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Adaptive control of 2-wheeled balancing robot by cerebellar neuronal network model

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***Abstract*— A new adaptive motor controller was constructed, and tested on the control of a 2-wheeled balancing robot in simulation and real world. The controller consists of a feedback (PD) controller and a cerebellar neuronal network model. The structure of the cerebellar model was configured based upon known anatomical neuronal connection in the cerebellar cortex. Namely it consists of 120 granular (Gr) cells, 1 Golgi cell, 6 basket/stellate cells, and 1 Purkinje (Pk) cell. Each cell is described by a typical artificial neuron model that outputs a weighted sum of inputs after a sigmoidal nonlinear transformation. The 2 components of the proposed controller work in parallel, in a way that the cerebellar model adaptively modifies the synaptic weights between Gr and Pk as in the real cerebellum to minimize the output of the PD controller. We demonstrate that the proposed controller successfully controls a 2-wheeled balancing robot, and the cerebellar model rapidly takes over the PD controller in simulation. We also show that an abrupt load change on the robot, which the PD controller alone cannot compensate for, can be adaptively compensated by the cerebellar model. We further confirmed that the proposed controller can be applied to the control of the robot in real world.**

I. INTRODUCTION

The cerebellum is known to play a pivotal role in biological adaptive motor control. Its anatomical neuronal circuitry is among the best identified in the brain, and the basic structure of the cerebellum is shared from fish to primate [1]. Further, the synaptic plasticity in cerebellar cortical neuronal circuitry has been physiologically well characterized as an underlying neural mechanism of the cerebellar adaptive motor control [1] and its plausible learning rule has been proposed [2]. Thus many researchers have constructed mathematical models of the cerebellum to reproduce and explain various experimental data [3]. However, little attempt has been made to employ those models for engineering applications. Here we constructed a new cerebellar neuronal network model for engineering application, especially for a 2-wheeled balancing robot. We configured the model based upon anatomical and physiological evidence of the cerebellum, enabling a real-time adaptive robot control. A 2-wheeled balancing robot was chosen to test validity of the cerebellar model as an adaptive motor controller for unstable systems.

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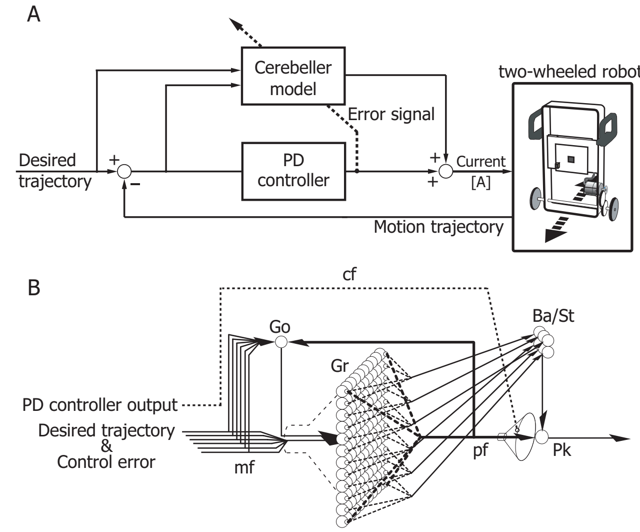

Fig. 1. The proposed controller (A) and configuration of the cerebellar model (B).

II. METHODS

A. Structure of the proposed controller

The proposed adaptive controller consists of the cerebellar neuronal network model and a PD controller (Fig.1A). We used a 2-wheeled balancing robot “e-nuvo Wheel” (ZMP inc.) as a control object. The parameters of the PD controller (K_p and K_d) were adjusted so that the PD controller alone can initially balance the robot. The cerebellum model was configured based upon anatomical connection of each neuron type (Fig.1B). Namely, granular (Gr) cells and Golgi (Go) cells receive mossy fiber (mf) inputs that carry a desired trajectory of the robot, and a control error (desired trajectory - actual trajectory). Go cells receive excitatory input from Gr cells as well, and simultaneously inhibit Gr cells, forming a negative feedback loop. The excitatory outputs of Gr are also received by Purkinje (Pk) cells, and basket and stellate (Ba/St) cells. Ba/St cells inhibit Pk cells, forming a negative feed-forward pathway. Pk is the sole output cell type from the cerebellar cortex. Each Pk cell receives another input from inferior olivary nucleus through a climbing fiber (cf) that is considered to convey a control error signal [1]. The output of a Pk is considered to be modified to reduce the error signal by adjusting the synaptic efficacies between Gr and Pk. When Gr and cf are co-activated the synaptic efficacies decrease (Long-term depression: LTD) whereas when Gr alone is active they increase (Long-term potentiation: LTP) [4]. The proposed cerebellar model is formed by 120 Gr cells, 1 Go cell, 6 Ba/St cells, and 1 Pk cell. The number of each cell was determined so that the controller works on a PC in real time, preserving the actual ratio of the cell population as much as possible. Effects of this scale reduction on the performance of the controller is not a scope of this study, but will be addressed in the future study. The connections between Gr cells and a Pk cell, and a Gr cell and Go cells are full connection. Namely, each Pk and Go cell receives input from all the 120 Gr cells. Each of 6 Ba/St cells receives input from 1/6 of 120 Gr cells and innervates a Pk cell. Synaptic weights for these connections were either positive or negative random numbers depending on the type of synapse, that is, excitatory (positive) or inhibitory (negative). Only the synapses between Gr cells and a Pk cell were modifiable. There are two control variables: the rotational angle of the 2 wheels which always move together, and the tilt angle of the robot body. For the sake of simplicity, we gave a desired trajectory only for the angle of the 2 wheels, while the desired trajectory for the tilt angle was always set to 0. There are 6 mf projecting to each Gr: 1) desired trajectory in angle for the 2 wheels, 2) desired trajectory in angular velocity for the 2 wheels, 3) control error in angle for the 2 wheels, 4) control error in angular velocity for the 2 wheels, 5) control error in angle for the body tilt, 6) control error in angular velocity for the body tilt. Each cell type is described as in the following equations:

•Granule cell

$$X_{Gr} = \sum_{mf=1}^{6} W_{Grmf} \cdot Y_{mf} + W_{GrGo} \cdot Y_{Go} \quad (1)$$

$$Y_{Gr} = \frac{2}{1+e^{-\frac{X_{Gr}}{\mu}}} - 1 \quad (2)$$

•Golgi cell

$$X_{Go} = \sum_{mf=1}^{6} W_{Gomf} \cdot Y_{mf} + \sum_{Gr=1}^{120} W_{GoGr} \cdot Y_{Gr} \quad (3)$$

$$Y_{Go} = \frac{2}{1+e^{-\frac{X_{Go}}{\mu}}} - 1 \quad (4)$$

•Basket cell

$$X_{Ba} = \sum_{Gr=1}^{20} W_{BaGr} \cdot Y_{Gr} \quad (5)$$

$$Y_{Ba} = \frac{2}{1+e^{-\frac{X_{Ba}}{\mu}}} - 1 \quad (6)$$

•Purkinje cell

$$Y_{Pk} = \sum_{Gr=1}^{120} W_{PkGr} \cdot Y_{Gr} + \sum_{Ba=1}^{6} W_{PkBa} \cdot Y_{Ba} \quad (7)$$

where Y is the output of each cell, W_{ji} is the synaptic weight between a cell i and a cell j. Subscripts Gr, Go, Ba, Pk, and mf indicate parameters for Gr, Go, Ba/St, Pk, and mf, respectively.

Both the cerebellar model and the PD controller were implemented on MATLAB Simulink running on a PC (Apple MacPro CPU: 2 x 3GHz Quad-Core Intel Xeon/ Memory: 9 GB). We utilized MATLAB xPC Target running on another PC (CPU: 3.4GHz Pentium 4/ Memory: 1024MB) for real world testing.

TABLE I

PARAMETERS OF THE 2-WHEELED ROBOT USED IN SIMULATION.

Parameter name	Symbol	Value	
Mass of the body	m	0.5157	[kg]
Mass of the cart	M	0.0.071	[kg]
Length between the wheel axle and the Gravity center of the body	l	0.1390	[m]
Radius of the wheel	r_t	0.02485	[m]
Moment of inertia of the body	J_p	$2.797 \cdot 10^{-3}$	$[\mathrm{kg} \cdot \mathrm{m}^2]$
Moment of inertia of the cart	J_t	$8.632 \cdot 10^{-6}$	$[\mathrm{kg} \cdot \mathrm{m}^2]$
Moment of inertia of the motor rotor	J_m	$1,30 \cdot 10^{-7}$	$[\mathrm{kg} \cdot \mathrm{m}^2]$
Torque constant of the motor	K_t	$2.79 \cdot 10^{-3}$	$[\mathrm{N} \cdot \mathrm{m/A}]$
Reduction ratio of the gear	i	30	
Drive-train efficiency	η	0.75	[–]
Friction of the wheel axle	c	$1.00 \cdot 10^{-4}$	$[\mathrm{kg} \cdot \mathrm{m}^2/\mathrm{s}]$
Gravity acceleration	g	9.80665	$[\mathrm{m/s}^2]$

B. Learning algorithm

We employed the feedback-error learning scheme [5] for the learning algorithm of the cerebellar model. Namely, the synaptic efficacies between Gr and Pk cells are updated to minimize the output of the PD controller (error in motor commands), which can be implemented as follows:

$$\Delta W_{PkGr}(t) = \gamma \cdot Y_{Gr} \cdot E_{cf} \quad (8)$$

$$W_{PkGr}(t) = W_{PkGr}(t-1) + \Delta W_{PkGr}(t) \quad (9)$$

where $W_{PkGr}(t)$ is a synaptic weight between a Gr cell and a Pk cell at time t, γ is a learning rate, and E_{cf} is the activity of climbing fiber input. We adjusted γ to be 0.0001 or 0.0005 to successfully execute all the simulation and real world control performed in the present study. In this algorithm, when signs of Y_{Gr} and E_{cf} are same, LTP occurs at the Gr-Pk synapse, whereas when their signs are different, LTD occurs. The synaptic weights were confined to positive values, as the synapses between Gr and Pk cells are excitatory.

C. Simulation and real world testing

We tested the performance of the proposed controller in simulation and real world. The mathematical model of the e-nuvo Wheel used for the simulation is described as follows [6], and the values of the parameters are shown in Table.I.

$$\begin{aligned} au &= ((M+m)r_t^2 + mlr_t\cos\theta + J_t + iJ_m)\theta^{''}\theta \\ &- mlr_t\sin\theta \cdot \theta^{'2} + c\phi^{'} \\ &+ ((M+m)r_t^2 + J_t + iJ_m)\phi^{''} \end{aligned} \quad (10)$$

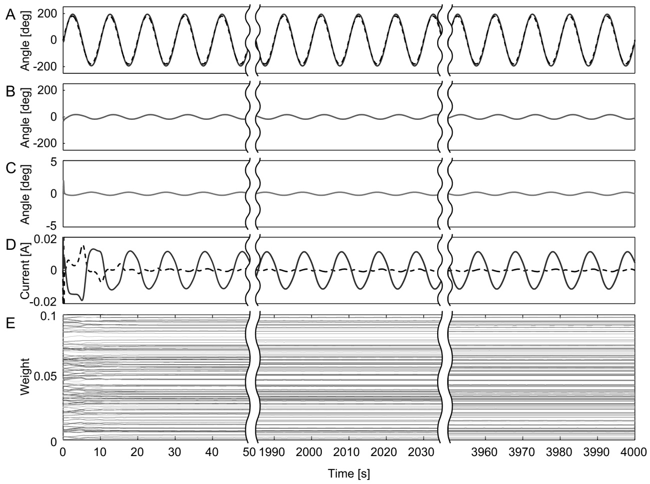

Fig. 2. Control of the 2-wheeled robot when the desired trajectory is a single frequency (0.1Hz) sinusoid in simulation. A: superposition of desired (dotted line) and actual (solid line) trajectories, B: control error (desired minus actual trajectory), C: body tilt angle, D: superposition of PD controller output (dotted line) and the cerebellar model output (solid line), E: superposition of the synaptic weights between Gr and Pk. The initial, middle and last 50 seconds are shown out of the 4000 seconds simulation.

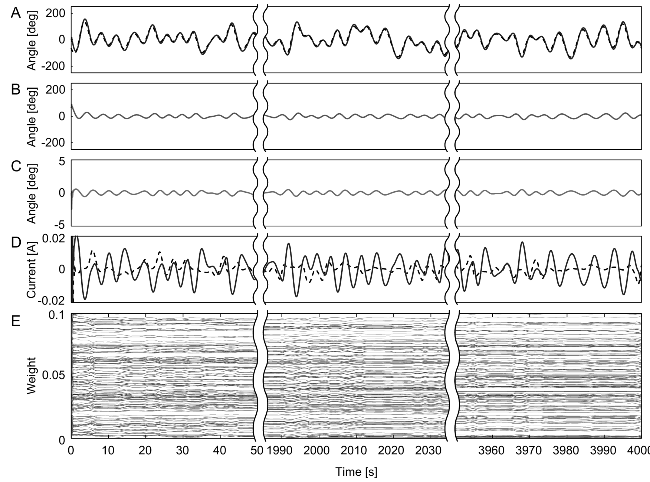

Fig. 3. Control of the 2-wheeled robot when the desired trajectory is a band-limited noise (<0.3Hz) in simulation. The format is the same as in Fig.2.

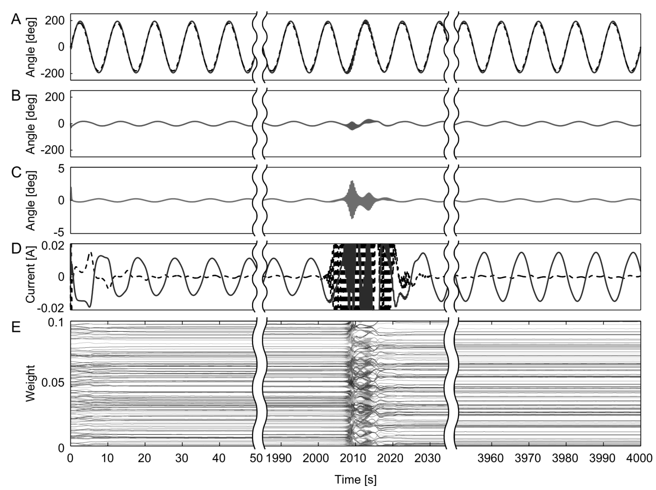

Fig. 4. Control of the 2-wheeld robot when the desired trajectory is a single frequency (0.1Hz) sinusoid and an extra-weight was imposed on the robot at the middle of the control (at 2000 seconds) in simulation. The format is the same as Fig.2.

$$
\begin{aligned}
&((M+m)r_t^2 + 2mlr_t\cos\theta + ml^2 + J_p + J_t + J_m)\theta^{''}\theta \\
&- mlr_t\sin\theta\cdot\theta^{'2} - mgl\sin\theta \\
&+ ((M+m)r_t^2 + mlr_t\cos\theta + J_t + iJ_m)\phi^{''} \\
&= 0 \qquad (11)
\end{aligned}
$$

where θ is the tilt angle of the body, ϕ is the rotational angle of the 2 wheels that always move together. u and a are a desired trajectory in current and a gain between the current and the generated torque.

III. RESULTS

A. Test in simulation

When a 0.1Hz sinusoid is given as a desired trajectory for the angle of the 2 wheels, the proposed controller can stably control the robot (Fig.2) . During the initial cycle of the desired trajectory, the output current of the PD controller is large, but it rapidly decreases afterwards, demonstrating that the cerebellar model learned to minimize the output of the PD controller and took over the control after a few cycles of the desired trajectory. This relationship is kept long until the end of the simulation (4000 seconds). Changes in the synaptic weights between Gr and Pk cells reflect this relationship between the PD controller and the cerebellar model (Fig.2E). These synaptic weights changed only for the initial cycle, and afterwards they showed minimal changes.

When a more challenging desired trajectory consisting of band limited noise ($<$ 0.3Hz) is given, the results are qualitatively the same (Fig.3).

Next, we put an extra-load on the robot in the middle of the control to evaluate the adaptive capability of the proposed controller. In this simulation, the proposed controller can handle the abrupt increase (30%) in its weight at 2000 seconds and keep stable control by the learning capability of the cerebellar model (Fig.4). If the PD controller alone is employed, it cannot compensate for the same extra-load, and looses the control (data not shown).

B. Test in real world

Using the same controller implemented on MATLAB Simulink as in the simulation, we tried to control an e-nuvo Wheel in real world. The output of the controller was conveyed to the robot, and its resultant trajectory was fed-back to the controller via MATLAB xPC target (Fig.5).

The controller successfully controlled the robot with small errors in its trajectory (Fig.6B). Changes in the contribution of the PD controller and the cerebellar model to the input current to the robot are qualitatively the same as in the

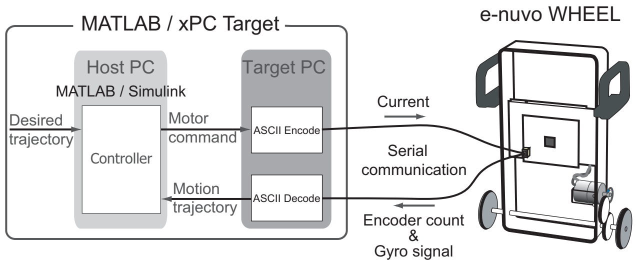

Fig. 5. Configuration of the 2-wheeled robot control in real world.

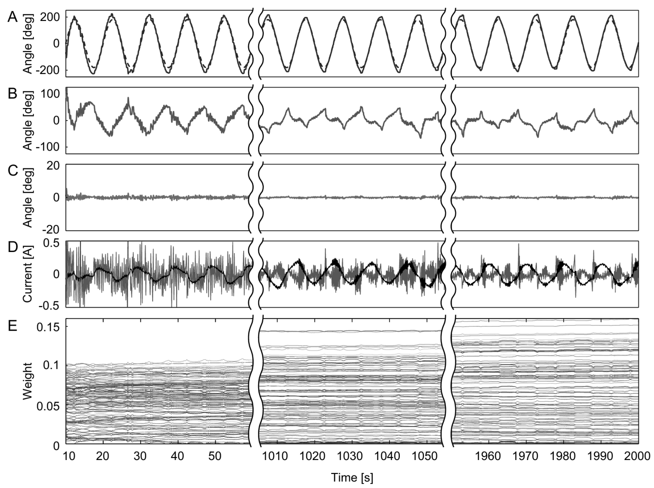

Fig. 6. Control of the 2-wheeled robot when the desired trajectory is a single frequency (0.1Hz) sinusoid in real world. The format is the same as Fig.2.

simulation (Fig.2). Namely, for the first few cycles, the contribution from the PD controller is greater, but after that it decreases as the cerebellar model learns to minimize it. Note also that the amplitude of the control error gradually decreases.

IV. Discussion

The cerebellar model we employed in the present study has an anatomically realistic structure of the cerebellar cortical neuronal network, yet works in real time on a PC. Thus it is testable not only in simulation but in real world as well. Recently we demonstrated that this cerebellar model alone can adaptively control a direct current (dc) motor [7]. Namely, it can adaptively reduce the control error for a pseudo random desired trajectory, and compensate for an extra-load suddenly put on the dc motor in the middle of the control [7]. Presently we improved the configuration of this model and applied it for more challenging problems, i.e., the control of an unstable 2-wheeled balancing robot. As the cerebellar model with the initial random weights alone cannot control the 2-wheeled robot, we combined a PD controller in parallel with the cerebellar model. We employed the feedback-error learning scheme [5] in which the cerebellar model learns to minimize the output of the PD controller. We demonstrated that the proposed controller successfully controlled an unstable 2-wheeled balancing robot, and adaptively compensated for a sudden increase in its body weight. These results confirm validity of the proposed controller in the control of unstable systems, and further support the hypothesis that the cerebellum learns to minimize the error in motor commands [5].

In the future study, we will test the performance of the proposed controller in more complex tasks, and compare with conventional adaptive control methods. On the other hand, we will evaluate roles of each inter neuron (Go, Ba/St cells) in motor control to understand signal processing in the cerebellar cortical neuronal network. Our cerebellar model in the current configuration, receives both desired trajectory and error in motion via mossy fibers. Thus we expected that the cerebellar model would acquire both feed-forward and feed-back natures of motor control, which also should be evaluated in the future study.

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