AN ARTIFICIAL SENSORY COMPONENT IN A MAN–MACHINE SYSTEM WITH COMBINED FEEDBACK

O. V. Kubryak* and S. V. Kovalchuk**

*National Research University Moscow Power Engineering Institute, Moscow Russia
**ITMO University, Saint Petersburg, Russia

*✉ kubriakov@mpei.ru, **✉ kovalchuk@itmo.ru

Abstract. This paper proposes a conceptual approach to constructing combined feedback in a human–machine interaction system through introducing an artificial sensory feedback component controlled by a technical subsystem. The approach is intended to systematize the role of combined feedback in the control of multi-agent systems with additional elements, humans, and artificial agents. This approach is studied for human vertical posture control and in synthetic experiments (within the CartPole model) considered using reinforcement learning as an example. The efficiency of the control problem solution is investigated by varying the characteristics of information transmission channels and the properties of the artificial sensory feedback component. According to the results, natural experiment observations are conceptually similar to those of the artificial numerical experiment in terms of additional feedback channel operation: there are a similar overshoot effect and prospects for improving control performance by tuning the artificial sensory component.

Keywords: human–machine interaction, optimal control, feedback, reinforcement learning, multi-agent systems.

INTRODUCTION

Human–robot interactions, including multimodal ones [1], are a rapidly growing topical interdisciplinary field [2, 3]. It directly relates to the development of artificial intelligence and machine learning for various industries, particularly medicine; for example, see [4, 5]. In this field, the assessment of human states in a human–machine system can be treated as one important application. The sensory support of a human's target activity, potentially including here artificial components, is a crucial aspect that can significantly influence the efficiency of a human–machine system.

The idea of this paper is based on previous biological feedback studies (e.g., see [6]), which demonstrated that the influence of an artificial sensory component can both increase and decrease the human's performance in an instruction-driven task. Here, we endeavor to describe and extend the concept of the nature of such an artificial sensory component by presenting a general approach to the interaction between natural and artificial intelligent agents jointly solving a control task, by supporting a human (a natural intelligence agent) directly performing control. The main contribution of this paper is the idea of formalizing a feedback system that includes the main (natural) and additional (artificial) channels within the control task. The control agent model can be of any nature, which allows conducting research within artificial intelligence (AI) approaches and assessing the efficiency of solving the control task under different parameters of the feedback components. In addition, the explicit consideration of feedback in various human–machine systems should allow us to generalize this idea to a wide class of such systems and, moreover, analyze the role of such interaction in generalized multi-agent systems that include living agents (humans) and technical components.

This paper is organized as follows. After a brief review of fundamental works in the interdisciplinary field considered, bringing physiology and engineering closer together, we describe the approach proposed as well as the basic and conducted numerical experiments. Finally, the results are briefly analyzed, and the findings are summarized.

1. THE INTERDISCIPLINARY NATURE OF CONTROL IN HUMAN–MACHINE SYSTEMS

The field of human–machine interaction research is developing mainly in terms of information interaction and the design of information systems [7]. However, in some scenarios, the issue of interaction requires considering the physiological features of a human (as a “living” control system) and the technical features of a machine. Such problems may arise in robotics, the development of bionic systems (including prostheses), motor rehabilitation, etc. Thus, the interdisciplinary research area linking biology and engineering within a single interacting field becomes particularly relevant. This section provides a brief review of publications on the topic under consideration.

1.1. Subject Area Formation

Attempts to explain thinking, human actions, and organism functions based on experience in the creation of technical means have been known since ancient times. For example, Descartes metaphorically compared the organization of human activity with the work of mechanical clocks [8]. The comprehension of the theory of automatic control and, later, cybernetics, which developed rapidly in the 20th century, led to the consideration of a human operator as a kind of feedback “controller” [9]. In the pre- and post-war USSR, system ideas in life sciences were originally developed, e.g., as Anokhin’s theory of functional systems [10]. Here, the key role is given to goal-setting, the anticipation, prediction, and planning of the result, the original Russian contribution [11] illustrating the unified direction of two “branches” of the general scientific ideology of feedback, which stem from life sciences and engineering [12]. As noted by Bernstein in the early 1960s, the whole period from the publication of Wiener’s first work to our days is permeated with the search and use of analogies between living and artificial systems, the analogies that helped physiologists to comprehend the systemic relationships of the organism and gave engineers new and valuable ideas for building automata [13].

1.2. Boundaries of Physiology and Engineering

The current upsurge of global interest in AI and the development of robotics again demand the mutual approach of physiology and technology, which is manifested in attempts to generalize the available experience and develop a theoretical basis [4, 14, 15]. This also concerns part of the answers to the “watershed” question, once formulated by Bernstein: Whether this “honeymoon” of identifying and practically using analogies and similarities has been over or not, questions of the opposite direction are beginning to appear more and more often in the literature of the most recent time: after all, is there an essential, fundamental difference between living and nonliving systems? If it exists, where is the watershed forming the boundary between the two? [13]. This question can be slightly modified: find conditions under which the interaction between living and artificial would be provided by something that can be compared, very conditionally, with “biological convergence” (a kind of approach or even overlapping of control systems). That is, for example, when the human activity specified by an instruction is “included” in the loop of the control system common with the machine, and the result of the technical system of machine control is close to the final useful effect of the common system [6]. In this case, it is possible to obtain measurable parameters of such a “common” system, which would more accurately describe the living system and its action (compared to a single-value characteristic, e.g., body temperature), approaching the digital twin concept in technology. The corresponding approaches can be based on the ideas of anticipation and prediction capabilities, inherent in living systems and, apparently, in developed AI [16].

1.3. Biological Feedback and Sensory Redistributions

Besides the usually perceived signaling from sensory organs, biological feedback implies additional information for a tested human about some of his/her physiological parameters (recorded by a device); thus, a machine indirectly participates in organizing the control process for some organism’s function. This can be an image displayed to the tested human on the screen, connected with signals of electroencephalogram, electrocardiogram, pneumogram, etc., or, as in the example provided in [6], biomechanical parameters displaying the positions of the common center of pressure (aerodynamic center) of a standing human on a support. As is believed today, a human conditionally has no “center-of-gravity sensor” in the form of a separate organ. Natural vertical (upright) posture control is based on the analysis of complex information from vision, vestibulars, and proprioceptors. Two different levels can be distinguished in the posture control system [17]: one level concerns the distribution of tonic muscle activity (posture) whereas the second the compensation of internal or external perturbations (balance). Thus, when considering, e.g., Anokhin’s scheme of a functional system [10] (a biological concept close to cybernetic ideas [12]), in the context of human upright posture regulation, we can discuss two separate “functional systems” referring to upright posture deflections. In both cases (posture and balance), the natural sensory component of regulation is represented by the same sensitive organs, the activity of which differs between modes. For example, in the case of upright standing, vestibulars “turn on” when the head is tilted. With varying conditions, the “sensory weight” of signals coming to the brain through different channels changes, including the modeling of reduced gravity by placing the human body on a special bench parallel to the real “surface of the planet” (and at an angle to the conditional one). In this case, a new representation of verticality is formed independent of the otoliths of the vestibular apparatus; as is believed, this representation is based on support afference according to the generalization of Kozlovskaya’s works [18]. When a human is on an inclined surface under “normal” conditions, sensory reweighting for balance control is thought to be based on the rate of deflection [19]. The occurrence of posture oscillations in healthy humans during quiet standing may be due to “vestibular noise” when the vestibular contribution to balance is higher [20].

As is also known, some sensory channels can exert a more powerful influence on the regulation of the function in humans; in this regard, researchers emphasize the role of vision in upright posture regulation [6, 21]. The phenomena of sensory reweighting and the peculiarities of sensitive organs functions demonstrate the adaptability of the living control system, sensitivity and receptivity to new conditions, and the multichannel nature.

2. RESEARCH METHODS

2.1. Artificial Sensory Component Formation

In connection with the above range of problems, the idea of an artificial sensory feedback component includes the possibility of organizing intentional sensory reweighting in the standardized (instruction-defined) activity of a tested human using biological feedback technologies. In this paper, it is realized by adding the objectively measured information function, significant for regulation, into the selected natural sensory channel. One way to realize the idea is creating an intentional dominance of vision in upright posture control (Fig. 1). Here, the addition of artificial sensory components can provide the purposeful, different from natural (conventional), sensory provision of the function, with the possibility of constructing and accurately quantifying the parameters of the artificial part. External sensors—the force sensors of the stability plate where a human stands—register data on the position of the aerodynamic center on the support, and the tested human receives visual program-generated information on holding a given posture or deflections on the screen.

In addition to the “functional system,” Bernstein’s ring [13] can be considered the conceptual precursor of an artificial sensory feedback component. This ring concept can be also supplemented by a conditional artificial sensory feedback component in an instruction-driven task. When an instruction is explicitly presented and executed, the goal of regulating the stability and controllability of upright posture converges with the goal of executing the instruction. In this case, a human–machine system includes an artificial receptor precisely linked to the properties of the useful effect (upright posture regulation) associated with instruction execution. When describing such a human–machine control system in more general terms, we can distinguish classical basic stages: receiving information about the control task, receiving information about the control result, analyzing the information received, and executing the solution.

2.2. The Real Dataset for Modeling

Real data from an observation carried out in compliance with modern ethical standards were used as benchmark data. The observation was supervised by Kubryak and described in detail in [6]. The dataset contained 25 young, almost healthy volunteers, namely, 10 women and 15 men, with an average age of 23 years. The original research procedure included the use of a visual biological feedback channel based on the support response to regulate the tested human’s upright posture (similar to the scheme in Fig. 1) in different modes (with the different sensitivity of the corresponding feedback, i.e., “depth,” “scale”) as well as control stages. The procedure was carried out in the following sequence.

Step 1 (the “R1o” phase): upright standing, feet on the force plate marking, gazing in front of oneself at the black screen, and arms free along the body, for 1 min.

Step 2 (the “R1c” phase): upright standing, feet on the force plate markings, eyes closed, and arms free along the body, for 1 min.

Step 3 (the “K = 15” phase): upright standing, feet on the force plate marking, gazing in front of oneself at the screen with the common aerodynamic center marker, and arms free along the body, in the biological feedback mode based on the support reaction, with the feedback depth characterized by a 15% increase of the normal conversion coefficient, for 1 min.

Steps 4-7. Similar to Step 3, but with the conversion coefficients sequentially increased by 15%, i.e., the phases encoded by “K = 30,” “K = 45,” “K = 60,” and “K = 75.”

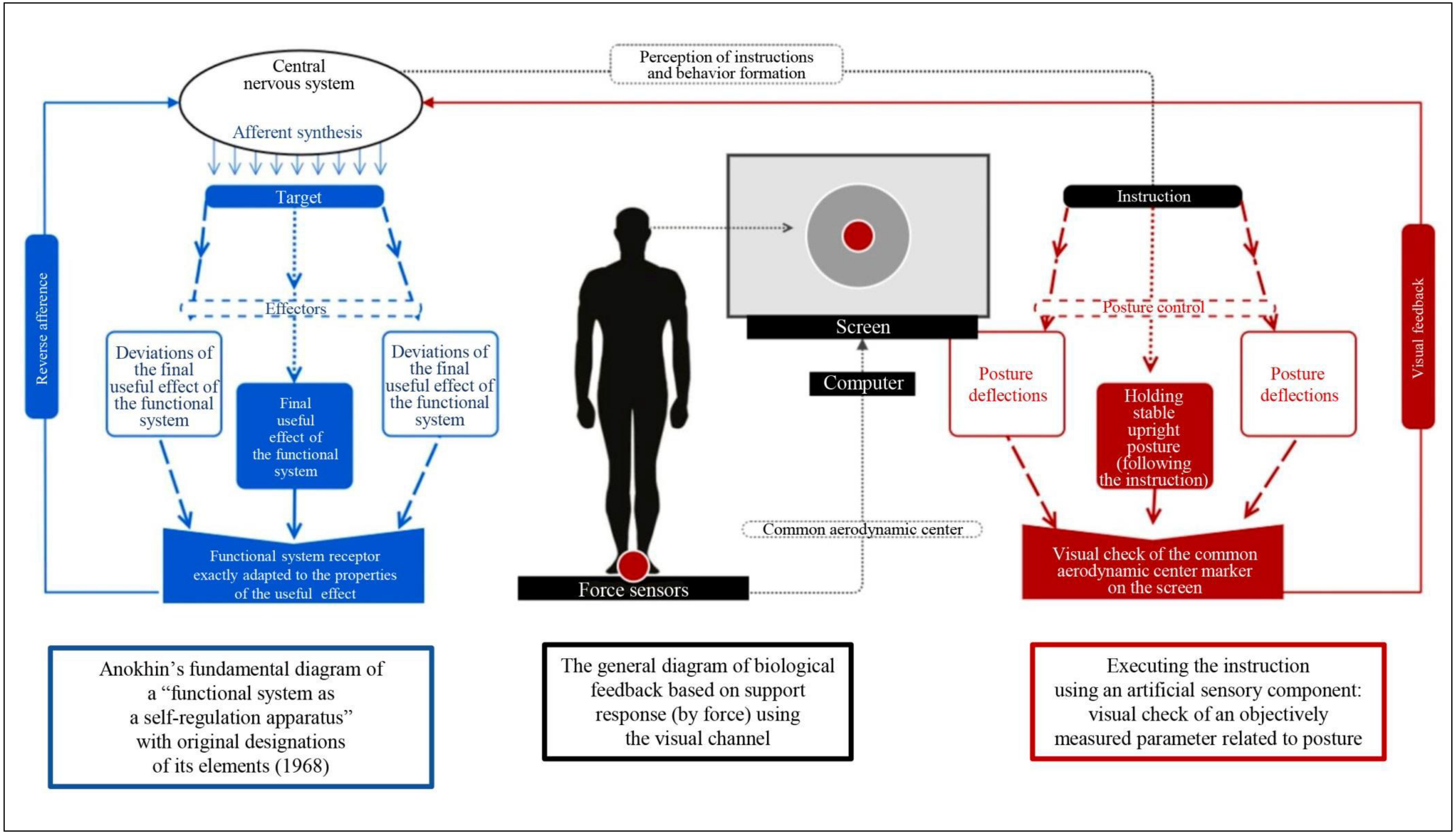

Fig. 1. An example of analogy: Anokhin's fundamental diagram of a functional system (left) **and a diagram with an artificial sensory feedback component included in an instruction-driven behavior (right).**

Steps 8 and 9. Repetition of Phases 1 and 2, encoded by "R2o" and "R2c."

In addition, the following conditions were met:

• During the controlled phases, the circle marker was kept in the target zone (the center of the circular target).

• A one-minute rest break was ensured between all phases.

The procedure was implemented using certified equipment, namely, an ST-150 stabilometric system with STPL software (Russia; Registration Certificate of the Federal Service for Surveillance in Healthcare (Roszdravnadzor) no. FSR 2010/07900 dated March 01, 2016; Pattern Approval Certificate of Measuring Instruments RU.C.39.004.A no. 41201). The result of the tested humans was estimated automatically in the STPL program in special units, which reflect the number of registered (discrete) holds of the common aerodynamic center marker in the target zone for one period relative to the maximum possible result. The dataset under analysis [6] included the numerical values of the result achieved by the tested humans in controlling their upright posture in the instruction-driven task of holding the common aerodynamic center marker, visible on the screen, in the target zone for each posture control mode.

2.3. The Multi-Agent Control System and Model Selection for Numerical Experimentation

When considering AI-based engineering solutions for interaction with humans (robots, bionic systems, medical devices, etc.), it is important to formulate the principles of interaction of an artificial intelligence agent (AIA) as a technical system complementing the capabilities of a natural intelligence agent (NIA, i.e., a human). In such situations, concepts like, e.g., hybrid augmented intelligence are often considered [22]. In technical systems, this issue concerns information processes and, moreover, the specifics of physical and biological feedback (see subsection 1.3). In these conditions, we should emphasize the intervention of intelligent agents in the operation of human's own control systems. Figure 2 illustrates the idea of a hybrid control system with several AIA influence vectors. The system state measurement by the NIA (the measuring unit M1) is the main control loop, which determines the internal feedback channel (FB1). In this case, AIA operates "outside" this loop but, nevertheless, has several possibilities to control the system using its own observation channel (the measuring unit M2). First, in several scenarios, AIA can perform joint control of the system (the channel C1). Examples of such solutions are automated control systems for technical objects (autopilots, control correction systems, etc.). Second, AIA can influence the human feedback channel (FB1), supplementing or modifying it (the channel C2). A typical example is augmented reality systems that modify visual information available to a human. Finally, AIA can form its own channel (C3) of the feedback loop (FB2), providing fundamentally different additional information.

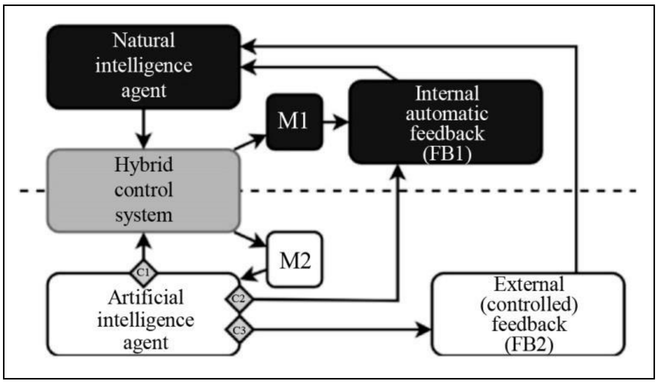

Fig. 2. Feedback channels in a hybrid two-agent system.

An example when the channel C3 becomes especially important is a system with limited access to the channels C1 and C2. This situation may arise due to no access, in principle, to the channels (e.g., when analyzing a control system with physiological feedback, i.e., regulation based on the vestibular apparatus, various parameters of well-being, etc.) or an external restriction (e.g., direct intervention ban for the reasons of ethics, safety, individual preferences). In this paper, operation with the channel C3 is a key opportunity to intervene in NIA control processes.

Note that, in general, the man–machine system can include many agents of each category (NIA and AIA). The artificial nature of AIA allows implementing additional mechanisms of controlled feedback via the feedback channels under consideration. The feedback structure and parameters can be optimized based on the collective efficiency of such multi-agent systems and their emergent properties [23]. In this case, the iterative change of systems enables adapting the AIA microparameters to improve efficiency at the system level (macro level) rather than within the local interaction of a pair of agents.

In the scenario of the basic observation [6], the task of the tested human is to hold a stable upright posture with an augmented (artificial) feedback component. In this case, FB1 is realized using sensory information from proprioceptors and vestibulars, and FB2 is realized through visual information. A fundamental question arises: how should one determine the optimal FB2 structure under a considerable error in the measurements of both M1 and M2? Accordingly, we attempted to assess the efficiency of this feedback channel by analyzing experimental observations and setting up a similar experiment in a reinforcement learning framework. By assumption, the measurements are the agent's observations $\mathcal{O}_1 = \mathcal{S} + \varepsilon_1$ and $\mathcal{O}_2 = \mathcal{S} + \varepsilon_2$ of the system state $\mathcal{S}$ via the FB1 and FB2 channels with some errors ε_1 and ε_2, respectively. The agent can choose actions based either on FB1 alone ($\mathcal{O}_1 \to \mathcal{A}$) or on the combination of observations ($\mathcal{O}_1 \times \mathcal{O}_2 \to \mathcal{A}$). Here, $\mathcal{A}$ denotes the agent's *action* space.

To develop a synthetic example of reinforcement learning, we used the classical CartPole model [24]: control a moving cart balancing a vertically mounted pole. This model was chosen for two reasons. First, it represents a benchmark example of reinforcement learning and optimal control problems, widely studied both in terms of system modeling and building physical systems (robots). Second, this balance holding model seems to be quite close to the human balance holding task [6], studied here as an example of a target feedback control problem. The system state $\mathcal{S}$ is described by a quadruple $s = (x, v_x, \theta, v_\theta)$ with the following notation: x is the horizontal coordinate of the cart; v_x is the horizontal velocity of the cart; θ is the deflection angle of the pole from the vertical position; finally, v_θ is the angular velocity of the pole relative to the vertical position. The action space consists of two actions, $\mathcal{A} = \{0, 1\}$, defining the application of force (pushing) to the cart to the left and right, respectively. In the example under consideration, the FB1 channel observation was constructed as a noisy measurement of the system state: $o_1 = s + \mathcal{N}(0, \sigma_1)$. For the artificial FB2 component, the pole deflection angle θ was specified by $o_2 = (\theta + \mathcal{N}(0, \sigma_2))a$, with the possibility to use the gain a. Here, the Gaussian noises $\mathcal{N}$ with zero mean and the standard deviations σ_1 and σ_2, respectively, are added to the observed state.

A two-layer fully connected neural network was implemented as the simplest reinforcement learning agent. The input layer of the network receives the concatenated observations $o_1 \oplus o_2$ of dimension 5. The inner layer consists of 128 neurons with the ReLU activation function. The output layer is an action classifier of dimension 2 (according to the dimension of the space $\mathcal{A}$) with the SoftMax activation function. The network was trained on synthetic data with variation of the noise levels of the FB1 and FB2 channels (σ_1 and σ_2). Reinforcement learning was performed using the Gymnasium library[1], which implements the logic of the CartPole experiment in the same-name environment. The Adam optimizer from the Keras library[2] was used for training (with a learning rate of 0.01 and the categorical cross-entropy loss function). The training session took place within 300 epochs, each representing an experiment with the given parameters σ_1 and σ_2. The Policy Gradient method was implemented for training with the gradient descent coefficient $\alpha = 10^{-4}$ and the reward discount coefficient $\gamma = 10^{-4}$. The total (undiscounted) reward was selected to estimate the efficiency of the control problem solution. To manage the experiment, values from the set $\{0,\ 10^{-2},\ 10^{-3},\ 10^{-4}\}$ were taken. The logic of the benchmark experiment corresponded to situations where $\sigma_1 > \sigma_2$. Scenarios with the presence and absence of the feedback component o_2 were used to simulate the optionality of the FB2 channel during agent training. (For the epochs with even numbers, $a = 0$.)

The trained model was used in an assessment experiment with checking the agent's efficiency in a noisy environment with different gains a. For the checking procedure, the trained models were executed similarly in CartPole with varying:

– the feedback noise coefficients σ_1 and σ_2 (different values from the training set);

– the gain a (in the range $[0, 300]$ with a step of 20).

For robustness, each assessment experiment was repeated five times with the results averaged. As a result, we assessed the influence of both the feedback channel noise (coinciding with or differing from the noise during training) and the gain on control performance.

From an experiment interpretation viewpoint, the assessment process can be treated as placing the agent in artificially formed augmented feedback conditions differing from his/her common (trained) ones. For example, in the experiment with the task of maintaining posture stability, an additional visual feedback component is formed by shifting the aerodynamic center in the support, in addition to the full (basic) observation in the form of a sensory component that includes this component as well as many others. Not fully reproduc-

[1] Gymnasium Documentation. URL: https://gymnasium.farama.org/ (Accessed October 1, 2024.)

[2] Keras. URL: https://keras.io/ (Accessed October 1, 2024.)

ing the balance holding scenario, this analogy nevertheless allows comparing control performance changes due to varying the values of the additional feedback component characteristics. In the next section, we consider the assessment results in comparison with the benchmark experiment.

3. EXPERIMENTAL ASSESSMENTS

3.1. Structuring the Benchmark Experiment Assessments

According to the benchmark experiment focused on assessing the efficiency of visual feedback [6], a significant rise in its gain worsens control performance (in the case under consideration, the task of holding a stable upright posture by a human). An overshoot occurs when increasing the sensitivity ("scale," "depth") of the feedback by about 20% or more. This approximately matches the properties of transients in linear automatic control systems. Compared to balance holding only by internal assessment with natural sensors, the presence of feedback outside of overshoot has often a positive influence on control performance. Note also that the effects manifested differently between humans. Probably, this can be explained by individual peculiarities: to reduce overshoot, it is necessary to decrease the speed of reaching a new state by the system, which leads to a higher regulation time (and smaller values of posture control characteristics in a given period).

According to a more detailed analysis, the reduction in control performance differs in intensity and time; see Fig. 3a, representing control performance in conditional units depending on the gain of the artificial visual feedback component for 25 tested humans). Within the study, the reduction curves were parameterized by the logistic curve $Y(x) = L/\left(1+e^{-k(X_0-x)}\right)$. As was established (Fig. 3b), "smoothness" (corresponding to the parameter k) and "delay" (corresponding to the parameter X_0 , interpreted as a half decrease in control performance) generally have an inversely proportional relationship. The scale parameter L in the experiment was equal to 107, which corresponds to the maximum control performance observed in the dataset (according to the original measurement methodology [6]).

3.2. Implementation of Artificial Intelligence Agents

The behavior of reinforcement learning agents in the CartPole task demonstrates clear reward degradation under feedback scaling. Figure 4 shows the cumulative reward reduction as a function of the gain a for different values of the parameter σ_2 and $\sigma_1 = 10^{-3}$ (Fig. 4a) and different values of σ_1 and $\sigma_2 = 10^{-3}$ (Fig. 4b). The resulting data can be interpreted as follows. When varying the noise level of the artificial feedback FB2 (see Fig. 4a), the earlier reduction in the cumulative reward is typical for the models with $\sigma_2 = 0$ (i.e., those expecting the exact value of FB2 without noise) and the models with $\sigma_2 = 10^{-3}$ (i.e., $\sigma_2 = \sigma_1$, presumably due to the inconsistency of the

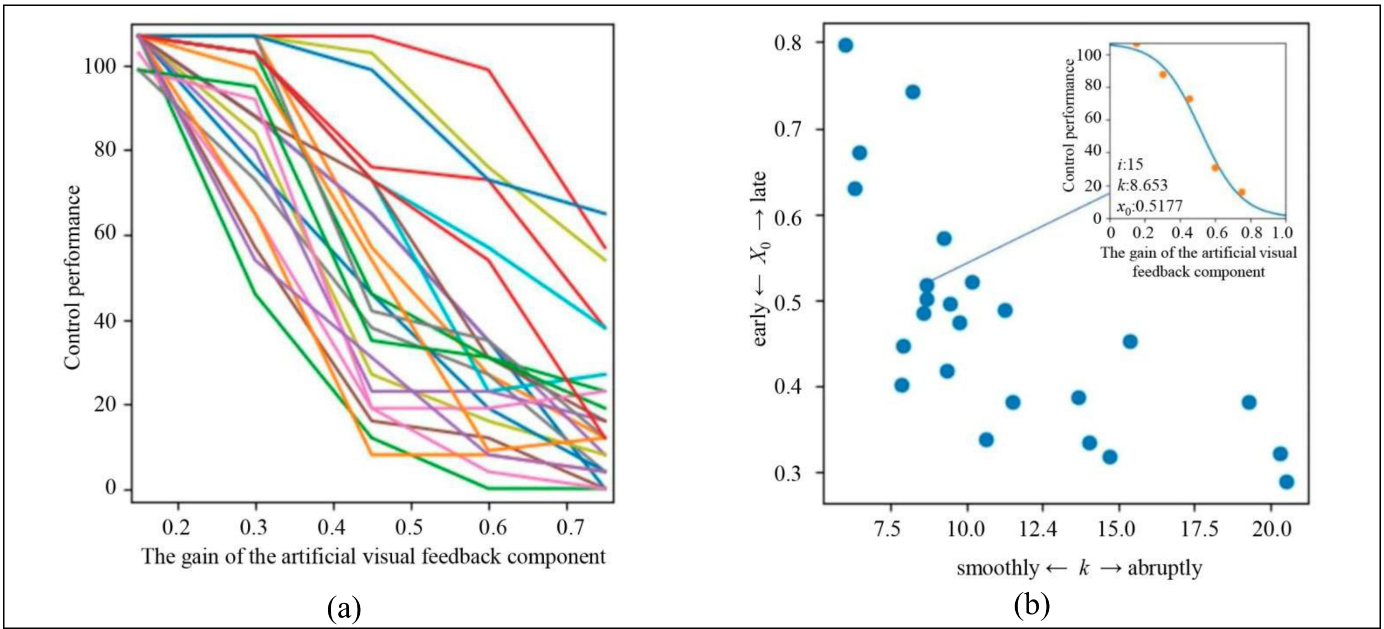

Fig. 3. Regulation and overshoot in the assessed feedback influence of tested humans under experimental conditions: (a) reduced control performance for different tested humans and (b) the parameterization results of the control performance reduction curves for different tested humans.

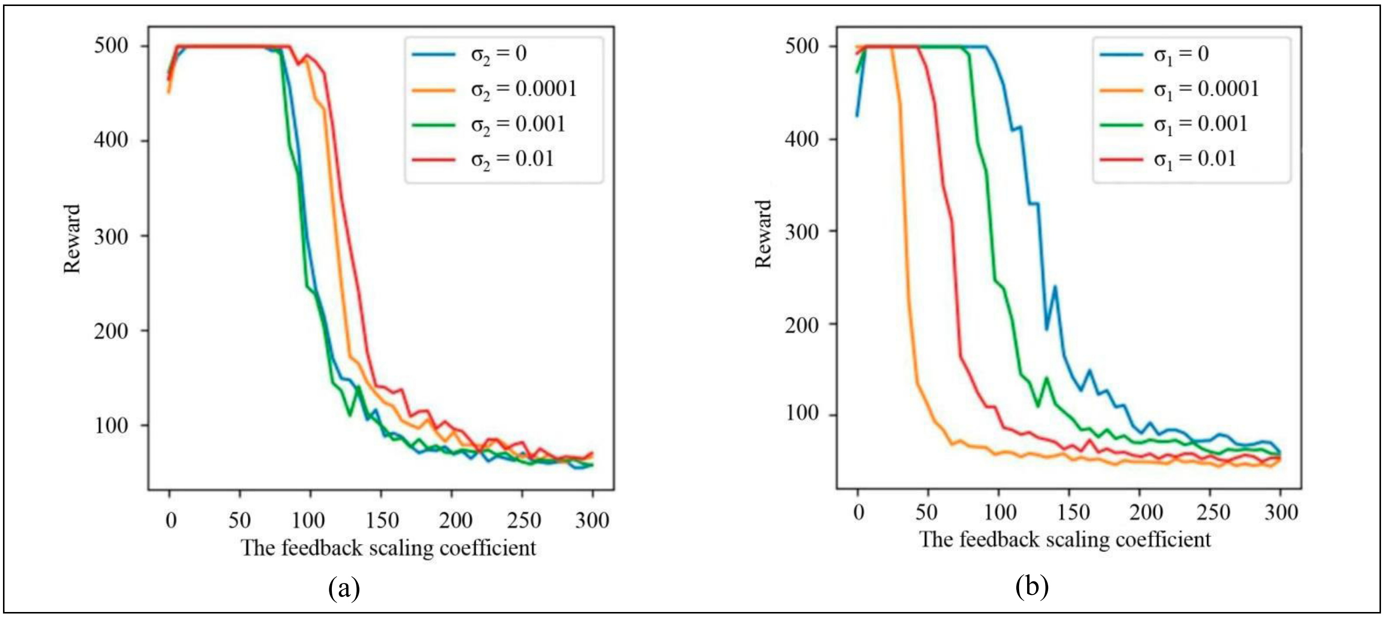

Fig. 4. Assessed feedback influence in reinforcement learning: (a) when varying the noise level of the artificial feedback FB2 and (b) when varying the noise level of the basic feedback FB1.

unamplified and amplified signals in FB1 and FB2, respectively). When varying the noise level of the basic feedback FB1 (see Fig. 4b), in contrast, these options are characterized by the latest performance reduction due to the possibility of the best recovery of the system state.

At the same time, it seems interesting to note the observed relationship between the noise levels of the FB1 and FB2 signals, in terms of their connection with the effective feedback scaling influence. Figure 5 shows the change of the FB2 scaling value that decreases control efficiency (cumulative reward) twofold

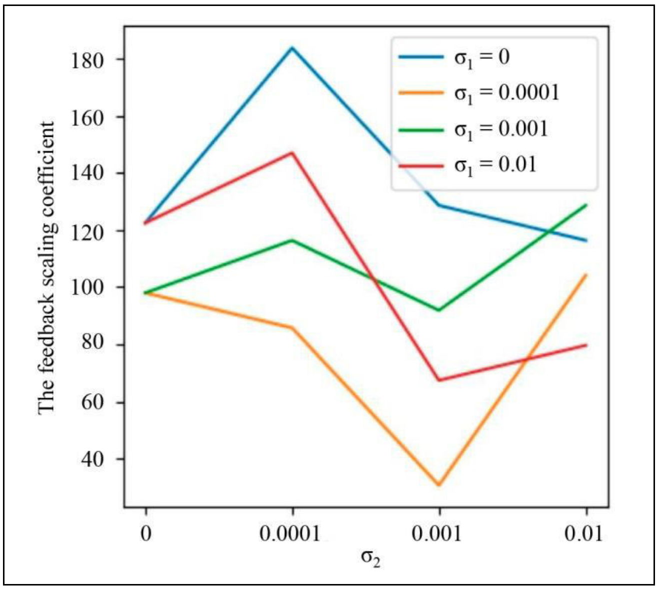

Fig. 5. Feedback scaling of feedback with a twofold reward reduction.

depending on the noise levels of the FB1 and FB2 signals. Presumably, certain "phase transitions" in terms of control performance in different states can be observed in the behavior of the considered system.

DISCUSSION AND CONCLUSIONS

A striking example of multisensory integration for the human's self-perception of the body or its part is "rubber hand" experiments: under illusion conditions, the tested human perceives a dummy as his/her hand [25]. According to the authors, this illusion can also be compared with the ideas about sensory reweighting. As is believed, the probability of the rubber hand illusion increases with proprioceptive noise (the signal from muscles, ligaments, etc.) and fits well with the Bayesian model of causality. This noise can be described by a change in the a priori probability of activity for the central part of the visual and proprioceptive analyzer [26]. In other words, under certain conditions, the brain's analysis of incoming information treats as "its own" some additional information that can only be passed off as "its own" (in the case of an illusion) or understood as "external" but overcoming the conditional boundary of "its own" (in the case of the artificial sensory component paradigm proposed in this paper). Note that increasing the share of uncertainty (deficit of suitable signaling) of sensory support "switches" the analysis to the use of additional information. This allows organizing "rubber hand illusion" experiments as well as other experiments with artificial sensory support components of a certain activity and, moreover, expanding the ideas of the boundaries and interaction of "living" and "inanimate" in man–machine systems and the adaptability of the human brain.

According to the individual peculiarities of posture control based on the benchmark data [6], the behavior of a man–machine system (one of the variants) is similar to linear automatic control systems. In particular, overshoot and changes in the system performance are observed. Similar effects have been discovered both in numerical "artificial" experiments and in observations with human participation. As we believe, this fact points to the conceptual similarity of the observed effects. An important aspect of this paper is the quantifiable characteristics of artificial components; in the future, it may yield a more accurate description of the states of a man–machine system and its main link (human). The second important conclusion is the possibility of incorporating artificial intelligence agents in the control system of man-machine systems (see the diagram in Fig. 3), with the possibility of optimizing the functional structure and parameters of the feedback channels to improve the efficiency of the multi-agent system (in the general case) at the macro level. Shortly, this possibility may be valuable, e.g., in medical rehabilitation via replacing or supporting the deficient functions of the patient by introducing adaptive combined feedback elements.

Acknowledgments. *This work was supported by the Russian Science Foundation, project no. 24-11-00272.*

REFERENCES

1. Su, H., Qi, W., Chen, J., et al., Recent Advancements in Multimodal Human–Robot Interaction, *Frontiers in Neurorobotics*, 2023, vol. 17, art. no. 1084000.
2. Belhassein, K., Fernandez Castro, V., Mayima, A., et al., Addressing Joint Action Challenges in HRI: Insights from Psychology and Philosophy, *Acta Psychologica*, 2022, vol. 222, no. 1, art. no. 103476.
3. Leichtmann, B., Nitsch, V., and Mara, M., Crisis Ahead? Why Human–Robot Interaction User Studies May Have Replicability Problems and Directions for Improvement, *Frontiers in Robotics and AI*, 2022, vol. 11, no. 9, art. no. 838116.
4. Al-Hamadani, M., Fadhel, M.A., Alzubaidi, L., and Harabgi, B., Reinforcement Learning Algorithms and Applications in Healthcare and Robotics: A Comprehensive and Systematic Review, *Sensors*, 2024, vol. 24, no. 8, art. no. 2461.
5. Knudsen, J.E., Ghaffar., U., Ma, R., and Hung, A.J., Clinical Applications of Artificial Intelligence in Robotic Surgery, *Journal of Robotic Surgery*, 2024, vol. 18, no. 1, art. no. 102.
6. Kubryak, O.V., Panova, E.N., and Kriklenko, E.A., Effect of Biological Feedback Depth on the Performance of Instruction by Healthy Volunteers, *Human. Sport. Medicine*, 2018, vol. 18, no. S, pp. 19–26. DOI: 10.14529/hsm18s03 (In Russian.)
7. *Foundations and Fundamentals in Human-Computer Interaction*, Stephanidis, C. and Salvendy, G., Eds., Boca Raton: CRC Press, 2024.
8. Sokolov, V.V., *Filosofiya Rene Dekarta* (René Descartes' Philosophy), Moscow: Gospolitizdat, 1950, pp. 5–76. (In Russian.)
9. Tustin, A., The Nature of the Operator's Response in Manual Control, and Its Implications for Controller Design, *Journal of the Institution of Electrical Engineers – Part IIA: Automatic Regulators and Servo Mechanisms*, 1947, vol. 94, no. 2, pp. 190–206.
10. Anokhin, P.K., *Biologiya i neirofiziologiya uslovnogo refleksa* (Biology and Neurophysiology of the Conditioned Reflex), Moscow: Meditsina, 1968. (In Russian.)
11. *Anticipation: Learning from the Past: The Russian/Soviet Contributions to the Science of Anticipation*, Nadin, M., Ed., Cham: Springer, 2015.
12. Novikov, D.A., *Cybernetics: From Past to Future*, Cham: Springer, 2016.
13. Bernstein, N.A., *Novye linii razvitiya v fiziologii i ikh sootnoshenie s kibernetikoi* (New Lines of Development in Physiology and Their Relationship to Cybernetics), Moscow: Institute of Philosophy, the USSR Academy of Sciences, 1962. (In Russian.)
14. Gunes, H., Broz, F., Crawford, C., et al., Reproducibility in Human-Robot Interaction: Furthering the Science of HRI, *Current Robotics Reports*, 2022, vol. 3, no. 3, pp. 281–292.
15. Scibilia, A., Pedrocchi, N., and Fortuna, L., Human Control Model Estimation in Physical Human–Machine Interaction: A Survey, *Sensors*, 2022, vol. 22, no. 5, art. no. 1732.
16. Kubryak, O.V., Kovalchuk, S.V., and Bagdasaryan, N.G., Assessment of Cognitive Behavioral Characteristics in Intelligent Systems with Predictive Ability and Computing Power, *Philosophies*, 2023, vol. 8, no. 5, art. no. 75.
17. Ivanenko, Y. and Gurfinkel, V.S., Human Postural Control, *Frontiers in Neuroscience*, 2018, vol. 20, no. 12, art. no. 171.
18. Levik, Yu.S., Space Researches and New Concepts in the Physiology of Movements, *Aerospace and Environmental Medicine*, 2020, vol. 54, no. 6, pp. 80–91. (In Russian.)
19. Missen, K.J., Carpenter, M.G., and Assländer, L., Velocity Dependence of Sensory Reweighting in Human Balance Control, *Journal of Neurophysiology*, 2024, vol. 232, no. 2, pp. 454–460.
20. Karmali, F., Goodworth, A.D., Valko, Y., et al., The Role of Vestibular Cues in Postural Sway, *Journal of Neurophysiology*, 2021, vol. 125, no. 2, pp. 672–686.
21. Assländer, L. and Peterka, R.J., Sensory Reweighting Dynamics Following Removal and Addition of Visual and Proprioceptive Cues, *Journal of Neurophysiology*, 2016, vol. 116, no. 2, pp. 272–285.
22. Zheng, N., Lui, Z., Ren, P., et al., Hybrid-augmented Intelligence: Collaboration and Cognition, *Frontiers of Information Technology & Electronic Engineering*, 2017, vol. 18, no. 2, pp. 153–179.
23. Guleva, V., Shikov, E., Bochenina, K., et al., Emerging Complexity in Distributed Intelligent Systems, *Entropy*, 2020, vol. 22, no. 12, art. no. 1437.
24. Barto, A.G., Sutton, R.S., and Anderson, C.W., Neuronlike Adaptive Elements That Can Solve Difficult Learning Control Problems, *IEEE Transactions on Systems, Man, and Cybernetics*, 1983, vol. SMC-13, no. 5, pp. 834–846.
25. Botvinick, M., Cohen, J. Rubber Hands 'Feel' Touch That Eyes See, *Nature*, 1998, vol. 391, p. 756.
26. Chancel, M. and Ehrsson, H.H., Proprioceptive Uncertainty Promotes the Rubber Hand Illusion, *Cortex*, 2023, vol. 165, pp. 70–85.

This paper was recommended for publication by O.P. Kuznetsov, a member of the Editorial Board.

Received October 11, 2024, and revised December 23, 2024.
Accepted December 26, 2024.

Author information

Kubryak, Oleg Vital'evich. Dr. Sci. (Biol.), National Research University Moscow Power Engineering Institute, Moscow, Russia
✉ kubriakov@mpei.ru
ORCID iD: https://orcid.org/0000-0001-7296-5280

Kovalchuk, Sergey Valer'evich. Cand. Sci. (Eng.), ITMO University, St. Petersburg, Russia
✉ kovalchuk@itmo.ru
ORCID iD: https://orcid.org/0000-0001-8828-4615

Cite this paper

Kubryak, O.V. and Kovalchuk, S.V., An Artificial Sensory Component in a Man–Machine System with Combined Feedback. *Control Sciences* **6,** 22–31 (2024).

Translated into English by *Alexander Yu. Mazurov*,
Cand. Sci. (Phys.–Math.),
Trapeznikov Institute of Control Sciences,
Russian Academy of Sciences, Moscow, Russia
✉ alexander.mazurov08@gmail.com