Optimization of Training in Weightlessness with Respect to Personal Preferences

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Abstract. This paper contributes to the problem of life support in weightlessness conditions during manned flight in space. We consider an element of prospective autonomic decision support system aimed at training control of cosmonauts on board. Using a regression model, we consider one approach to training optimization with respect to personal preferences of crew members. This approach aims at optimal choice of treadmill mode of operation and the amount of axial load subject to maintenance of the level of physical performance at the pre-flight level. The results of tentative computations based on the experimental data collected on board the International Space Station are reported and discussed.

Keywords: Physical exercise · Regression · Long space flight · Locomotor training · Exercise

1 Introduction

The training process is a complex of activities that affect the athlete. In addition, each athlete has individual psychological and physiological characteristics that must be considered for proper management of training.

The essence of countermeasure effect in long duration space flight is prevention of decrease of physical performance of cosmonauts. The main means of countermeasure is locomotor training on treadmill in passive (leg-driven) and active (motor-driven) mode of operation [1]. The load parameters can be set and controlled by:

- duration
- heart rate

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- velocity of locomotion
- axial load (system of bungee cords creates a gravitational load during the exercise)
- treadmill mode of operation (passive or active)

In long duration space flight, the control of physical condition of cosmonauts is complicated by the remoteness of ground specialists. In such conditions, the task of maintaining the physical form of the cosmonauts can be solved using an on-board automated system that monitors the current state of each crew member and is aimed at optimizing it. A control system of training process has been developed and tested in Mars-500 experiment [3]. The system [3] consists of the following subsystems: the collection and processing of information, the organization of the measurements, the analysis of the measurements, and the summarizing. The decisions of this system correspond to the coach's actions aimed at the implementation of a certain program of actions and the resolution of emerging problems. The work reported in the present paper, aims at development of an alternative approach to design of a decision support system based on machine learning techniques which may be applied not only for training control during autonomous space flights, but also for training on Earth.

2 Optimisation of Training with Respect to Physiological Cost of Work

The analysis is based on data that describes the daily physical training of Russian cosmonauts on board of the International Space Station, with respect to the parameters of locomotor training, such as duration, velocity of locomotion, axial load, treadmill mode of operation (passive or active), heart rate and so on.

The efficiency of physical training was determined in flight on the basis of the test with stepwise increasing locomotor activity, which was carried out in passive treadmill motion mode with an axial load not less than 60% of body weight. The test consisted of the following five stages: 3 min of warm-up walk, 2 min of slow running, 2 min of running at moderate speed, 1 min of running at maximum speed, and 3 min of cooling-down walk. In general, the duration of the locomotor sample was 11 min, and its energy value was about 100 kcal.

This test is characterized by standardization of the sequence and duration of each loading stage, allowing cosmonauts arbitrary choice of the intensity at each of the work stages. The speed of treadmill motion, selected by the cosmonaut, is an important informative indicator of his/her fitness level. This test is standard in assessing the working ability in the Russian system of medical provision of space flights.

To evaluate the effectiveness of applied training modes, we considered fast running stage as the most indicative. The *physiological cost of work* is calculated as the ratio of the heart rate to the product of the running speed and the change in the axial load according to the following formula [1]:

$$PhC = \frac{HR}{V \cdot AL},$$

where

- PhC is the physiological cost of work
- HR is the heart rate
- V is the average speed
- AL is the axial load.

The correlation analysis [2] revealed how the axial load value and the fraction of the passive mode influence on the change in physiological cost. Thus, the reverse dependence of the change in the physiological cost of work on the axial load value and the fraction of the passive mode was shown. That is, in order to maintain physical performance, a sufficient value of the axial load with which the cosmonaut performs locomotor physical training and the fraction of the passive mode play an important role, and when combined correctly, lead to minimal changes in physiological cost during a space flight. In [2], a linear model based on the multiple regression was constructed for prediction of physiological cost on the basis of the axial load value and the fraction of the passive mode. The adjusted coefficient of determination r^2, which shows the measure of the quality of the regression model, turned out to be equal to 0.64. An analysis of this model showed that the minimal change of physiological cost during the flight is achieved by a sufficient axial load and sufficiently high percentage of the passive mode.

In our research, we formulated a hypothesis that the linear function is too simplified for this problem and the regression analysis with quadratic functions might be more appropriate.

Let us introduce the following notations:

PhC is the physiological cost before the flight.
$\widehat{PhC}$ is the predicted physiological cost in the flight session.
$\Delta\widehat{PhC} := PhC - \widehat{PhC}$

The increment of physiological cost is represented as the quadratic form:

$$\Delta\widehat{PhC}(x, y) = b_1 x + b_2 y + b_3 xy + b_4 x^2 + b_5 y^2 + b_6 \tag{1}$$

Then we formulate a mathematical programming problem as follows:

$$\Delta\widehat{PhC}(x, y) \to 0, \tag{2}$$

where

$b_i \in \mathbb{R}$ are the regression coefficients,
$x \in [0, 1]$ is the axial load value, scaled to the [0,1] interval,
$y \in [0, 1]$ is fraction of the passive treadmill mode of operation.

This problem involves only two variables, which allows solving the problem analytically.

3 Evaluation and Preventing Overfitting

First, we define the machine learning problem using the notation introduced earlier:

$S_l = \{s_1, s_2, ..., s_l\}$ is the dataset.
$\Delta PhC : S_l \to \mathbb{R}_+$ is the target function.
$A_D = \{g(s,b) | b \in D\}$ is the predictive model, where
$D \subseteq \mathbb{R}^6$ is the parameter space,
$x : S_l \to [0,1]$ is the first feature,
$y : S_l \to [0,1]$ is the second feature,
$g(s,b) = b_1 x(s) + b_2 y(s) + b_3 x(s) y(s) + b_4 x^2(s) + b_5 y^2(s) + b_6$ is the responce function.
$\mathcal{L}(a,s) = (a(s) - \Delta PhC(s))^2$ is the loss function (square error), $a \in A_D$, $s \in S_l$.
$Q(a,S) = \frac{1}{|S|} \sum\limits_{s \in S} \mathcal{L}(a,s)$ is the empirical risk (MSE), $a \in A_D$, $S \subseteq S_l$.
$\mu(A_D, S) = \arg\min\limits_{a \in A_D} Q(a,S)$ is the model that fitted on S using parameter space D.

As will be shown later, using an entire parameter space of quadratic functions leads to overfitting in our case. Therefore, we also used limited parameter spaces:

$D_Q \ : b_i \in \mathbb{R}$
$D_L \ : b_i = 0, i \in \{3,4,5\}$
$D_{xy} \ : b_i = 0, i \in \{4,5\}$
$D_2 \ : b_3 = 0$
$D_c \ : b_i = 0, i \in \{1,2,3,4,5\}$

We have four data sets, which we consider as four independent (but naturally similar) tasks:

– fast run, first flight session
– average run, first flight session
– fast run, second flight session
– average run, second flight session

Each data set S_l consists of a very small number of samples ($l < 20$). This, however, allows us to use leave-one-out cross-validation to estimate the generalization error of each parameter space. Let us describe in detail the evaluation procedure.

Thus, consider a fixed D. We can define coefficient of determination as follows:

$$r^2(a,S) = 1 - \frac{Q(a,S)}{Q(\mu(A_{D_c}, S), S)}, S \subseteq S_l$$

So, we want to find $\widehat{\Delta PhC} = \mu(A_D, S_l)$ and calculate $r^2_{train} = r^2(A_D, S_l)$. And then, we can construct a_{LOO} (cross-predict function) as follows:

$$\forall s \in S_l : a_{LOO}(s) = \mu(A_D, S_l \setminus \{s\})(s)$$

And finally, we can get r^2 for cross-predicted values:

$$r^2_{LOO} = r^2(a_{LOO}, S_l)$$

We use r^2_{LOO} (instead of an optimistic r^2_{train}) as an adequate quality measure of the predictive model A_D defined by the parameter space D.

4 Taking into Account Individual Preferences

Our experiments have shown that for each of the four data sets and for each parameter space (except for the D_c) there is a pair (x, y) for which $\Delta\widehat{PhC}(x, y) = 0$.

Therefore, we solved each of the following problems (separately from each other):

$$x \to \min \tag{3}$$

and

$$y \to \min \tag{4}$$

considering that the following system of restrictions is fulfilled:

$$\Delta\widehat{PhC}(x, y) = 0 \tag{5}$$

$$x \in [0, 1] \tag{6}$$

$$y \in [0, 1] \tag{7}$$

5 Computational Results

For each task and parameter space we built the model on the entire data set and calculated the quality measures, including rank of the search space for each task by r^2_{LOO} (see Table 1).

For each parameter space we calculated average rank and number of different signatures among the constructed models (see Table 3). By the signature of the model, we have in mind the Boolean vector, determined by the sign of each coefficient of the model. This metric is designed to reflect some kind of consistency between models that are found in a given parameter space.

Finally, we solved the optimization problems (see Table 2).

Results indicate that the "semi-quadratic" predictive model $A_{D_{xy}}$ is the most reasonable among those considered, and also competes well with the linear one.

6 Conclusion

A new approach to training optimization with respect to personal preferences of crew members is evaluated. It is shown that given the sample of small size, usage of the quadratic regression model leads to an overfitting. The most adequate and robust results are obtained using the linear regression model and its extension

Table 1. Models and metrics

Speed	Session	D	r^2_{train}	r^2_{LOO}	b_1	b_2	b_3	b_4	b_5	b_6	rank
Avg	1	D_L	0.72	**0.59**	-372.70	-126.59	0.00	0.00	0.00	355.70	1
Avg	1	D_{xy}	0.74	0.57	-509.56	-349.72	415.50	0.00	0.00	431.58	2
Avg	1	D_2	0.72	0.52	58.96	-119.61	0.00	-379.08	-6.75	235.83	3
Avg	1	D_Q	0.77	0.48	-486.89	-751.65	861.07	-129.60	153.76	482.03	4
Avg	1	D_c	0.00	-0.14	0.00	0.00	0.00	0.00	0.00	96.81	5
Avg	2	D_{xy}	0.76	**0.62**	-530.64	-473.02	712.82	0.00	0.00	421.98	1
Avg	2	D_2	0.77	0.56	709.57	140.24	0.00	-904.92	-218.71	-8.26	2
Avg	2	D_L	0.67	0.51	-300.96	-90.18	0.00	0.00	0.00	294.34	3
Avg	2	D_Q	0.79	0.44	382.44	-179.33	427.01	-729.45	-133.18	129.36	4
Avg	2	D_c	0.00	-0.14	0.00	0.00	0.00	0.00	0.00	88.11	5
Fast	1	D_L	0.34	**0.10**	-257.43	-118.19	0.00	0.00	0.00	291.86	1
Fast	1	D_{xy}	0.35	-0.03	-407.63	-363.09	456.03	0.00	0.00	375.15	2
Fast	1	D_c	0.00	-0.14	0.00	0.00	0.00	0.00	0.00	102.21	3
Fast	1	D_Q	0.38	-0.22	-316.50	-800.72	944.08	-200.36	165.92	411.84	4
Fast	1	D_2	0.35	-0.37	281.97	-107.75	0.00	-473.89	-10.06	141.90	5
Fast	2	D_Q	0.79	**0.52**	-919.54	-1016.85	1349.81	134.87	186.81	634.46	1
Fast	2	D_{xy}	0.75	0.45	-645.08	-577.88	902.74	0.00	0.00	498.38	2
Fast	2	D_L	0.65	0.37	-364.25	-95.28	0.00	0.00	0.00	342.10	3
Fast	2	D_2	0.66	0.15	3.47	-23.57	0.00	-325.27	-67.00	232.19	4
Fast	2	D_c	0.00	-0.14	0.00	0.00	0.00	0.00	0.00	98.85	5

Table 2. Preferences optimisation

Speed	Session	D	$x \to min$	y	x	$y \to min$
Avg	1	D_L	0.615	1.000	0.954	0.000
Avg	1	D_{xy}	0.847	0.000	0.847	0.000
Avg	1	D_2	0.621	1.000	0.870	0.000
Avg	1	D_Q	0.000	0.759	0.814	0.000
Avg	2	D_{xy}	0.000	0.892	0.795	0.000
Avg	2	D_2	0.000	0.066	0.012	0.000
Avg	2	D_2	0.000	0.576	0.772	0.000
Avg	2	D_L	0.678	1.000	0.978	0.000
Avg	2	D_Q	0.000	0.520	0.758	0.000
Fast	1	D_L	0.675	1.000	1.000	0.291
Fast	1	D_{xy}	0.350	1.000	0.920	0.000
Fast	1	D_Q	0.000	0.585	0.847	0.000
Fast	1	D_2	0.671	1.000	0.920	0.000
Fast	2	D_Q	0.000	0.719	0.779	0.000
Fast	2	D_{xy}	0.000	0.862	0.773	0.000
Fast	2	D_L	0.678	1.000	0.939	0.000
Fast	2	D_2	0.665	1.000	0.850	0.000

Table 3. parameter spaces ranking

D	Avg rank	Signatures
D_{xy}	**1.75**	1
D_L	2	1
D_Q	3.25	3
D_2	3.5	3
D_c	4.5	1

that takes into account the combined impact of both factors, the axial load and the percentage of passive treadmill mode.

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References

1. Fomina, E.V., Lysova, N.Y., Chernova, M.V., Khustnudinova, D.R., Kozlovskaya, I.B.: Comparative analysis of preventive efficacy of different modes of locomotor training in space flight. Human Physiology 42(5), 539–545 (2016)
2. Lysova, N.Y.: Efficiency of physical training in different modes and axial loads as a countermeasure of negative effects of weightlessness in motor system. Synopsys of candidate of biological sciences thesis. Moscow (2015), (in Russian)
3. Son'kin, V.D., Egorov, A.D., Zaitseva, V.V., Son'kin, V.V.: Expert system on managing of physical training of crews in prolonged space flights. Aviokosm. Ekol. Med. 37(5), 41–46 (2003)