

Forecasting the game role of volleyball players in accordance with the methodology of artificial intelligence

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Abstract:

Purpose of study: to develop models of morphofunctional state of the body of volleyball players to predict the success of sports activities. **Materials and methods.** The study was attended by male athletes aged 19-21 (n=27) who are core members of the student volleyball team «Burevisnik» acting on the basis of the Faculty of Physical Education of the T. H. Shevchenko National University «Chernihiv Colehium» (20 masters of sports of Ukraine; 7 first level athletes). **Research methods:** theoretical analysis and generalization of literary and Internet data; pedagogical observation; methods of functional diagnostics; modeling methods; pedagogical experiment; methods of mathematical statistics. **Results and conclusions.** The result of the analysis was the separation of the six most influential features, which, with high probability, differentiate athletes by game roles and domination in the realization of activity of players of attacking or protective actions. Use of multiclass classification allowed to obtain logistic linear models that differentiate students-volleyball players in accordance with the game roles. Analysis of the error matrix, which allows to detail the compliance of a particular volleyball player with a specific role, indicates the ability of some individuals to perform the gaming duties of other team players. The methodology proposed by the authors will help to ensure a higher efficiency of the player and team rating, more accurate forecasts of sports results, team formation and optimization of the training process, taking into account the individual characteristics of the players. The proposed research methods can be used in other sports.

Key Words: Volleyball team formation, game role, artificial intelligence, volleyball.

Introduction

The functions of artificial intelligence are the development and implementation of computer simulation methods for implementing multidirectional tasks in various fields of science and technology. The use of sophisticated analysis tools allows you to identify features that can not be determined by descriptive statistical methods of data interpretation. Methods of artificial intelligence have recently been used to provide management of complex cybernetic systems related to the training of specialists in physical education and sports (Priymak, SG, Zavorotynskiy, AV, 2018). In particular, sophisticated methods of machine learning and the intellectual analysis of data in physical culture and sports analysis take place to substantiate decision-making on multidirectional aspects of sporting activities (Wicker P., Breuer C., 2010). Retrospective analysis of the research issue points to a diverse approach to the modeling of the morphofunctional state of the body of athletes of various sports. In particular, the following questions are considered in individual works: simulation of cardiac rhythm indices for assessing the ability of runners and cyclists to work on training sessions (Dimitri de Smet, Marc Francaux, Julien M. Hendrickx and Michel Verleysen, 2016); simulation of physiological processes that affect physical efficiency in the preparation of athlete strollers, cyclists and biathletes (Alonso F., Caraça-Valente JP, González AL, Montes C., 2002 D'Ascenzi F., Alvino F., Natali BM, 2013; Priymak, SG, Terentieva, NO, 2017; Priymak Serhij, Kolomiets Nataliia, Goletc Vitaliy (2019)); development of methods for quantitative assessment of pedagogical impact in the exercise of physical activity (Churchill T. 2014); cycling speed optimization, determined by the regime of power supply of training and competitive loads (Aftalion A., Bonnans JF, 2014); development of methods for quantitative assessment of pedagogical influence in the form of physical activity (Churchill T. 2014); power supply of the playing activities of volleyball athletes (Nosko, MO, Danilov, OO, Maslov, VM, 2011; Pryimak Serhiy, 2017); the ranking of basketball players according to physical preparedness through multicriteria decision-making methods (MCDM) (Dadelo, S., Turskis, Z., Zavadskas, EK, Dadeliene, R.). At the same time, as the authors rightly state, in sports games there is a complexity of the prediction of the game role according to the morphofunctional capabilities of the athlete. In the literature there is

almost no data on the conditionality of the morphofunctional state of the body systems of athletes-volleyball players in accordance with the game role, that determines the relevance of the scientific search. These provisions provide for the creation of model characteristics of the morphofunctional state of the body systems of volleyball players for the prediction of the game role.

Hypothesis: It is assumed that the model morphofunctional state of the body systems of volleyball players will predict the game role and ensure the success of sports activities.

Purpose of study: forecasting of the game role of volleyball players in accordance with the characteristics of morphofunctional state of the body systems.

Material & methods

Participants: in the research the following athletes participated (boys $n = 27$, age 19-21 years) who attend the volleyball sport-pedagogic perfection group. All students are included into the main part of the student team «Burevisnik», which operates on the basis of the Faculty of Physical Education of the T. H. Shevchenko National University «Chernihiv Colehium». They all are elite athletes.

Organization of research. The research was conducted during December 2010 - March 2013 on the basis of the laboratory of psychophysiology of muscular activity of the T. H. Shevchenko National University «Chernihiv Colehium».

Research methods. The features of total body size were studied according to the standardized methodology: metrics of body length and individual segments (torso length, upper body, lower and upper limbs), body weight, ovulation of the chest (OC) at rest, inhalation and exhalation phases, vital capacity of the lungs, wrist and back muscles strength were recorded (Ivanickij MF, 2008). Features of autonomic regulation of the heart rate were studied on the basis of the analysis of the VRS indices of the 5-7-minute fragment of the electrocardiogram with a heart rate monitor Polar RS800 (Polar Electro, Finland). Data analysis was carried out using the software Kubios HRV 2.1 (Kuopio, Finland). Artifacts and extrasistals were removed from the electronic recording manually. Among the indices of the spectral (frequency) analysis of heart rate variability (HRV), the following was measured: the total power of the spectrum (Total Power, TP), High Frequency (HF), Low Frequency (LF) and Very Low Frequency (VLF) components, the contribution of these components to the total power of the spectrum, as well as the ratio of LF to HF waves calculated according to absolute (ms^2) units ($\text{LF} \cdot \text{HF}^{-1}$, units) (Mikhailov VM, 2000; Priymak Serhij, 2017; Priymak SG, 2018). Registration of the studied indicators was carried out in accordance with the recommendations of the joint meeting of the European Society of Cardiologists and the North American Society for Electrostimulation and Electrophysiology on the common standards for analysis of heart rate variability. During the registration of the above-mentioned indicators, the research object was limited to the impact of audiovisual stimuli with the help of a light-insulating black mask and sound-absorbing headphones that did not create discomfort. The execution of the PWC₁₇₀ test was performed on a cycle ergometer VE-02 using 2 loads of 5 minutes duration and 3 minutes of rest between the loads in accordance with the standards for its implementation (Belotserkovskiy ZB, 2005). In the state of rest, after the 1st and 2nd load, in the restitution phases (3 minutes after 1 and 7 minutes after the 2nd load), the above indicators were registered. Athletes were acquainted with the content of the tests and agreed to their conduct. In conducting complex surveys, Ukraine's health legislation, the Helsinki Declaration of 2013, and the European Community Directive 86/609 on the participation of people in biomedical research were respected.

Statistical analysis. For the classification of volleyball players by game role one of the methods of machine learning - decision tree - was applied. For this purpose Python (v. 3.6.3 Anaconda custom) software with Skelit machine learning (scikit-learn, v. 0.19.1) using the method of decentrication was used. Models were built using Python (v. 3.6.3 Anaconda custom) (Müller A., Guido S., 2017). With the help of this methodical approach, a decision tree was constructed, indicators that influence the differentiation of athletes by game role were found. In order to develop linear models that allow differentiation of athletes on an integrative basis, the method of multiclass logistic regression, which is adequate to the task, optimal linear classification algorithm implemented in the class `linear_model LogisticRegression`, was applied (Müller A., Guido S., 2017). Methodological method, which allows to spread the binary classification algorithm for multiclass classification is called «one vs rest» (one-vs.-rest). Applying the binary classifier for each class, we have one vector of coefficients (w) and one constant (b) for each class:

$$k = w \times x + b,$$

where k is the target function (classifier), w - matrix of coefficients of logline regression equation, b - free term of a logilinear regression equation.

The class that receives the largest value according to the formula is an integral index of a separate defining sign. Since the model is linear, the selected signs have been standardized. This procedure allows to provide a numerical representation of the data in the appropriate range for the application of the specified algorithm. The StandardScaler algorithm implemented in the scikit-learn package (v. 0.19.1) has been applied. For each sign the average is «0», and the variance «1», which allowed to ensure the uniformity of the scaling of the signs (Müller A., Guido S., 2017).

The level of correlation dependence (according to Pearson) between predictors of regression equations was determined, which revealed their interdependence. The presence of a probable connection, in which $p \leq 0.05-0.001$, ensures that only one component of the correlation pair is included in the model.

In order to assess the quality of the classification, accuracy, completeness, integral sign of the significance of the proposed models (F-measure) and error matrix are calculated (Müller A., Guido S., 2017). Since Precision and Recall of the developed models are metrics for the estimation of classifiers, the corresponding coefficients depending on the distinguished class (role) are calculated. Accuracy points to a part of the objects of the positive class, which is predicted correctly. Completeness characterizes the correspondence of the expert estimation of the forecast of the developed model (Müller A., Guido S., 2017). Two possible results are considered in the binary classification of the problem: positive (P) or negative (N). Based on these results and their predictions, there are four combinations of the results of the problem (Fig. 1) (Müller A., Guido S., 2017).

1. True Positive (TP): If predicted and actual results are positive.
2. False Positive (FP): if prediction is positive and the actual result is negative - false positives.
3. True Negative (TN): predicted and actual results are negative.
4. False Negative (FN): predicted result is negative, but the actual one is positive.

		<i>The actual value</i>	
		actually positive class P	actually negative class N
<i>Prediction result</i>	predicted positive class P'	True Positive (TP)	False Positive (FP)
	predicted negative class N'	False Negative (FN)	True Negative (TN)

Fig. 1. Error matrix for binary classification

Precision and Recall of developed models are calculated according to the formulas:

$$Precision = \frac{TP}{TP + FP}; \quad Recall = \frac{TP}{TP + FN}.$$

where TP – True Positive; FP – False Positive; FN – False Negative.

The integral sign of the significance of the proposed models is the F-measure, which is a harmonious mean between accuracy and completeness, and indicates that the predicted result correspond to an expert assessment of the success of students of different specializations (Müller A., Guido S., 2017).

$$F = 2 \times \frac{precision \times recall}{precision + recall}.$$

Since the predictors of the regression equations are in different ranges of quantitative values, the standardization procedure was performed, which allowed to eliminate the additional influence on the integral index and lead to erroneous conclusions. Under standardization, we mean the procedure of bringing the values of signs to a common interval, which ensures that the signs do not have an artificial surcharge caused by the difference in the ranges in which their values are. This procedure is implemented by the formula (Müller A., Guido S., 2017):

$$z = \frac{x - a}{s},$$

where z – the standardized value of the sign; a – the arithmetic mean of the predictor; s – corrected sample variance.

Data iterations for the preparation of data allowed to obtain model-classifiers for prediction of the game role of volleyball players.

Results

The result of the analysis was the separation of the six most influential indicators, which, with high probability, differentiate athletes by game roles and domination in the realization of activity of players of attacking or protective actions (Fig. 2).

As it is clear from the determined indicators that determine the morphofunctional state of the systems of the body of volleyball players, the most informative is the indicator of the absolute value of the power of the high-frequency component of the spectrum of the heart rate variability (High Frequency, ms^2), in the restitution phase 7 minutes after the PWC_{170} test, which identifies 2 groups of students with a range of oscillations of this indicator in the range of 59,770-171,365 ms^2 (37,04% of the subjects under study) and 198,4064-1902,859 ms^2 (62,96% of the subjects under study) (Fig. 2).

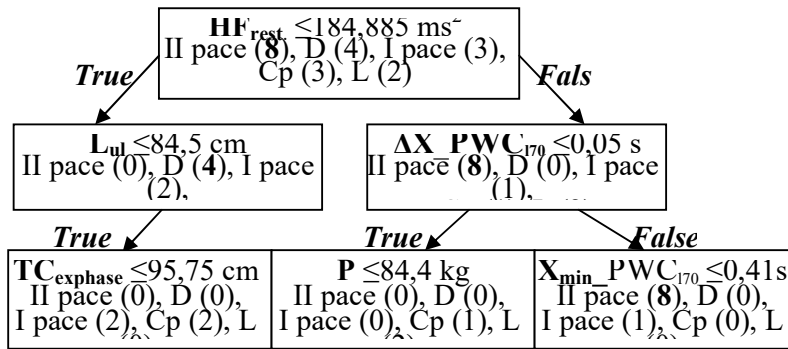


Fig. 2. Decisions tree of differentiation of athlete-volleyball players according to the game role
 Note: **II pace** – attacker of the II pace; **D** – diagonal attacker; **I pace** – attacker of the I pace; **Cp** – connecting player; **L** – libero; HF_{rest} – The power of the high-frequency component HRV (High Frequency, Hz) in the basal conditions; $\Delta X_{PWC_{170}}$ – variation of the cardiointervals N-N (ΔX , s) after the execution of the PWC_{170} test; $X_{min_PWC_{170}}$ - the minimum value of N-N cardiointervals in the variation series after the PWC_{170} test; **P** – body weight, kg; L_{ul} – the length of the upper limb, cm; $TC_{exphase}$ – thorax circumference in the exhalation phase.

Application of the multiclass classification made it possible to obtain linear logistic models that differentiate students according to the volleyball integral index:

$$K_1 = -0,33807181 + (-0,35813386 \times P) + (-0,14989044 \times L_{ul}) + (0,12790101 \times TC_{exphase}) + (0,03268799 \times X_{min_PWC_{170}}) + (0,25594099 \times \Delta X_{PWC_{170}}) + (-0,29593272 \times HF_{rest.}) \quad (1)$$

$$K_2 = -1,52804642 + (-0,12655827 \times P) + (0,8585778 \times L_{ul}) + (0,50596521 \times TC_{exphase}) + (-0,91418912 \times X_{min_PWC_{170}}) + (-0,51838079 \times \Delta X_{PWC_{170}}) + (-0,51599514 \times HF_{rest.}) \quad (2)$$

$$K_3 = -1,62468326 + (0,17381624 \times P) + (0,48307689 \times L_{ul}) + (-0,24502371 \times TC_{exphase}) + (0,70558673 \times X_{min_PWC_{170}}) + (0,60537915 \times \Delta X_{PWC_{170}}) + (-0,02269505 \times HF_{rest.}) \quad (3)$$

$$K_4 = -1,46437351 + (-0,12392984 \times P) + (-0,39595848 \times L_{ul}) + (-0,02571708 \times TC_{exphase}) + (0,35433876 \times X_{min_PWC_{170}}) + (0,12451507 \times \Delta X_{PWC_{170}}) + (0,08107729 \times HF_{rest.}) \quad (4)$$

$$K_5 = -1,95568495 + (0,30404021 \times P) + (-0,81192363 \times L_{ul}) + (-0,39313947 \times TC_{exphase}) + (-0,23291348 \times X_{min_PWC_{170}}) + (-0,37831343 \times \Delta X_{PWC_{170}}) + (0,47012473 \times HF_{rest.}) \quad (5)$$

where K_1 is the integral index for identifying the attackers of the II pace; K_2 – integral index for identifying diagonal attackers; K_3 – integral index for the identification of attackers of the I pace; K_4 – integral index for identifying connecting players; K_5 – integral index for the identification of a libero; **P** (kg), L_{ul} (cm), $TC_{exphase}$ (cm), $X_{min_PWC_{170}}$ (ms), $\Delta X_{PWC_{170}}$ (s), $HF_{rest.}$ (ms^2) – standardized indices (Table 4).

Accordingly, the class that receives the largest value by the formula is the integral index of a separate deflecting indicator. The separation of volleyball students according to the integral indicator (game role) allows them to be highly differentiated into subgroups, namely: attacker of the II pace ("1"), "the diagonal attacker ("2)", the attacker of the I pace ("3") , connecting player ("4"), libero ("5"). The greatest accuracy of the forecast is observed in the subgroup of the libero, which is 100%, which provides the absolute predictive value of the positive result in the subgroup of this game role (Table 1).

Table 1. Qualitative indicators of prognostic value of a positive result in the group of athlete-volleyball

Class	Precision	Recall	Harmonic mean of the accuracy and completeness (F-measure)	Total number (support)	Expert score	Δ
«1»	0,60	0,82	0,69	11	9	-2
«2»	0,80	0,80	0,80	5	4	-1
«3»	0,67	0,50	0,57	4	2	-2
«4»	1,00	0,25	0,40	4	1	-3
«5»	1,00	1,00	1,00	3	3	0
avg/total	0,75	0,70	0,69	27	19	-8

The completeness of the model, analogously to the accuracy, indicates a high level of compliance with the expert score of the forecast (82.00%) (Table 1). In this case, the F-measure, as an integral indicator of the significance of the proposed models, is in the range of 40.00-100%, which provides 69.00% of the predicted result to the expert score of the success of volleyball students (Table 2). The overall accuracy of the model is 70.4%, which indicates the high explanatory adequacy of the model and accurately differentiates the volleyball students according to their game roles. The analysis of the error matrix, which allows us to detail the correspondence of a particular volleyball student to a particular role, indicates the ability of individual individuals to perform the gaming responsibilities of other team players. As in the case of a binary classification, each line corresponds to the actual label of the class, and each column is the predicted label of the class (Fig. 3). The actual number of people in the first class (attacker of the II pace) is 11, of which 9 students (81.82%) can act as diagonal attacker and attacker of the I pace. The class that identifies the diagonal attackers, in 4 cases out of 5, predicts the game role. In this case, one student from this subgroup may perform the duties of the attacker of the II pace. In the 3rd class, which distinguishes attackers of the I pace, 2 students out of 4 are identified accordingly, and 2 – can perform the duties of 1st class players (attackers of the II pace).

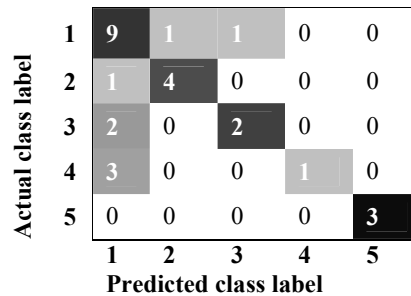


Fig. 3. The error matrix for the classification of athlete-volleyball players according to the game role

Note: according to the actual (vertical scale) and predicted (horizontal scale) class labels: 1 – attacker of the II pace; 2 – diagonal attacker; 3 – chest perimeter attacker of the I pace; 4 – connecting player; 5 – libero.

Connecting players, concentrated in the 4th class, confirm the universality of gaming duties by the possibility to perform the functions of the attackers of the II pace (3 out of 4). The correspondence of the libero (5th class) to the game role is absolute and indicates the high accuracy and correctness of the forecast (Fig. 3).

Dicussion

The developed equations with application of methods of machine learning (decision trees) and logistic regression have allowed to create logistic linear models for the purpose of identification of volleyball players in accordance with the game roles.

Example. Atlet N has the following indices of the absolute value of the high-frequency component of the spectrum of the Heart Rate Variability (High Frequency, ms²) in the restitution phase 7 minutes after the PWC₁₇₀ test, the variation of the N-N cardiointervals (ΔX , s) and its minimum value (X_{min} , s) just after performing the PWC₁₇₀ test, the length of the upper limb (cm), body weight (kg), and thorax circumference in the exhalation phase ($TC_{exphase}$, cm) (Table 2, 3).

Table 2. Absolute values of the athlete-volleyball player N predictors for the game role forecast

Index	P, kg	L _{ul} , cm	TC _{exphase} , cm	X _{min} _PWC ₁₇₀ , s	ΔX _PWC ₁₇₀ , s	HF _{rest} , ms ²
x	72,5	83,50	92,00	0,38	0,06	198,4064

Table 3. Absolute values of a and s predictors of volleyball athletes

Index	P, kg	L _{ul} , cm	TC _{exphase} , cm	X _{min} _PWC ₁₇₀ , s	ΔX _PWC ₁₇₀ , s	HF _{rest} , ms ²
a	85,167	82,426	95,852	0,360	0,076	458,195
s	10,435	3,817	5,140	0,034	0,022	485,300

After the standardization process, the predictors have the following meanings (table 4).

Table 4. Standardized values of predictors of volleyball player N for prediction of game role

Indicator	P, kg	L _{ul} , cm	TC _{exphase} , cm	X _{min} _PWC ₁₇₀ , s	ΔX _PWC ₁₇₀ , s	HF _{rest} , ms ²
z	-1,21384642	0,281375449	-0,74938872	0,592748978	-0,69388867	-0,53531464

According to the formulas (1-5), taking into account the standardization of data (Table 4), we obtain the following integral indices of differentiating indicators:

$$K_1 = -0,33807181 + \underbrace{(-0,35813386 \times -1,21384642)}_D + \underbrace{(-0,14989044 \times 0,281375449)}_{L_{ul}} + \underbrace{(0,12790101 \times -0,74938872)}_{TC_{\text{exphase}}} + \underbrace{(0,03268799 \times 0,592748978)}_{X_{\text{min-PWC170}}} + \underbrace{(0,25594099 \times -0,69388867)}_{\Delta X_{\text{PWC170}}} + \underbrace{(-0,29593272 \times -0,53531464)}_{HF_{\text{rest.}}} = -0,041177032;$$

$$K_2 = -1,52804642 + \underbrace{(-0,12655827 \times -1,21384642)}_D + \underbrace{(0,8585778 \times 0,281375449)}_{L_{ul}} + \underbrace{(0,50596521 \times -0,74938872)}_{TC_{\text{exphase}}} + \underbrace{(-0,91418912 \times 0,592748978)}_{X_{\text{min-PWC170}}} + \underbrace{(-0,51838079 \times -0,69388867)}_{\Delta X_{\text{PWC170}}} + \underbrace{(-0,51599514 \times -0,53531464)}_{HF_{\text{rest.}}} = -1,417972382;$$

$$K_3 = -1,62468326 + \underbrace{(0,17381624 \times -1,21384642)}_D + \underbrace{(0,48307689 \times 0,281375449)}_{L_{ul}} + \underbrace{(-0,24502371 \times -0,74938872)}_{TC_{\text{exphase}}} + \underbrace{(0,70558673 \times 0,592748978)}_{X_{\text{min-PWC170}}} + \underbrace{(0,60537915 \times -0,69388867)}_{\Delta X_{\text{PWC170}}} + \underbrace{(-0,02269505 \times -0,53531464)}_{HF_{\text{rest.}}} = -1,505806426;$$

$$K_4 = -1,46437351 + \underbrace{(-0,12392984 \times -1,21384642)}_D + \underbrace{(-0,39595848 \times 0,281375449)}_{L_{ul}} + \underbrace{(-0,02571708 \times -0,74938872)}_{TC_{\text{exphase}}} + \underbrace{(0,35433876 \times 0,592748978)}_{X_{\text{min-PWC170}}} + \underbrace{(0,12451507 \times -0,69388867)}_{\Delta X_{\text{PWC170}}} + \underbrace{(0,08107729 \times -0,53531464)}_{HF_{\text{rest.}}} = -1,325850141;$$

$$K_5 = -1,95568495 + \underbrace{(0,30404021 \times -1,21384642)}_D + \underbrace{(-0,81192363 \times 0,281375449)}_{L_{ul}} + \underbrace{(-0,39313947 \times -0,74938872)}_{TC_{\text{exphase}}} + \underbrace{(-0,23291348 \times 0,592748978)}_{X_{\text{min-PWC170}}} + \underbrace{(-0,37831343 \times -0,69388867)}_{\Delta X_{\text{PWC170}}} + \underbrace{(0,47012473 \times -0,53531464)}_{HF_{\text{rest.}}} = -2,385800639.$$

Since, in this case: $\max \{K_1; K_2; K_3; K_4; K_5\} = \max \{-0,041177032; -1,417972382; -1,505806426; -1,325850141; -2,385800639\} = -0,041177032$, the athlete is classified as a class «1» (K_1) as a attacker of the II pace, which coincides with the results of expert score.

Conclusions

The management of team sports is usually based on subjective assessments and decisions. Only a systematic study of the functional state of the body of the team players can provide an effective solution in the choice of the role. Meanwhile, the subjective decisions taken by the coach or the desire of volleyball players to improve their own rating, and not the desire of the team to win, can influence the game. Consequently, in order to optimize the training process of team players, issues of development and adaptation of mathematical systems for practical use, taking into account the individuality and uniqueness of athletes, are decisive. Integrated models using machine learning (decision trees) and logistic regression based on data on objective indicators of athletes have been developed to provide greater efficiency in the evaluation and selection of volleyball players. The player monitoring system may be used to complete and prepare individual training plans for athletes, in accordance with the volume, intensity and content of training sessions. The described research methods may be used in other sports, and the developed suggestions require further study.

Conflicts of interest - The authors state that there are no conflicts of interest.

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