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Mining of an electrocardiogram

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Abstract

The widespread use of medical information systems and rapid growth of medical databases require methods of efficient computer-assisted analysis. In this paper we focus on the QRS complex detection in electrocardiogram but, the idea of further recognition of anomalies in QRS complexes based on the immunology approach is described, as well. In order to detect QRS complexes, a neural network ensemble is proposed. It consists of three neural networks. The details of this solution are described and the results of the experimental study are shown.

1. Introduction

An electrocardiogram (*ECG/EKG*) is an electrical recording of the heart activity and is used in heart diagnoses. ECG allows evaluating the rhythm and frequency of the heart work and enables investigating people's heart defects. On the basis of ECG recording one can evaluate the size of the heart chambers. The knowledge of the ECG image for healthy and defective cases is the base for the heart diagnosis. The ECG signal provides information concerning electrical phenomena occurring in the heart, that cause in the change of shape of an individual part of the signal. Because of the direct relationship between the ECG waveform and the cardiac cycle, it is possible for the doctor to diagnose a cardiac disease and monitor the patient's condition on the basis of ECG waveforms. The basic analysis of ECG signal is based on the following elements (Fig. 1): wave P, spike Q, spike R, spike S, wave T. The QRS complex is essential for every heart anomaly detection. Traditionally, such detection is done by physicians in order to examine whether the patient's heart works properly or not.

In recent years, a significant amount of research effort has been devoted to the automated detection of spikes in the ECG signal [1-4]. In general, the effort

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can be divided into linear methods of signal processing and methods of nonlinear transformation. The most important techniques [5] are:

– calculation and analysis of the first derivative of the ECG signal,
– pattern matching,
– using DFT or wavelet for discovering the periodic parts of the signal [6,7],
– using a digital filter (e.g. FIR, IIR),
– heuristic equations,
– neural networks,
– nonlinear principal component analysis of the ECG signal.

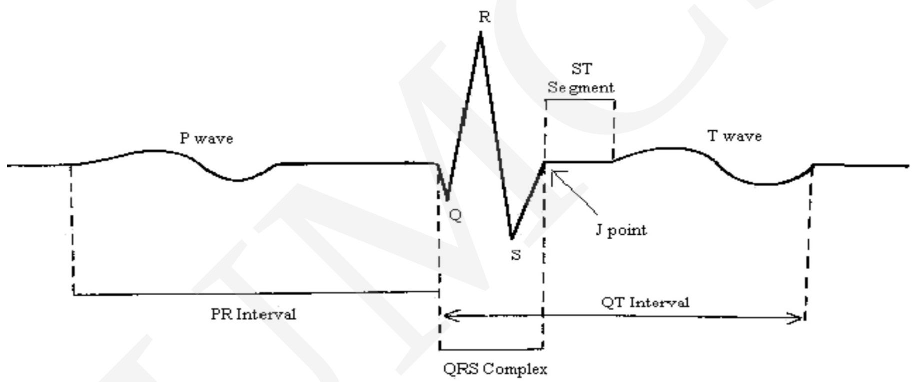

Fig. 1. The characteristics of an electrocardiogram

The performance of an automated ECG analysis systems depends heavily on the reliable detection of the QRS complex. The difficulties in the detection of characteristic waves lie in oscillations of the baseline, irregularities of the waveform and overlapping among wide band distribution of the characteristic waves. These arguments explain why there are so many different approaches in the automatic detection of the QRS complexes.

In the paper we focus on the automatic detection of the QRS complex using an ensemble of neural networks. The QRS complex detection is the starting point for further analysis of the ECG signal that allows to determine the type of anomaly occurring at the ECG signal. In other words, QRS complexes (or features acquired from them) are the basis of classification of the ECG signal that facilitates patient's diagnosis. Classification is one of the datamining tasks – new emerging technique, well suited for the analysis of data. It is becoming an important tool in science, healthcare and medicine.

2. The idea of ECG mining

In the presented study, signals from twelve leads of the ECG recording are delivered to the preprocessing module, where they are processed in order to produce input features for detection of characteristic points of the signal such as the QRS complex, wave P or T.

A signal is represented by the sequence of voltage values relating to the activity of the heart. It is sampled every 4 ms. Because the measurement lasts 5 s. the sequence is composed of 1200 values. The signal is displayed to the user, which allows him to mark patterns (parts of the signal) that will be subsequently used for the detection module's training(Fig. 2). This module is based on an ensemble of neural networks. Each neural network in the ensemble has its own input representation of the signal so that different aspects of information hidden in the signal may be shown. The final decision of the neural network ensemble follows the voting procedure, and this decision has to be unanimous.

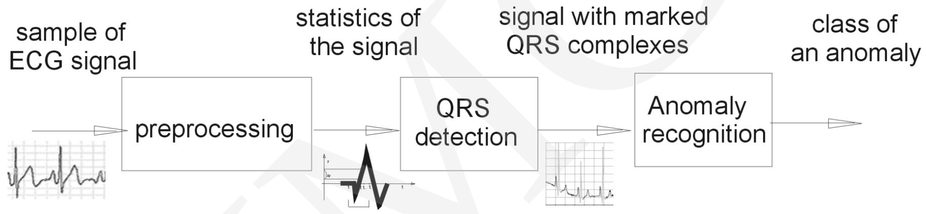

Fig. 2. The idea of ECG mining

The output of the detection module can be processed further either manually by the physician to diagnose the state of a patient or can be delivered to the anomaly recognition module. This module classifies the part of signal to the proper category on the basis of the characteristic spikes in the signal (QRS complex, T or P wave). The solution to this problem in our approach is inspired by the immune system. In the paper we concentrate mostly on the detection module, describing its details and presenting the obtained results whereas the idea of anomaly recognition the idea is sketched only. It determines the direction we will follow in our research in the nearest future.

3. Detection of QRS spikes

Due to the differences in the sizes of hearts, their orientation in the body and the healthiness the automatic detection of the QRS complex is not an easy task. In order to improve the reliability of spike detection we used a neural network ensemble. It is composed of three neural networks (NN1, NN2, NN3). Each network is the classical multilayered neural network, trained by means of the backpropagation algorithm with momentum. It classifies an input pattern into one of the following classes: QRS complex, wave P or T, or a meaningless pattern. Therefore there are three neurons in the output layer of each neural network.

The number of input neurons for each network depends on the size of the input pattern. Because we decided to deliver different kind of information about the ECG signal to each neural network, the number of inputs in each network is adjusted to match the size of the input vector. The idea of the neural network ensemble detecting the QRS complex is shown in Fig. 3.

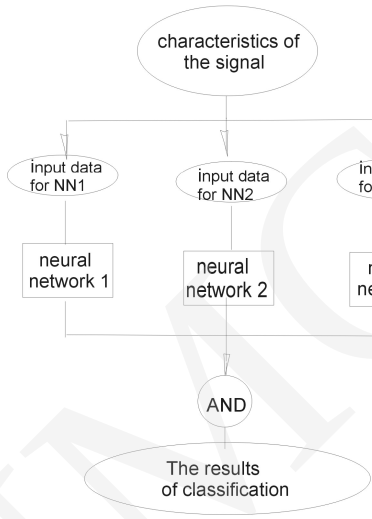

Fig. 3. The idea of spike detection in an electrocardiogram

It has to be pointed out that the input pattern of each neural network refers to the same part of the signal but it contains different parameters. When the networks are trained, the decision of the detection module concerning the pattern classification is made on the basis of the common decision of all neural networks in the ensemble. The principle is that the decisions of all neural networks have to be unanimous. Otherwise the classification is incorrect and the user is informed about it.

3.1. Input data for neural networks

The recorded ECG signal is stored as a sequence of discrete samples describing the electrical activity of the heart in a given discrete time interval t_i (Fig. 4). The training set for the neural networks in the ensemble is prepared on the basis of patterns in the signal (QRS complex, T and P wave) marked on the screen by an expert. Such a rough representation of the signal takes the form of a sequence of real values that are not suitable for processing by a neural network (NN). That was why we have to preprocess the input data.

3.1.1. Input data representation for NN1

The aim of the first representation of the signal, which refers to NN1, is to find points of similarity between different fragments of signal. The trigonometric representation of the signal was used in this case. It is based on transforming the value of the signal's amplitudes into a sequence of angles (represented by its sine value). This representation allows to preserve the important characteristic of the signal,independently of its absolute value. It refers to the rate of growth or decline of the signal.

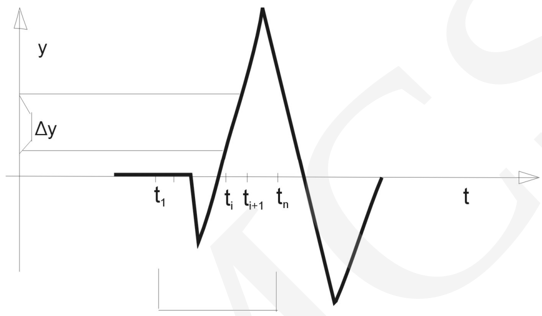

Fig 4. The form of data prepared for a neural network

In order to transform the *value(i+1)* of the signal in the timestep *(i+1)* to its angle representation (the value of sine) it is necessary to calculate the difference Δy according to the eq. 1:

$$\Delta y = value(i+1) - value(i). \tag{1}$$

Then, the distance between points is calculated as follows:

$$dist = \sqrt{\Delta y^2 + \Delta t^2}\ . \tag{2}$$

We assumed that each timestep was equal to 1, so the *dist* can be expressed as:

$$dist = \sqrt{\Delta y^2 + 1} \tag{3}$$

These parameters are used for determining the new value expressed as the sine of the angle in the signal:

$$value_{ang}(i) = \frac{\Delta y}{dist} \tag{4}$$

This representation could be good enough to detect QRS complexes if they occurred regularly and had exactly the same shape. The reality is more complex therefore we decided to introduce the other networks with different input data.

3.1.2. Input data representation for NN2

The problem with the first representation appears when we try to consider the following two patterns as QRS complexes. Let's assume that the first one rises in the range [0,20] and falls in the range [21,40] while the second one increases in the range [10;30] and its decrease is in the range [31;50]. In such a case, a neural network provided with the first representation would obviously fail to find these patterns as similar due to the shift between them and an opposite gradient in the range [21;30]. That was the reason why another representation had to be prepared. First, the range of angles (-90, 90) is divided into the following 14 ranges:

(85, 90); (75, 85); (60, 75); (45, 60); (30, 45); (15, 30); (0, 15);
(-15, 0); (-30, -15); (-45, -30); (-60, -45); (-75, -60); (-85, -75); (-90, -85)

Afterwards, the frequency of the occurrences of a given angle range in the sample of the signal is calculated. Then the input vector is built of 14 elements corresponding to the angle ranges. The number of ranges was chosen on the basis of experiments. In consequence the number of neurons in the input layer of NN2 is set to 14, as well.

3.1.3. Input data representation for NN3

The next input data representation is similar to the previous one. The difference between this representation and the previous one is that now, we take the absolute value of angle's sine into account. As a result fourteen ranges will be reduced to the following seven: (85,90); (75, 85); (60, 75); (45,60); (30, 45); (15, 30); (0,15). Thus a value that would previously belong e.g. to (-60, -45), will be now assigned to (45,60). In this case for a given part of the signal we obtain an input vector consisting of seven elements. Each of them informs about the frequency of the occurrences of a given angle range.

While the number of input neurons in networks NN2 and NN3 is fixed, the number of neurons for NN1 is set by the user. In summary, the representation of the signal for each network was designed to show some specific features of the ECG signal. The first one helps to discover a similarity between parts of the signal and to preserve information about the spike. The second representation delivers information about the functiongradient (without any knowledge about its location). The last one identifies and distinguishes spikes located in 'flat' parts.

3.2. Training set for the neural network ensemble

The training set is prepared by the user. He or she marks the appropriate part in the signal displayed on the screen and assigns the type of the pattern (QRS spikes or P/T wave or 'meaningless pattern') to it. Then, the representation of the patterns for each neural network is prepared by the application. It means that for NN1 each pattern has to be scaled depending on the number of inputs assumed for this network. For other networks the frequency of occurrences of values within the defined ranges is calculated.

3.3. Detection of QRS complexes by the neural network ensemble

When the process of the neural network ensemble's training ends, the system is ready to identify characteristics of the ECG signal (QRS complexes, P and T waves). Afterwards, the examined signal has to be loaded. Next, the user decides which type of the signal's characteristic should be automatically marked on the screen.

The identification of QRS complexes is based on progressive signal processing during which a window moves along the *t* axis of the signal. It is initially set to a small value and increased during the progress of detection. The rate of the window's movement and its growth influence the duration of signal processing, but also the efficiency of spike detection.

The moving and increasing window enables the detection of patterns independently of their width but the complexity of this algorithm is high. Each of the neural networks gets a transformed sample of the signal from the window, performs its classification and produces a vector of three elements at the output. As an output of each neural network, the vector of three elements is produced. Each output is responsible for detecting a specified characteristic of the signal, i.e. QRS complex, wave P or T. In cases when the neural networks answers are unanimous, the decision of the neural network ensemble is assigned to the pattern. It becomes the basis for marking the detected spikes in the image of the signal.

3.4. Procedure of detected spike visualisation

After the signal has been processed by the neural network ensemble, we obtain many patterns with a class assigned to each of them (detected a QRS complex, wave P/T or meaningless pattern). Because values obtained from the signal are repeatedly processed in various patterns, they may be classified in a different way. In order to mark the spikes sought by the user, the overlapping parts of the signal have to be joined together. A new parameter – a *sensitivity* is vital in the process of joining those parts. It is used for deciding how many detected parts of a single pattern in a particular point has to appear in to be recognized as a part of the marked answer. Next, those points are connected so that they become a cohesive range – one of the detected intervals. It is a kind of a treshold that allows to decide whether the value belongs to the sought pattern. As we can see in the experimental part of the paper this parameter plays a crucial role in successful spike detection.

3.5. QRS complex detection – experimental studies

In the first phase of the experiments we investigated the influence of the neural networks parameters on the efficiency of the pattern recognition in the signal. The number of neurons in the hidden layer was chosen on the basis of the rule of thumb as the average of the number of input and output neurons for each network. The best setting of neural networks' parameters in the ensemble was as follows: initial weights were randomly chosen from the range [-0.1;0.1], learning coefficient = 0.001, training error = 0.0001. The last two parameters need some comments. If their values are increased, the networks in the ensemble fail to produce unanimous decisions, thus making the ensemble unable to classify patterns properly. For example we observed that for the purpose of P/T waves detection it would be better to make the learning coefficient even smaller than 0.001, but on the other hand it would take more time to train neural networks. In further experiments the neural network ensemble was trained by means of a training set composed of 60 training patterns (20 patterns for each class). The next phase of experiments was focused on the role of the sensitivity parameter. The proper setting of its value is essential for the quality of results produced by the application. It is visualized in Fig. 5.

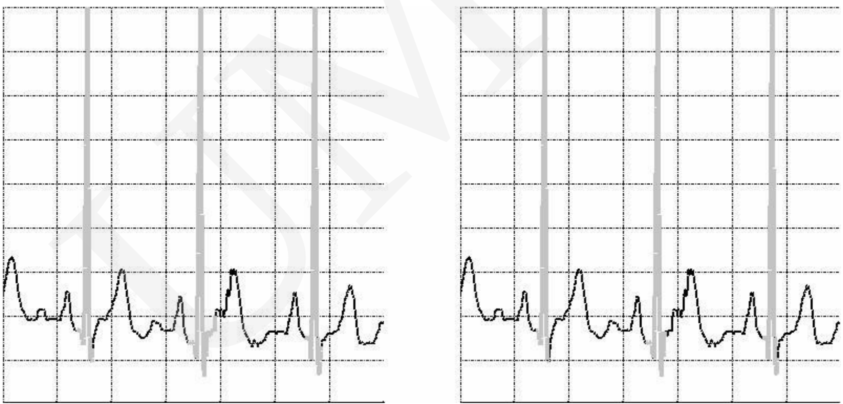

Fig 5. The comparison of QRS complex recognition for two cases a) sensitivity = 1 and b) sensitivity = 10

It is worth mentioning that the recognition of QRS complexes is more accurate when a larger value of sensitivity is used. The higher is its value, the narrower is the range of detected pattern. In case when the sensitivity value is too small, unwanted regions belong to the marked part of the pattern. On the other hand, the large values of parameters cause that recognized patterns may be narrower than expected, or even ignored (see Fig. 7). The necessity of tuning the sensitivity value for each ECG signal individually becomes an additional difficulty. The experiments show, that properly prepared numerous training sets (ca. 150 patterns) are relatively resistant to fluctuations of the sensitivity parameter. In Fig. 6 the results of QRS recognition are shown for an ensemble consisting of two neural networks (a) or three neural networks (b).

Having compared both cases, we may conclude that the extended neural network ensemble produces narrower ranges of patterns, which gives more accurate results.

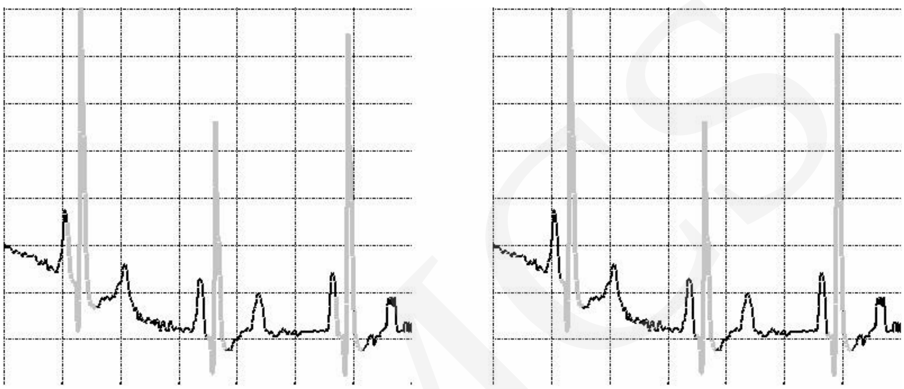

Fig 6. The results of QRS spikes recognition by the neural network ensemble
a) composing of two neural networks and b) three neural networks

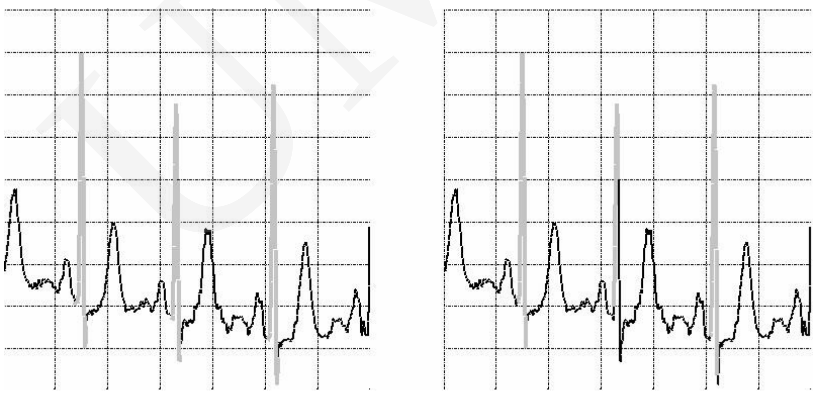

Fig. 7. The comparison of QRS complex recognition for two cases
a) sensitivity = 10 and b) sensitivity = 30

The proper evaluation of the described approach of the QRS complexes detection still needs more experiments, but we may conclude that the application gives satisfying results especially in detection of QRS complexes. The detection of P/T waves was also satisfying, but because their shapes are not as specific as in the case of QRS complexes, sometimes the detection failed.

4. Anomaly recognition – future works

A recognized sample of signal (QRS complex) should be properly interpreted so that additional knowledge may be acquired (to allow determining whether a given person is healthy or not). An expert can easily verify whether the signal includes any anomalies. The algorithm of the automatic anomaly recognition described in this document requires samples of an ECG signal, but can also cope with anomaly recognition even if provided with positive patterns only. It is inspired by a natural immune system activity based on a negative selection phenomenon (a self-nonself discrimination process that takes place in the thymus), which is also the origin of the Negative Selection Algorithm (NSA), discussed in more details in [2,8,9].

The parts of the signal corresponding to QRS complexes have to be recognized by immune system receptor, so that their membership in the group of proper or abnormal structures may be determined. Both – samples of signals and receptors consist of strings (binary or real values – depending on the problem idiosyncracy). The initial set of receptors is created on the basis of model signals transformed by random mutations (fluctuations in higher or lower level). Then, those receptors from the previously created set, that have the ability to recognize anomalous parts of the signal properly, are selected.

The process of choosing those effective receptors rests on stimulating them with self structures (proper signal samples). Those receptors, that do not recognize any of the self structures are added to the effective receptors set (see Fig. 8) and shall become the base of the anomaly recognition algorithm. Anomaly recognition relies on presenting an already recognized QRS complex to the NSA system. In the case of a positive answer (recognition by any receptor), the signal presented to the receptor is marked as abnormal. That fact is alerted by the system. The key feature of the NSA is an affinity function, used for measuring the similarity between a receptor and a presented structure similarity.

Lack of model signals may become a problem. A solution presented below attempts to avoid the necessity of possessing many model signals and allows the algorithm to work using a single positive sample. In that case anomaly detection becomes more complex, because the creation of both positive and negative samples is necessary. The idea of NSA modification, presented in the paper meets the problem. It rests on using a set of positive detectors, that work in the opposite way to NSA receptors. The first, original detector is an exact copy of a model sample signal for QRS complex of a lead. Afterwards, random mutations are used for creating patterns. Those new patterns are presented to the detectors. In the case of a detector's stimulation by the pattern, the pattern is marked as a self structure, otherwise as a nonself structure. Self structures join the detectors set, whereas the rejected ones join the nonself structures set. This process lasts until the cardinality of the detectors set reaches a previously assumed value. The algorithm can be compared to negative selection phenomenon that takes place in the thymus, with one main difference: detectors work in the opposite way to receptors (the idea is inspired by the T cells performance, whose job is to detect nonself structures) and their set is enlarged by those detectors, whose structure is similar to that of other detectors.

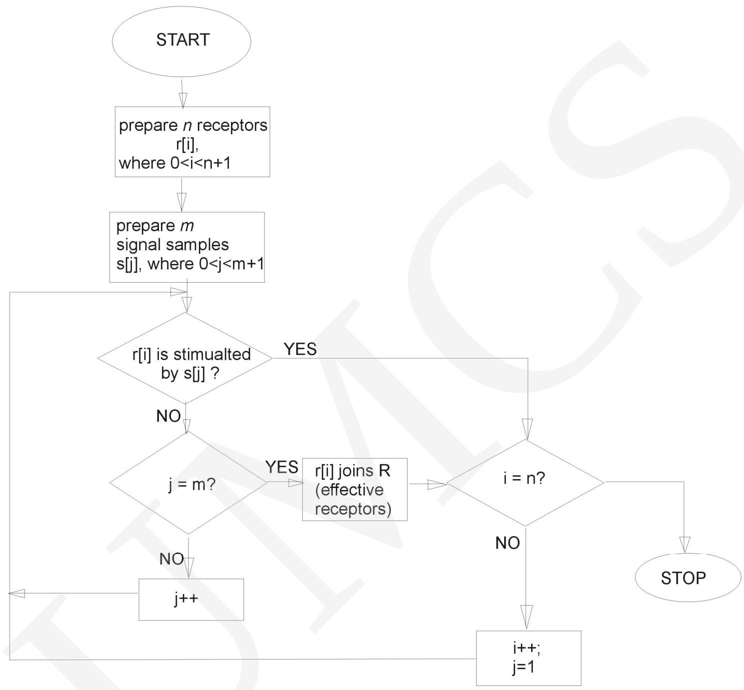

Fig 8. The algorithm of effective receptors set creation

In order to find out whether a sample signal classified (by an expert or a neural networks ensemble) as a QRS complex includes an anomaly, it is introduced to the described immune system (with an already prepared set of detectors and nonself structures) and the system assigns it to one of the groups – detectors (self) or nonself.

5. Conclusions

In the paper the idea of ECG mining is presented. It consists of the QRS complexes detection and anomaly recognition in samples of the ECG signal. To detect QRS complexes we propose a neural network ensemble. Each network in the ensemble obtains information about the signal expressed in different form. The results obtained during experiments with the application were promising, but further experiments are necessary to evaluate the proposed approach to a greater extend. All details of the proposed QRS detection method are precisely described in the paper. The idea of anomaly recognition based on an immune system is proposed, as well, but its implementation and experiments are planned in the nearest future.

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