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The cerebellum as computed torque model

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Abstract. *In this article we consider the cerebellum in the vertebrate motor control system. Analyzing the delays in this control loop as well as the complexity of the dynamics of the skeletomuscular system, we £nd that two well-known interpretations of the function of the cerebellum—that of a Smith predictor, or of an inverse model controller—are insuf£cient to solve the control problem at hand.*

1 Introduction

Apart from the fact that it has only just begun, the impact that recent advances in the £eld of mechatronics have on the development in robotics are almost as strong as microelectronics has had on computer science. No longer are heavy industrial robots required, but new drive concepts which are both strong and light-weight have enabled the construction of robot arms with an impressive force-to-weight ratio.

Controlling such a robot is, however, a different story. The light-weight character of such arms has as disadvantage that the joints are not stiff but ¤exible, and therefore the interdependencies between the joints make stable control of a robot arm with at least 6-DoF problematic. A solution which does not use adaptive control will not solve all problems at hand.

Taking a look at nature, the cerebellum seems to be a very likely candidate for solving these problems. In the cerebellum, sensor signals combined with motor plans are used to generate motor signals. Cerebellar models were £rst applied for robot dynamics control after Albus' CMAC model was published in 1975 [3]. Especially the later implementations by Miller [16] for control of a 4 DoF robot arm as well as biped control have demonstrated the power of this approach. Developments in cerebellar modelling has led to the further development of computational cerebellar models (see, e.g., [8]). Nevertheless, applications of such models remain limited to toy problems, not exceeding the complexity of (simulated) two-link robot arms. Are indeed cerebellar models advanced enough to be used as an alternative to existing control methods? Are these models used correctly? In order

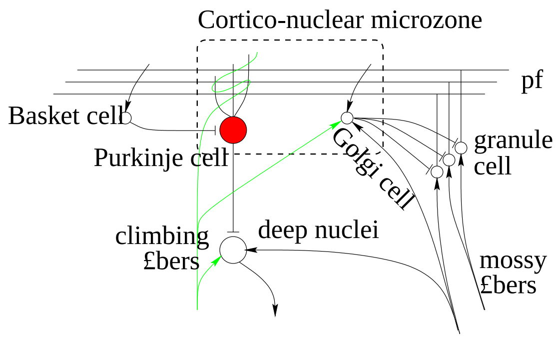

Figure 1: Major components of the cerebellum.

to investigate this problem, we consider two existing interpretations of the function of the cerebellum: that of it being either a forward or an inverse model of the motor apparatus.

This paper is organized as follows. Section 2 shortly describes the structure of the cerebellum, and discusses the problem of dynamics control is more deeply discussed. In section 3, two popular theories about the function of the cerebellum are elucidated, and we £nd that neither one of these theories alone can explain the control success of the biological motor system. An alternative is proposed. A discussion is found in section 4.

2 Background

2.1 The cerebellum

The cerebellum (see Figure 1) functions as a feed-forward control center for the motor commands originating in the cerebrum. Containing learned models of the skeletomuscular system, it provides timing control of opposing muscles, and force as well as stiffness control. The human cerebellum consists of about 10 million Purkinje cells (pc), each receiving about 150,000 excitatory synapses via the parallel £bers (pf) [22, 13]. The pf are the axons of the granule cells; these cells are excited by the mossy £bers (mf) originating from the spinal cord. Each pf synapses on about 200 Purkinje cells. A Purkinje cell receives further excitatory synapses from one single climbing £ber (cf); this can £re a cell when active. Basket cells, being activated by pf afferents but also inhibited by pc, can inhibit a Purkinje cell, thus ensuring activation of a single pc within a local neighbourhood. Finally, Golgi cells receive input from pf, mf, and cf, and inhibit granule cells.

The granule cells operate as pattern separators. The densely 'coded' patterns, originating from the spinal cord, have to be 'preprocessed' by the granule cells, such that the imprecise giant Purkinje cells can discriminate them. The output of a Purkinje cell is an inhibitory signal to the cerebellar nuclei.

The £rst mechanistic model of the cerebellum was introduced by Braitenberg and Atwood [4]. In¤uenced by Eccles *et al.* [7], two other early models by Marr [14] and Albus [2] view the cerebellum as a learning pattern recognition system. Their more detailed models, as well as a subsequent computational model by Albus [3], have contributed to a wide acceptance of the pattern recognition theory.

2.2 Dynamic control

In order to instantiate a joint trajectory $\ddot{\theta}[t]$, an accurate controller is required to solve the inverse dynamics problem. When a joint angle increment is available at each Δt, the controller must compute the necessary forces or torques at the motor side to realize the requested motion. In traditional industrial robotics, a PD (*P*roportional-*D*erivative) controller is customarily used, with which all the joints are independently controlled, and centrifugal and Coriolis forces are assumed to be nonexistent. This control law is known as *servo control.*

The forces that the robot structure exerts at the actuators are given by

$$\boldsymbol{\tau} = M(\theta)\ddot{\theta} + V(\theta, \dot{\theta}) + G(\theta) \tag{1}$$

where $\boldsymbol{\tau}$ is an N-vector of torques exerted by the links, and θ, $\dot{\theta}$, and $\ddot{\theta}$ are N-vectors denoting the positions, velocities, and accelerations of the N joints. $M(\theta)$ is the the mass matrix, $G(\theta)$ is the gravity working on the joints, and $V(\theta, \dot{\theta})$ is the combined Coriolis, centrifugal, and friction forces.

2.2.1 Joint elasticity

The simplest kind of robot arm consists of rigid links which are connected by rigid joints. This assumption is approximately true for industrial robots; the construction of the robot arm is thus that any yield in the links as well as the joints can be neglected. This usually does not hold for light-weight robot arms; due to weight and space limitations, the actuators that are employed are not powerful enough to eliminate the

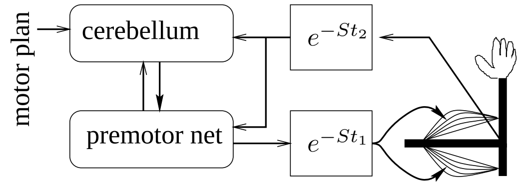

Figure 3: Motor system. The motor plan, generated in the cerebral cortex, is '£ltered' by the cerebellum, and sent through the premotor network to the spinal cord. The delays in the control loop are primarily due to nerve delays; t_1 and t_2 are typically in the order of 50ms.

in¤uence of gravity, friction, and Coriolis and centrifugal forces. This means that, apart from having to take the full matrices M and V into account, they are parameterized by the joint positions and velocities. Also, due to the limited torque that such actuators can exert, high-ratio gear boxes, which are known for their high elasticity, are required [21].

Due to these highly nonlinear components in the dynamics, and the interdependence of the dynamics of the joints, a simple PD controller will lead to instabilities, and a better control mechanism is required.

2.2.2 Partitioning the control law

A standard approach solve to these problems is *control law partitioning* or *computed torque control*: the controller is dissected in a *model based part* and an *error based part* [6]. The model-based part uses the (known) parameters of the system such that the control part can consider the plant as a unit-mass system. If $\boldsymbol{\tau}_d$ is the input torque to the robot, we can write $\boldsymbol{\tau}_d = \alpha\boldsymbol{\tau}_d{}' + \beta$ where $\boldsymbol{\tau}_d{}'$ is the torque applied to the unit mass system.

Now, for manipulator control we £nd that (1)

$$\alpha = M(\theta), \tag{2}$$

$$\beta = V(\theta, \dot{\theta}) + G(\theta). \tag{3}$$

The control law now is

$$\boldsymbol{\tau}_d{}' = \ddot{\theta}_d + \mathbf{k}_v(\dot{\theta}_d - \dot{\theta}) + \mathbf{k}_p(\theta_d - \theta) \tag{4}$$

where $(\theta_d, \dot{\theta}_d, \ddot{\theta}_d)$ is the desired joint trajectory.

The main problem is to £nd an optimal α and β; traditionally, this problem is solved by minute modeling of robot structures. PD control is a special case with $\alpha \equiv I$ and $\beta \equiv 0$.

3 Cerebellar models in control

When applying cerebellar models to robot control, an obvious approach is to use the cerebellum as *controller* of the skeletomuscular system. Consider the motor system depicted in Figure 3. Of importance are the delays t_1 and t_2, which are in the order of

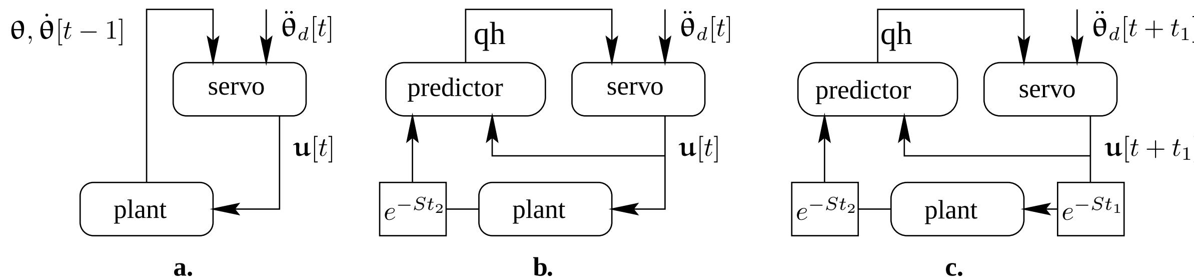

Figure 2: Servo control without and with delays. In **a**, a standard servo control loop is shown. Feedback delays are added in **b**: in this case, the sensor feedback signals have to be predicted using the input to the system as well as the (delayed) feedback from the plant. In **c**, there is also a forward delay; in this case, the desired motion (motor plan) has to be planned ahead.

30–70ms [1]. Such delays cannot be handled by standard servo control loops [20], such as shown in Figure 2a. Instead, in order to take the feedback delay into account, the state signals originating from the plant must in some way be predicted (see Figure 2b). From the delayed feedback from the plant and the undelayed control signals $\mathbf{u}[t]$ originating in the servo unit, the predictor estimates the state of the plant over a time frame t_2 ahead. Using the feedback of this predicted signal, the servo controller can still control the robot arm. In Figure 2c, the signal from the controller to the plant is also delayed: the motion $\ddot{\theta}_d$ has to be planned ahead.

3.1 Theorem 1: the forward model

The control scheme shown in Figure 2c is known as the *Smith predictor* [19], and is typically used to control systems which have very long delays in their feedback loop. In effect, the predictor module is a feedforward model of the plant, and mimics its input-output behaviour accurately.

The interpretation of the cerebellum as Smith predictor (i.e., taking the role as the predictor module) has been previously propagated by Miall et al. [15]. However, for arguments put forth in section 2.2, it is unlikely that a Smith predictor and a servo control loop suf£ce to control the skeletomuscular system. In particular, the joint interdependencies which result of the ¤exible joint approach require a control method taking all joint state variables into account; controlling each joint separately with a servo control method does not lead to stable control [12, 17]. Although the Smith-predictor theory is very plausible, it alone does not suf£ce.

3.2 Theorem 2: the inverse model

A second, totally different interpretation is that of the cerebellum functioning as an inverse model of the skeletomuscular system [11]. A well-known cerebellar model used as an inverse controller is the APG, which has been tested on 2 DoF simulated robot arm control [9].

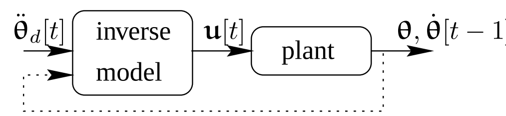

Figure 4: Using an inverse model as controller.

An exact inverse model can be used to compute the torque necessary to realize a desired joint trajectory (Figure 4). When the model is exact, in the absence of external in¤uences (fast) feedback is not required.

A problem with using the cerebellum as inverse models while incorporation the effect of the feedback delays, however, is increased complexity of the model. First of all, obtaining such a model from analyzing the complex nonlinear forward dynamics system is infeasible. But secondly, learning an inverse model, apart from being extremely dif£cult [18], leads to highly unstable control when the feedback loop is slow [10]. Furthermore, the method of learning inverse dynamics does not scale to higher-dimensional problems.

3.3 Biological motor control needs both

From the model evaluation in section 2.1 it seems likely that the functionality of a Smith predictor is incorporated in the cerebellum. On top of that, however, in order to solve the high-dimensional nonlinear control problem, a control mechanism more complex than a per-joint servo control is required.

A possible solution to the problem is using computed torque control. When combining this approach in a feedback loop with a Smith predictor, the resultant structure is as shown in Figure 5. Here the delayed feedback from the plant is used to update the forward model, whereas the fast feedback from the model is incorporated in the computed torque control loop. Stability of such a system has been demonstrated [10].

But how can this dissection of the cerebellar function be explained with respect to its uniform structure? The plant, as well as the forward model, are steered with the control signal $\mathbf{u}$. When considering

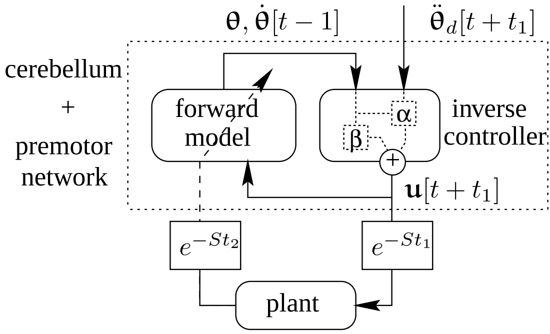

Figure 5: The cerebellum and premotor network implement both a forward model and an inverse controller.

only the rigid joint robot, the computations that have to be performed by the forward model equal [21]

$$\ddot\theta \leftarrow \underbrace{M(\theta)^{-1}}_{\alpha^{-1}}\Big[\mathbf{u}\underbrace{-V(\theta,\dot\theta) - G(\theta)}_{-\beta}\Big]. \qquad (5)$$

When the inverse controller is implemented using control law partitioning, we obtain

$$\mathbf{u} = \overbrace{M(\theta)}^{\alpha}\left[\ddot\theta_d + \mathbf{k}_v\Delta\dot\theta + \mathbf{k}_p\Delta\theta\right] \qquad (6)$$
$$\underbrace{+V(\theta,\dot\theta) + G(\theta)}_{\beta}.$$

From Eqs. (5) and (6) we can see that their implementation requires similar computations, and an implementation of such transformations can be realized with similar components and a feedback loop [5].

4 Discussion

There exists a large gap between the applicability of cerebellar models to robot dynamics control, and existing applications of such. Nevertheless, the emerging interest in cerebellar models demonstrate an enormous possibility. Although many cerebellar models exist which can be applied to robot dynamics control, the applications of such models are almost exclusively restricted to 2-link simulated robot arms.

We have tried to show that existing cerebellar models as either inverse or forward model of the skeletomuscular system are incapable of solving complex inverse dynamics control problems. Instead, we have proposed a system including both inverse and forward models of the skeletomuscular system. An implementation of such a control system is currently attempted to validate this theory.

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