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ECG Classification Using Combination of Linear and Non-Linear Features with Neural Network

Tetiana BILOBORODOVA[a], Inna SKARGA-BANDUROVA[b,1], Illia SKARHA-BANDUROV[c], Yelyzaveta YEVSIEIEVA[d] and Oleh BILOBORODOV[e]

[a] *G.E. Pukhov Institute for Modelling in Energy Engineering, Ukraine*
[b] *Oxford Brookes University, United Kingdom*
[c] *Luhansk State Medical University, Ukraine*
[d] *School of Medicine, V.N. Karazin Kharkiv National University, Ukraine*
[e] *Central Research Institute of Armament and Military Equipment of Armed Forces of Ukraine, Ukraine*

Abstract. In this paper, we present an approach to improve the accuracy and reliability of ECG classification. The proposed method combines features analysis of linear and non-linear ECG dynamics. Non-linear features are represented by complexity measures of assessment of ordinal network non-stationarity. We describe the basic concept of ECG partitioning and provide an experiment on PQRST complex data. The results demonstrate that the proposed technique effectively detects abnormalities via automatic feature extraction and improves the state-of-the-art detection performance on one of the standard collections of heartbeat signals, the ECG5000 dataset.

Keywords. ECG, neural network, ordinal partition network, conditional permutation entropy, global node entropy

1. Introduction

An electrocardiogram (ECG) is a standard test to evaluate the heart condition owing to the time change in the total electrical potential. Diagnosis of heart diseases by ECG is based on a morphological analysis of the amplitude-time parameters of the PQRST complex. An ECG is accurate at diagnosing many heart diseases, although it does not always pick up every heart problem. Moreover, an abnormal ECG is highly diverse and can mean even a normal variation of a heart rhythm, not affecting the health. The traditional approaches to differentiate between norm and pathology mainly rely on time series or frequency domain data. The reliable models can be achieved using the nonlinear state-space dynamics analysis that display system behavior in n-dimensional space. Although the nonlinear methods have shown promising results for ECG signal analysis, they can be extended to improve the performance of classification algorithms. For this purpose, the research community is witnessing a rising interest in applying neural

[1] Corresponding Author, Inna Skarga-Bandurova; E-mail: skarga_bandurova@ukr.net.

networks that have shown promising results. The study [1] proposed neural network architecture for classifying PQRST segments of ECG complexes to diagnose cardiovascular diseases. The authors of [2] presented a deep neural network model trained on a dataset of 2,322,513 ECG records to detect six cardiac pathologies.

The further improvement of ECG classification can be achieved through combination neural networks with complementary approaches. The study [3] proposes a method based on the CNN for heartbeat classification using a dual-beat ECG coupling matrix that shows an adequate representation of both heartbeat morphology and rhythm. The use of time-frequency features in addition to neural networks demonstrates a high quality of ECG classification [4, 5]. However, as mentioned, many diagnostic features do not always provide the necessary reliability of diagnostic results and need further exploration [6]. In this concern, we refer to the analysis of the nonlinear ECG dynamics and the ordinal network [7] as an appropriate tool that provides valuable information about cardiac activity changes. We analysed various measures of consistency used to compare time series and distinguish between regular (periodic), chaotic, and random behaviour [8]. The main types of constant measures are entropies, fractal dimensions, and Lyapunov exponents. There are different types of entropy measures applied for ECG analysis, Renyi phase permutation entropy [9], Lempel-Ziv complexity and Lyapunov exponent [10], Kolmogorov-Sinai entropy [11]. Some recent studies use permutation entropy (PE), conditional permutation entropy (CPE), global network entropy (GNE) [7]. The paper [12] demonstrated a change in the degree of the ECG complexity in the event of pathology. All these criteria to some extent characterise the randomness of the mechanisms of cardiac activity and can be used to increase the reliability of assessing the nature of the cardiac activity. This paper proposes a new methodology for analysing ECG time series data, considering linear and nonlinear dynamics. The methodology includes the application of neural networks (NNs) in combination with ECG ordinal network (ON) complexity estimation to classify cardiac activity.

2. Materials and Methods

Our hypothesis is based on the assumption that the ON improves the classification accuracy of NNs and, thus, provides an honestly significant difference in the dynamics deviations of the PQRST cycle. The proposed methodology includes combination of NN and ON analysis, in particular the calculation of complexity measures, to ECG time series data. The mapping the time series in ON is based on its ordinal partition, having regard to sequential patterns of PQRST ECG complexes [7]. Ordinal partitioning is parameterized by the dimension of embedding vector m and embedding delay τ.

We denote the ECG time series as a series of equidistant observations $\mathbf{x} = \{x_1, \ldots, x_m, \ldots, x_M\}$, where m is an integer representing the dimension of the embedding vectors of the time series and M is the number of time steps in the time series being split. The embedding vectors $\mathbf{z} = \{z_1, z_2, \ldots, z_{M-(m-1)\tau}\}$ are calculated using patterns of dimension m and delay τ. For ECG, longer embedding vectors can define PQRST complexes, while shorter embedding vectors can define PQRST complex segments associated with functional components: waves or segments of the complex. Each vector $z_i = \{x_1, x_{i+\tau}, x_{i+2\tau}, \ldots, x_{i+(m-1)\tau}\}$ is mapped into a sequence of symbols according to the amplitude of each element in it. If two z_i elements have the same value ($x_i = x_j$), the character is assigned in order of occurrence. The unique set of all character sequences s is represented by a time series $\mathbf{s} = \{s_1, s_2, \ldots, s_{M-(m-1)\tau}\}$, each $s_i \in \mathbf{s}$ being a node to construct an ordinal network.

The proposed methodology is shown in Fig. 1 and includes the following steps: (1) building an ON and estimating randomness using complexity measures such as conditional permutation entropy (CPE) or global node entropy (GNE); (2) combining the obtained score with ECG data and classifying cardiac activity using NN.

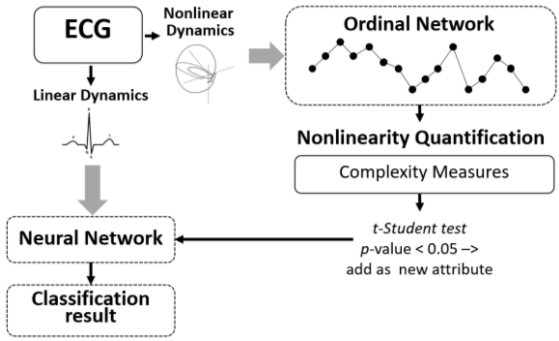

Figure 1. Structure of proposed methodology.

The proposed complexity measures (CPE, GNE) are calculated based on the permutation entropy (PE) of the time series, which corresponds to the Shannon entropy of the corresponding set of ordinal symbols **s**.

$$PE = -\sum_i p_i \log p_i, \tag{1}$$

where p_i denotes the probability mass function $P(S=s_i)$ for $s_i \in \mathbf{s}$ and is estimated by counting the relative occurrence of each symbol in the symbolic dynamics S. PE is discussed in detail in [7, 8]. The stationary distribution is calculated by finding the stochastic matrix P with elements $p_{i,j}$.

Conditional permutation (CPE) was proposed in [13] and is expressed as follows (2)

$$CPE = \sum_i \left(-p_i \sum_j p_{i,j} \log p_{i,j}\right), \tag{2}$$

where p_i is the probability mass function, same as for equation (1), and $p_{i,j}$ is an element of the stochastic matrix P that represents the transition probability from s_i to s_j estimated on the basis of the symbolic dynamics of S.

Global node entropy is calculated based on the elements $p_{i,j}^T$ of the modified stochastic matrix P^T of the ordinal network by averaging over the network based on the stationary distribution (3).

$$GNE = \sum_i p_i \left(-\sum_j p_{i,j}^T \log p_{i,j}^T\right). \tag{3}$$

3. Results

The proposed methodology, in particular CPE, GNE calculation was applied to analyse features of the PQRST segments of the ECG5000 dataset cycle [14]. ECG5000

contains ECG time series examples with 140 time steps. Each sequence corresponds to a single heartbeat, i.e. PQRST cycle from a single patient with congestive heart failure. In this study, two types of PQRST cycles (classes) were used: class 1 – normal (500 examples) and class 2 – R-on-T premature ventricular contraction (500 examples).

To estimate the individual components of the PQRST cycle from the CPE ordinal split, the GNE of each time series was calculated for a short embedding delay. The value of embedding vector is set to $m = 5$, the value of embedding delay is set to $\tau = 8$. The results of statistical analysis are shown in Fig.2.

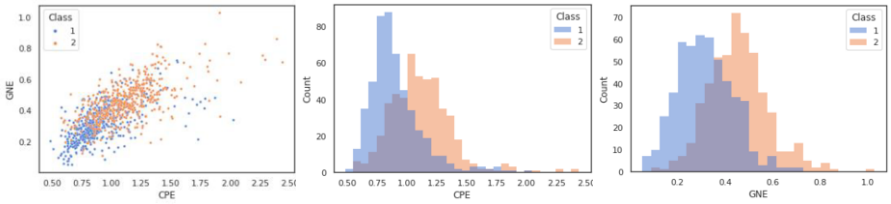

Figure 2. Visualization of the statistical analysis of the CPE and GNE for the test set: (a) the scatter plot of the correlation between the CPE, GNE estimates and data classes, (b) overlaying kernel density plots CPE, (c) kernel density plots GNE.

The scatter plot shows the presence of a certain correlation between the CPE, GNE scores and data classes. By overlaying kernel density plots, we can judge the distribution of score values between classes and infer the presence of a large number of CPE and GNE values that are inherent in a certain class, what gives a certain degree of reliability in their differentiation. Student t-test was applied (p-value lower than 0.05 was considered statistically significant, with a confidence interval of 95%) to test the null hypothesis about the equality of the variances of the obtained estimates of the two classes and obtain a quantitative estimate. For both the CPE and GNE, a p-value of less than 0.05 was obtained, therefore the difference in variances is considered statistically significant, the null hypothesis of equality of variances is rejected. Thus, we start from the assumption that the variances of the CPE, GNE scores for class 1 and class 2 are not equal. The same way, the values of the CPE, GNE estimates were calculated for each PQRST cycle and added as new attributes. For stage 2, the PQRST cycles classification was carried out using a simple implementation of NN - the Sequential model by Keras. NN training was perfomed using the following network hyperparameters: layers activation functions are ReLU and softmax, optimizer is Adam, epochs=100. The models quality results obtained on the test data set are presented in Table 1.

Table 1. Comparative analysis with and without complexity measures.

Attributes	Cross-entropy loss	Accuracy (%)
PQRST complexes attributes	0.0833	99
PQRST complexes attributes +CPE+GNE	0.0213	99.5

Adding the CPE, GNE increases the classification accuracy by 0.5%, and decrease the cross-entropy loss by 0.062. Thus, we can conclude that the classification reliability is increased by using complexity measures as features of non-linear dynamics.

Comparison of our approach to NN-based studies based is presented in Table 2.

Table 2. Comparative analysis with previous research.

Approach	Accuracy (%)
CNN [1]	97.41
CNN+dual-beat ECG coupling matrix [3]	99.1
CNN+ STFT-Based Spectrogram [4]	99.0
CNN+ Continuous Wavelet Transform [5]	98.74
Proposed NN+ON	**99.5**

4. Conclusion

We present a technique that combines the signs of non-linear ECG dynamics with NN to classify ECG which shows 0.4% improvement in accuracy over the best benchmark approach. Hence no-linear dynamics is useful to achieve more regularised predictions and to obtain more reliable classification results for PQRST complexes.

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