## 'Coming Full Circle': Is Control More Important Than Prediction?

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## Abstract

Predictive (or feedforward) theories of motor control have replaced simple feedback theories. Yet the limitations of feedforward theories have been recognised and 'hybrid' models have attempted to reintegrate feedback, but within a secondary role. I critique hybrid models and propose that the field would progress by 'coming full circle' to make feedback control primary. Sensory feedback is critical because it corrects inaccurate predictions. One contemporary feedback theory (Perceptual Control Theory; PCT) can manage delays in neural signalling, circumvent limits in sensory feedback and learn to optimise control. I identify four original components of PCT as alternative ways of implementing feedforward processes to enhance feedback control over four different, parallel timescales. I discuss the implications for a unified understanding of control.

# Overview

I propose that 'hybrid' models of control overemphasise prediction at the expense of control and are superseded by returning 'full circle' to a feedback theory of control that subsumes feedforward processes within its architecture.

I plan to start the article with accessible examples. At the turn of the 20th century, John Dewey proposed that "the motor response determines the stimulus just as truly as the sensory stimulus determines movement" - while our environment can trigger changes in our behaviour, it is also the case that our behaviour is affecting the environment and we sense these effects as 'feedback'. Take the example of chasing a moving target during hunting - a vital skill for any predator's survival. Processing current sensory feedback is critical to control. The prey may change direction at any moment, as may the angle and terrain of the ground beneath the predator's feet. Moreover, as the predator shifts its speed and angle to compensate, the visual image of the prey it perceives on its retina will change instantly. The brain of the predator must process current sensory and motor information in such a way that it regularly, and efficiently, reaches its target – or ultimately it dies.

Early 20th century engineers, recognising the importance of feedback control, developed technologies we take for granted today, such as thermostats, amplifiers, flight control systems, and industrial and medical devices - some of which have an accuracy of up to four parts per million. Within psychology, feedback models peaked with the development of 'cybernetics' (Ashby, 1952; Wiener, 1948). Within a few decades, however, the pendulum had swung towards the development of feedforward theories of control (Oosting & Dickerson, 1987). Feedforward theories are varied, yet each compute the required actions for control based on either ongoing motor signals or computational models of the body and the environment that predict its state in advance. Despite many decades of this research, the importance of feedback did not go away. For example, Optimal Control Theory was converted to a 'hybrid' - Optimal *Feedback* Control Theory - to improve its match with observed data (Todorov & Jordan, 2002). Indeed, there are examples across wide domains where models utilising feedforward control rely critically on *feedback* processing for accurate performance (Perkell, in press; Saunders & Vijayakumar, 2011).

The limitations of recent hybrid models are increasingly well documented including their inability to learn their control parameters, to engage in hierarchical control, and to control cognition (Diedrichsen et al., 2010). Consequently, there have been recent calls for a more unified, parsimonious theory of motor control that is directly testable (Arjemian & Hogan, 2010).

In this article I heed this call and review evidence for a theory of feedback control that has the capacity to break the hiatus in the field: Perceptual Control Theory (PCT; Powers, Clark &

McFarland, 1960a,1960b; Powers, 1973, 2008). I make explicit four components of PCT that are subsumed within its architecture and 'feedforward' their effects in parallel over four different time scales (leaky integration of efferent signals, hierarchies, reorganisation learning, and self-generated feedback).

The article will initially critique five key reasons for the apparent advantages of feedforward control within current 'hybrid' models. These are summarised below:

- (1) Signal delays make feedback control ineffective. This view seems inconsistent with evidence of the performance advantages of sensory feedback during early stages of control, and for fast movements (Boer et al., 2011; Tunik et al., 2009). Moreover, when disturbances are not predictable, a model based on feedback processing can merely reduce its performance to the same as that of a feedforward system. A feedback model with nerve signal delays performs effectively over a range of simulated frequencies (Powers, 2008).
- (2) Sensory feedback is often unavailable. Under conditions of limited sensory feedback (e.g. blocked vision), the brain seems capable of sensory substitution whereby alternative streams of sensory feedback, such as proprioception, are used (Merabet & Pascual-Leone, 2010).
- (3) Feedforward motor signals improve control. There are examples of feedforward motor signals, such as the vestibulo-ocular reflex. Yet, these require stabilisation through *feedback* processing (Montfoort et al., 2008). The predicted sensory consequences of one's own actions do, however, appear to be used across a range of tasks; thus, a feedback theory needs to account for this.
- (4) Control parameters for feedback systems need to be learned. Learning enhances control, yet evidence shows that sensory feedback is typically required for this learning (Perkell, in press).
- (5) Internal models can predict the correct motor signal. The kinematic properties of the body and environment are associated with specific brain regions (Grafton et al., 2008). Yet, internal models can be complex, and inaccurate (e.g. Cloete & Wallis, 2009). Thus, a parsimonious account of internal model generation that is updated by sensory feedback is desirable.

At this point within the article, accessible pop-out boxes will be used to explain PCT and the evidence for the accuracy of models of behavioral tasks (Marken, 2009) and its explanation for observed behavior (e.g. Pellis & Bell, 2011). In summary, the reference values for a feedback unit in PCT are set by the efferent signals of a hierarchically superordinate feedback unit that operates over a longer timescale of perceptual input. The whole system therefore operates to 'control perception', within current motor and environmental constraints. The lowest control system is the tendon reflex, which causes a signal representing muscle tension to match a reference signal entering the spinal motor neuron; the inhibition from the sensory signal nearly matches the excitatory reference signal (on the agonist side), with the difference - error - being amplified by the muscle and converted to an output force to maintain a regulated tension (Powers, 1973).

Importantly, there are four original features of PCT that could be conceptualised as 'feed-forward' and subserve its feedback architecture (Powers et al., 1960; Powers, 1973). A pop-out box will provide equations of these components and their location in a diagram. They are as follows:

(1) *Leaky integration*: efferent signals are integrated over periods of several milliseconds. Therefore, the strength of a response to a disturbance in a constant direction will increase over very brief periods. The highly accurate tracking studies (e.g. Marken, 2009) utilise this component.

(2) *Hierarchies*: higher level systems perceive changes that unfold over fractions of a second or greater, and their efferent signals set the reference values for lower level systems; these are equivalent to the expected sensory consequences of action described by feedforward theories. For example, a higher level system for the desired angular position of a joint sets the desired velocity of the joint for the system below. A mid-level system controls this variable via the efferent signals that it, in turn, sends down to regulate acceleration via muscular forces at a lower level. Hierarchical PCT models accurately match observed data (Marken, 1986; Powers, 2008). Future research could test if a PCT model can utilise this information for a range of published tasks.

(3) *Reorganisation learning*: during repeated or ongoing situations, the control parameters are optimised through a trial-and-error learning process known as 'reorganisation', such that their values are fed forward for improved performance. Powers (2008) constructed and tested a

computer model of 14-joint arm movement that learned its optimal control parameters through this algorithm. Future research could utilise reorganisation more widely to develop optimal models.

(4) *Self-generated feedback*: In PCT, when sensory feedback is unavailable, sensory substitution has limited effectiveness, and/or when action is prevented, the control system can enter 'imagination mode'. In this state of arrangement, the reference values can be short-circuited internally to the organism such that approximate states of the self and world can be modelled 'as if' they are occurring in the environment. The motor plan that is modelled as most successful can then be fed forward when the opportunity to control the environment is next made available, subject to online alterations through feedback control. Convergent evidence is consistent with this process. Contemporary neuroscience indicates that hierarchically organised closed loops of biafferent neural signals are integral to the brain (Strick et al., 2011). Sensory deprivation in humans does indeed result in the formation of internally generated perceptions such as spontaneous visual imagery (Mason & Brady, 2009). Sensory deprivation in simulated robots leads to the emergence of spontaneous internal generation of perception via a closed loop process (Gigliotta, et al., 2010), and a study of robotic systems utilising sensory feedback models based on PCT outperformed competing models by up to 95% (Rabinovich & Jennings, 2010).

A summary of several further advantages of adopting a PCT model of control will follow in the article. First, a sense of control is recognised as an intrinsic need (Leotti et al., 2010) and therefore it is appropriate that PCT places present moment control, rather than prediction per se, at its core. Second, cognitive control can be embodied within a PCT model (Mansell, 2011). Third, the parsimony of PCT is making it highly adaptable to a variety of disciplines, e.g. mental health (e.g. Carey, 2011) and organisational psychology (Vancouver & Scherbaum, 2008). Finally, the limitations of PCT and directions for future research will be described.

## **Recent References**

Ajemian, R., & Hogan, N. (2010). Experimenting with theoretical motor neuroscience. *Journal of Motor Behavior, 42,* 333-342.

Carey, T. A. (2011). Exposure and reorganization: The what and how of effective psychotherapy. *Clinical Psychology Review, 31,* 236-248.

Cloete, S. R., & Wallis, G. (2009). Limitations of feedforward control in multiple-phase steering movements. *Experimental Brain Research, 195,* 481-487.

Diedrichsen, J., Shadmehr, R., & Ivry, R. B. (2010). The coordination of movement: optimal feedback control and beyond. *Trends in Cognitive Sciences*, *14*, 31-39.

Gigliotta, O., Pezzulo, G., & Nolfi, S. (2010). Emergences of an internal model in evolving robots subjected to sensory deprivation. *Lecture Notes in Computer Science, 6226,* 575-586.

Grafton, S. T., Schmidt, P., Van Horn, J., & Diedrichsen, J. (2008). Neural substrates of visuomotor learning based on improved feedback control and prediction. *Neuroimage, 39,* 1383-1395.

Leotti, L. A., Iyengar, S. S., & Ochsner, K. N. (2010). Born to choose: the origins and value of the need for control. *Trends in Cognitive Sciences, 14,* 457-463.

Mansell, W. (2011). Control of perception should be operationalised as a fundamental property of the nervous system. *Topics in Cognitive Science, 3,* 257-261.

Merabet, L. B., & Pascual-Leone, A. (2010). Neural reorganization following sensory loss: The opportunity of change. *Nature Reviews Neuroscience, 11,* 44-52.

Marken, R. S. (2009) You say you had a revolution: Methodological foundations of closed-loop psychology. *Review of General Psychology, 13,* 137-145

Mason, O. J., & Brady, F. (2009). The psychotomimetic effects of short-term sensory deprivation. *Journal of Nervous and Mental Disease, 197,* 783-785.

Montfoort, I., Van Der Geest, J. N., Slijper, H. P., De Zeeuw, C. I., & Frens, M. A. (2008). Adaptation of the cervico- and vestibulo-ocular reflex in whiplash injury patients. *Journal of Neurotrauma*, *25*, 687-693.

Tunik, E., Houk, J. C., & Grafton, S. T. (2009). Basal ganglia contribution to the initiation of corrective submovements. *Neuroimage, 47,* 1757-1766.

Pellis, S., & Bell, H. (2011). Closing the circle between perceptions and behavior: A cybernetic view of behavior and its consequences for studying motivation and development. *Developmental Cognitive Neuroscience*, *1*, 404-413.

Perkell, J. S. (in press). Movement goals and feedback and feedforward control mechanisms in speech production. *Journal of Neurolinguistics.* 

Saunders, I., & Vijayakumar, S. (2011). The role of feed-forward and feedback processes for closed-loop prosthesis control. *Journal of Neuroengineering and Rehabilitation, 8,* 60.

Powers, W. T. (2008). Living Control Systems III: The Fact of Control. Benchmark Publications.

Rabinovich, Z., & Jennings, N. R. (2010). A hybrid controller based on the egocentric perceptual principle. *Robotics and Autonomous Systems, 58,* 1039-1048.

Strick, P. L., Dum, R. P., Fiez, J. A. (2011). Cerebellum and Nonmotor Function. *The Annual Review of Neuroscience*, *32*, 413-434.

Vancouver, J. B. & Scherbaum, C. A. (2008). Do we self-regulate actions or perceptions? A test of two computational models. *Computational and Mathematical Organizational Theory*, *14*, 1-22.

#### **Earlier References**

Ashby, W. R. (1952). A Design for a Brain. Chapman & Hall.

Oosting, K. W. & Dickerson, S. L. (1987). Feed forward control for stabilisation. ASME

Powers, W. T. (1973). Behavior: The Control of Perception. Chicago, IL: Aldine.

Powers, W. T., Clark, R. K., & McFarland, R. L. (1960a). A general feedback theory of human behavior. Part I. *Perceptual and Motor Skills, 11,* 71-88.

Powers, W. T., Clark, R. K., & McFarland, R. L. (1960). A general feedback theory of human behavior. Part II. *Perceptual and Motor Skills, 11,* 309-323.

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

Wiener, N. (1948). *Cybernetics: Or Control and Communication in the Animal and the Machine*. MIT Press.