Control of Goal-Directed Movements Within (or Beyond) Reach?

Comment on “Muscleless Motor Synergies and Actions without Movements: From Motor Neuroscience to Cognitive Robotics” by Vishwanathan Mohan et al.

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The Challenge

About 40 years ago a seminal study by Morasso[1] set the stage for much of the ensuing research in motor neuroscience: pointing to targets in the horizontal plane revealed consistently smooth straight-line hand trajectories, while the corresponding joint angle trajectories lacked invariance. This result was the first to show that locations in extrinsic space determined the recruitment and configuration of joints, rather than the other way around—a motor parallel to the cognitive concept of allocentrism[2,3]. Given the many-to-one mapping, such inversion from external coordinates to joint coordinates necessitates some form of representation of the body—an ‘internal model’.

In subsequent decades many lines of research strove to ‘flesh out’ this internal model. Its existence was demonstrated by elegant studies of sensorimotor adaptation to externally-imposed force fields[4] and visual distortions[5]. A host of subsequent studies, many on-going, remained in ‘flat land’, constraining arm movements to a horizontal plane, frequently eliminating redundancy by confining motion to arm and forearm[6-8]. While simplified experiments constrain the ubiquitous variability of human movements to facilitate mathematical modeling and neuroimaging, these highly-controlled movements are a far cry from what humans do in day-to-day activities. Was “the baby thrown out with the bathwater”? Were the real challenges inadvertently removed?

The human body has well over 200 degrees of freedom and natural actions typically involve most of them, either in goal-directed fashion or to stabilize posture[9]. The challenge for sensorimotor control is exacerbated when actions involve physical interaction with the environment[10-12]. Humans routinely use a vast repertoire of tools, ranging from simple rigid utensils that extend the hand (e.g. a knife, a cane) to flexible and playful objects with prodigiously complex internal dynamics (e.g. a whip, a skipping rope). To ‘scale up’ from highly-reduced laboratory studies to such complex physical interactions is a daunting challenge. The proposal by Mohan et al.[13] faces up to this challenge.

Covert Simulation and Overt Execution

A glib answer to the challenge might be that humans and animals acquire their rich behavioral repertoire by practice; impressive recent advances in machine learning appear to validate this position. But that fails to appreciate the depth of the problem. The kinematic map from joint angles to end-effector position in extrinsic coordinates is well-posed; its inverse is notoriously ill-posed, with multiple branches and singular manifolds. Ill-posed-ness is often ‘regularized’ using optimization theory, but optimization suffers from Bellman’s ‘curse of dimensionality’[14].

Dating back to the 19th century, ideomotor theories have already argued that an ‘idea’ of the action, i.e. simulation or prediction of sensory consequences—covert action, is essential for goal-directed overt action[15-17]. But what should this ‘idea’ look like? The key proposal of Mohan et al. is that the ‘internal model’ or body schema has the same structure as control of the neuro-mechanical periphery. Based on extensive literature review, the authors argue that the equilibrium-point hypothesis (introduced in the

1960's and debated ever since) may provide the structure that governs both covert and overt actions[18-22]. The core idea is that setting an equilibrium point for the end-effector establishes attractor dynamics in joint space, generating limb configurations that take the endeffector to the desired target. As muscle activation patterns in overt movements are termed 'synergies', the coordinative structures in covert simulation are termed "muscleless motor synergies".

One advantage of this framework is that it applies equally well to end-effectors other than the hand (e.g. the elbow, the knee) and seamlessly to extensions of the body by tools, thereby accounting for the well-known phenomenon of 'ego-extension'[23,24]. Applied to covert simulations of another person, it can embrace social interactions. While this role of covert simulation has been argued before[25], this paper lays out the notion in a specific computational form that affords testable implementation in robot control. Using iCub with its 54 degrees of freedom (one of the most complex robots to date), its performance of complex multi-degree of freedom tasks shows that this framework can generate convincing purposive behavior.

This paper spans an unusually wide arc, going beyond current fashions to address an impressive range of challenges in motor control: from high-dimensional coordination, to tool use, mental simulation and learning. This integration of such a wide range of challenges is a welcome contrast to much current work in motor neuroscience that often remains too focused, thereby—intentionally or unintentionally—side-stepping the challenge of scaling up specific mechanisms to tackle the real problem.

Body Schema Networks and Dynamic Primitives

To achieve configurable and plastic coordination, the paper proposes a modular approach with the 'body schema' as its building block. Coupling these modules into a network of networks can incrementally encompass higher-dimensional behaviors, including tools and social interactions (see Fig.1). While the computational exposition and its implementation in robot control are valuable, we would like to point out some extensions.

The authors invoke the attractor dynamics of force fields analogous to the equilibrium-point hypothesis. However, their analysis is confined to quasi-static actions. For example, none of the examples include rhythmic movements, yet they are one of the canonical organizing patterns that emerge from nonlinear dynamics. Numerous studies of locomotion have shown that rhythmic leg or body movements are well accounted for by coupled nonlinear oscillators[26,27]. Rhythmic movements are not simply sequences of back-and-forth movements, but are governed by limit-cycle dynamics[28,29]. In fact, the neural substrates for discrete and rhythmic movements are strikingly different[30]. A variety of nonlinear oscillator models have successfully accounted for interlimb coupling, both in upper limb movements and in legged locomotion[31-34], as well as for entrainment to periodic perturbations[35-37].

Embracing goal-directed discrete and rhythmic movements, and incorporating physical interaction with objects, Hogan and Sternad proposed *dynamic primitives* that include both submovements and oscillations, with mechanical impedance to manage interaction[38,39]. Submovements are possibly governed by fixed-point dynamics that underlie non-rhythmic movements, either in sequence or as overlapping elements. They have been demonstrated in the movements of stroke patients as they recover[40] and when movements become very slow such that smooth trajectories 'fall apart' into stereotyped submovements[41]. Complex movements may be generated by coupling discrete fixed-point and rhythmic limit-cycle dynamics[42,43]. The primacy of rhythm was evident when subjects who performed a long sequence of discrete movements spontaneously merged their actions into a continuous stream of rhythmic movements[44]. Mechanical impedance is a third building block for dynamic interactions. When subjects manipulated an object with internal dynamics, they selected strategies consistent with adjusting their hand impedance to improve the predictability of object motion, even at the expense of increased effort[45,46]. Each of these dynamic primitives is conceived to be a stable attractor in the sense of nonlinear dynamics. This confers an important advantage: In contrast to the precision attributed to robots, the biological system is remarkably noisy[47,48]. The stability properties of an attractor offer a robust way to attenuate these ubiquitous fluctuations and obviate computationally expensive corrective actions[10,49].

Challenging the Perception-Action-Cognition Divide

Dynamic primitives highlight the importance of dynamics in actions and interactions. That points to a further essential function: prediction. Given the simultaneity of 'actio et reactio' together with the achingly slow signal transmission in the neuro-mechanical system, successful coordination requires predictive control. Recent work showed that predictability is favored over effort when transporting a complex object[45,50]. Prediction is a cognitive process and requires a dynamic model to determine neural activities that would produce a desired action. Perception is another cognitive process; it, too, requires a model that can serve to estimate dynamic state from noisy sensory data using processes, analogous to a Kalman filter. We propose that the structure of this covert dynamic model resembles or 'recycles' the organization of the overt action—dynamic attractor landscapes. For a theory that bridges between movement control, perception and cognition, we speculate that cognitive processes may arise from the same neural structures used for motor function. This line of reasoning meshes with the burgeoning literature on embodied cognition[51,52]. However, aside from philosophical lines of work and speculations, more quantitative and experimental work is needed. The present paper is a step in this direction.

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