Application of the Discriminant Analysis for Diagnostics of the Arterial Hypertension

Analysis of Short-Term Heart Rate Variability Signals

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Abstract: The investigation of the diagnostic possibilities for the arterial hypertension is presented. The 41 features of the statistical, geometric, spectral and nonlinear methods during functional loads were considered for two groups: healthy volunteers and patients suffering from the arterial hypertension of the II-III degree. Application of the linear and quadratic discriminant analysis showed particular features that have high classification efficiency.

1 INTRODUCTION

Nowadays, vascular disorders of the brain are in the spotlight due to alarming epidemiological state of the insult morbidity in the Russian Federation, disastrous consequences of different cerebrovascular pathologies for physical and mental health of the nation.

Mortality from the cerebrovascular diseases in the Russian Federation is among the highest in the world and has an increasing trend. The number of the insults in the Russian Federation is higher than 400000. Only 10% of the insult cases appear to be relatively mild and can be cured during the first weeks of the diseases. In other cases, sick people who survive, retain, at some degree, pronounced neurological defect that often leads to sustained disability and loss of the ability to work. Up to 15 % of the sick people after the insult are chained to bed to the end of their lives.

Moreover, in the Russian Federation there are no less than 1,5 mln people suffering from the chronic cerebrovascular diseases with vascular dementia as the end result. Among the variety of the cerebrovascular diseases, there is significant share of the chronic forms of the vascular disorders of the brain, like hypertonic and atherosclerotic encephalopathy.

A number of factors contribute for development of the chronic forms of the brain blood flow disorders: high prevalence of the arterial hypertension, improper treatment of it for people with diagnosed disease, significant prevalence of the cerebrovascular risk factors (smoking, stress, excessive consumption of alcohol, dyslipidemia), high frequency of the acute forms of the brain flow disorders (Suslina and Varakin, 2015).

Therefore, problem of the cerebrovascular disease in the Russian Federation can be without a doubt labeled as extreme. Specialists of the different disciplines should unite their efforts to solve it.

Aftermath of the arterial hypertension mainly manifest in the cardiovascular, cerebrovascular and renovascular systems. Complications after the arterial hypertension include common cerebrovascular disorders: insult, transient ischemic attacks, dementia, hypertonic encephalopathy (Wilkinson and Waring, 2005).

Study of the heart rate variability (HRV) signals (or R-R intervals) is one of the popular methods for functional diagnostics of the human. Accumulated experience of the HRV signals analysis by means of the most common methods was generalized in methodological recommendations of the Europeen craniological and North-American electrophysical societies(Malik, 1996), and in works of the Russian experts (Baevskiy, 2001). These recommendations are meant for the short-term records of the heart rate. The results of these recommendations can be applied to improve diagnostic efficiency. Such data can be

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recorded not only in stationary medical institutions, but also in case of outpatient and remote monitoring.

Various factors, like neurohumoral mechanisms of the higher autonomic centers, influence on the HRV signals. These factors cause nonlinear nature of the heart rate changes. Methods of the non-linear dynamics are promising tools to describe internal structure of the R-R intervals time series.

In general, R-R intervals time series manifest features of the determined chaos. This makes methods applied for theory of chaotic systems suitable for HRV analysis (Lin and Sharif, 2012). Among the variety of non-linear dynamics approaches commonly applied for the biomedical signal processing the most perspective are methods for estimation of the scale invariance, like fractal and multifractal analysis (Lewis *et al.*, 2012).

Thus, application of the multifractal analysis for evaluation of the HRV signals allows one to obtain new knowledge about patient state and effectiveness of the treatment process. For the diagnostic means multifractal approach can be considered both, separately and in combination with more common (traditional) methods of the data analysis.

In works of many authors the Discriminant analysis is used as the classifying method: in tasks of automatic sleep staging (Ebrahimi *et al.*, 2013), mental load estimation (Cinaz *et al.*, 2013), arrhythmia detection (Sivanantham and Shenbaga Devi, 2014), real-life stress detection (Melillo *et al.*, 2011) and for automatic assessment of heart failure severity (Melillo *et al.*, 2014).

To our knowledge, our study is the first to attempt to apply Discriminant analysis for evaluation of the various HRV features descriptiveness for diagnostics of arterial hypertension. The goal of this works is to analyze possibilities and informativeness of the different classes of methods for evaluation of the short-term heart rate variability signals in task of the arterial hypertension diagnostic during functional loads.

2 MATERIALS AND METHODS

2.1 Recorded Data

The study was conducted on two groups: 21 relatively healthy volunteers and 60 patients suffering from the arterial hypertension of the II–III degree before treatment. The clinical records were performed in Sverdlovsk Clinical Hospital of Mental Diseases for Military Veterans (Yekaterinburg, Russian Federation). For the R-R interval signals registration corresponding channel of the electroencephalograph-analyzer “Encephalan-131-03” was used. The records of the signals were obtained in two functional states: functional peace (to be referred as state F) and passive orthostatic load (to be referred as state O). Both states were recorded for approximately 300 seconds. The rotating table Lojer performed the spatial position change of the patient during state O.

2.2 Heart Rate Variability Features

In this work, we investigated diagnostic possibilities of the arterial hypertension by the different methods of the short-term HRV signals analysis. 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 analyses *NN* time series were interpolated using cubic spline interpolation with the 10 Hz sampling frequency. All calculations were computed using the in-house software in the Matlab.

2.2.1 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:

$$M = \frac{1}{N}\sum_{\mathrm{i}=1}^{N} NN_{\mathrm{i}}, \tag{1}$$

where N is the number of elements in the NN, NN_{i} is the i-th element in time series;

- *SDNN*, the standard deviation of the R-R intervals

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{\mathrm{i}=1}^{N}(NN_{\mathrm{i}} - M)^2}; \tag{2}$$

- RMSSD is the square root of the mean of the squares of the differences between successive elements in *NN*:

$$RMSDD = [\frac{1}{N}\sum_{\mathrm{i}=1}^{N-1}(NN_{\mathrm{i}+1} - NN_{\mathrm{i}})^2]^{0,5}; \tag{3}$$

- *NN*5O,the number of pairs of successive elements in *NN* that differ by more than 50 ms;
- *CV*, the coefficient of variation, defined as ratio of standard deviation *SDNN* to the mean *M*, expressed in percent:

$$CV = \frac{SDNN}{M} \cdot 100\ \%. \tag{4}$$

2.2.2 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;
- 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;
- *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).

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

$$SI = \frac{\mathrm{AM_0}}{2\mathrm{M_0} \cdot VR}; \tag{5}$$

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

$$IAB = \frac{\mathrm{AM_0}}{VR}; \tag{6}$$

- *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:

$$ARI = \frac{1}{\mathrm{M_0} \cdot VR}; \tag{7}$$

- *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

$$IARP = \frac{\mathrm{AM_0}}{\mathrm{M_0}}. \tag{8}$$

2.2.3 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, Baevskiy, 2001). For 300 seconds short-term time series ULF spectral component is not analyzed.

HF spectral component characterize activity of the parasympathetic department of the ANS and activity of the autonomic regulation loop. LF spectral component mainly characterize activity of the sympathetic vascular tone regulation center. VLF spectral component is defined by the suprasegmental regulation of the heart rate, as the amplitude of the VLF waves is related to the psycho-emotional strain and functional state of the cortex(Baevskiy, 2001).

The 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

$$IC = \frac{\mathrm{HF+LF}}{\mathrm{VLF}}. \tag{9}$$

2.2.4 Wavelet Transform Features

For nonstationary time series one can also use the wavelet transform (wt), that can simultaneously study time-frequency patterns. 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.

Moreover, one can study informational characteristics of the wavelet transform by the analyze of the $F[\frac{\mathrm{LF_{wt}}}{\mathrm{HF_{wt}}}(t)]$ function, where $\mathrm{LF_{wt}}(t)$ and $\mathrm{HF_{wt}}(t)$ are time series of the LF and HF spectral components acquired by means of the wavelet transform.

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 $F[\frac{LF_{\mathrm{wt}}}{HF_{\mathrm{wt}}}(t)]$ that suppress decision threshold Δ. According to our previous studies Δ=10 (Egorova *et al.*, 2014). For wavelet transform computation in this work, we used wavelet Coiflet of the fifth order.

2.2.5 Nonlinear 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).

The main steps of the method include:

- the detrending procedure with second degree polynomial on non-overlapping segments, length of the segments corresponds to the studied time scale boundaries;
- determination of the fluctuation functions for q in range q=[-5,5]

$$F_{\mathrm{x}}(q,s) = \{\frac{1}{\mathrm{N_s}}\sum_{\mathrm{v}=1}^{\mathrm{Ns}}[\frac{1}{s}\sum_{k=1}^{s}[NN(k) - NN_{\mathrm{v}}(k)]^2]^{\mathrm{q}/2}\}^{1/\mathrm{q}}, \qquad (10)$$

where NN_v is the local trend in the segment ν, N_s is the number of segments, s is the scale;

- estimation of the slope exponent H_x in log-log plot of the fluctuation function against scale s for each q

$$F_{\mathrm{x(q,s)}} \approx s^{H_{\mathrm{x}}(q)}; \qquad (11)$$

- calculation of the scaling exponent $\tau(q)$

$$\tau(q) = q \cdot H_{\mathrm{x}}(q) - 1; \qquad (12)$$

- the Legandre transform application for the probability distribution of the spectrum estimation

$$D(\alpha) = q \cdot \alpha - \tau \qquad (13)$$

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 this study, we investigated time scale boundaries that correspond to the LF and VLF

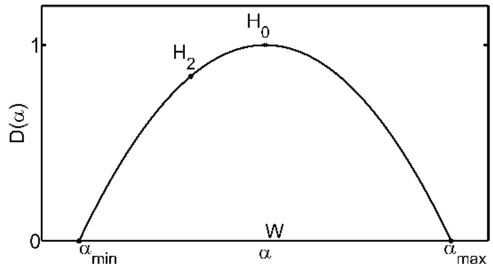

Figure 1: The characteristic features of the multifractal analysis.

frequency bands: (6-25) sec and (25-300) sec respectively. Previously it was shown that multifractal analysis of the HF component is not informative because of the noising, that was noted in our earlier works and by other authors (Makowiec *et al.,* 2012).

2.3 Classification

As the classification method, we adopted linear and quadratic discriminant analysis (DA) (Krzanowski, 2000). 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 typical measures for binary classification performance. Let us make following abbreviations:

- P, the number of patients with arterial hypertension;
- N, the 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.

Then, in accordance with the abbreviations, binary classification measures are:

- Total classification accuracy (ACC)

$$ACC = \frac{TN+TP}{TP+FP+FN+TN}; \qquad (14)$$

- Sensitivity (*SEN*)

$$SEN = \frac{TP}{P}; \quad (15)$$

- Specificity (*SPE*)

$$SPE = \frac{\mathrm{TN}}{\mathrm{N}}; \quad (16)$$

- Positive Predictive Value (*PPV*)

$$PPV = \frac{TP}{TP+FP}; \quad (17)$$

- Negative Predictive Value (*NPV*)

$$NPV = \frac{TN}{FN+TN}. \quad (18)$$

For the performance measures evaluation estimation we adopted 3-fold cross-validation scheme (Jain *et al.*, 2000). This technique imply developing 3 classifiers according to following steps:

- division of the original dataset randomly into 3 subsamples (i.e. 20 patients for a group with arterial hypertension and 7 volunteers for healthy group);
- successive exception of one subsample (testing subset);
- development of a classifier with the remaining 2 subsamples (training subset);
- testing of classifier with the excluded subsample;
- computation of the binary classification measures;
- averaging of the performance measures over 3 classifiers.

Division of the original dataset into 3 subsamples allowed to obtain person-independent testing.

3 RESULTS AND DISCUSSIONS

The classifier efficiency was tested for 41 features in two-dimensional space "state F – state O". Tables 1 and 2 presents mean values and standard deviations of the tested features, for group of healthy volunteers and for group of patients with the arterial hypertension respectively.

Data in tables 1 and 2 shows that such statistical and geometric features as *M*, *SDNN*, *CV*, *RMSSSD*, M_0, *VR*, has no significant difference between state F and state O for group of healthy volunteers. On the other hand, same features changes significantly for group of patients with arterial hypertension.

Moreover, mean values of the autonomic balance features (N_d, LF/HF(wt), $(LF/HF)_{int}$, LF/HF(Fr), $(LF/HF)_{max}$) are much greater compared to those of healthy volunteers, especially in state O. This can be interpreted as the shift of the autonomic balance to the sympathetic department of the ANS in case of arterial hypertension (Baevskiy, 2001).

Finally, one can note increase of the the Multifractal exponents H_0 and H_2 for group of people

Table 1: Mean values and standard deviation of tested features for state F and state O for group of healthy volunteers.

Feature	State F	State O
M	955±88	940±89
SDNN	88±40	82±28
CV	9,2±4,1	8,8±2,8
RMSSD	55±20	56±21
NN50	42±5	48±9
M_0	949±100	935±111
VR	208±61	214±64
AM_0	37±7	41±9
SI	127±71	129±65
IAB	240±132	235±108
ARI	6,2±2,3	5,9±2,0
IARP	40±9	45±12
HF(Fr)	576±322	625±408
LF(Fr)	766±685	779±658
VLF(Fr)	480±259	491±225
TP(Fr)	1821±1090	1895±1099
HFn(Fr)	35±13	35±11
LFn(Fr)	31±11	32±12
VLFn(Fr)	34±16	33±13
LF/HF(Fr)	1,28±0,88	1,33±0,90
IC	3,44±2,25	3,21±2,04
HF(wt)	585±310	616±432
LF(wt)	835±707	731±636
VLF(wt)	542±294	451±191
HFn(wt)	38±13	38±11
LFn(wt)	28±10	29±10
VLFn(wt)	34±16	34±14
LF/HF(wt)	1,03±0,66	1,00±0,53
$(LF/HF)_{max}$	60±38	68±49
$(LF/HF)_{int}$	5553±6018	4859±5093
N_d	215±197	189±158
α_{max} LF	0,65±0,29	0,65±0,24
α_{min} LF	0,09±0,12	0,05±0,13
W LF	0,56±0,24	0,61±0,25
H_2 LF	0,19±0,10	0,17±0,11
H_0 LF	0,33±0,11	0,30±0,10
α_{max} VLF	0,24±0,13	0,24±0,13
α_{min} VLF	-0,04±0,11	-0,06±0,10
W VLF	0,28±0,19	0,30±0,19
H_2 VLF	0,03±0,08	0,01±0,06
H_0 VLF	0,12±0,07	0,13±0,09

Table 2: Mean values and standard deviation of tested features for state F and state O for group of patients with arterial hypertension.

Feature	State F	State O
M	892±111	766±111
SDNN	49±27	54±24
CV	5,3±2,6	7,0±2,8
RMSSD	39±28	19±12
NN50	42±6	49±20
M_0	883±106	756±113
VR	163±80	160±61
AM_0	48±12	55±14
SI	285±160	415±318
IAB	461±244	545±358
ARI	10,3±4,5	12,3±6,9
IARP	57±17	79±30
HF(Fr)	375±467	143±171
LF(Fr)	474±528	455±438
VLF(Fr)	482±428	586±356
TP(Fr)	1331±1384	1184±899
HFn(Fr)	22±12	9±6
LFn(Fr)	33±8	31±10
VLFn(Fr)	44±14	60±11
LF/HF(Fr)	2,38±1,53	5,55±3,47
IC	1,67±1,02	0,79±0,41
HF(wt)	206±858	47±183
LF(wt)	238±1037	103±419
VLF(wt)	348±718	161±543
HFn(wt)	23±12	9±7
LFn(wt)	31±8	28±10
VLFn(wt)	46±15	63±12
LF/HF(wt)	2,19±1,54	5,66±3,67
$(LF/HF)_{max}$	132±73	251±134
$(LF/HF)_{int}$	14675±12107	26929±19043
N_d	469±321	628±383
α_{max} LF	0,66±0,20	0,85±0,21
α_{min} LF	0,21±0,15	0,37±0,37
W LF	0,47±0,22	0,56±0,26
H_2 LF	0,30±0,15	0,52±0,26
H_0 LF	0,40±0,16	0,64±0,23
α_{max} VLF	0,25±0,08	0,60±0,27
α_{min} VLF	0,04±0,05	0,08±0,09
W VLF	0,21±0,09	0,51±0,24
H_2 VLF	0,09±0,05	0,19±0,09
H_0 VLF	0,14±0,05	0,36±0,18

with arterial hypertension. It is worthy to mention that for patients in state O for the time scale boundary that correspond to the LF frequency band there is qualitative change of the multifractal behavior: on average estimates become persistent (Makowiec *et al.*, 2012).

Tables 3 and 4 presents binary classification measures of the features, that has *ACC* higher than 75, for linear and quadratic DA respectively.

Table 3: Efficiency of the classification for the linear DA,%.

Feature	SEN	SPE	ACC	PPV	NPV
M	92	85	90	95	78
HF_n(wt)	93	79	90	94	79
M_0	92	80	89	93	77
HF_n(Fr)	93	74	89	92	78
VLF_n(Fr)	92	74	87	92	75
HF(Fr)	97	55	86	87	87
VLF_n(wt)	90	74	86	92	70
H_0 LF	88	75	85	92	70
H_2 VLF	90	69	85	90	77
RMSSD	95	55	85	87	81
H_2 LF	87	65	81	88	63
SDNN	95	39	81	83	75
H_0 VLF	92	45	80	84	62
LF/HF(Fr)	93	38	80	84	40
LF/HF(wt)	93	38	80	85	55
AM_0	90	50	80	84	66
α_{max} VLF	93	34	79	81	75
IARP	88	50	79	85	69
IC	100	14	79	78	33
α_{min} VLF	97	24	79	80	44
W VLF	100	14	79	78	67
HF(wt)	95	30	79	80	80
VR	93	31	77	80	67
$(LF/HF)_{int}$	92	33	77	84	19
N_d	87	50	77	85	53
CV	95	25	77	79	75
$(LF/HF)_{max}$	93	24	76	80	19
TP (Fr)	95	20	76	78	75
SI	98	5	75	76	33
ARI	95	14	75	77	20
VLF(wt)	97	10	75	76	44
LF(wt)	95	15	75	77	75

Table 3 shows that highest 3-fold cross-validation estimate of the total classification accuracy was achieved by *M*, HF_n(wt), M_0, HF_n(Fr), VLF_n(Fr), HF_n (Fr), VLF_n(wt), H_0 LF, H_2 VLF and *RMSSD*. However, only features *M*, HF_n(wt), M_0 has high level of Specificity and Sensitivity at the same time. Overall, the highest classification efficiency is achieved by the feature *M* (*SEN* = 92,% *SPE* = 85,% *ACC*=90%).

Table 4: Efficiency of the classification for the quadratic DA, %.

Feature	SEN	SPE	ACC	PPV	NPV
M	92	90	91	96	79
HF_n(wt)	93	79	90	94	79
RMSSD	93	69	87	90	76
M0	90	80	87	93	75
VLF_n(wt)	92	74	87	92	73
N_d	87	85	86	95	69
HF_n(Fr)	90	74	86	92	70
VLF_n(Fr)	90	74	86	92	70
IC	93	60	85	88	72
H_2 LF	93	55	84	86	79
AM_0	87	75	84	92	65
LF/HF(wt)	82	90	84	96	62
$(LF/HF)_{int}$	82	90	84	96	62
H_0 LF	83	85	84	94	63
α_{max} LF	85	79	84	93	66
H_2 LF	83	84	84	94	63
HF(wt)	95	45	82	84	83
HF(Fr)	90	55	81	86	64
α_{max} VLF	95	35	80	81	75
LF/HF(Fr)	77	90	80	96	56
H_0 VLF	82	74	80	91	59
W VLF	97	19	77	79	27
α_{min} VLF	78	74	77	91	55
SDNN	87	51	77	84	67
TP (Fr)	92	35	77	81	67
IARP	77	75	76	90	55
LF(wt)	97	15	76	77	44
TP	93	25	76	79	63
$(LF/HF)_{max}$	70	90	75	96	51
NN50	97	10	75	76	17
LF,%	100	0	75	75	0
VR	90	31	75	80	59

Data in table 4 shows that application of the quadratic DA, in general, improves classification efficiency. At the same time classification efficiency of the features *M*, HF_n(wt), M_0 does not change much compared to the results of linear DA.

One can notice that for both linear and quadratic DA, most features has low level of the Specificity. At the same time application of the quadratic DA allows to improve this index for the following features: N_d, LF/HF(wt), $(LF/HF)_{int}$, LF/HF(Fr), $(LF/HF)_{max}$, H_0 LF, H_2 LF. In this case total accuracy and sensitivity do not change much.

Wavelet and Fourier transform spectral features has almost comparable results, with wavelet transform features having slightly higher classification efficiency for most of features.

Figure 2 presents classification rule for the *M* feature, which has the highest level of total accuracy. There and below circles are healthy people, squares are people with arterial hypertension; solid line is the classification rule.

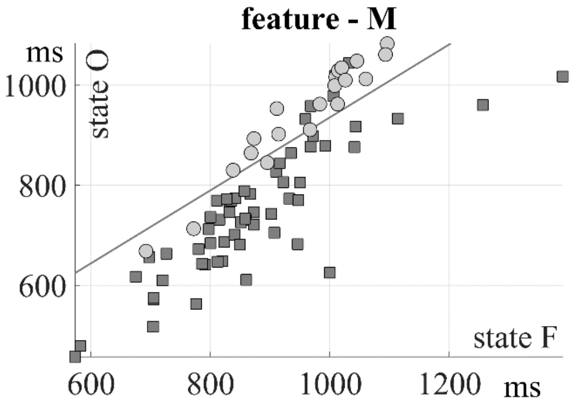

Figure 2: Classification rule of the linear DA for the feature M.

Figure 3 presents classification rule for the feature LF/HF(wt), which has of the highest level of specificity.

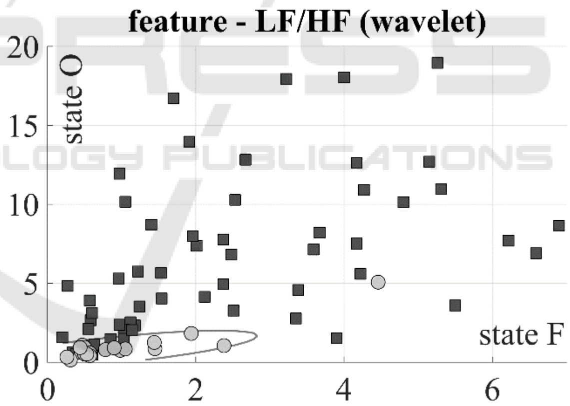

Figure 3: Classification rule of the quadratic DA for the feature LF/HF(wt).

4 CONCLUSIONS

In this article, the diagnostic possibilities of the features of the statistical, geometric, spectral and nonlinear methods were investigated as the indicators of the arterial hypertension during functional studies. The results of current study suggests particular features that could be effective for diagnostics of the arterial hypertension.

The highest estimates of the classification efficiency was obtained for the following features:

mean value of the R-R intervals, mode of the R-R intervals and normalized spectral power in HF frequency band, for both linear and quadratic discriminant analysis. However, most features have low specificity rate. In addition, it was noted, that for quadratic discriminant analysis features of wavelet transform LF to HF ratio and multifractal exponents in LF frequency band has highest rate of specificity, while having relatively high rates of sensitivity and accuracy.

Nevertheless, it is of great interest for further research on a larger sample size to increase specificity of the classification. One of the subject for our future investigation, which is currently underway, is to evaluate robustness of the classifier based on either linear or quadratic combination of features set.

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