Benefits of active inference method for training process analysis in elite alpine skiing sport

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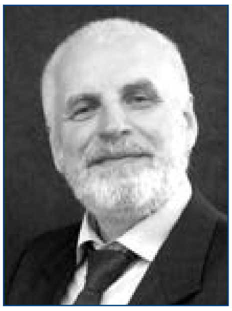

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Abstract

Objective of the study was to theoretically analyze and test benefits of an active inference method for training process in elite ski jumping sport.

Methods and structure of the study. We sampled for the active inference method testing experiment national alpine skiers (n=20, equal gender split), qualifiers for the World Cup finals, and tested their training progress by Stabilan-01 biomechanical test system with a biological feedback capacity.

Results and conclusion. During the precompetitive conditioning periods in a yearly macro-cycle, the alpine skiing elite is known to make progress in the tracking movement control system due to special physical practices with different goals and focuses. As provided by the modern theory of active inference, these progresses are largely due to improvements in the somatosensory system performance and, as a result, progress forecasts depending on the somatomotor system state at a specific time point.

Keywords: *Alpine skiing, tracking moves, active inference, motor control.*

Background. Modern movement control studies apply a few theoretical concepts based on the idea of that the central nervous system develops certain internal models for efficiency [8]. These internal models are a interpreted by a theoretical hypothesis of the informational exchanges between the somatomotor and somatosensory systems that largely contribute to the computational capacity of the nervous system and help master and excel every highly coordinated movement. It is traditional to classify these internal models into the direct and inverse ones with the relevant motor system dynamics [8]. In a movement process, the direct model forecasts states of the motor apparatus with the relevant sensory stimuli at every time point, whilst the inverse model designs the movement execution program. In other words, the inverse model transmits a motor control command, whilst the direct model converts an efferent copy of the motor control command into sensory forecasts [12] to optimize the target state of the motor system as programmed by the inverse model.

It was in the late XX century that the research community started applying the Bayesian decision-making (optimal behavior) theory with the relevant mathematical statistics tools to develop a range of perceptual processing and sensory-motor control models [9].

Active inference in this context may be defined as the control model under the Bayes theory [2] or the forecast error minimizing approach.

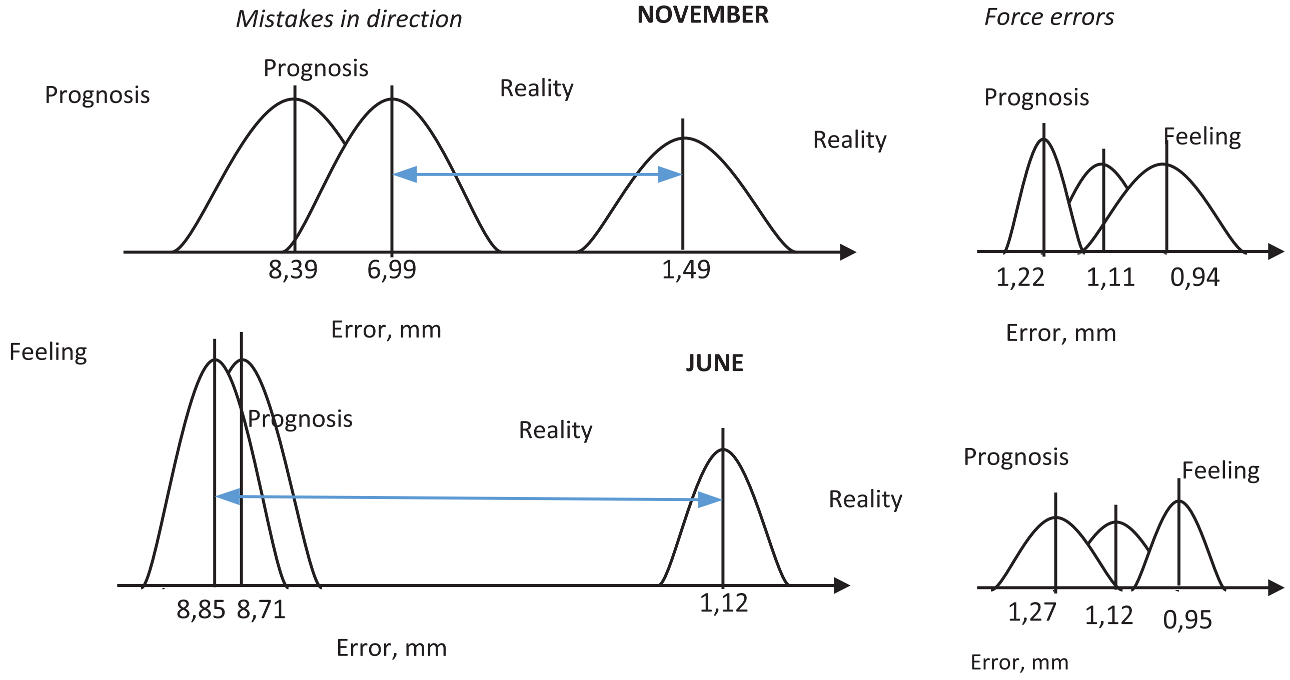
The core idea of the model provides for the work of the cognitive system to minimize errors in prediction using motor activity (movements) in such a way that the sensory input best corresponds to the predictions of the model [7]. In the theory of active inference, it is argued that descending signals are predictions of the sensory consequences of movement. Descending signals determine sensory trajectories, the fixed point of which is the equilibrium point; i.e., the dynamics of movement (including speed, acceleration, jerks, etc. d.), and not only the position and torque at the end point [5]. In the active inference model the mechanical cost functions are replaced by the person's ideas of the desired movement trajectories in external frames of reference. The active inference transforms the desired (expected) motion paths in external coordinates into motor tasks in internal coordinates. In this case, the inverse task, which is to cause excitation in a certain stretch receptor and contract the corresponding muscle fiber, is transferred to the spinal level [6]. Numerous studies of dopamine show its involvement in the movement control process [1]. Dopamine plays a key role in active inference. In recent works, the effects of the dopamine neurotransmitter are shown as one of the possible neural accuracy encoding mechanisms. Greater precision (no matter how it is encoded) means less uncertainty. Uncertainty can be encoded by the same postsynaptic neuronal enhancement that is modulated by dopamine meaning that changing the dopamine level alters the level of uncertainty about different representations. Physiologically, this is a process of short-latency surges of dopamine in the basal ganglia that occur after any significant event, beneficial or not.

Objective of the study was to theoretically analyze and test benefits of an active inference method for training process in elite ski jumping sport.

Methods and structure of the study. National Alpine skiers (n=20, equal gender split), qualifiers for the World Cup finals, were subject to experiment and tested monthly from April to November and their training progress was recorded on a daily basis by Stabilan-01 biomechanical test system with a biological feedback capacity (Rhythm, Taganrog) [10]. The testing procedure was to curvilinear motion of the body in the ankle joints at a speed of 30 mm/s, called “Evolvens”, which was displayed on the monitor screen as a cursor. The subject had to hold the marker of the common center of pressure (CCP) as close as possible to the marker that sets the circular trajectory. The speed and deviation of the CCP trajectory from the template were recorded.

Based on numerical simulation using the Kalman filter methods or Linear-QuadraticEstimator, and Linear-QuadraticRegulator, a numerical assessment of the contribution of the components of motor errors was made: x^{plan} planning, estimated (i.e., the athlete’s feelings based on previous experience) x^{perf} and performed x^{targ} movement, deviation from the template in direction a and force n [11]. The athletes also had their blood tested to reveal the quantitative dopamine level. The method of high performance liquid chromatography was used in combination with tandem mass spectrometry (HPLC–MS/MS) [3]. The integration of chromatographic peaks was carried out automatically using LabSolutions software version 5.97.

Results and discussion. Two months with the maximum (November, state B) and minimum (June, state A) ($p<0.01$) dopamine levels in the athletes were selected for analysis (Table 1). The nature of the training loads in these months is fundamentally difference in the use of strength-building and technical exercises. In June, athletes performed maximum muscle strength building sessions using exercises that lead to a change in the muscle structure, aimed at increas-



Errors associated with movement direction and applied forces during test procedure

Table 1. *The results of the stabilometric test "Evolvens"*

State	Dopamine, pg/ml	V, mm/s	SummErrX, мм	SummErrY, мм	MidErrX, мм	MidErrY, мм	KorrCount
B, November	26,46±5,20	30,24±3,84	25667,1±6239,7	25180,6±4869,9	5,68±1,38	5,57±1,07	192±41,19
A, June	88,87±22,58	29,50±3,17	24393,6±4504,9	23861,4±4412,3	5,39±0,99	5,28±0,97	185±48,24
Difference, %	-29,77*	2,45	4,97	5,24	5,11	5,21	3,78

Note:V,mm/s – velocity of displacement of CCP,SummErrX – total error in the frontal plane; SummErrY – total error in the sagittal plane; KorrCount – number of corrections. A – state of athletes subject to testing in November,B – in June.

ing the volume of myofibrils and increasing the myofibril density in the muscle fiber. The exercises close in structure to competitive ones were lacking during this period. In November, the athletes performed a lot of technical, complex coordination work, and strength training was geared to maintain the strength level using explosive strength and maximum strength building methods in the modes similar in structure to schussing. Technical trainings performed on the mountain amounted to 9% of the maximum recorded throughout the season

In June, the lower test performance speed and longer CCP distance were recorded. In November, the speed of movement, on the contrary, exceeds the required speed of movement, and the distance is shorter. As for the error in performing the tracking movement, the total and average errors in the frontal and sagittal planes are bigger in November rather than in June, but in both cases the error values are within the norm [10].

The decrease in this kind of errors and the approximation of the data to the real performance is probably associated with the process of training athletes to control in variable external conditions. But this, in both cases, occurs with the spatial characteristics of tracking motions, but not strength ones. In all cases, the x^{plan} scheduling error rates remain unchanged. In November, the x^{perf} sensation error corresponds more to the actual movement execution, i.e. the difference between x^{perf} and x^{targ} (actual) is less. In June, the planning error is somewhat less consistent with the actual movement, and the x^{perf} feel values are further from the real x^{targ}.

Thus, active inference can minimize prediction errors by predicting the motion path. In our data, this is clearly seen in changes in the errors associated with the trajectory, since power manifestations remain practically unchanged. This is especially interesting from the point of view of comparing the training work performed by the athletes in June (general preparatory stage) and November (pre-season). The difference at these stages is in the biomechanical specificity of the performed exercises compared to competitive movements. In June, exercises with non-specific movements were performed and geared to increase the muscles functionality in the athletes.

Accordingly, the receptor date from the neuromuscular spindles and Golgi tendon organs was dominant in the control of movements, the athletes' consciousness was focused on feeling of the amount of the applied efforts and, accordingly, was associated with the internal coordinate system. Control information is associated with changes in the neuromuscular system and the control system solves the problem of balancing internal ascending and descending information flows, which leads to an increase in the load on the basal nuclei and an increase in blood dopamine in the athletes. In November, a significant number of descents was used.

To perform exercises focus should be made on obtaining extraceptive information about the place of the athlete in the surrounding world and conditions in which he moves, which determines the visual system leading, information from which forms the basis of the external control model. The specificity of the control model and sensory information are extremely consistent with each other, which reduces errors in predicting the path of the skiing movement being performed, so surprises are less likely [5]. In this case, the load on the basal ganglia is lower, which leads to a decrease in blood dopamine in the athletes. In active inference, this corresponds to predictions based on the accuracy of the sensory input, and optimizing the postsynaptic amplification of prediction error units. The process of forming the second type of prediction is slower in time than the process of the first type, in which neuromodulators are used, including dopamine, and not a quick switch on - switch off of the data transfer [4].

Conclusion. The use of the theory of active withdrawal made it possible to interpret in a new way the influence of different, in essence, training influences on the organization of movement control. The fundamental difference is in the transition to assessing the probability of sensory information when performing voluntary movements, instead of the traditional performance assessment.

References

1. Christiansen L., Thomas R., Beck M.M. et al. (2019) The Beneficial Effect of Acute Exercise on Motor Memory Consolidation is Modulated by Dopaminergic Gene Profile. J Clin Med.;8(5):578.
2. Clark A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. Behavioral and Brain Sciences, 36, 181-204.
3. Dikunets M., Dudko G., Glagovsky P., Mamedov I. (2020) Simultaneous quantitation of plasma catecholamines and metanephrines by LC-MS/MS. J. Braz. Chem. Soc. Vol. 31, No 7. pp. 1467 – 1474.
4. Feldman H., Friston K. (2010) Attention, uncertainty, and free-energy. Frontiers in human neuroscience. V. 4. p. 215.
5. Friston K. (2010). The free-energy principle: a unified brain theory? Nat Rev Neurosci 11(2):127.
6. Friston, K. (2011). What is optimal about motor control? Neuron,72(3), 488-498.
7. Trends Cogn Sci 13(7):293–301.
8. Hohwy J. (2013). The predictive mind. Oxford University Press.
9. Mang C.S., McEwen L.M., MacIsaac J.L., Snow N.J., Campbell K.L., Kobor M.S., Ross C., & Boyd L.A. (2017). Exploring genetic influences underlying acute aerobic exercise effects on motor learning. Scientific reports, 7(1), 12123.
10. Rescorla M. (2015) Bayesian perceptual psychology. In: The Oxford handbook of philosophy of perception, New York, NY: Oxford University Press, pp. 694–716.
11. Shestakov M.P. (2012) Stabilometry in sport. Palmarium Academic Publishing, 116 p.
12. Shevtsova I.G.., Navolotskii A.A., Eremich N.A., Shestakov M.P. (2020) Way of Assessing an Athlete's Upright Posture Control while Performing Tracking Movements. Vestnik Moskovskogo Universiteta, Seriya 15: Vychislitel'naya Matematika I Kibernetika, , No. 4, pp. 46–60.