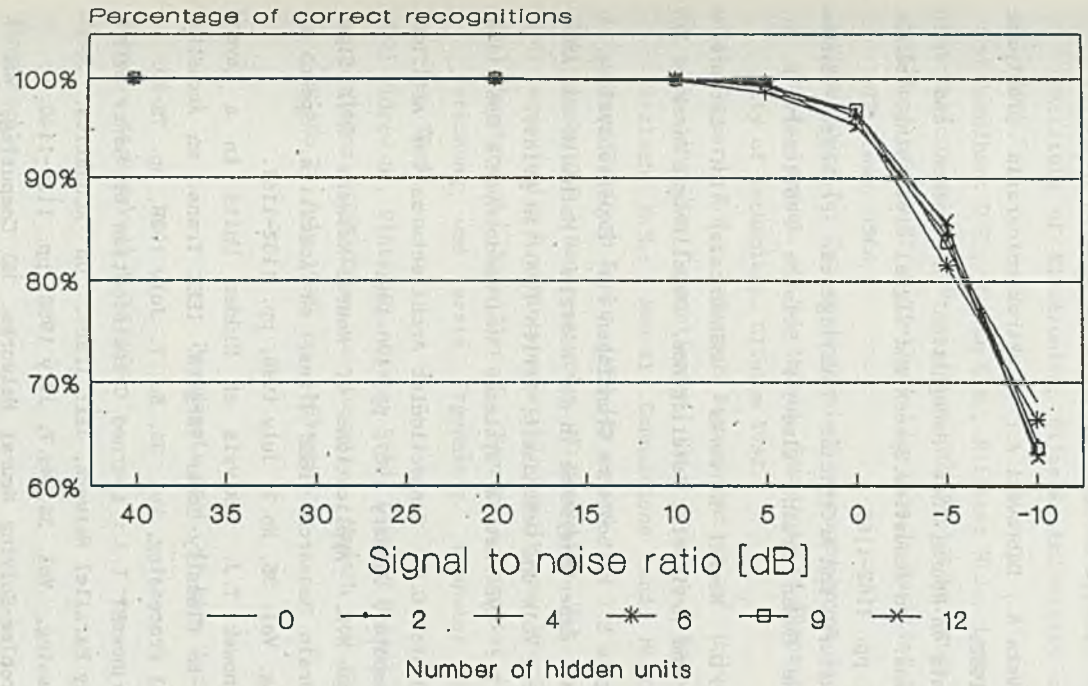

Fig. 4. Recognition quality after 300 rounds (summarized testing results for the set of 50 disturbed patterns)

Rys. 4. Jakość rozpoznania po 300 cyklach uczenia (wyniki zbiorcze testu dla 50 obrazów zakłóconych)

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Wpłynęło do Redakcji 1.03.1990.

Streszczenie.

W artykule pt. "Application of a three-layer feedforward neural network for classifying electromedical signals" omówiona jest próba zastosowania warstwowych sieci neuropodobnych bez sprzężeń zwrotnych do klasyfikacji sygnału EKG. Badane sygnały dane są w dziedzinie czasu w postaci zespołów PQRST i klasyfikowane są do jednej z dwóch grup: przebiegów prawidłowych lub patologicznych. Do klasyfikacji wykorzystano sieci dwu- i trójwarstwowe ze

zmienną liczbą elementów w warstwie ukrytej. Stosowanym algorytmem uczenia był uogólniony algorytm wstecznej propagacji błędów. W opisanych doświadczeniach przeprowadzono badanie jakości klasyfikacji w zależności od liczby elementów w warstwie ukrytej. Dodatkowo wykonano badanie wpływu zakłócenia sygnału wejściowego szumem modelującym rzeczywiste zakłócenia mięśniowe na jakość klasyfikacji. Z przeprowadzonych doświadczeń wynika, że sieć neuropodobna jest w stanie prawidłowo rozpoznawać nawet silnie zakłócone sygnały; jednocześnie nie stwierdzono wyraźnego wpływu liczby jednostek ukrytych na jakość rozpoznania, co może mieć swoją przyczynę w stosunkowo dobrym rozdzieleniu klas.