Diagnostics of the Arterial Hypertension by Means of the Discriminant Analysis
Analysis of the Heart Rate Variability Signals Features Combinations

Vladimir Kublanov[1], Anton Dolganov[1] and Yan Kazakov[2]
[1]*Research Medical and Biological Engineering Centre of High Technologies, Ural Federal University, Mira 19, 620002, Yekaterinburg, Russian Federation*
[2]*Ural State Medical University, Repina 3, 620028, Yekaterinburg, Russian Federation*

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Abstract: The paper presents investigation of the diagnostic possibilities of the arterial hypertension using linear and quadratic combinations of the heart rate variability signals features. For this study, two groups were considered: healthy volunteers and patients suffering from the arterial hypertension of the II-III degree. For the study, features of statistical, geometric, spectral, nonlinear and multifractal methods were investigated. Results of the analysis have shown that among studied combinations four feature sets (heart rate, features of the VLF frequency band and LF/HF ratio) have the highest classification accuracy – 93%.

1 INTRODUCTION

According to the World Health Organization, arterial hypertension is among the most common diseases in the world nowadays. In (Feng *et al.,* 2014) it had been shown that nearly 40% of people aged 45 years had a hypertensive disorders. Among the individuals with hypertension around 40% were unaware of their condition. In the 2000 there were 972 million people suffering from the arterial hypertension. According to current predictions this number will increase to 1,56 billion.

One of the main problems concerning arterial hypertension is late detection for apparently healthy people. Therefore, the task of the detection of the arterial hypertension symptoms is among urgent ones. The heart rate variability (HRV) signals (R-R intervals) can be used in this task. Among the advantages of this signals are safeness, prevalence, repeatability, ease of the record and relative cheapness (Kamath *et al.,* 2012).

Studies of the hypertension patients generally use just couple of statistical and/or spectral features for the analysis (Scheffler *et al.,* 2013). Most of the studies devoted to this topic imply analysis of the long-term Holter monitor (Melillo *et al.,* 2012). However, for the clinical diagnostics in many cases it is more appropriate to use short-term signals, about 5 minutes length.

Nowadays, great variety of methods are applied for the HRVy signals processing: statistical, spectral, non-linear and multifractal. For the most part, during one study features of single method are used. As an example in (Melillo *et al.,* 2014) authors have studied different features of the non-linear methods for detecting stress state – Poincare plot, approximate entropy, correlation dimension and recurrence plot . On the other hand, there were studies that compares informativeness of features set of different methods. In (Ebrahimi *et al.,* 2013) authors have studied 4 sets of features – time domain features, non-linear features, discrete wavelet transform features and empirical mode decomposition features. Results of that study have shown possibilities of different sets for automatic sleep staging. However, in that work, as well as in other known works, the possibilities of each methods were studied separately and combinations of features from different methods were not tested.

Application of different methods combination may increase classification accuracy as incorporation of various methods data increase informative capacity of knowledge about the studied object (Wiener, 1961). Because of that, the goal of this work is to develop methodology of the arterial hypertension diagnostic by the short-term time series (TS) of HRV

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signals using combined estimates, and to study effectiveness of this methodology.

2 MATERIALS AND METHODS

As the combined estimates in this study, we have used linear and quadratic combination of two and more features. Features were obtained by the statistical, geometric, spectral and multifractal methods. For evaluation of the diagnostic (classification) robustness the discriminate analysis have been applied. All quantifications were performed by the in-house software developed in MATLAB version 2014b (The MathWorks Inc., Natick, MA).

2.1 Recorded Data

The clinical part of the study was performed in the Sverdlovsk Clinical Hospital of Mental Diseases for Military Veterans (Yekaterinburg, Russian Federation). For the HRV signals registration the electroencephalograph-analyzer "Encephalan-131-03" ("Medicom-MTD", Taganrog, Russian Federation) was used. The rotating table Lojer (Vammalan Konepaja DY, Finland) performed the spatial position change of the patient during passive orthostatic load – the lift of the head end of the table was up to 70^o from the horizontal position.

Participants of this study: 30 relatively healthy volunteers and 41 patients suffering from the arterial hypertension of II and III degree. The signals of HRV were recorded in two functional states: functional peace (state F) and passive orthostatic load (state O). Length of the signal in mentioned state was about 300 seconds.

2.2 Classification

As the classification method, we adopted discriminant analysis (DA) (Jain, 2010). For this study, we have trialed linear and quadratic DA. Linear DA aims to find such linear combination of the features that can be used for adequate separation between two classes. In turn, quadratic DA aims to find quadratic combination of the features for separation. In case of the current study, two classes are healthy volunteers and patients with the arterial hypertension.

Evaluation of the classifiers efficiency was computed with standard measures for binary classification performance:

- Total classification accuracy (*ACC*)

$$ACC = \frac{TN+TP}{TP+FP+FN+TN}; \quad (1)$$

- Sensitivity (*SEN*)

$$SEN = \frac{TP}{P}; \quad (2)$$

- Specificity (*SPE*)

$$SPE = \frac{\mathrm{TN}}{\mathrm{N}}; \quad (3)$$

where: *P*, the total number of patients with arterial hypertension; *N*, the total number of healthy volunteers; *TP* – True Positive, the number of correctly classified patients with arterial hypertension; *TN* – True Negative, the number of correctly labelled healthy volunteers; *FP* – False Positive, the number of people incorrectly classified as patients with arterial hypertension; *FN* – False Negative, the number of people incorrectly classified as healthy volunteers (Sokolova and Lapalme, 2009).

For the performance measures evaluation estimation we adopted 5-fold cross-validation scheme (Bock *et al.,* 2010). This technique imply developing five classifiers according to following steps:

- division of the original dataset randomly into 5 subsamples (i.e. 8 patients for a group with arterial hypertension and 6 volunteers for healthy group);
- successive exception of one subsample (testing subset);
- development of a classifier with the remaining 4 subsamples (training subset);
- testing of classifier with the excluded subsample;
- computation of the binary classification measures;
- averaging of the performance measures over 5 classifiers.

Division of the original dataset into 5 subsamples allowed obtaining person-independent testing.

2.3 Properties of Short-Term HRV Measures

In this work, we investigated diagnostic possibilities of the arterial hypertension by the combination of the different methods of the short-term HRV signals analysis estimates. Prior to the processing the original time series were cleaned from the artifacts. By the artifacts in this study, we considered values of the R-R intervals that differed from the mean by more than three values of standard deviation. *NN* is the abbreviation for the "normal to normal" time series, i.e. without artifacts. For spectral and multifractal analysis *NN* time series were interpolated using cubic spline interpolation with the 10 Hz sampling frequency. Interpolation was performed in MATLAB software by the *interp1* function with method '*spline'*.

2.3.1 Statistical Features

Statistical methods are used for the direct quantitative evaluation of the HRV time series. Main quantitative features are:

- *M*, the mean value of the R-R intervals;
- *HR*, the Heart Rate, in inverse ration to the *M*;
- *SDNN*, the standard deviation of the R-R intervals;
- *CV*, the coefficient of variation, defined as ratio of standard deviation *SDNN* to the mean *M*, expressed in percent;
- RMSSD is the square root of the mean of the squares of the differences between successive elements in *NN*;
- *NN*5O, the number of pairs of successive elements in *NN* that differ by more than 50 ms (Malik, 1996).

2.3.2 Geometric Features

Geometric methods analyze distribution of the R-R intervals as a random numbers. The common features of these methods are:

- M_0, the mode, the most frequent value in the R-R interval. In case of the normal distribution is close to the mean *M*;
- *VR*, the variation range, is the difference between the lowest R-R interval and the highest R-R interval in the time series. *VR* shows variability of the R-R interval values and reflects activity of the parasympathetic department of the autonomic nervous system (ANS);
- AM_0, the amplitude of the mode, is a number of the R-R intervals that correspond to the mode value. AM_0 shows the stabilizing effect of the heart rate management, mainly caused by the sympathetic activity (Malik, 1996).

The following indexes are derived from common geometric features:

- *SI*, the Stress Index that reflects centralization degree of the heart rate and mostly characterize the activity of the sympathetic department of the ANS

$$SI = \frac{\mathrm{AM_0}}{2\mathrm{M_0} \cdot VR}; \tag{4}$$

- *IAB*, the Index of the Autonomic Balance, depends on the relation between activities of the sympathetic and parasympathetic department of the ANS:

$$IAB = \frac{\mathrm{AM_0}}{VR}; \tag{5}$$

- *ARI*, the Autonomic Rhythm Index, which shows parasympathetic shifts of the autonomic balance: smaller values of the ARI correspond to the shift of the autonomic balance to the parasympathetic activity:

$$ARI = \frac{1}{\mathrm{M_0} \cdot VR}; \tag{6}$$

- *IARP*, the Index of Adequate Regulation Processes, that reflects accordance of the autonomic function changes of the sinus node as a reaction of the sympathetic regulatory effects on the heart

$$IARP = \frac{\mathrm{AM_0}}{\mathrm{M_0}}. \tag{7}$$

2.3.3 Spectral Features

Spectral analysis is used to quantify periodic processes in the heart rate by the means of the Fourier transform (Fr). The main spectral components of the HRV signal are High Frequency – HF (0.4 – 0.15 Hz), Low Frequency – LF (0.15 – 0.04 Hz), Very Low Frequency – VLF (0.04 – 0.003 Hz), and Ultra Low Frequency – ULF (lower than 0.003 Hz) (Malik, 1996). For 300 seconds short-term time series ULF spectral component is not analyzed.

The studied quantitative features of spectral analyzes are

- Spectral power of the HF, LF, VLF components
- Total power of the spectrum – TP;
- Normalized values of the spectral components by the total power - HF_n, LF_n and VLF_n;
- The LF/HF ratio, also known as the autonomic balance exponent;
- *IC*, the Index of centralization

$$IC = \frac{\mathrm{HF+LF}}{\mathrm{VLF}}; \tag{8}$$

- *IAS*, the Index of the Subcortical nervous centers Activation

$$IAS = \frac{\mathrm{LF}}{\mathrm{VLF}}. \tag{9}$$

2.3.4 Wavelet Transform

For nonstationary time series one can also use the wavelet transform (wt), that can simultaneously study time-frequency patterns. The general equation for continuous wavelet transform is as follows:

$$W(a,b) = \frac{1}{\sqrt{a}} \int s(t) \cdot \psi(\frac{t-b}{a})\, dt, \qquad (10)$$

where: a – the scale, b – the shift , ψ – the wavelet basis , $s(t)$ – analyzed signal (Addison, 2005).

In MATLAB continuous wavelet transform is implemented by the *cwt* function. Moreover, the connection between the scale and the analyzed frequency is in accordance with the following:

$$a = \frac{f_c * f_s}{f}, \qquad (11)$$

where: f_c – the central frequency of the wavelet basis, called by the *centfrq* function, f_s – sampling frequency of the analyzed signal, f – the analyzed frequency (Mallat, 2009).

It is possible to acquire same spectral features by means of the wavelet transform:

- Spectral power of the HF, LF, VLF components
- Normalized values of the spectral components by the total power - HF_n, LF_n and VLF_n;
- The LF/HF ratio.

Additionally, standard deviations SDHF(wt), SDLF(wt), SDVLF(wt) of the $HF_{wt}(t)$, $LF_{wt}(t)$ and $VLF_{wt}(t)$ TS were tested as features. $HF_{wt}(t)$, $LF_{wt}(t)$ and $VLF_{wt}(t)$ are TS of the HF, LF and VLF spectral components respectively, acquired by means of the wavelet transform.

Moreover, one can study informational characteristics of the wavelet transform by analyzing the $F[\frac{\mathrm{LF_{wt}}}{\mathrm{HF_{wt}}}(t)]$ function. As the features of $F[\frac{\mathrm{LF_{wt}}}{\mathrm{HF_{wt}}}(t)]$ is possible to use number of the dysfunctions N_d, maximal value of the dysfunction $(LF/HF)_{max}$, and intensity of the dysfunction $(LF/HF)_{int}$. By the dysfunction, we consider values of function that suppress decision threshold Δ. According to our previous studies Δ=10 (Kublanov, 2008). For wavelet transform computation in this work, we used wavelet *Coiflet* of the fifth order.

2.3.5 Nonlinear Feature

As the nonlinear feature in this study we have used the Hurst exponent calculated by the aggregated variance method. The variance can be written as followed

$$Var\left|\left(X(t_2) - X(t_1)\right)^2\right| = \sigma^2 |t_2 - t_1|^{2H}, \qquad (12)$$

where H is the Hurst exponent (Rubin *et al.* 2013).

H can be defined as the slope exponent in the following equation:

$$\log \sigma_{rms}(\Delta X) = c + H \log|s|, \qquad (13)$$

where $\sigma_{rms}(\Delta X)$ – is the standard deviation of the ΔX increments, corresponding to the time period s, c – the constant.

Note, that $H > 0{,}5$ correspond to the process with trend, so-called persistent process, contrary $H < 0{,}5$ correspond to anti-persistent processes that have a tendency for trend change, $H = 0{,}5$ is the random process (Mandelbrot, 2003).

2.3.6 Multifractal Features

As the nonlinear method we adopted the multifractal detrended fluctuation analysis (MFDFA) (Stanley *et al.,* 1999). Algorithm and application features of the MFDFA method to estimation of short-term TS are described in details in (Ihlen, 2012).

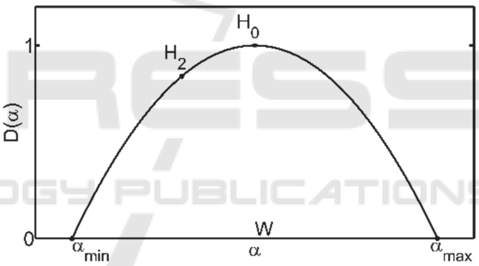

Figure 1: The characteristic features of the multifractal analysis.

Fig. 1 represents the main features of the multifractal spectrum estimated by the MFDFA method. Here, H_0 is the height of the spectrum, represents the most probable fluctuations in the investigated time scale boundary of the signal; H_2 is the generalized Hurst exponent (also known as correlation degree); α_{min} represents behavior of the smallest fluctuations in the spectrum; α_{max} represents behavior of the greatest fluctuations in the spectrum; $W = \alpha_{max} - \alpha_{min}$, is the width of multifractal spectrum that shows the variability of fluctuations in the spectrum. Multifractal characteristics are quantitative measures of the self-similarity and may characterize functional changes in the regulatory processes of the organism.

In addition, we also tested so-called $_{1/2}$width measure of the spectrum, which is defined as $W_{1/2}=|H_2-H_0|$ (Makowiec *et al.,* 2011)

In this study, we investigated time scale boundaries that correspond to the LF and VLF frequency bands: (6-25) sec and (25-300) sec respectively. In our earlier works and by other authors it was noted that multifractal analysis of the HF component is not informative because of the noising, (Makowiec *et al.,* 2012).

3 RESULTS AND DISCUSSION

In this study, we wanted to test all possible combinations of the features. However, the number of k-combinations of 53 features is quite high for k equaled to 2, 3 and 4 - 1378, 23426 and 292825, respectively. In order to decrease computation time and remove redundant results (formed by the features that are already combination of previous features) we have decided to use for further test only those combinations that are formed by non-correlated features.

The correlation coefficient was calculated in MATLAB software by the *corrcoef* function. The threshold for the correlation coefficient was set to be lower than 0,25. Using this threshold number of combination was reduced to 629 for two features combinations, to 1985 for three features combinations and to 1995 for four features combinations.

3.1 Single Feature Test

For the F state none of the tested features showed ACC higher than 75 %. The best results of the classification efficiency estimation for the state O are presented in table 1. Another 8 combinations have ACC higher than 76%.

Table 1: Efficiency of the classification for the linear DA for state O of the single features, %.

feature	SEN	SPE	ACC
H_2 VLF	90	73	83
VLFn(Fr)	83	76	80
VLFn(wt)	85	73	80

According to the data shown in table 6 one can conclude that application of the single feature for the arterial hypertension classification is not sufficient. Therefore, application of two and more features combinations is justified.

3.2 Two Features Combination Test

Three combinations of features combinations (M and VLFn(wt),VLFn(Fr) and VLF(wt), VLFn(Fr) and SDVLF(wt)) for the signals recorded in state F obtained by the linear DA. achieved the highest results (ACC 77%). Another 14 combinations that are formed by the statistical and spectral features, have ACC not less than 75 %.

Table 2 presents the highest results of the classification efficiency for two features combinations of the signals recorded in state O obtained by the linear DA. Another 42 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 80 %.

Table 2: Efficiency of the classification for the linear DA for state O of the two feature combinations, %.

features	SEN	SPE	ACC
HFn(Fr), $W_{1/2}$ LF	95	73	86
VLFn(Fr), LF/HF(Fr)	93	76	86
VLFn(Fr), LF/HF(wt)	93	76	86
VLFn(Fr), H	95	73	86
LF/HF(Fr), VLFn(wt)	93	76	86
HFn(wt), $W_{1/2}$ LF	95	73	86
VLFn(wt), LF/HF(wt)	93	76	86
VLFn(wt), H	93	76	86

Two combinations of features (VLFn(Fr) and LF/HF(Fr), VLFn(wt) and H) for the signals recorded in state F obtained by the quadratic DA achieved the highest results (ACC 76%).

Table 3 presents the highest results of the classification efficiency for two features combinations of the signals recorded in state O obtained by the quadratic DA. Another 42 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 80 %.

According to the data presented in tables 2-3 one can conclude:

- features of the signals recorded in state O allows to reach higher classification results than those recorded in state F;
- for two features combinations the highest results are obtained by combinations of the spectral and multifractal features;
- application of two features combination improves classification efficiency compared to application of single feature, however it is not possible to achieve simultaneously high specificity and sensitivity.

Table 3: Efficiency of the classification for the linear DA for state O of the two feature combinations, %.

features	SEN	SPE	ACC
VLFn(Fr), H	95	73	86
LF/HF(Fr), VLFn(wt)	88	83	86
HR, H2 VLF	93	73	84
VLFn(Fr), SDVLF(wt)	88	79	84
VLFn(Fr), LF/HF(wt)	83	86	84
VLFn(Fr), $(LF/HF)_{max}$	85	83	84
SDVLF(wt), VLFn(wt)	90	76	84
VLFn(wt), LF/HF(wt)	85	83	84
VLFn(wt), $W_{1/2}$ LF	88	80	84
VLFn(wt), H	93	73	84

3.3 Three Features Combination Test

The highest result of the classification efficiency for the signals recorded in state F obtained by the linear DA was achieved by the combination of M0, (LF/HF)max, H2 VLF (ACC 78%). Another 17 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 77 %.

Table 4 presents the highest results of the classification efficiency for three features combinations of the signals recorded in state O obtained by the linear DA. Another 83 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 85 %, while having SPE and SEN not less than 75 %.

Table 4: Efficiency of the classification for the linear DA for state O of the three feature combinations, %.

features	SEN	SPE	ACC
HR, VLFn(Fr), H_2 LF	95	87	91
VLFn(Fr), LF/HF(Fr), $W_{1/2}$ LF	93	87	90
VLFn(Fr), LF/HF(wt), $W_{1/2}$ LF	93	87	90
VLFn(Fr), (LF/HF)int, $W_{1/2}$ LF	93	87	90

The highest result of the classification efficiency for the signals recorded in state F obtained by the quadratic DA was achieved by three combinations (VLFn(Fr), (LF/HF)int, H; VLFn(wt), (LF/HF)int, H; VLFn(wt), H0 LF, H) with ACC 77%.

Table 5 presents the highest results of the classification efficiency for three features combinations of the signals recorded in state O obtained by the quadratic DA. Another 65 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 85 %, while having SPE and SEN not less than 75 %.

Table 5: Efficiency of the classification for the quadratic DA for state O of the three feature combinations, %.

features	SEN	SPE	ACC
LF/HF(Fr), SDVLF(wt), VLFn(wt)	90	89	90
SDVLF(wt), VLFn(wt), LF/HF(wt)	90	89	90
HR, VLFn(Fr), SDVLF(wt)	85	93	89
VLFn(Fr), LF/HF(Fr), VLF(wt)	88	89	89
VLFn(Fr), LF/HF(Fr), SDVLF(wt)	88	89	89
VLFn(Fr), LF/HF(Fr), $W_{1/2}$ LF	90	87	89
VLFn(Fr), VLF(wt), LF/HF(wt)	88	89	89
VLFn(Fr), $(LF/HF)_{max}$, W VLF	93	83	89
LF/HF(Fr), VLFn(wt), $W_{1/2}$ LF	90	87	89
SDVLF(wt), VLFn(wt), $(LF/HF)_{int}$	93	83	89
VLFn(wt), $(LF/HF)_{max}$, W VLF	90	87	89

According to the data presented in tables 4-5 one can conclude:

- features of the signals recorded in state O allows to reach higher classification results than those recorded in state F, same result as for two feature combinations;
- for three features combinations the highest results are obtained by combinations of the spectral features as well as combination of spectral, statistic and multifractal features;
- application of three features combination improves classification efficiency compared to application of two features combination, it is possible to achieve high accuracy (more than 90 %), while maintaining high level of specificity(up to 89 %) and sensitivity (up to 95 %).

3.4 Four Features Combination Test

Five feature combinations of the signals recorded in state F obtained by the linear DA (IAB, IAS, (LF/HF)int, W1/2 VLF; VLF(Fr), IAS, LF/HF(wt), α_{max} VLF; LF/HF(Fr), IAS, VLF(wt), α_{max} VLF; IAS, VLF(wt), LF/HF(wt), α_{max} VLF; HF(wt), (LF/HF)int, H2 VLF, H) achieved the highest results of the classification efficiency (ACC 79%). Another 27 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 77 %.

Table 6 presents the highest results of the classification efficiency for four features combinations of the signals recorded in state O obtained by the linear DA. Another 93 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 85 %, while having SPE and SEN not less than 75 %.

Table 6: Efficiency of the classification for the linear DA for state O of the four feature combinations, %.

features	SEN	SPE	ACC
HR, VLFn(Fr), VLF(wt), $(LF/HF)_{max}$	90	93	91
HR, SDVLF(wt), VLFn(wt), $(LF/HF)_{max}$	90	93	91
HR, VLFn(Fr), SDVLF(wt), $(LF/HF)_{max}$	87	93	90
HR, VLF(wt), VLFn(wt), $(LF/HF)_{max}$	90	90	90

Three feature combinations for the signals recorded in state F obtained by the quadratic DA (ARI, IAS, Nd, W1/2, VLF; ARI, IAS, (LF/HF)int, W1/2 VLF; VLFn(Fr), (LF/HF)max, α_{min} LF, W1/2 VLF) achieved the highest classification efficacy (ACC > 75%).

Table 7 presents the highest results of the classification efficiency for four features combinations of the signals recorded in state O obtained by the quadratic DA. Another 77 combinations that are formed by the statistical, spectral and multifractal features have ACC not less than 85 %, while having SPE and SEN not less than 75 %.

Table 7: Efficiency of the classification for the quadratic DA for state O of the four feature combinations, %.

features	SEN	SPE	ACC
HR, SDVLF(wt), VLFn(wt), $(LF/HF)_{max}$	93	93	93
HR, VLFn(Fr), SDVLF(wt), $(LF/HF)_{max}$	93	90	91
M, VLFn(Fr), VLF(wt), $(LF/HF)_{max}$	93	86	90
HR, VLFn(Fr), VLF(wt), $(LF/HF)_{max}$	90	90	90
HR, VLF(wt), VLFn(wt), $(LF/HF)_{max}$	90	90	90
VLF(Fr), VLFn(Fr), $(LF/HF)_{int}$, W VLF	93	87	90

According to the data presented in tables 6-7 one can conclude:

- features of the signals recorded in state O allows to reach higher classification results than those recorded in state F, same result as for two and three feature combinations;
- for four features combinations the highest results are obtained by combinations statistical features HR and M and spectral features;
- application of four features combination further improves classification efficiency compared to application of three features combination; it is possible to achieve relatively high accuracy, specificity, sensitivity; the specific combinations of HR and spectral features achieves ACC, SPE and SEN, all higher than 90 %.

4 CONCLUSIONS

The paper described results of the diagnostic possibilities test of statistic, geometric, spectral, non-linear and multifractal features for discrimination of the arterial hypertension.

Obtained results have shown that classification efficiency increases as number of features in combination increases. For four features combination, formed by HR, VLF estimates and LF/HF ratio, accuracy, sensitivity and specificity suppress 90%. Linear and quadratic DA have shown about the same results of the classifier efficiency.

Results of the current study have higher classification efficiency compared to our previous works. There we analyzed comparable sample of subjects, using single feature in two-dimensional space: “state F – state O” (Kublanov *et al.,* 2016). Furthermore, current results suppress classification efficacy of some other authors. In particular results of the Artificial Neural Network and Logistic Regression Analysis models for patients with hypertension (Tang *et al.,* 2013).

In our opinion this results confirms scientists’ interpretation of the arterial hypertension development mechanisms. The activation of the sympathetic nervous system takes important part in the initialization of the arterial hypertension, maintenance of the increased vascular tone as well as increased cardiac output. Role of the vascular system regulation central mechanisms disorders, including lost balance of suprasegmental autonomic regulation and development of the anxiety and depression disorders (Parati and Esler, 2012, 2013 ESH/ESC guidelines for the management of arterial hypertension, 2013).

Results of our study shows application possibilities of the combined estimates of the short-term time series heart rate variability signals for the arterial hypertension diagnostics. In future works, our research group will continue study this problem on larger sample of subjects in order to improve robustness of the classification as well as compare discriminate analysis performance versus other methods on the same sample of subjects.

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