Deep Learning Approach for QRS Wave Detection in ECG Monitoring

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***Abstract* — Paper describes an approach of deep learning for QRS wave detection for using in mobile heart monitoring systems. Authors analyze a deep learning approach and its advantages in the field of feature extraction and detection, and deep network architecture. Two different variants of deep network are proposed. ECG data processing scheme that includes a neural network is described. It presumes preprocessing, filtering, windowing of ECG signal, buffering, QRS wave detection and analysis. Network training process is mathematically founded. Two variants of neural network are experimentally tested. Training sets and test sets are obtained from free ECG data bank PhysioNet.org. Experimental results show that network with decreasing number of neurons in hidden layers has a better generalization capability. Next steps of research will include experiments with training set size and determining of its' influence on the quality of detection.**

Keywords* — *ECG signal analysis, data processing, QRS wave, cardiology, neural networks.

I. INTRODUCTION

ECG recording and analysis are common processes for systems of heart diagnostics and monitoring. Mobile portative systems for long-term ECG monitoring are used increasingly at present [1, 2]. The main challenge of modern heart monitoring systems is to detect the signs and to predict a risk of dangerous heart conditions during day-to-day activity. Thus, mobile systems need reliable and accurate methods for extraction of significant ECG features in conditions of free movement of the patient.

Most of the last achievements in signal and image processing related to applying deep learning approach [3, 4, 5, 6]. This approach presumes creation of the neural networks 7, 8] with more than one hidden layer. This architecture and application of unsupervised pretraining methods allows to generate features for pattern recognition tasks automatically.

This approach has valuable advantages. With sufficient number of learning samples obtained features have stability and good generalizing capability [9, 10]. Neural networks technologies have good potential of parallel implementation. Algorithms based on neural networks are performed relatively fast on modern multi core processors (CPU's and GPU's) and in real-time too. [11]. They have the ability of data transmission between the networks that resolve tasks which aret different in their definition and similar in principles of decision (for example detection of different objects on the image).

II. DEEP ARCHITECTURE

The basic architecture of deep network presumes several layers for extraction of the features and several layers for resolving of classification tasks (Fig. 1).

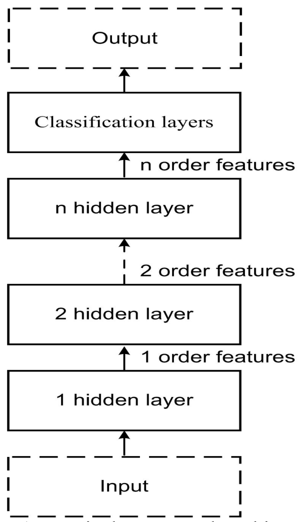

Fig. 1. Basic deep network architecture

Initially restrict Boltzmann machine (RBM) is used as an element for features extraction. These networks are used to build a deep belief network (DBN). However, RBM learning procedure is quite complex [12]. This causes wide application of autoencoder (AE) in deep networks for feature extraction [13]. AE is a simple feedforward network that consists of 3 layers without recurrence (Fig. 2), but as distinct from multi layer perceptron number of neurons on input and output layers is the same. Input signal is playing a role of answers for AE during training process. As the number of neurons in hidden layer is smaller than the number of input neurons or there is a limitation for the number of active neurons in hidden layer, AE have to implement a generalization by extracting most specific features of input data.

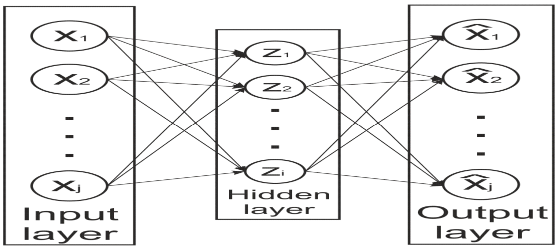

Fig. 2. Autoencoder architecture

Stacked autoencoders are used for constructing deep networks. Algorithm of backpropagation is used for layer-by-layer learning of hidden layers [14]. First layer is learnt with input data set. Then the extracted features are used as learning data set for the second layer and so on until all associative layers are learnt. This is a means of unsupervised pretraining of a deep network. Then the features extracted by associative layers with class labels are used for learning of classification layer. After learning of all layers fine tuning of whole network is done with the help of backpropagation.

III. Deep Network for QRS Complex Detection

Most of the existing algorithms for QRS wave detection in ECG signal [15, 16] are created with the rule based approach or classical machine learning. This approach presumes that the features on the base of which a decision is made are formalized. Features extracting process in this case is quite complex and subjective. In addition, a form and parameters of individual ECG signals are variable. It is caused by individual characteristics of human organism and conditions of ECG signal recording. Total influence of these factors leads to errors and the necessity of manual algorithms correction.

In that way, automatic feature extraction provided by deep learning approach seems to be one of the most promising directions in this field.

As ECG signals belong to streaming data, window-based approach is used for learning of the neural network and next data analysis. The average duration of the cardiac cycle is 0.7-1 sec. ECG signal is quite low frequency signal. The most informative frequency range is up to 30 Hz. Thus, sampling rate should be limited by 60 Hz. In this case window duration can be 60 samples. It is enough to include the whole cardiac cycle up to 1 sec.

ECG signal processing scheme is shown in the Fig. 3.

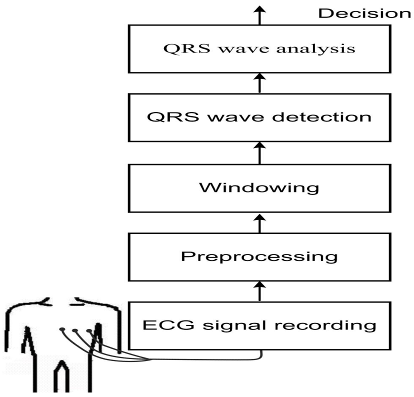

Fig. 3. ECG processing scheme

Preprocessing consists of excluding abnormal areas from analysis and filtering. Signal samples are accumulated in FIFO buffer that includes 60 samples. Samples from this buffer are forwarded to the neural network. The output of this network shows decision about QRS wave presence in the current signal window.

Two variants of neural networks are considered in this research. The first variant (see Fig. 4) has a hidden layer (L2) with dimension twice larger than signal. The number of neurons in next layers (L3-L5) is decreasing from layer to layer. But sparsity proportion of hidden layers is increased.

In the second variant (see Fig. 5) a number of neurons in hidden layers (L2-L4) is increasing from layer to layer. But sparsity proportion is decreased. Softmax layer is a classificatory layer in both variants.

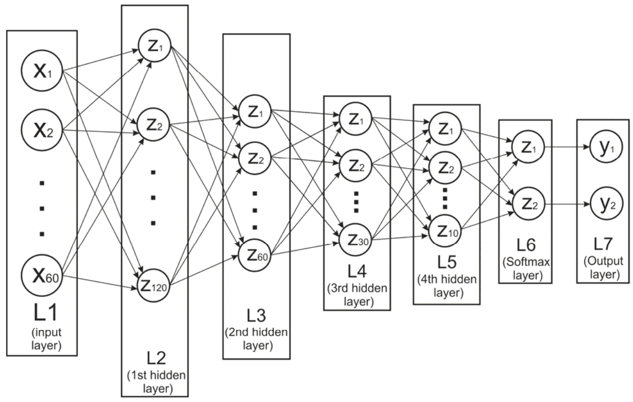

Fig. 4. Architecture of neural networks – variant 1

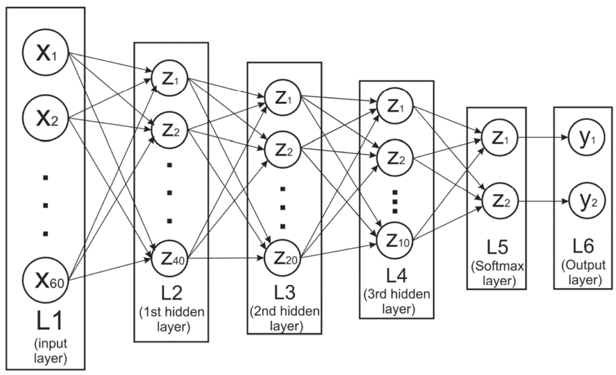

Fig. 5. Architecture of neural networks – variant 2

Pretraining of network is done in a layer-by-layer manner. For learning of AE (layers L2-L5 in the first variant and layers L2-L4 in the second variant) loss function is used.

$$E = \frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{K}(x_{kn} - \hat{x}_{kn})^2 + \lambda \cdot \Lambda + \beta \cdot \Omega \qquad (1)$$

where N – the number of examples of training set, K – the number of input variables, x – the value of a input variable, $\hat{x}$ – the value of estimation of a input variable (output of autoencoder), λ – the coefficient for the L2 regularization term Λ, β – the coefficient for the sparsity regularization term Ω.

The L2 regularization term is:

$$\Lambda = \frac{1}{2}\sum_{j}^{n}\sum_{i}^{k}(w_{ji})^2 , \quad (2)$$

where w_{ji} – vector of weights for a i neuron on the j th example of training set.

The sparsity regularization term is:

$$\Omega = \sum_{i=1}^{D} KL(p \,\|\, \hat{p}_i) = \sum_{i=1}^{D} p \cdot \log\left(\frac{p}{\hat{p}_i}\right) + (1-p)\cdot \log\left(\frac{1-p}{1-\hat{p}_i}\right), (3)$$

where KL – Kullback-Leibler divergence, p – the desired average activation value, $\hat{p}$ – average output activation measure of a i neuron.

Average output activation measure of a i neuron is

$$\hat{p}_i = \frac{1}{n}\sum_{j=1}^{n} z_i(x_j) = \frac{1}{n}\sum_{j=1}^{n} h(w_i^T x_j + b_i) \quad (4)$$

where h – activation function.

Neural network is accurately tuned with the help of learning data after layer-by-layer learning.

IV. Experiments and Evaluations

In the experimental part of the research training set consists of 218 ECG records of different people. It includes 6178 cardiac cycles of 60 samples long and 4000 records with noise of 60 samples long too. Test set consists of 1235 cardiac cycles 1000 records with noise. All ECG records are obtained from physionet.org. Records of cardiac cycles with noise and without it are used for learning of neural network.

Results of two variants of neural networks are shown in Table I.

TABLE I. Results of training and testing

Data set	Noise	Probability of errors	
		Variant 1	Variant 2
Training	No	0	0
Training	Yes	0.01	0
Testing	No	0.04	0.09
Testing	Yes	0.02	0.06

Data from Table I show that first variant of network has a better generalization capability because estimations of errors probabilities of with testing set are lower for that variant. It is determined that addition of noise into training data increases the quality of test data processing.

The results of experimental research allow to determine that buildup of the network leads to its' degradation. The quality of detection is sharply deteriorated. It is possibly concerned with insufficient amount of the learning data.

V. Future Work

Next step of the research is to examine how the size of the training set influences the quality of detection and what the ability to increase a depth of the network is. It is also planned to try using denoising autoencoder in the first hidden layer (L2) and estimate its' influence on the detection quality.

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