Self-Organizing Neural Networks for Spatial Planning and Flexible Arm Movement Control

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Abstract

This talk will survey recent results concerning how the brain self-organizes its planning and control of flexible arm movements to accomplish spatially defined tasks at variable speeds and forces with a redundant arm that may be confronted with obstacles. Recent work from our group on this topic includes the following four themes.

Theme 1 concerns the design of a neural controller for generating handwriting at variable speeds, sizes, and styles. This model, called VITEWRITE, was first described in Bullock, Grossberg, & Mannes (1993). The VITEWRITE model addresses a number of key issues concerning the skilled performance of sequential actions: What is a motor program? How can a complex movement be flexibly performed at will with variable speed, size, and style without requiring new learning? How does the brain control a redundant manipulator that possesses more degrees of freedom than the space in which it moves? How can smooth curvilinear movements be organized by such a redundant manipulator? In particular, how is the timed launching of different groups, or synergies, of muscles achieved so that the desired directions, distances, and curvatures of movement are achieved? How, moreover, can "acts of will" that vary the speed and size of movements change distances and curvatures of movement without disrupting the correct directions of movement that preserve its overall form through time? A schematic of the model is provided in Figure 1.

The VITEWRITE model introduces a new concept of how a "motor program" can control skilled sequential movements. This concept introduces a solution of the problems of how writing can preserve its form when acts of will change its size and speed, and of how acts of will can change writing style by perturbing an invariant representation of the program. This motor program is not explicitly represented in the model. Rather, it is an emergent property of feedback interactions between a working memory representation of desired movement directions (called a Vector Plan), and a trajectory generator for moving the limb (called a VITE circuit). Simple volitional commands for changing the speed (GO) or size (GRO) of writing have the desired effect when they are input to these processes at the correct processing stages (see Figure 1). The VITEWRITE model also shows how the use of a redundant manipulator can simplify the problem of motor planning with these invariant properties by enabling the velocity profiles that control individual motor synergies to be unimodal. A simple rule for reading out new synergy commands exploits this unimodal form. During a movement, when the velocity profile of one synergy reaches its (unimodal) maximum, a new synergy's planning vector can be read out. This rule preserves written form in response to variable GO-controlled speeds.

The VITEWRITE model exhibits a number of properties of human handwriting. For example, the "two-thirds power law" of Lacquaniti et al. (1983), which says that angular velocity is the two-thirds power of curvature, is an emergent property of network interactions.

In summary, the VITEWRITE model demonstrates how a working memory can control writing movements that exhibit many properties of human handwriting when it interacts reciprocally with a suitably defined trajectory generator coupled to a model hand with redundant degrees of freedom. These results extend the applicability of the earlier VITE model (Bullock & Grossberg 1988) from the control of reaching behaviors to the control of complex curvilinear trajectories.

The VITEWRITE model plans movements in motor coordinates. Many skilled tasks, however, carry out movements that are described in spatial coordinates. This raises the question of how a body-centered representation of 3-D target positions can be learned in a way that accommodates itself to the idiosyncratic properties of an individual's operating parameters? Such a model was progressively developed in a series of articles (Greve et al. 1993; Grossberg et al. 1993; Guenther et al. 1994).
The model suggests how the brain may autonomously learn a body-centered representation of a three-dimensional (3-D) target position by combining information about retinal target position, eye position, and head position in real time. Such a body-centered spatial representation enables accurate movement commands to the limbs to be generated despite changes in the spatial relationships between the eyes, head, body, and limbs through time. The model learns a vector representation — otherwise known as a parcellated distributed representation — of target vergence with respect to the two eyes, and of the horizontal and vertical spherical angles of the target with respect to a cyclopean egocenter. Elements of such a vergence-spherical representation has been reported in the caudal midbrain and medulla of the frog, as well as in psychophysical movement studies in humans and neurophysiological studies in monkeys (Foley 1980; Grobstein 1991; Grobstein & Staradub 1989; Masino & Grobstein 1989; Sakata, Shibutani, & Kawano 1980).

A head-centered vergence-spherical representation of foveated target position can be generated by two stages of opponent processing that combine corollary discharges of outflow movement signals to the two eyes. Sums and differences of opponent signals define angular and vergence coordinates, respectively. The head-centered representation interacts with a binocular visual representation of nonfoveated target position to learn a visuomotor representation of both foveated and nonfoveated target position that is capable of commanding yoked eye movements. This head-centered vector representation also interacts with representations of neck movement commands to learn a body-centered estimate of spatial position.
target position that is capable of commanding coordinated arm movements. Learning occurs during head movements made while gaze remains fixed on a foveated target. An initial estimate is stored and a VOR-mediated gating signal prevents the stored estimate from being reset during a gaze-maintaining head movement. As the head moves, new estimates are compared with the stored estimate to compute difference vectors which act as error signals that drive the learning process, as well as control the on-line merging of multimodal information.

Once spatial representations are available, one can approach the problem of designing a system capable of motor-equivalent movements (Figure 2). This model extends the VITE model in a different direction. It is called the DIRECT model (Bullock, Grossberg, & Guenther 1993). Motor equivalence computations allow humans and other animals to flexibly employ an arm with more degrees of freedom than the space in which it moves to carry out spatially defined tasks under conditions that may require novel joint configurations. During a motor babbling phase, the model endogenously generates movement commands that activate the correlated visual, spatial, and motor information that are used to learn its internal coordinate transformations. After learning occurs, the model is capable of controlling reaching movements of the arm to prescribed spatial targets using many different combinations of joints. When allowed visual feedback, the model can automatically perform, without additional learning, reaches with tools of variable lengths, with clamped joints, with distortions of visual input by a prism, and with unexpected perturbations. These compensatory computations occur within a single accurate reaching movement. No corrective movements are needed. Blind reaches using internal feedback have also been simulated.

The DIRECT model achieves its competence by transforming visual information about target position and end effector position in 3-D space into a body-centered spatial representation of the direction in 3-D space that the end effector must move to contact the target. The spatial direction vector is adaptively transformed into a motor

![Cortical position-speed-force control circuit model](image)

Figure 3: Cortical position-speed-force control circuit model. Thick connections represent the kinematic feedback control aspect of the model, with thin connections representing additional compensatory circuitry. GO - scalable gating signal; DVV - desired direction vector; OPV - outflow position vector; PPV - perceived position vector; DV - difference vector; TPV - target position vector; $\gamma^d$ - dynamic gamma motoneuron; $\gamma^s$ - static gamma motoneuron; $\alpha$ - alpha motoneuron; Ia - type Ia afferent fiber; II - type II afferent fiber (position error feedback); c.s. - central sulcus; i.p.s. - intraparietal sulcus. The symbol + represent excitation, - represents inhibition, x represents multiplicative gating, and $+\int$ represents integration.
direction vector, which represents the joint rotations that move the end effector in the desired spatial direction from the present arm configuration. Properties of the model have been compared with psychophysical data on human reaching movements, neurophysiological data on the tuning curves of neurons in the monkey motor cortex, and alternative models of movement control. Guenther (1995) has shown how similar principles can be used to self-organize a system for motor-equivalent speech production.

All of the above models concern the planning of movements and their realization as variable speed and sized trajectories, without regard to the forces encountered while making the movements. The final model analyses how planning and trajectory control circuits are embedded in the neocortical circuits that compensate for variable forces, including forces created by obstacles (Bullock, Cisek, & Grossberg 1995). Additional circuitry clarifies how these planned movement trajectories may be accurately realized under variable force and tension conditions (Figure 3). This circuit offers an integrated interpretation of the functional roles of diverse cell types in movement related areas of primate cortex. The circuit maintains accurate proprioception while controlling voluntary reaches to spatial targets, exertion of force against obstacles, posture maintenance despite perturbations, compliance with an imposed movement, and static and inertial load compensations. Computer simulations show that properties of model elements correspond to the properties of many known cells types in cortical areas 4 and 5. Among these properties are delay period activation, response profiles during movement, kinematic and kinetic sensitivities, and latency of activity onset. In particular, area 4 phasic and tonic cells compute velocity and position commands, respectively, that are capable of activating alpha and gamma motor neurons, thereby shifting the mechanical equilibrium point. Anterior area 5 cells compute the position of the limb using corollary discharges from area 4 and feedback from muscle spindles. Posterior area 5 neurons use the position perception signals and a target position signal to compute a desired movement vector. The cortical loop is closed by a volition-gated projection of this movement vector to the area 4 phasic cells. An auxiliary circuit allows phasic-tonic cells in area 4 to incorporate force command components needed to compensate for static and inertial loads. The model simulates prior experimental results, and predicts the behavior of both motor and parietal cell types under novel experimental protocols.

Taken together, these several models embody an emerging proposal for how the brain can flexibly plan and execute movement sequences that exhibit key invariant properties even as the size, speed, and force of these movements is modified on-line to adapt to varying environmental contingencies.

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References


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