ECG ANALYSIS WITH USING OF NEURAL NETWORKS

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ABSTRACT

The article deals with possibilities of automatically marking of pseudo-orthogonal ECG with using of neural models for parameters acquiring, and multi-layer self-organizing maps for automatic classification of stand-alone ECG waves.

1. INTRODUCTION

The processing and analyze of Electrocardiogram has became a focal point of interest in a past few years. It comes out from time and professional heftiness especially in long-term ECG records. In this time, discrete transformations are used for example discrete Fourier transformation, discrete cosine transformation and especially discrete wavelet transformation. ECG processing by neural network is less common. Neural networks are usually used for pre-processing or as a filter.

According to the successive implementation of computer technology and new medical technologies in common general practice, orthogonal ECG leads are replacing a 12 lead ECG. Classic 12 lead ECG contain three bipolar leads (I, II, III), three unipolar limb leads (aVR, aVL, aVF) and six unipolar chest leads $(V_1 - V_6)$. Orthogonal system contains three leads ***x*** (transversal lead), ***y*** (vertical lead) and ***z*** (sagittal lead). Orthogonal system gives us three-dimensional and high accuracy information about heart more then a 12 leads ECG. System that is more common then an orthogonal leads is pseudo-orthogonal leads. Pseudo-orthogonal system contains a leads from 12 lead ECG nearest to leads ***x***, ***y*** and ***z***. For ***x*** lead is nearest lead I, V_5, V_6 for ***y*** lead is nearest lead aVF, III and for ***z*** lead is nearest lead from 12 lead ECG an $V_2, (V_1 - V_3)$.

The aim of this article is to explore possibilities of three-dimensional ECG wave descriptions with using of neural model for parameters estimation and self-organizing maps for classification.

2. PROCESSING OF ECG

My project of ECG processing can be separate into three layers.

I) Detection layer – this layer contain QRS detector and functions for data pre-processing

II) Model layer – contain neural model learning and estimation of parameters for chosen ECG wave and

III) Classification layer – use SOM for classification of parameters acquired from neural models.

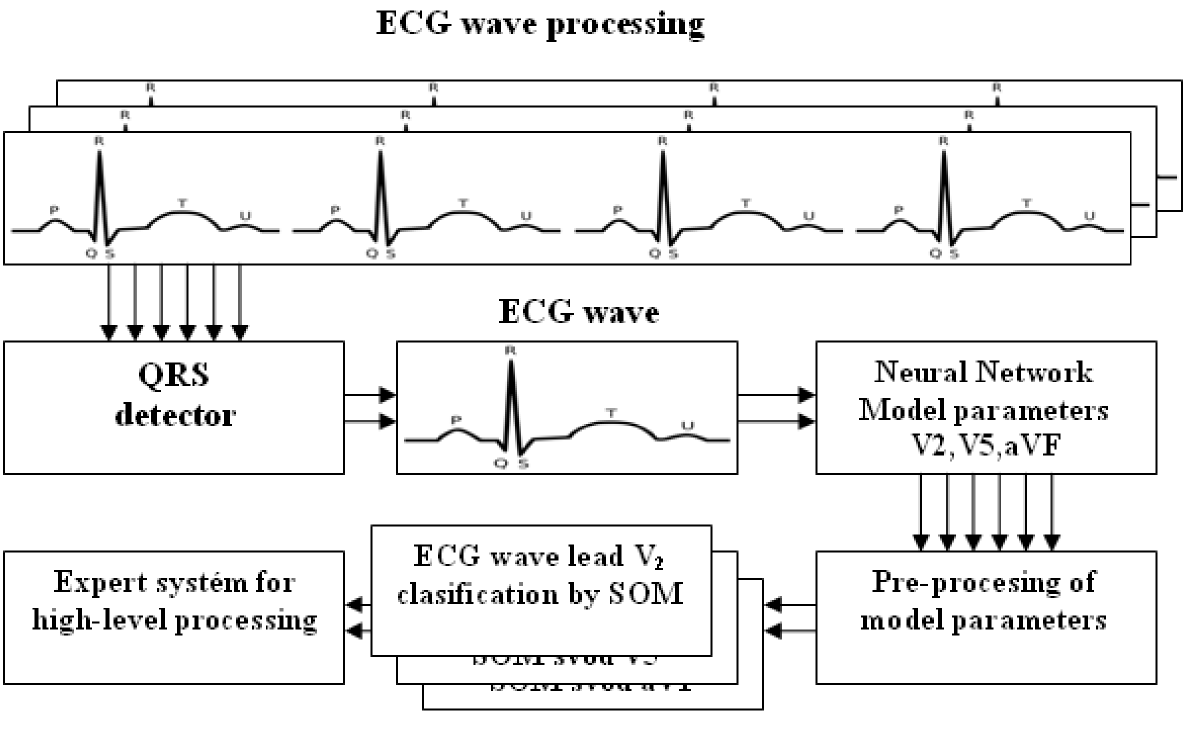

Figure 1: Process of ECG wave processing

2.1. DETECTION LAYER

Detection of QRS complex and valid data choosing is essential for accuracy and quality of estimated parameters. Marked waves from PhysioBank archive MIT-BIH Arrhythmia Database were used and problematic of QRS complex detection was not solved in this article. For future work, an existing QRS detector can be used.

2.2. MODEL LAYER

From existing models (*Autoregressive moving average, Output Error* act.) a *Finite Impulse Response* has been chosen. FIR model predicate output value from input values. A sampled data from pseudo-orthogonal leads V_2, V_5, aVF in step k marked as V_{2k}, V_{5k}, aVF_k . From known values of V_2, V_5, aVF in steps from $(k-1)$ to $(k-n)$ where $n \in Z \cup 0 < n$ we predicate values of leads V_2, V_5, aVF in step k. We mark predicated values as $V_{2\,predik}, V_{5\,predik}, aVF_{predik}$. Equations for predicated values calculation are following.

$$V_{2\,predik} = p_1 V_{2(k-1)} + p_2 V_{2(k-2)} + \cdots + p_n V_{2(k-n)} \tag{1}$$

$$V_{5\,predik} = q_1 V_{5(k-1)} + q_2 V_{5(k-2)} + \cdots + q_n V_{5(k-n)} \tag{2}$$

$$aVF_{predik} = r_1 aVF_{(k-1)} + r_2 aVF_{(k-2)} + \cdots + r_n aVF_{(k-n)} \tag{3}$$

Difference between, true value of leads V_{2k}, V_{5k}, aVF_k and predicated values, in step k, give us prediction error. Based on predication error parameters of neural models e.g. $(p_1 \div p_n), (q_1 \div q_n), (r_1 \div r_n)$ are updated by Levenberg-Marquardt algorithm. After finishing learning, vectors of parameters obtained from neural models are placed to banks for future processing in SOM. There are two examples of vector banks on figure 2 and 3. On the left side of figure, there are placed marks for individual heartbeats from MIT-BIH archive represented by color and on the right side of figure; there are vectors of parameters for stand-alone heartbeats with the same color representation. There are similarities on both sides.

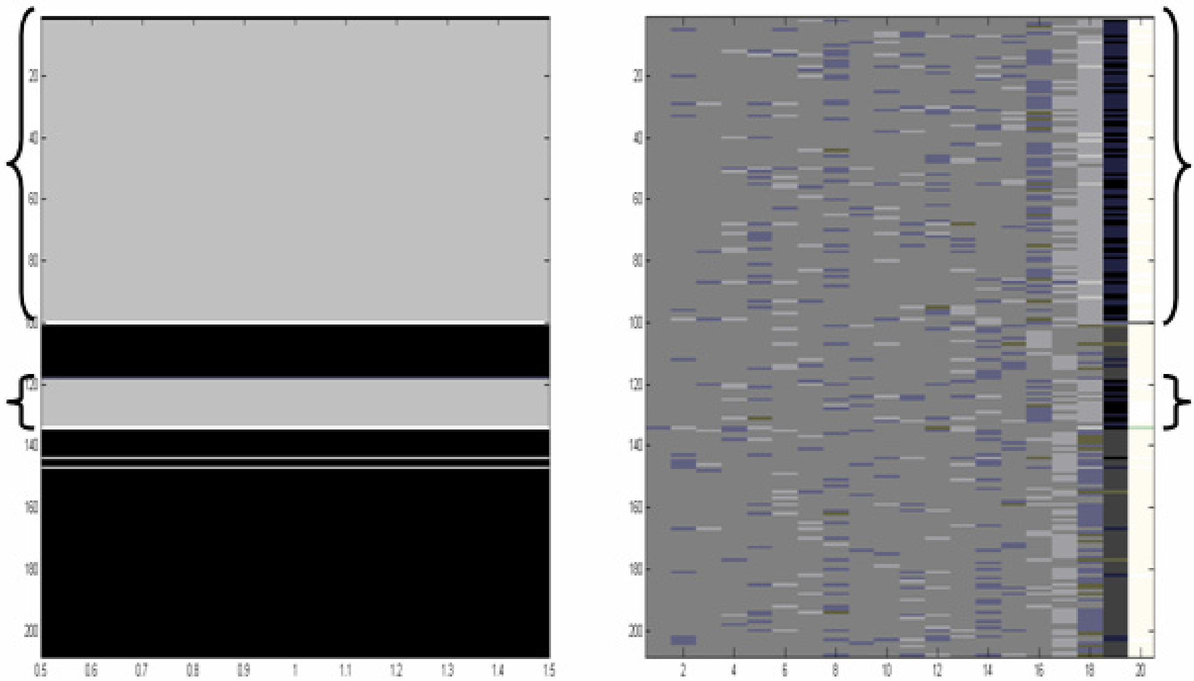

Figure 2: ECG record 102,60 000 samples, left side marks from MIT archive and vectors of parameters on the right side, normal rhythm and paced beats

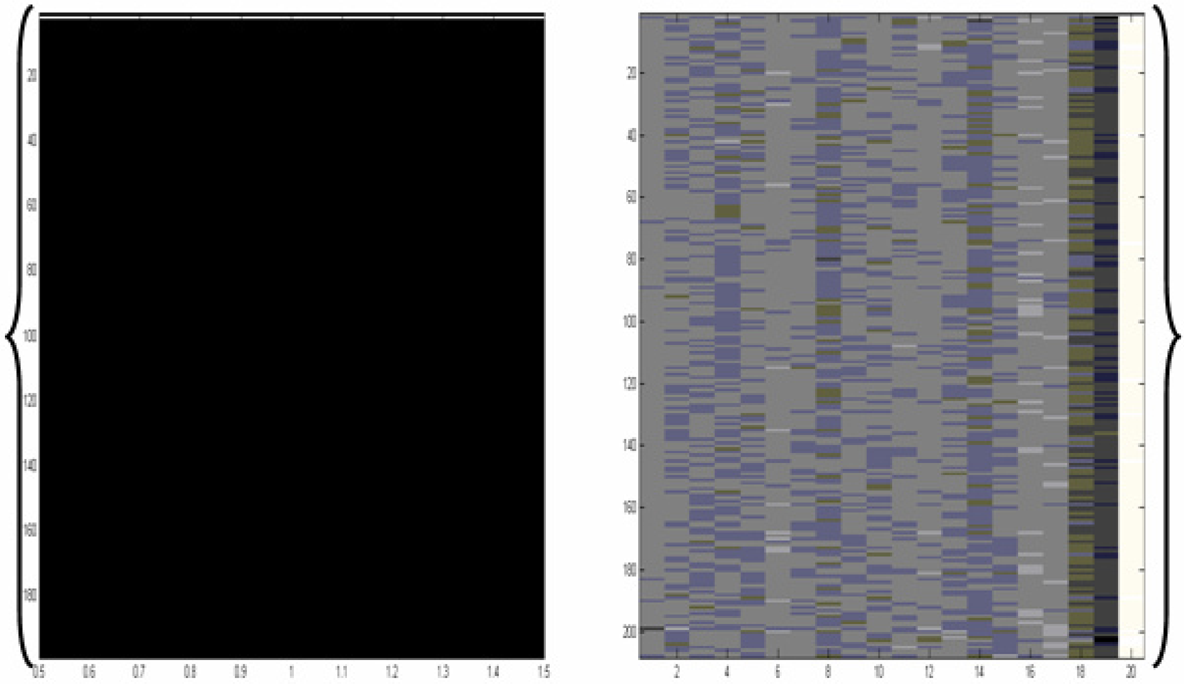

Figure 3: ECG record 103,60 000 samples, left side marks from MIT archive and vectors of parameters on the right side, normal heart beat

2.3. CLASSIFICATION LAYER

Vectors of parameters from neural models are being inserted in vector banks. Every vector corresponds to an individual heartbeat. At first, this data are used for learning self-organizing maps and after that the other vectors are classified to existing clusters. For accuracy of classification there can be used multi-layer SOM.

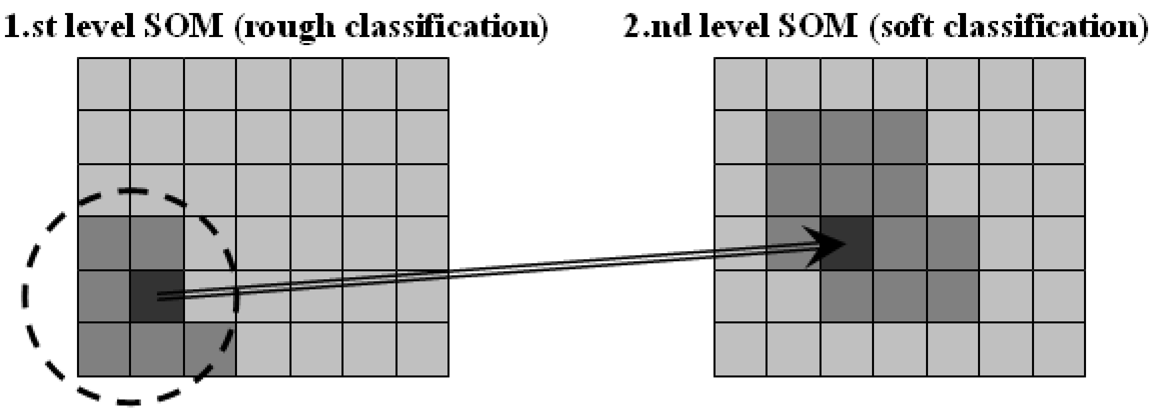

Figure 4: Multi-layer SOM classification

3. CONCLUSION

The possibility of modeling heartbeat by neural model was verified. For modeling of individual heartbeat, a neural model FIR was selected. Gained vectors of parameters from neural models were used for classification by self-organizing maps. For improving accuracy, different types of neural models will be tested. For better classification, a multi-layer SOM will be tested. MIT BIH arrhythmia database contains only two leads ECG in consequence only one lead neural models and banks of vectors was tested. One-layer SOM was tested for recognizing differences in different kinds of heartbeats with one lead. For more testing, marked 12 lead ECG will be necessary.

ACKNOWLEDGEMENTS

The paper has been prepared with the support of the research plan MSM0021630529 “Intelligent systems in automation”.

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