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Neurobiologically inspired distributed and hierarchical system for control and learning

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1. Introduction

This chapter discusses potential features of neural systems that may provide insights into biomimetic system design. Recent modeling studies on the cerebrocerebellar and spinal level systems have been of huge interests because they motivate advanced biologically inspired approaches to solve various complex engineering problems in the area of control, automation, and learning. In the view of control scheme, we argue that the cerebrum loosely specifies the control space, while the cerebellum implements modular controllers that are designated to task and performance specifications. The translation of the control commands from the central nervous system to muscles is in the single-to-multiple manner. The neural circuits operate in a simple control space and distribute the commands through synergies rather than directly treat the whole redundant set of actuators. Furthermore, considering a motion task as a sequence of sub-motions controlled by multiple modules of cerebrocerebellar systems, the movement control, which can be seen as a hybrid combination of sequential command generation mechanism coupled with state dependent gain-scheduled controllers, proposes interesting biomimetic design schemes. We summarize two possible such schemes: Sequential module-based or parallel module-based gain scheduling approaches. Control variables used in neural motor control may be interpreted as a hybrid of kinematic and kinetic quantities and be chosen to simplify the control dimensionality. Furthermore, mirror neuron studies show majority of those neurons are multi-modal, i.e., they appear to respond to shapes and kinematics of objects, such as limbs, of other subjects and also respond similarly to internally generated motor command for execution. Thus more biological extensions to the proposed schemes become enable to learn from imitations more efficiently. By introducing conceptual computational neural models, we suggest several functionally important *in vivo* neural circuitry and its connection which are very useful for designing biomimetic systems.

2. Cerebrocerebellar control system

Animals including humans can make a wide repertoire of limb movements effortlessly without consciously thinking about joint trajectories or muscle contractions to bring about specific motions. These movements are the outcome of a series of processes and computations carried out by the central nervous system (CNS). Even to make a simple reaching movement, for example, a number of distinct neuroanatomical areas participates to complete the task, and each area consists of numerous neurons that are densely interacting to each other. Among the supraspinal structures, the cerebrocerebellar system is central to motor control (Allen & Tsukahara 1974; Brooks 1986; Kelly & Strick 2003) and has been characterized in terms of its anatomical connections among the areas in the system. In this section, the two structures, the cerebral cortex and the cerebellar cortex are introduced, with their relevant anatomical and physiological features, as components of the cerebrocerebellar system and their functional interrelationship.

2.1 Cerebral cortex

The cerebrum is the evolutionarily newest and largest part of the brain. It participates in many different functions such as perception, decision making, memory, motor control, motion planning/execution, etc. It has been traditionally thought that each subregion of the cerebral cortex has a functionally distinct and significant role in the highly complex hierarchical cerebral structure. An interesting feature of the cerebral cortical region, particularly in sensory regions, is that the spatial extent of pyramidal cell association collaterals approximately construct a columnar assembly. The columnar assembly is a collection of cortical columns. The cortical column is a bundle of minicolumns sharing the same input connection from another cortical region or from sensory thalamic nuclei. Each cortical column may contain a specific feature presentation of sensory information such as orientation of visual stimuli. In the primary motor cortex, there has been an extensive study on modulation of spiking activities on upcoming movement direction (Georgopoulos et al. 1982). Cells with similar preferred directions tended to segregate into vertically oriented minicolumns 50-100 microm wide and at least 500 microm high. Such minicolumns are aggregated across the horizontal dimension in a secondary structure of higher order. In this structure, minicolumns with similar preferred directions were approximately 200 microm apart and were interleaved with minicolumns representing nearly orthogonal preferred directions. In addition, nonoverlapping columns, representing nearly opposite preferred directions, were approximately 350 microm apart. (Amirikian & Georgopoulos 2003). For a specific piece of movement, a group of neurons in a specific column have the most vigorous firing compared to the other columns. The specific population directional vector of the column may be regarded as a functional quantitative measure (Amirikian & Georgopoulos 2003). The activity dominated from the winning columnar assembly may be transmitted to other sensorimotor cortical columns and thence to cerebellum by larger tufted layer 5 pyramidal cells.

Experimental observations have shown task-related neural activity in both the premotor and motor cortex (Johnson & Ebner 2000). Neural activities of M1 cells in apes are directionally tuned during an epoch of reaching task movement and the preferred directions of M1 cells are very different (Cisek 2003). It is known that a population distribution in an ensemble of M1 neurons adequately points a specific direction, which is mathematically expressed by a

unit vector while the discharge of single neurons rarely identifies any direction with accuracy (Georgopoulos 1988). These observations may be related to the functional organization of the columnar assemblies in cortex.

It is shown that complex movements with multiple velocity peaks can be decomposed into a superposition of elementary, and potentially stereotypical, sub-movements that form the basis of an intermittent sub-movement-based planning mechanism (Krebs et al. 1999, Rohrer et al. 2004, Fishback et al. 2005). Such sub-movements have been identified in many types of movements: pursuit tracking (Miall et al. 1988), interception of moving targets (Lee et al. 1997), and cursor movement during isometric force task (Massey et al. 1992). Segmentations were found even in the EMG patterns during slow finger movements (Vallbo & Wessberg 1993) and during point-to-point reaching movement with a wide range of speeds (Dipietro et al. 2005), thus demonstrating that the descending command can also be inherently intermittent. Those studies suggest that the sub-movement play a fundamental role in the control or planning of primate limb movements and they may be the behavioral manifestation of neural mechanisms. Potentially a piece of sub-movement has a corresponding neural substrate so that a sequential activation of those substrates produce an overall movement. A complete motion can be repetitive such as walking such that it can be constructed by a repeated sequence of sub-movements. Each sub-movement is probably encoded within a specific spatial region. To generate a whole movement, switchings from one spatial region to another will be necessary because each sub-movement is best encoded separately in an individual region. Thus, a hypothesis is that cerebral cortex separately includes an appropriate principal spatial coordinate for each sub-movement, and the signal to the lower central nervous system from cerebral cortex informs a sequence of spatial coordinates for the whole movement. Tanji and Wise (Tanji & Wise 1981) argued that the motor cortex plays an important role in the sequencing of multiple movements. Specific spatial information at the level of intracortical processing within M1 may represent a transformation between extrinsic and intrinsic presentations. Sensed external information is in a high dimensional coordination, and internal motor system is in a low dimensional coordination (Kalaska et al. 1983). Therefore, spatial dimensional complexity of a behavior may be reduced in the world of the internal neural system. Cortical assembly may distributedly encode spatial information in a low and local dimensional space. The brain presumably can also store and combine the principal modes as needed to generate different behaviors. Thus, many situations which we encounter would be derived from combinations of previously experienced contexts (Haruno et al. 2001).

Learning a set of specific regions and corresponding neural activation patterns are probably describable by utilizing an engineering algorithm such as reinforce algorithm that provides a synaptic implementation between pre- and post-synapses (Williams 1992). The update rule consists of two components, Hebbian and anti-Hebbian. The former increases the synaptic connection strength and the latter decreases it. The update rule principally seeks to find a primary principal vector (i.e., principal mode) of correlation of a certain error trajectory. A simple generalization can find the first n principal directions with n linear neurons (Sanger 1994).

By combining those two ideas, i.e., cortical columnar organization and its functional organization in terms of spatial, and contextual, variables, it is hypothesized, to explain individual cerebellar Purkinje cell (PC) spiking activities, (Takahashi 2006) that a group of neurons in a particular cortical column in Area 3a are broadly tuned to a particular direction

of internal error signals. Each cerebral cortical column in sensorimotor cortical (SMC) area 3a (as explained in section 2.1.) is expressed by a neural population-based representation of the error-like signal (Georopoulos 1988; Georopoulos et al. 1983).

Fig. 1. A proposed cerebral cortical model from the perspective of a single Purkinje cell.

The error-like signal e_{cb} is distributed to different PCs via SMC columns in area 3a each of which has a preferred direction ϕ_{cb}^{dir} . Then, the output of each column to PCs contains the magnitude of the projection of e_{cb} vector to unit vector along ϕ_{cb}^{dir} direction. Thus the firing intensity of neurons in a given SMC column in area 3a at a given time depends on the ongoing error-like signal and its nominal tuning direction. Fig. 1 illustrates the proposed cerebral cortical model.

2.2 Cerebellar cortex

The cerebellum is the most numerous in terms of the number of the neurons and is known to coordinate and control posture and movement, and implement motor learning. Its neural circuitry is globally uniform in its cytoarchitectonics as shown in Figure 2. The cerebellar cortex can be divided into a number of sagittal zones, or microzones (Oscarsson 1979) each of which form, with its group of neurons, the operational unit of the cerebellum. This organization may be analogous to the modular columnar organization in the cerebral cortex. In microarchitecture, three layers, e.g., molecular, Purkinje cell, and granular layers, organize the cerebellar cortex and contain five types of neurons (Kandel et al. 2000). These granule cells make excitatory connections with all the other cells, and basket, stellate, and golgi cells are inhibitory neurons. A Purkinje cell receives excitatory signals, but its output to deep cerebellar nuclei is inhibitory. Two types of inputs are conveyed to the cerebellar microzone: Mossy fibers (MFs) and Climbing fibers (CFs) (Kandel et al. 2000). MF input produces a stream of simple spikes in PCs throughout relayed circuits. The firing rate of simple spikes can extend to above a few hundred spikes per second. The frequencies encode either peripheral sensory information or central commands. CF input is composed of error-type signals originating from the inferior olivary nucleus. CFs have powerful synaptic connection with Purkinje neurons and provoke a complex spike on the dendrites of a PC, but its firing rate is very low (around 1 per second). Climbing fiber pathway is regarded as a "teaching" line for the adaptation at the parallel fiber-Purkinje cell synapse (Ito 1984).

Granule cells, the most numerous, receive neural signals through mossy fibers and transmit output signals to the Golgi cells and parallel fibers. Mossy fibers convey various forms of information (assumptions on a set of specific signals are presented in the model below). Golgi cells in the granule layer receive excitatory inputs from both mossy fibers directly and granule cells. Inhibitory inputs from stellate, basket, and Purkinje cells are also conveyed to Golgi cells which then inhibit granule cells. The signal conveyed to parallel fibers is relayed to Purkinje cells. The signal is a brief excitatory potential that evokes high frequency firing on the dendrites of the PC which has fan-like dendrites and projects into the white matter under the granular layer. A PC also receives the other input through a CF. Stellate and basket cells modulate inhibitory connections with parallel fiber to a PC.

Fig. 2. The cerebellar neural circuit.

The outputs of the cerebellar cortex are sent to other areas through deep cerebellar nuclei. The neural output signals reach either motor cortex via thalamus (ventrolateral nuclei) or spinal cord via brainstem. Impairments related to the deep cerebellar nuclei indicate different behavioral functions (Thach 1998). The neural output signals from fastigials contain mainly the information on upright stance and gait. Interposed nuclei (Interpositus) in the medial region are related to reaching movements or alternating agonist-antagonist muscle. Impairment of Dentate in the lateral region causes curved motion trajectory, overshoot on reaching movement, and uncoordinated finger movements.

Many neuroanatomically feasible models to explain the cerebellar mechanism with respect to either movement control or motor learning have been proposed. The models can be roughly categorized into two types, feedback and feedforward control systems. Models (Barto et al. 1999; Kazutaka 2006) describing the cerebellar function as the feedback control system put emphasis on more robustness against the parameter variation or disturbances. The feedforward type cerebellar model implements the plant inverse dynamics (Kawato & Gomi 1992; Schweighofer et al. 1998; Miall et al. 1993) while the crude feedback controller, the cerebral system, performs. An example of each case is introduced here.

The Recurrent Integrator Proportional Integral Derivative (RIPID) cerebrocerebellar model regards the cerebellar function with the feedback controller (Jo ; Kazutaka 2006). In the RIPID model (Fig. 3), the ascending signals that percolate through the control systems are

posited to be functions of a principal tracking error formed in parietal area 5, $\theta_{target}(t) - F_3\theta(t - t_{aff})$ where t_{aff} is a sum of the spinal and peripheral delay, and more direct afferent information received via Area 3a (via F_2). The signal from area 3a is proposed to travel to intermediate cerebellum and that from area 4 to intermediate and lateral cerebellum. Those principal signals in the cerebellum and precerebellar nuclei undergo scaling, delay, recombination and reverberation to affect proportional-derivative-integral processing ($G_b s$, G_k , and I_1/s , I_2/s , and I_3/s , respectively, where s denotes a Laplace variable). The cerebellar computational processing is derived from neuroanatomy (Takahashi 2006; Jo & Massaquoi 2004). These actions contribute to phase lead (by I_2/s recurrent loop) for long-loop stabilization and sculpting forward control signals ($G_b s$, G_k , I_1/s) that return to motor cortex where they are collected and redistributed before descending through the spinal cord as motor command u . There is additional internal feedback to the parietal lobe and/or motor cortex via I_3/s that contributes to loop stability in the principal transcerebellar pathway. An important set of inputs is posited to consist of modulating signals (indicated by η) from spinocerebellar tracts. These signals effectively switch the values of G_b , G_k , I_1 according to limb configuration and velocity as in Fig.(3). The RIPID model also includes the direct command path from motor cortex (via MC) to spinal cord, and a hypothetical cerebral cortical integrator (I_a/s).

Fig. 3. The RIPID model. Numbered circles designate functional subcategories of sensorimotorcortical columns explained in section 2.1.

On the other hand, the adaptive feedback error learning (FEL) model has been rigorously investigated to describe the cerebellar function in the manner of the feedforward inverse dynamics control (Gomi & Kawato 1993; Kawato & Gomi 1992; Katayama & Kawato 1993). The cerebellum is regarded as a locus of the approximation of the plant inverse dynamics. The FEL model describes the motor learning scheme explicitly. Initially, a crude feedback controller operates influentially. However, as the system learns the estimation of the plant

inverse, the feedforward controller commands the body more dominantly. Fig. (4) illustrates the FEL scheme proposed by Gomi and Kawato (Kawato & Gomi 1992). The feedback controller can be linear, for example, as

$$\bar{\tau}_{fb} = K_1(\ddot{\bar{\theta}}_b - \ddot{\bar{\theta}}) + K_2(\dot{\bar{\theta}}_b - \dot{\bar{\theta}}) + K_3(\bar{\theta}_b - \bar{\theta}) \quad (1)$$

To acquire the inverse model, different learning schemes could be used. In general, a learning scheme $\bar{\tau}_{ff} = \phi(\bar{\theta}_d, \bar{\theta}, \dot{\bar{\theta}}_d, \dot{\bar{\theta}}, \ddot{\bar{\theta}}_d, \ddot{\bar{\theta}}, W)$ can be expressed, where W represents the adaptive parameter vector, $\bar{\theta}_d$ the desired position vector, and $\bar{\theta}$ the actual position vector. The adaptive update rule for the FEL is as follows.

$$\frac{dW}{dt} = \eta \left(\frac{\partial \phi}{\partial W} \right)^T (\bar{\tau}_{fb} + \bar{\tau}_{ext}) \quad (2)$$

where $\bar{\tau}_{ext}$ is the external torque and η the learning ratio which is small.

Fig. 4. The FEL model. Adapted from Kawato and Gomi (1992).

The convergence property of the FEL scheme was shown (Gomi & Kawato 1993; Nakanishi & Schaal 2004). The FEL model has been developed in detail as a specific neural circuit model for three different regions of the cerebellum and the learning of the corresponding representative movements: 1) the flocculus and adaptive modification of the vestibulo-ocular reflex and optokinetic eye movement responses, 2) the vermis and adaptive posture control, and 3) the intermediate zones of the hemisphere and adaptive control of locomotion. The existence of inverse internal model in the cerebellum is argued based on studies (Wolpert & Kawato 1998; Wolpert et al. 1998; Schweighofer et al. 1998) that the Purkinje cell activities can be approximated by kinematic signals.

There have been many other models of the cerebellum (Barto et al. 1998; Miall et al. 1993; Schweighofer et al. 1998). In those models, the cerebellum is also either feedforward or feedback control system. Yet, uniform descriptions for various models would be necessary to support one model over the other as there are multiple ways to describe one model. Interestingly, a probabilistic modelling approach has been applied to explain the inverse

internal model in the cerebellum (Käording & Wolpert 2004). The model takes into account uncertainty which is naturally embedded in human movements and applies the Bayes rule to interpret human decision making process. Further investigation is necessary to verify the cerebellar mechanism and to better understand the principle of movement control. It is highly expected that biological principles will teach us an outstanding scheme of robotic control to perform close to that of human. Model designs to evaluate both dynamic behaviors and internal signal processing are worthwhile for neuroprosthetic device or humanoid robotics development.

2.3 Cerebellar system as a modular controller

Neural computation of microzone in cerebellar cortex under a specific principal mode may control a sub-movement over a certain spatial region. Experimental observations have shown that the directional tunings of cells in cerebellar cortex, motor cortex, and parietal cortex are strikingly similar during arm reaching tasks (Frysinger et al. 1984; Kalaska et al. 1983; Georgopoulos et al. 1983). It is also reported that directional tunings of Purkinje cells, interpositus neurons, dentate units, and unidentified cerebellar cortical cells are nearly identical (Fortier et al. 1989) so that cerebellar computational system may be considered to be in a specific coordinate. Those experimental observations suggest that the cerebrocerebellar mechanism is implemented in a similar spatial information space. A possible neural scheme can be proposed as follows. Suppose that there are some groups of mossy fiber bundles, and each individual group conveys the neural information described in a different spatial coordinate from cerebral cortex. As spatial information becomes available, some groups of mossy fiber bundles receiving the cerebral signal becomes more active. Similarly in cerebellar cortex, inhibition between different modules by stellate and basket cells accelerates competition to select a winner module. The winner module is framed in a spatial coordinate encoded in cerebral cortex. As a result, cerebellar neural computation is implemented in the restricted spatial coordinate. Thus it appears that the cerebrum determines a spatial coordinate for a specific task, and then the cerebellum and other motor system control the motion with respect to the coordinate. Therefore, a pair of modular cortical assembly and cerebellar microzone can be probably seen as a neural substrate for movement control and learning.

From the point of view of control theory, gain scheduling is an appropriate approach to describe a control system with distributed gains: each set of control gains is assigned to a specific coordinate. Furthermore, switching or scheduling of gains may depend on a command for a sub-movement. In general, gain scheduling scheme involves multiple controllers to attempt to stabilize and potentially increase the performance of nonlinear systems. A critical issue is designing controller scheduling/switching rules. It is quite possible that an internal state, probably a combination of sensed information, may define switching condition. For instance, a gain switching scheme is demonstrated by a computational model of human balance control. Two human postural strategies for balance, ankle and hip strategies (Horak & Nashner 1986), are respectively implemented by two different control gains that are represented by the cerebellar system. (Jo & Massaquoi 2004). Depending on external disturbance intensities, an appropriate postural strategy is selected by comparing sensed position and switching condition defined by an internal state (Fig.(5)). The internal state is adapted to include information on approximated body position and external disturbance (i.e., a linear combination of sensed ankle and hip angles and angular

speed at ankle). A neural implementation of the switching mechanism is shown in Fig. (5) where a beam of active parallel fibers (PF) inhibits PCs some distance away ("off beam") via basket cells (Eccles et al. 1967; Ito 1984). This diminishes the net inhibition in those modules, allowing them to process the ascending segment input through mossy fibers (AS). Conversely, the beam activates local PCs, thereby suppressing the activity of "on beam" modules. The principal assumption of PFs in this scheme is that, unlike ascending segment fibers, they should contact PCs relatively more strongly than the corresponding cerebellar deep nuclear cells - if they contact the same DCN cells at all. This appears to be generally consistent with the studies of Eccles et al (Eccles et al. 1974; Ito 1984). A prime candidate source for PFs is the dorsal spinocerebellar tract (DSCT). The elements of the DSCT are known to convey mixtures of proprioceptive and other information from multiple muscles within a limb (Oscarsson 1965; Bloedel & Courville 1981; Osborn & Poppele 1992) while typically maintaining a steady level of background firing in the absence of afferent input (Mann 1973).

Fig. 5. Proposed switching mechanism: (left) neural circuit, and (right) postural balance switching redrawn from Jo & Massaquoi (2004). PF: parallel fibers, MF: Mossy fibers, DCN: deep cerebellar nuclei, AS: ascending segment; $\hat{\theta}_1$: sensed ankle angle, $\hat{\theta}_3$: sensed hip angle, $\hat{\theta}_1$: sensed angular speed at ankle.

The gain scheduling mentioned so far uses an approach that spatially distributed control modules are recruited sequentially to achieve a motion task. Another possible approach is to weight multiple modules rather than pick up a module at a specific time. A slightly more biologically inspired linear parameter varying gainscheduling scheme including multiple modules each of which was responsible over a certain region in the joint angle space was developed for a horizontal arm movement (Takahashi 2007). Another example of multiple module approach is Multiple forward inverse model proposed by Wolpert and Kawato (1998). Each module consists of a paired forward inverse model and responsibility predictor. Forward models learn to divide a whole movement into sub-movements. The degree of each module activity is distributively selected by the responsibility predictor. The inverse model in each module is acquired through motor learning similar to FEL. While the degree of each contribution is adaptively decided, several modules can still contribute in synchrony unlike the previous sequential approach. The modules perform in parallel with different contributions to a movement. Learning or adaptation algorithms could be used to describe the parallel modular approach (Doya 1999; Kawato a& Gomi 1992). However, more explicit neural models based on observations have been proposed to explain adaptive behaviors

(Yamamoto et al. 2002; Tabata et al. 2001). The computational analyses generalize the relationship between complex and simple spikes in the cerebellar cortex. Error information conveyed by complex spikes synaptic weights on PCs and such changes functionally correspond to updating module gains. Further investigation is still required to understand the generality of such results and their computational counterparts as previous studies have looked mostly on simple behaviors such as eye movements or point-to-point horizontal arm movements.

2.4 Control variables and spatial coordination

Primates have many different sensors. The sensors collect a wide range of information during a specific motor task. The high-level center receives the sensed information. Neurophysiological studies propose that motor cortex and cerebellum contain much information in joint coordinates (Ajemian et al. 2001; Scott & Kalaska 1997), Cartesian coordinates (Georgopoulos et al. 1982, Ajemian et al. 2001; Scott & Kalaska 1997; Poppele et al. 2002, Roitman 2007). However other studies are consistent with the possibility that parietal and some motor cortical signals are in Cartesian (Kalaska et al. 1997) or body-centered (Graziano 2001), shoulder-centered (Soechting & Flanders 1989) workspace coordinates, or a combination (Reina et al. 2001). However, it would be highly likely that a coordinate at an area is selected to conveniently process control variables from high level command to low Level execution.

Fig. 7. Neural computational network between controller and plant.

For example, Freitas et al (2006) proposed that voluntary standing movements are maintained by stabilization of two control variables, trunk orientation and center of mass location. The control variables could be directly sensed or estimated via neural processing. It is really difficult to see what control variables are selected internally in the brain. However, redefining appropriate control variables in the high-level center can lower control dimensionality to enable efficient neural computation. Moreover, computational studies have demonstrated that workspace to sensory coordinate conversion can occur readily within a servo control loop (Ayaso et al. 2002; Barreca & Guenther 2001). As in Fig. 7, the

dimensional reduction and synergies (and/or primitives) can be viewed functionally as the inverse network of each other. The control variables in the high-level nervous center may need to be purely neither kinematic nor kinetic. A composite variable of both kinematic and kinetic information can be used, where both force and position control variables are simultaneously processed. Moreover, the position variable could be in joint or Cartesian-coordinate. Spinocerebellar pathways apparently carry a mixture of such signals from the periphery (Osborn & Poppele 1992), but the details of force signal processing in the high-level nervous center are not well understood.

Based on various investigations, it is considerable that the neural system controls behaviors using hybrid control variables. The advantage of using such types is verified in engineering applications. For teleoperation control applications, such a linear variable combination of velocity and force is called wave-variable (Sarma et al 2000). It is demonstrated that the wave-variable effectively maintains stability in a time-delayed feedback system. Application of the force controller with the position controller to a biped walker has been tested (Fujimoto et al 1998; Song et al 1999). The force feedback control mode during the support phase is effective in directly controlling interaction with the environment. The force/torque feedback controller in a computational model of human balancing facilitated attaining smooth recovery motions (Jo and Massaquoi 2004). The force feedback provided the effect of shifting an equilibrium point trajectory to avoid rapid motion.

3. Mirror neuron and learning from imitation

One form of learning a new behaviour is to imitate what others do. In order to imitate, an integration of sensory and motor signals is necessary such that perception of an action can be translated into a corresponding action. Even an infant can imitate a smile of an adult, actual processes of that consist of multiple stages. It seems that many areas in the primate brain participate in imitation. In superior temporal sulcus (STS), Perrett et al. (1985) found neurons responding to both form and motion of specific body parts. Responses of those neural systems are consistent regardless of the observer's own motion. Then, Rizzolatti's group found neurons in ventral premotor cortex, area F5, that discharged both when individuals performed a given motor task and when they observed others performing the same task. Those neurons are referred to mirror neurons which are found in premotor (F5) and inferior parietal cortices. The relation between those two areas remains unclear, but it can be hypothesized, given a known connection between F5 and area 7b in parietal cortex, that perception of a performer's objects and motions in STS is sent to F5 via 7b. Furthermore, there exist anatomical connections between dentate in cerebellum and multiple cerebral cortical areas that are related to perception, imitation, and execution of movements, i.e., area 7b, PMv, and M1 respectively (Dum & Strick 2003). Anterior intraparietal area (AIP) is a particular subregion in area 7b and sends projections to PMv (Clower et al. 2005). In addition, AIP has a unique connection to dentate nuclei in that it receives significant inputs from areas of dentate that are connected to PMv and M1. Thus, it can be further hypothesized that AIP/7b is a site where object information is extracted and can be compared to an internal estimate of actual movement, particularly of hand, and F5 recognize external and internal actions before an execution.

In relation to the RIPID model which does not have specific representation of premotor cortex and AIP, it seems that visuospatial function of cerebrocerebellar loops, particularly

through area 7b, AIP, and PMv, may contribute to a feedforward visual stimuli dependent scheduling of cerebellar controllers that compute signals for internal or external uses. Thus, there are multiple almost simultaneous recruitment of cortical columnar assemblies and cerebellar modules based on the task specification and real time sensed state information to narrow down “effective” controller modules in the cerebellum. To train such complex dynamical control system, first a set of local controllers in the cerebellum needs to be trained (such as Schaal & Atkinson 1998 or based on limitation of the effective workspace (Takahashi 2007)). Then, a set of sub-tasks such as reaching and grasping object needs to be characterized so that the observed actions can be mapped a set of meaningfully internalized actions through a parietofrontal network of AIP/7b to PMv. Then, to perform a whole task, a higher center needs to produce a sequence of internalized actions. A model to realize this particular part of the system including mirror neurons is developed by Fagg and Arbib (1998) and a further refined version to reproduce specific classes mirror neuron responses by Bonaiuto et al. (2007) whose learning scheme was the back-propagation learning algorithm for use with anatomically feasible recurrent networks. However, no model for imitation learning has exclusively incorporated cerebellar system. Thus, it is interesting to investigate how contributions of the cerebellum and its loop structure with AIP, 7b, and PMv to learning can be realized.

4. Conclusion

In neuroscience society, the concept of modules and primitives has popularly been proposed. It facilitates controllability of redundant actuators over a large state space along the descending pathways. Meaningful control variables are extracted from the whole sensed information over the ascending pathways. The process may be interpreted that specific spatial coordinates are selected for the high nervous control system. Therefore, this provides a way to construct the control problem in the simpler dimensional description compared with body movement interacting with the environment as long as fewer control variables can be sufficient for performance. The control variables seem to be chosen in such a way as to decouple functional roles. In this way, the adjustment of a local neural control with respect to a control variable can be fulfilled substantially without affecting the neural controls related to other control variables. Furthermore, a hybrid control variable of kinematic and kinetic states may be advantageous. Under the assumption that cerebral cortex specifies an appropriate coordinate for a motion task and cerebellar cortex controls the motion in the coordinate, neural activities around the cerebrocerebellar system may be viewed as a gain scheduling or multiple modular control system with multi-modal scheduling variables. The integrated system seems to enable to estimate appropriate efforts to achieve desired tasks. Mirror neurons inspire learning algorithms, based on imitations, that specify local controllers. To shed light on the biomimetic designs, we summarize the features from human neural systems as follows.

- Functional decoupling of each controller
- Dimensional reduction in the control space
- Piecewise control by multiple modules and gain scheduling
- Hybrid control variables
- Learning from imitations

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Nature's evolution has led to the introduction of highly efficient biological mechanisms. Imitating these mechanisms offers an enormous potential for the improvement of our day to day life. Ideally, by bio-inspiration we can get a better view of nature's capability while studying its models and adapting it for our benefit. This book takes us into the interesting world of biomimetics and describes various arenas where the technology is applied. The 25 chapters covered in this book disclose recent advances and new ideas in promoting the mechanism and applications of biomimetics.

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