HOW DOES THE NEUROMUSCULAR SYSTEM UTILIZE SENSORY FEEDBACK FOR THE CONTROL OF SKILLED MOVEMENTS IN SPORT? A PERSPECTIVE

Peter Federolf

Department of Sport Science, University of Innsbruck, Innsbruck, Austria

This perspective article explores concepts for how sensory information is utilized by the neuromuscular system for the correction of ongoing movements within the sports domain, highlighting its significance for movement stability, accuracy, precision, injury prevention, and performance enhancement. This paper aims to introduce a simplified model for feedback control and discusses implications of this model and approaches for experimental corroboration.

KEYWORDS: Optimal feedback control theory, efferent copy, state estimator, automatized movement, skilled movement.

INTRODUCTION: Many important questions in sports biomechanics—e.g., about stability, precision and accuracy of movement, about injury mechanisms and injury prevention, or about performance and performance improvement—involve a fundamental understanding of how the neuromuscular system controls movement. In the last decades, the neurosciences have made substantial progress in the development of tangible motor control theories. One such theory is the Optimal Feedback Control Theory (OFCT) (Todorov & Jordan, 2002), which, on the one hand, interprets the control of human motion as an optimization problem, and on the other hand, provides a model for how sensory feedback information can be utilized for the control and corrections of ongoing movements. However, to date, only very few studies in the sports sciences are based on or explore this theory (van Andel et al., 2021).
The aim of the current perspective article is to synthesize a simplified model derived from OFCT and related concepts, illustrating how sensory feedback could be utilized to control and correct ongoing movements in the context of sports—i.e., in highly automatized and skilled movements, which are the result of extensive practice. Some implications of this model for sports related movements are discussed, as well as experimental approaches and findings that support the suggested perspective.

MODEL: Some of the defining papers on OFCT were presented by Todorov & Jordan (2002) and Todorov (2004). For the context of skilled or automated movements as in sports, van Andel and colleagues present a control model schematic with two loops (Figure 1 in (van Andel et al., 2021)). The coordination loop programs the optimal feedback controller and sets the boundary conditions for each movement. It thus defines the movement task and produces the necessary motor commands for its execution (van Andel et al., 2021). The function of the second loop, the control loop, is to utilize sensory feedback information for the correction of ongoing movements. Key component of this secondary loop is the state estimator, whose function is the focus of the current paper. The schematic in Figure 1 shows both loops with the state estimator (grey box) expanded to include representations of internal mechanisms.
The state estimator receives as input the afferent sensory information about the state of the body (biomechanical system) provided by the various sensory systems. It also receives a copy of the outgoing motor commands (“efference copy”), from which it calculates an internal model, i.e. a neural simulation of the biomechanical system and of its future states (Wolpert, Ghahramani, & Jordan, 1995). In the control of ongoing movements, the internal model allows for predicting the sensory signals associated with predicted future states (Wolpert et al., 1995). The comparison of incoming sensory information (Figure 1, yellow box in the state estimator) with the predicted sensory signals (left green box) allows for fast recognition of deviations in the movement execution (Crevecoeur & Scott, 2014).

In sports, movements become highly automatized and skilled through extensive practice and learning (Wolpert, Diedrichsen, & Flanagan, 2011). For automated movements the internal model does not only produce predictions of expected sensory states for the correct movement execution, but it has also learned to anticipate typical deviations from the correct movement execution. For those deviations that require correction, the state estimator can then prepare a signature sensory pattern that identifies the deviation (Figure 1, green boxes on the right), together with motor command modifications (blue circles), that correct for this deviation. If the comparison between sensory deviation signature and the incoming afferent sensory information is positive, then the pre-prepared motor command modifications launch immediately to correct the deviation (Figure 1, fourth deviation pattern). In other words, for automatized movement, the motor control system creates repertoires of expected sensory states coupled with pre-prepared corrective motor command modifiers.

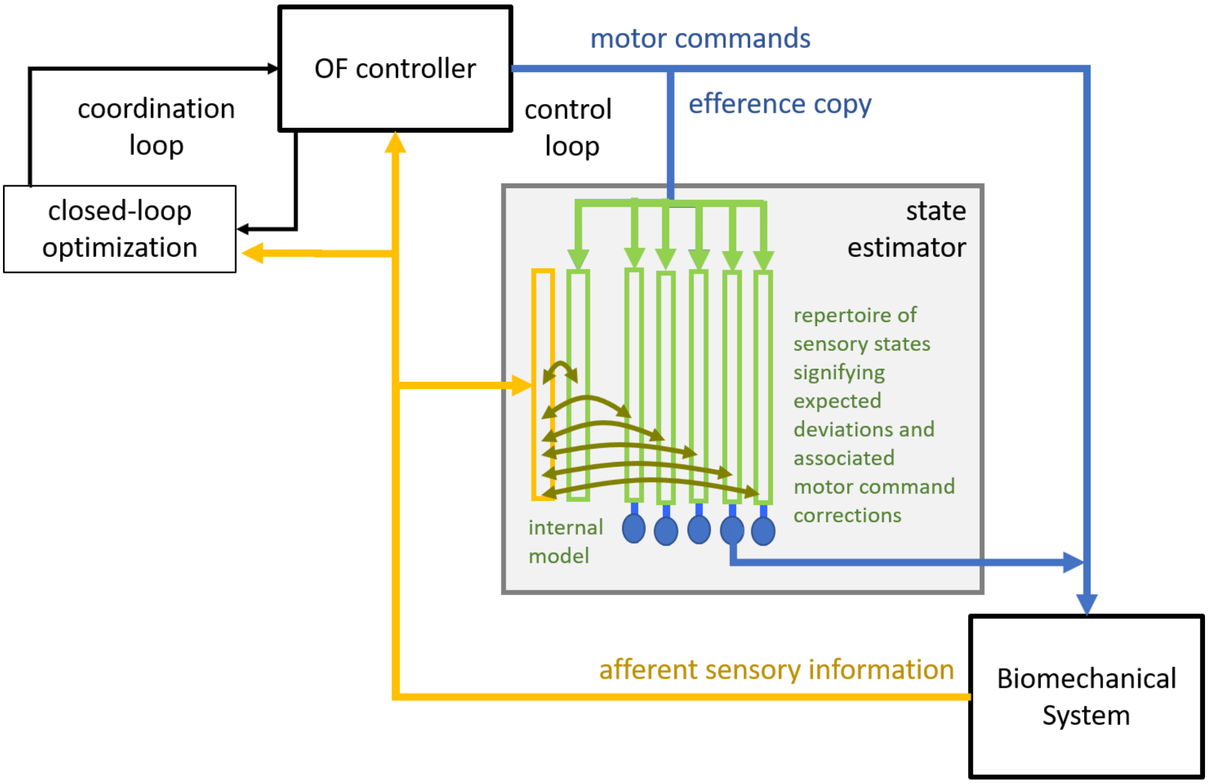

Figure 1: A schematic for the coordination and control loops in the OFCT. The key component of the control loop is the state estimator, which receives an efference copy of the outgoing motor commands and creates an internal model of expected sensory states. The processing of sensory information is then reduced to a comparison of incoming sensory signals with the expected sensory patterns calculated from the efference copy. In automated or skilled movements, the state estimator has also learned what sensory patterns would signify a known deviation from the intended movement and has established corrective motor commands, pre-prepared for immediate launch when its associated sensory signature is recognized in the incoming afferent sensory information.

An important feature of this model is, that the repertoire of expected deviations is build up from distinct deviation patterns coupled with specific motor command modifiers. This model thus predicts the Minimum Intervention Principle (Todorov & Jordan, 2002) stating that motor variability is only corrected if the variability compromises the underlying task: only deviations that require correction are added to the repertoire of anticipated deviation patterns. Deviations not requiring immediate correction are not represented and thus not corrected.
Also other motor control phenomena can be deducted from this property of the model, e.g. the specificity of balance training (Giboin, Gruber, & Kramer, 2015; Kümmel, Kramer, Giboin, & Gruber, 2016): the training of a specific balance task creates and refines the repertoire of

characteristic sensory signatures and their corresponding motor corrections, both of whom are situation specific. The more another task deviates from the trained situation, the less applicable are the sensory signatures and their corrections, leading to poor transfer.
One experimental example where the corrective motor commands no longer fit to sensory deviation patterns is the so-called “reverse-steering bicycle” (Hoedlmoser et al., 2015; Serrano et al., 2020), a bicycle where a set of gears in the steering tube produces opposite steering effects (steering to the right will turn the front wheel to the left and vice versa). Without extensive practice it is impossible to ride this bicycle in a stable manner. Interpreted according to the proposed model, this is a case where the sensory patterns for imbalances are still valid, but corrective motor commands that involve steering produce the wrong movement.

EXPERIMENTAL APPROACHES to support the proposed model need to first consider, what variables would be most suitable to find effects of such corrective feedback interventions. Thereto, it should be recognized that the internal model, expected sensory states and anticipated deviation patterns are likely representing the whole biomechanical system. It would be impractical and inefficient for the motor control system to establish such control mechanisms for individual degrees of freedom. Consequently, whole body representations rather than variables representing, for example, only single joint angles, should be analysed. In the author’s opinion, Principal Movements (PMs), i.e. kinematic synergies obtained from a principal component analysis of body posture data (Federolf, 2016), are particularly well suited as they offer a set of variables that characterize the movement of the whole biomechanical system (Federolf, Tecante, & Nigg, 2012).
Another aspect to consider is under which circumstances the effects of such a control mechanism become apparent. Quasi-static balance exercises (for example, two-leg quiet stances and one-leg stances) are particularly relevant, as the primary motor task in these situations is to maintain stability. In these scenarios, the ratio between movements generated through primary motor commands compared to those triggered by corrective motor commands favours the latter, especially in comparison to dynamic movements.
Actions by the State Estimator, according to this model, correct recognized deviations in movement, drawing on discrepancies between expected and actual sensory feedback. These corrective actions can be understood as discrete responses to specific errors, impacting the continuity of movement trajectories. Consequently, they likely influence the smoothness of these trajectories, with greater smoothness indicating more efficient control and fewer necessary corrections. Therefore, measures of movement smoothness, such as jerk metrics or trajectory variability, are plausible variables for detecting changes in control loop activity. Equally suitable are non-linear measures of temporal variability, such as entropy and the Lyapunov exponent for cyclic dynamic movements.
Many results of the author’s research group can be interpreted in accordance with this model. For example, we studied one-leg postural control differences between standing on the dominant versus the non-dominant leg (Promsri, Haid, & Federolf, 2018). Laterality is the result of different functional specializations of the left and right brain hemispheres, in other words, we compare two similar but not identical controllers. We analysed how tightly the movements of PMs are controlled. Interpreted through the lens of our proposed model, we might predict that differences in controller or limb characteristics will lead to different movement deviation characteristics. In other words, which and how frequently specific motor corrections get triggered differs between the two legs. These specific correction patterns will project onto specific PMs, and consequently, the smoothness of some PM-control characteristics will increase while that of others will decrease. Conversely, if the differences in movement smoothness were not due to feedback response adjustments but rather to inherent limb characteristics (such as muscle strength differences) or disparities in the main controller, one would anticipate uniform changes—either general increases or decreases in movement smoothness. Given that our findings revealed both increased smoothness in some PMs and decreased smoothness in others (Promsri et al., 2018), the results of this study corroborate the assumptions of the proposed model.

Other postural control research, for example on age differences between young and older adults (Haid et al., 2018) or adolescents and young adults (Wachholz et al., 2020) or on effects of dual tasking (Haid & Federolf, 2019; Wachholz et al., 2019), and investigations into the stability of gait (Promsri et al., 2023) collectively demonstrate the model's applicability across various contexts and populations.

DISCUSSION: This perspective paper introduces a simplified model for understanding the involvement of the OFCT's state estimator in the control and correction of ongoing movements. Aligned with established motor control paradigms, such as the Minimum Intervention Principle, this model corroborates a wide range of experimental findings, including those from our own research on postural control and stability of human walking. The proposed model can serve as a foundation for future studies, enabling the formulation of hypotheses regarding variations in feedback control across different contexts or in response to specific interventions.

REFERENCES

Crevecoeur, F., & Scott, S. H. (2014). Beyond muscles stiffness: importance of state-estimation to account for very fast motor corrections. *PLoS Computational Biology, 10*(10), e1003869.

Federolf, P. (2016). A novel approach to study human posture control:“Principal movements” obtained from a principal component analysis of kinematic marker data. *Jurnal of Biomechanics, 49*(3), 364-370.

Federolf, P., Tecante, K., & Nigg, B. (2012). A holistic approach to study the temporal variability in gait. *Journal of Biomechanics, 45*(7), 1127-1132.

Giboin, Gruber, Kramer (2015). Task-specificity of balance training. *Hum Mov Sci, 44*, 22-31.

Haid, T., & Federolf, P. (2019). The effect of cognitive resource competition due to dual-tasking on the irregularity and control of postural movement components. *Entropy, 21*(1), 70.

Haid, T. H., Doix, A.-C. M., Nigg, B. M., & Federolf, P. A. (2018). Age effects in postural control analyzed via a principal component analysis of kinematic data and interpreted in relation to predictions of the optimal feedback control theory. *Frontiers in aging neuroscience, 10*, 22.

Hoedlmoser, K., Birklbauer, J., Schabus, M., Eibenberger, P., Rigler, S., & Mueller, E. (2015). The impact of diurnal sleep on the consolidation of a complex gross motor adaptation task. *Journal of Sleep Research, 24*(1), 100-109.

Kümmel, J., Kramer, A., Giboin, L.-S., & Gruber, M. (2016). Specificity of balance training in healthy individuals: a systematic review and meta-analysis. *Sports Medicine, 46*, 1261-1271.

Promsri, Cholamjiak, Federolf (2023). Walking Stability and Risk of Falls. *Bioengineering, 10*(4), 471.

Promsri, A., Haid, T., & Federolf, P. (2018). How does lower limb dominance influence postural control movements during single leg stance? *Human movement science, 58*, 165-174.

Serrano, et al. (2020). Prior cortical activity differences during an action observation plus motor imagery task related to motor adaptation performance of a coordinated multi-limb complex task. *Cognitive Neurodynamics, 14*, 769-779.

Todorov, E. (2004). Optimality principles in sensorimotor control. *Nat Neuroscie 7*(9), 907-915.

Todorov, E., & Jordan, M. I. (2002). Optimal feedback control as a theory of motor coordination. *Nature Neuroscience, 5*(11), 1226-1235.

van Andel, S., Pieper, R., Werner, I., Wachholz, F., Mohr, M., & Federolf, P. (2021). Implications of optimal feedback control theory for sport coaching and motor learning: a systematic review. *Motor Control, 26*(1), 144-167.

Wachholz, F., Tiribello, F., Mohr, M., van Andel, S., & Federolf, P. (2020). Adolescent awkwardness: alterations in temporal control characteristics of posture with maturation and the relation to movement exploration. *Brain Sciences, 10*(4), 216.

Wachholz, F., Tiribello, F., Promsri, A., & Federolf, P. (2019). Should the minimal intervention principle be considered when investigating dual-tasking effects on postural control? *Brain Sciences, 10*(1), 1.

Wolpert, D. M., Diedrichsen, J., & Flanagan, J. R. (2011). Principles of sensorimotor learning. *Nature reviews neuroscience, 12*(12), 739-751.

Wolpert, D. M., Ghahramani, Z., & Jordan, M. I. (1995). An internal model for sensorimotor integration. *Science, 269*(5232), 1880-1882.

ACKNOWLEDGEMENTS: ChatGPT 4 (OpenAI, Inc., San Francisco, USA) was used to refine the wording in this manuscript. No AI tool was used for creating or editing the graph in Figure 1. The author assumes full responsibility for every aspect of this abstract.