

Cerebellar adaptive control of a biomimetic manipulator

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Abstract

We present a learning cerebellar model to control reaching movements of a simulated biomimetic manipulator. The system utilizes the servo mechanism of the spinal reflex circuitry to allow kinematic control of slow movements while learning predictive dynamic compensation. Key elements of the model are: (1) parallel postural and dynamics controllers; (2) a neural network model explicitly based on the physiology of the cerebellum, utilizing the cerebello-olivary loop for stable learning; (3) modulation of gamma-motoneurons during movements to sense trajectory errors from Ia spindle efferents. Results demonstrate the ability to rapidly learn to accurately control stereotyped fast movements. © 1999 Published by Elsevier Science B.V.M All rights reserved.

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1. Introduction

Schweighofer et al. [12] proposed a model of the role of the intermediate cerebellum in the control of voluntary movement. The model embeds a neural network based on known cerebellar circuitry in a simulation of the mammalian motor control system to control a 6-muscle 2-link planar arm. In this model the cerebellar module acts in parallel with a controller composed of a proportional-derivative feedback controller, and a feedforward controller (PDF + F), the latter implementing a crude inverse

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dynamic model of the arm. Learning in the Schweighofer cerebellum model is driven by trajectory errors sensed by the inferior olive using convergent cerebral desired kinematic signals and arm state variables obtained from joint sensors. Their simulation results [13] suggest that this cerebellar model was able to learn parts of the inverse dynamics model not provided by the PDF + F controller, as indicated by an improved tracking performance of desired trajectories after learning.

In this study we augmented the Schweighofer model in a number of ways: We

- added a postural control system utilizing spinal reflexes;
- utilize spindle afferents as more plausible trajectory error detectors;
- exploit the cerebello-olivary loop for stable learning in a way that drives the cerebellum to provide predictive torque compensation for accurate movements; and
- explicitly address the problem of long delays.

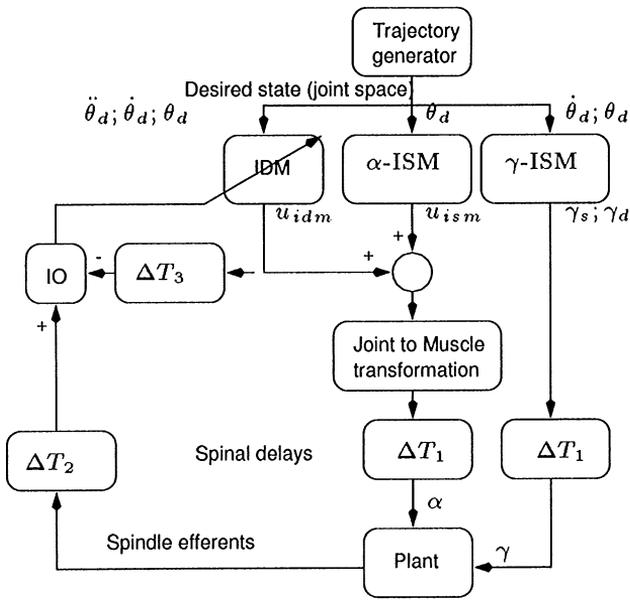
2. Arm model (Plant)

To provide a more realistic test-bed of the cerebellar model, we have provided detailed simulations not only of cerebellum but also of a six-muscle, two-segment planar arm [7] and the spinal segment circuitry implementing the basic motor servo. We used a spinal segment model that was implemented in DSP hardware by Chou and Hannaford [2] for single joint posture control. The model incorporates Alpha- and Gamma-motoneurons, Renshaw cells, Ia- and Ib interneurons. Ia-pathway kinematic feedback is provided from each muscle by static- and dynamic spindle pairs: separate gamma drive inputs can set a “desired” length and velocity so that the spindle output is a clipped (positive only) function of position or velocity errors.

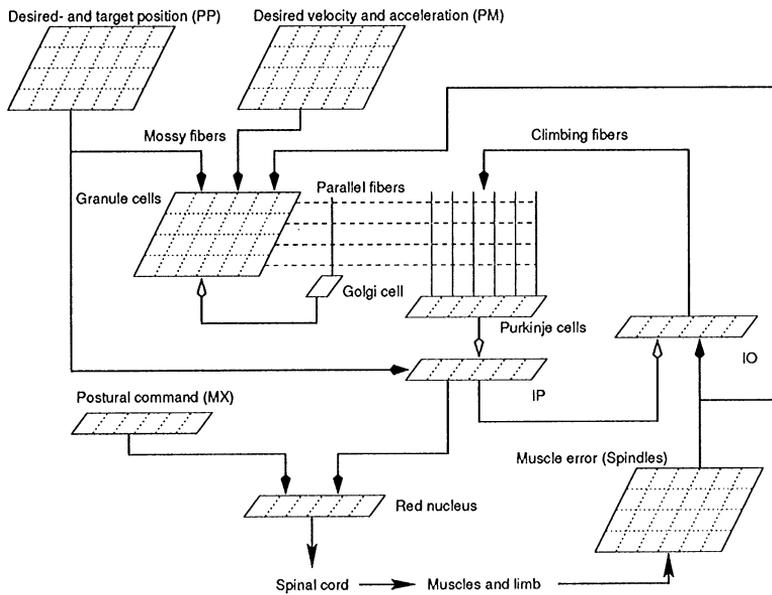
3. Control system

The model uses parallel inverse static and dynamic controllers as shown in Fig. 1(A) and is conceptually similar to the parallel hierarchical control scheme proposed by

Fig. 1. (A) Simplified schematic of the control system. The trajectory generator defines a minimum jerk kinematic trajectory, i.e., at each time step, the desired position, velocity and acceleration is computed for each joint so that the hand would move along a straight line towards the target with bell-shaped velocity profile. The inverse static model (ISM) provides alpha-muscle control input to define a static equilibrium point for the limb at the current desired position, but also generates static and dynamic gamma drive for the spindles to detect length and velocity errors. The IDM (Inverse Dynamic Model, implemented as a cerebellar model) uses the sensed muscle tension produced by the spinal reflex circuitry as teacher signal and learns to associate this with the system state (provided by the trajectory generator and muscle spindles as discussed in the text) to provide corrective control signals in a feed-forward manner. (B) The neural implementation of the IDM with input and output connections. Brain areas and distinct cell types are implemented as either 1D or 2D layers of neurons, and variables are coarse coded.



(A)



(B)

Katayama and Kawato [7]. The principle is that the ISM learns the part of the inverse dynamics that depend only on posture, such as gravity terms, while the IDM learns terms that depend on derivatives of joint angles.

A major problem facing biological controllers is delays in afferent and efferent pathways. We explicitly inserted such delays in the model as shown in the figure with $T_1 = T_2 = 30$ ms.

In our implementation the ISM, whose output is a simple function of two variables, is implemented as a lookup table which is generated off-line. The IDM is implemented as a neural cerebellar model and learns on-line using a biologically plausible mechanism.

Our postural module (ISM) provides alpha drive to set muscle tensions so that the limb would have an equilibrium point at the position specified by the trajectory generator. Muscles are modeled as damped springs with resting length determined as a function of the alpha motor command [9]. The result of this property is that a given vector of motor commands to a set of antagonistic muscles defines a point attractor for the limb in joint space.

We propose that the ISM also drives intrafusal muscle spindles through the gamma system so that deviations from the desired position would activate the spinal servo to provide additional restoring force. This feedback system ensures that novel trajectories are approximately followed, but as suggested by Gomi and Kawato [5] and Contreras-Vidal et al. [3], also serves to train the IDM.

4. Cerebellar inverse dynamics model

We extend the idea that the cerebellum effects its output on a sidepath alongside the descending commands from motor cortex and that it does this by learning part of the inverse dynamics of the limb so that it can provide predictive feedforward compensation during fast coordinated movements to compensate for delays. Our neural model, shown in Fig. 1(B), is based on the physiology and connections of the intermediate cerebellum in the motor system [6].

Inputs: Both proprioceptive information (Ia afferents) and joint-space desired kinematic variables (postulated to originate in posterior parietal and premotor cortices) are provided as mossy fiber inputs. Following Georgopoulos et al. [4], variables (θ) are coded in the activity of a population of neurons with each neuron “tuned” to a specific value (θ_0) and its output O defined by

$$O = \cos(\theta - \theta_0), \quad (1)$$

500 mossy fibers (MF) so convey the desired kinematic variables (position, velocity and acceleration for each joint), while 60 fibers represent Ia afferents from the six muscles.

Processing: The following set of equations summarize the neural model:

$$GC = F_{gc} \frac{1}{1 + \exp(-s_{gc}(m_{gc} - o_{gc}))}, \quad \tau_{gc} \frac{dm_{gc}}{dt} = -m_{gc} - w_{go}GO + \sum_{i \in \mathcal{M}} w_{mf} MF_i,$$

Table 1
Simulation parameters for the different cerebellar neurons

	GC	GO	PC	IP
Time constant (τ)	0.02	0.05	0.02	0.02
Slope (s)	8	0.5	0.005	0.08
Offset (o)	0.5	15	750	– 50
Maximum rate (F)	100	50	200	100

$$\begin{aligned}
 \text{GO} &= F_{\text{go}} \frac{1}{1 + \exp(-s_{\text{go}}(m_{\text{go}} - o_{\text{go}}))}, & \tau_{\text{go}} \frac{dm_{\text{go}}}{dt} &= -m_{\text{go}} + w_{\text{gc}} \text{GC}, \\
 \text{PC} &= F_{\text{pc}} \frac{1}{1 + \exp(-s_{\text{pc}}(m_{\text{pc}} - o_{\text{pc}}))}, & \tau_{\text{pc}} \frac{dm_{\text{pc}}}{dt} &= -m_{\text{pc}} + \sum_{i \in \mathcal{P}} w_{\text{pf}} \text{GC}_i, \\
 \text{IP} &= F_{\text{ip}} \frac{1}{1 + \exp(-s_{\text{ip}}(m_{\text{ip}} - o_{\text{ip}}))}, & \tau_{\text{ip}} \frac{dm_{\text{ip}}^j}{dt} &= -m_{\text{ip}}^j + \sum_i w_{\text{pc}} \text{PC}_{ij} \quad (2)
 \end{aligned}$$

with parameters as listed in Table 1.

Each of 400 (20×20) Granule cells (GC) receives excitatory input ($w_{\text{mf}} = 0.5$) from four randomly selected MFs (the set \mathcal{M}) and an inhibitory input ($w_{\text{go}} = -0.02$) from the Golgi cell (GO). The single Golgi cell receives input from all the granule cells ($w_{\text{gc}} = 0.0025$) and inhibits the entire population in a negative feedback loop. Two hundred (20×5) Purkinje cells each receives input from a beam of GCs (the set \mathcal{P}) comprising about a third of the GC population. The weights w_{gc} are initialized with random numbers in the range $[0:1]$. A vector of 20 (4 groups of 5) interpositus cells (IP) each receive inhibition ($w_{\text{pc}} = -0.2$) from a column of PCs. IP parameters are chosen to ensure a high spontaneous rate, so that PCs “carve out” the IP firing profile.

Outputs: The IDM outputs four torque-like synergies: Shoulder/elbow flexion/extension. Each synergy is determined by summing the activity of a group of 5 IP cells, e.g.,

$$S_{\text{shoulder flex}} = \sum_6^{10} \text{IP}. \quad (3)$$

5. Learning rule

Adaptation is driven by the inferior olive (IO). In this simulation each IO cell receives excitatory spindle afferents and a topographic inhibitory projection from an IP cell. In turn it projects to the column of PCs connected to that IP cell where its effect is to modify w_{pf} : the strength of parallel fiber-Purkinje cell synapses. Activity of IO cell is computed as

$$\tau_{\text{io}} \frac{dm_{\text{io}}^j}{dt} = -m_{\text{io}}^j - \text{IP}^j + \sum_i w_{\text{ia}(S)}^i \text{Ia}_{\text{static}}^i + 0.5 w_{\text{ia}(D)}^i \text{Ia}_{\text{dynamic}}^i. \quad (4)$$

The weights $w_{Ia(S)}^i$ and $w_{Ia(D)}^i$ are set to $+1$ for muscles that contribute to torques in the same direction as the IDM microcomplex that the IO cell forms part of; -1 for antagonist muscles. This setup will train the system to provide additional torque if a muscle is stretched more than expected, while at the same time penalize cocontraction.

Inferior olive cells are known to have spontaneous firing rates of around 1 Hz and peak rates of not much more than 10 Hz. To simulate this low rate, an *integrate-and-fire* model was used rather than the real-valued rate output used for the other neurons:

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IF  $m_{io} > V_{\text{threshold}}$ 
THEN  $m_{io} = m_{io} - V_{\text{rebound}}$ ;  $IO = 1$ 
ELSE  $IO = 0$ 

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with $\tau_{io} = 0.055$; $V_{\text{threshold}} = -0.0001$; and $V_{\text{rebound}} = 1$.

The traditional view of cerebellar learning is that $\Delta w_{\text{pf}} \propto -[\text{GC}][\text{IO}]$, but note that the Ia efferents (and therefore the IO error signals) are delayed, so when updating weights, we have to change them proportional to the GC activity some time earlier. We use the concept of synaptic eligibility [14] – more specifically the version proposed by Schweighofer et al. [11] where

$$\Delta w = -\alpha e[\text{IO} - \beta], \quad (5)$$

$$\tau_e \frac{de_1}{dt} = -e_1 + \text{GC}, \quad (6)$$

$$\tau_e \frac{de}{dt} = -e + e_1 \quad (7)$$

with $\tau_e = 0.16$. The second-order differential equation effectively keeps a memory trace of GC activity (e) in each synapse, peaking approximately 100 ms after the event.

Note that the IO input from spindles determine output of IP cells. Thus the w_{Ia}^{ij} determine the IDM controller. The net effect is that the IDM produces a signal “like” the Ia spinal efferents (which are muscle errors) which opposes the error and causes improved trajectories. But, delays would cause this signal to be applied too late. Eligibility fixes this by shifting the blame earlier in time so that the corrective actions are associated with an earlier system state, allowing the IDM to provide adaptive, *predictive* control, as shown by Barto et al. [1].

The next important point is that the cerebello-olivary loop produces a stable learning system as shown by Kenyon et al. [8] in which the nuclear cells will learn to copy any excitatory input to the IO, but we need to once more line IP activity values up temporally, accomplished by ΔT_3 (set to 100 ms). Such a long-latency response has been shown to exist in cats by Ruigrok and Voogd [10].

6. Results

Simulation results are presented in Fig. 2. Movements are made from a central position to eight radial targets at a rate of 0.6 s per movement. The trajectory in

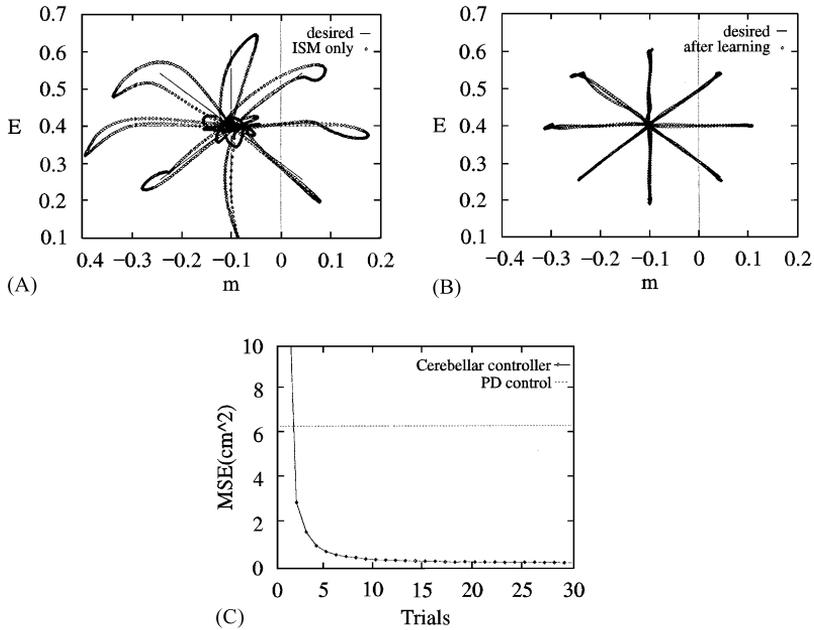


Fig. 2. Tracking results. Movements are made from a central position to eight radial targets. Each segment of the pattern is completed in 0.6 s. (A) tracking performance before learning, i.e., using only postural control; (B) performance after learning; (C) tracking error as a function of learning trials (MSE in cm^2).

Fig. 2(A) was produced using only the ISM and spinal reflex controllers by moving the equilibrium point along the desired trajectory. Coriolis, centripetal and inertial forces cause the limb to stray from the prescribed path. The trajectory in Fig. 2(B) was produced by the full system after 30 learning trials. The trajectory is almost perfect. Fig. 2(C) confirms that accurate trajectories can be generated in a small number visits of to each target.

7. Conclusion

We have implemented a biologically inspired version of the parallel hierarchical control model proposed by Katayama and Kawato [7] and have shown that our cerebellar network was able to learn accurate trajectory control. The new features of our model are: (1) the use of the spinal reflex feedback circuit as a source for *training* signals to the IDM in a feedback-error learning scheme; (2) an ISM that also generates motor expectations as gamma drive so that muscle-state errors can be detected at the spindles with no delay; (3) the use of synaptic eligibility to learn inverse dynamics feedforward control.

For robotic applications, we have shown that the cerebellar architecture is suitable for fast, on-line learning of a complex control function.

In terms of cerebellar modeling, we demonstrate that the low-frequency climbing fiber spikes can be used as an effective training signal; the effectiveness of the cerebello-olivary loop for on-line motor control; synaptic eligibility can be used to overcome delays and give predictive feedforward control.

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Michael A. Arbib currently directs a major interdisciplinary project, Neural Plasticity: Data and Computational Structures, which integrates studies of learning and neural compensation for disease with research on tools for multimedia database construction, data discovery, visualization, and multilevel simulation. The author of 20 books and the editor of 11 more, Arbib edited in 1995 “The Handbook of Brain Theory and Neural Networks”. Arbib’s latest book, “Neural Organization: Structure, Function, and Dynamics” (MIT Press, 1997), offers a multidisciplinary, multistrategic approach to the interaction of brain models and neurobiological experiments.

Nicolas Schweighofer received a Diplome d’Ingenieur from the Ecole Superieure de Mecanique de Nantes in 1990, and a Ph.D. degree in Computational Neuroscience from the University of Southern California in 1995. Since then he has been working at the ERATO Kawato Dynamics at the crossroad between neural network theory and biology and include neural control, biological learning, neural development, and biophysics.