Towards Simplifying Assessment of Athletes Physical Fitness: Evaluation of the Total Physical Performance by Means of Machine Learning

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Abstract: The paper describes the methodology for the evaluation of the total physical performance of athletes on the basis of simultaneously recorded signals of stabilography and heart rate variability. An objective assessment of the level of physical performance was carried out using testing on the bicycle ergometer. The use of genetic programming and linear discriminant analysis allowed obtaining the set of diagnostically significant features. The set of diagnostically significant features is able to determine the level of physical fitness using only data from stabilographic studies and heart rate variability with an accuracy of at least 97%. Strength and weaknesses of the proposed approach are discussed.

1 INTRODUCTION

Currently, in various areas of human activity, machine learning is increasingly being used in the most varied application of this term: classification, clustering, regression, etc (Pedregosa et al., 2011). Applied tasks are also found in various areas, and their number is constantly growing. For example, medical diagnostics, where patients act as objects of classification. From various patient data, a number of features characterizing this patient are formed. By analyzing these features, it is possible to solve the following tasks: to classify the type of disease, to determine the most appropriate method of treatment, to find syndromes, and so on (Pombo et al., 2015, López-Martínez et al., 2018). Specially selected functional tests are used to assess the functional state of the cardiovascular, nervous and neuromuscular systems of a person, as a result allowing one to study the patient's condition in detail.

It is known that the autonomic nervous system (ANS) plays an exceptional role in the organization of the organism functioning (Cardinali 2017). Therefore, the application of the study of heart rate variability (HRV) – an indirect method of ANS evaluation – is promising when solving the above-mentioned tasks. The HRV features are good indicators of not only changes in the state of the ANS, but also the ability of a person to adapt to environmental changes (Aubert et al., 2012).

The use of stabilometric studies is less common. However, this is not a consequence of the insufficient information on this method: the reason is the insufficient knowledge of the mechanisms of control of the vertical posture of a person (McArdle et al., 2010).

Regular exercise and physical activity develop motor skills, increase strength, endurance, agility, etc. Depending on the type of sport a person competes, its body and skeleton are formed and a certain level of movement is established. The functional development of the motor apparatus and its regulatory centers are directly related to the equilibrium system, the reliability of which predetermines the success of the training and sports performance (Tucker and Collins, 2012).

In this paper, a description of the methodology for studying the physical performance of volunteers by means of simultaneously recorded signals of stabilography and HRV is given. The possibility of classifying volunteers with different levels of physical fitness from these data is considered.

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2 MATERIALS AND METHODS

2.1 Testing on a Bicycle Ergometer with Maximum, Stepwise Increasing Load and Gas Analysis

To determine physical performance, direct methods were used, which are usually applied in the examination of highly trained people, and based on direct determination of the amount of work that the subject can perform under various loads (Noreen et al., 2010). With all these loads, the subject reaches the maximum level of oxygen consumption. The obtained indicators are objective criteria for physical fitness of a person in those activities, the results of which are closely related to aerobic performance (cyclic endurance sports, etc.).

In this study used the maximum load test with gas analysis (ergospirometry) and registration of the electrical activity of the heart in real time (including the first 5 minutes of recovery).

The test in the “step load increase” test was carried out using an Oxycon ergospiometric installation from Jaeger (Germany). Before testing, gas analyzers were calibrated using a gas mixture with standard O2 and CO2 concentrations, and volumetric calibration of the instrument used was carried out. The load was carried out on the Monark Ergomedik 839E bicycle.

The main parameter used to determine the level of overall physical performance was - Wmax Wt/kg - the maximum power of the performed load, in terms of a kilogram of body weight.

Conversion of power to the level of total physical performance was determined in accordance with Table 1

Table 1: Total physical performance.

Wmax, Wt/kg	Male	Female
1,0-1,5	-	Low
1,5-2,0	Low	Below average
2,0-2,5	Below average	Average
2,5-3,0	Average	Above average
3,0-3,5	Above average	High
3,5-4,0	High	-

2.2 Athletes Data Description

The study was conducted in Moscow Research Center of Medical Rehabilitation and Sports Medicine.

The study involved 38 athletes involved in various sports, including team sports, wrestling, and athletics. Of these, 28 athletes were male, 10 - female. Of the 38 athletes, 3 had the title of master of sports (equates to international champion), 10 were candidates for the master of sport (equates to nationally ranked player), 6 people had the 1st junior category (equates to regional champion), and 1 person had 2nd junior category (equates to state champion). The average age was 20.34±3.52 years.

According to the results of testing on a bicycle ergometer, the initial sample of athletes was divided as follows:

- 11 with a high level of total physical performance;
- 13 with a total level of physical performance above average;
- 11 with an average total level of physical performance;
- 3 with a total level of physical performance below average.

2.3 Stabilometric Studies

In addition to the ergometer application in the study the stabilometric studies were applied, which were effective in classification of physical training in earlier pilot studies (Dolganov et al., 2017). A stabilizer analyzer computerized platform with biological feedback "Stabilan-01-2" (Taganrog) was used.

The sequence diagram of the research includes three stages, in each of which the subject stood on the platform of a stabilo-analyzer:

- functional rest (Stage 1);
- research using the “Target” load test implemented by hardware and software of the Stabilan-01-2 stabilo-analyzer (Stage 2);
- aftereffect (Stage 3).

The time of each stage was 5 minutes. After carrying out the three stages of the study, the stabilography signals and the HRV signal were saved and exported in text format.

Athletes underwent stabilometric studies in one day with testing on a bicycle ergometer, no later than half hour after the testing.

2.4 Biomedical Signals

2.4.1 Stabilometric Features

Common stabilometric studies involve two signals in the frontal (X) and sagittal (Y) planes, which tracks position for the subject center of mass (CM). In addition, stabilographic data in the polar coordinate system were considered. The amplitude R

of the stabilographic signal in this case was calculated as:

$$R = \sqrt{X^2 + Y^2},$$

where X is the value of the position of the CM on the frontal and Y is on the sagittal, planes.

The evaluation of X, Y and R signals was performed using statistical, spectral (Fourier and wavelet), as well as non-linear features. Overall, for each signal 38 features were evaluated. In addition, X and Y data was used for evaluation of 15 joint features – to be referred as *XY* data (Dolganov *et al.* 2017).

2.4.2 Heart Rate Variability Features

That list of 64 HRV features in this study, was used previously in prediction of the arterial hypertension (Kublanov et al., 2017). It included time-domain and frequency-domain features established by the European Society of Cardiology (Malik, 1996, Tarvainen et al., 2014), list of significant non-linear features (Sivanantham and Devi, 2014) as well as in-house wavelet transform features (Egorova et al., 2014).

2.5 Machine Learning

At this stage, it was decided to solve the problem of multi-class classification. The total level of physical performance was used as class labels. For even distribution between the classes, groups of athletes with "average" and "below average" were combined. As a method of machine learning, linear discriminant analysis was used, which is robust in calculation and relatively simple in interpretation (Cacoullos, 2014).

The formation of diagnostically significant features sets occurred in accordance with the previously proposed genetic algorithm (Kublanov et al., 2017), which proved itself in creating the decision support system for a physician in the diagnosis of arterial hypertension (Dolganov and Kublanov, 2018).

The main points to determine when applying genetic algorithms are the encoding, the initial population, the selection criterion and the evolution strategy.

In the evaluations, we encode features set by a binary encoding. Each of features set "chromosome" consists of 579 genes (3*38+15+64 features in 3 different stages). In particular, "1" in the chromosome means that the specific feature is "included" in the set, "0" means that the specific feature is not included in the set.

As the initial population, it was decided to choose 100 randomly created sets of three features. The selection criterion is the accuracy of the classification obtained using the leave-one-out cross-validation (Zhang and Yang, 2015).

As a rule, the strategy of evolution is determined by the ratio of the three main genetic operations - copying, crossing-over and mutation. In this case, 10 best representatives of population are directly copied to the next generation; 30 are created by randomly crossing chromosomes of best representatives. Finally, the 60 representatives in the next generation are created through mutation – each of 10 best representatives goes through six independent mutation iterations. In this case each gene in the chromosome can be flipped with a 5% chance.

Previous experience of applying the genetic algorithms has shown that an optimal number of generations is 20 for a classification tasks. For a greater accounting of different probabilities, the Genetic algorithm was applied 50 times total.

3 RESULTS

The Figure 1 shows the color map of the genetic algorithms application results for all 50 evolutions.

89	82	79	82	89	82	84	84	92	76
95	89	71	97	76	92	76	76	84	84
82	89	71	87	79	79	79	89	84	84
87	87	74	92	92	76	76	71	79	87
82	76	84	79	82	82	76	74	76	71

Figure 1: Total classification accuracy, %.

Data in figure 1 shows that in 21 cases the genetic algorithms failed to achieve good results – total classification accuracy was less than 80%. In 6 cases the classification accuracy was over 90%. Finally, there was a single evolution which resulted in best (97%) total classification accuracy scores.

The set of diagnostically significant features, which achieved highest classification score, is presented in table 2. The set is composed of features from all three stages and all signals.

In table 2, $F1$, $F2$, $F3$ correspond to the spectral components of the stabilometric signals.

Table 2: Diagnostically significant features set.

Stage	Signal	Feature
1	Y	F3n
1	Y	f(F2max)
1	R	M
1	R	En
1	XY	L
1	HRV	SDHF
1	HRV	SD1/SD2
2	Y	EnF3
2	R	F3max
2	XY	alpha
3	X	M
3	Y	f(F3max)
3	Y	F3n
3	R	CV
3	R	f(F1max)
3	R	f(F3max)
3	XY	α
3	HRV	AM0
3	HRV	IAS

*F*1 - spectral power of stabilogram in the first zone. The first zone is the zone of high-frequency fluctuations (6 - 2) Hz and characterizes the oscillations of the subject's CM, associated with physiological processes, tremor, etc;

*F*2 is the spectral power of the stabilogram in the second zone. The second zone is the zone of low-frequency fluctuations, (2 - 0.2) Hz, and characterizes the oscillations of the subject's CM associated with the regulation of posture;

*F*3 - stabilogram spectral power in the third zone. The third zone is a zone of fluctuations of a very low frequency, (0.2 - 0.003) Hz, and characterizes fluctuations of the subject's CM associated with slow, often uncontrolled, postural control processes.

*F*3*n*, refers to the ratio, between spectral power in *F*3 zone to the total spectral power of all three zones. *F*X*max* is a maximal value of the spectrum in the zone X, while *f*(*F*X*max*) is the corresponding frequency.

M , is the mean value of the time-series. *CV* is a Coefficient of Variation, which is defined as a ratio between standard deviation and mean value.

En is a Shannon entropy of the corresponding time-series (Shannon et al. 1993). *EnF*3 is a Shannon entropy, evaluated for a wavelet-based time-series in the *F*3 spectral zone.

L – is the total length of the stabilogramm, defined by the formula

$$L = \sum_{i=1}^{N-1} \sqrt{(X_{i+1} - X_i)^2 + (Y_{i+1} - Y_i)^2},$$

where N, is the number of points in the stabilometric signals.

α– is an average direction of the oscillations in the stabilogramm:

$$\alpha = 3$$

$$\begin{cases} 90^{\circ} - \frac{1}{2} \tan^{-1} 2 \frac{\mathrm{Cov}(X,Y)}{D(X) - D(Y)}, & D(X) > D(Y) \\ 90^{\circ} + \frac{1}{2} \tan^{-1} 2 \frac{\mathrm{Cov}(X,Y)}{D(X) - D(Y)}, & D(X) > D(Y) \end{cases},$$

where $\mathrm{Cov}(X, Y)$ – is a covariation of the X and Y; $D(.)$ – is a dispersion of the corresponding component.

The HRV features in table 2 are presented by:

- SDHF, is a Standard Deviation, evaluated for a wavelet-based time-series in the High Frequency range (from 0.4 to 0.15 Hz);
- SD1/SD2 is a ratio taken from the Poincare plot;
- AM0, is the Mode Amplitude, number of occurrences for a most frequent value in a time-series.
- IAS, is an index defined by the ratio of Low Frequency (from 0.15 to 0.04 Hz) and Very Low Frequency (from 0.04 to 0.003 Hz) HRV spectral components.

4 DISCUSSIONS AND CONCLUSIONS

In this paper, a description of the methodology for the evaluation of the total physical performance of athletes on the basis of simultaneously recorded signals of stabilography and HRV has been presented. The possibility of classifying athletes with different levels of physical fitness from these data was considered. An objective assessment of the level of physical performance was carried out using testing on the bicycle ergometer.

The use of genetic programming and linear discriminant analysis allowed to obtain the single set of diagnostically significant features, which in trun allowed to determine the level of physical fitness using only data from stabilographic studies and heart rate variability with an accuracy of at least 97%.

Among the strengths of proposed approach are the following: instead of a heavy and expensive load (bicycle ergometer) and rather complex equipment (gas analysis), an alternative method has been proposed, which is non-intrusive and requires less effort. This opens a possibility for creating a simple, efficient and cheap methodology.

However, at the moment the approach is not without the weaknesses: in the present work a set of diagnostically significant features was obtained, which consists of 19 parameters registered in 3 functional states (background-“target”-aftereffect). This makes it necessary to conduct a study lasting 15 minutes and requires video-feedback equipment. In addition it takes features of two signals.

It is advisable to further analyze the data in order to search for set of diagnostically significant features that would contain a smaller number of parameters, and at the same time - a smaller number of different stages. This can be done by changing the selection criterion, to value less features in sets. This can results in application of proposed approach during typical behaviors in real-world environments, instead of controlled laboratory conditions.

Among other perspective tasks that our scientific team is determined to solve are: search for way to reduce signal record time, analyzing the contribution of separate features to the decision made by the classifier, and conduction of additional studies to confirm the results.

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