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## A real-time spiking cerebellum model for learning robot control

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#### **1. Introduction**

Although the cerebellum architecture has been studied for more than 100 years [\(Ramón y Cajal, 1995; Golgi, 1967\), i](#page--1-0)ts functional role is still an open topic. The cerebellum plays a major role in coordinated and accurate movements [\(Bastian et al., 2000; Ito, 2001\). I](#page--1-0)t is thought to be an essential computing tissue for our daily manipulation tasks. Its regular topology has inspired many artificial neural network models in the past decades [\(Kettner et al., 1997; Medina](#page--1-0) [andMauk, 1999; Schweighofer et al., 1998a, b; Spoelstra et al., 2000;](#page--1-0) [Arbib et al., 1995; Eskiizmirliler et al., 2002\). F](#page--1-0)urthermore, there are many research groups modelling in detail its cells [\(D'Angelo et](#page--1-0) [al., 2001; Bezzi et al., 2004; Steuber et al., 2004\)](#page--1-0) in order to elucidate the specific computations that take place at each part of the cerebellum architecture.

There have been great advances in robotics, mainly in industrial applications. Yet most of the industrial robots use stiff joints

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#### ABSTRACT

We describe a neural network model of the cerebellum based on integrate-and-fire spiking neurons with conductance-based synapses. The neuron characteristics are derived from our earlier detailed models of the different cerebellar neurons. We tested the cerebellum model in a real-time control application with a robotic platform. Delays were introduced in the different sensorimotor pathways according to the biological system. The main plasticity in the cerebellar model is a spike-timing dependent plasticity (STDP) at the parallel fiber to Purkinje cell connections. This STDP is driven by the inferior olive (IO) activity, which encodes an error signal using a novel probabilistic low frequency model. We demonstrate the cerebellar model in a robot control system using a target-reaching task. We test whether the system learns to reach different target positions in a non-destructive way, therefore abstracting a general dynamics model. To test the system's ability to self-adapt to different dynamical situations, we present results obtained after changing the dynamics of the robotic platform significantly (its friction and load). The experimental results show that the cerebellar-based system is able to adapt dynamically to different contexts.

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and high-gain closed-loop control. The movement of stiff joints facilitates control since it reduces (or even avoids) the necessity of dynamics models. Industrial robots are able to perform accurate trajectory-following adopting online closed-loop error-correction schemes. This strategy became possible due to the outstanding processing speed of current circuits that calculate errors and deliver feedback correction signals on a microsecond time scale. Nevertheless, stiff-joint control does not take advantage of the robot dynamics, which results in unnatural control, wasted energy and reduced robot autonomy.

In contrast, biological limbs have joints of variable stiffness and use low-gain control schemes where the dynamics cannot be ignored. Indeed, the dynamics, for instance, of an arm–hand system, is likely to be significantly modified when manipulating objects of different weights. Moreover, biological systems have delays in sensorimotor pathways up to several hundreds of milliseconds. This makes it impossible to apply on-line closed-loop error-correction strategies without having predictor modules able to abstract the kinematics and dynamics models of the platform.

There are plenty of challenges in robotics such as the development of accurate low-gain control schemes for robotic platforms of several degrees of freedom (DOF) and compliant joints (non-stiff). Compliant joints and low-gain control are of particular interest for robots interacting with humans. For security reasons, a robot becomes a safer platform if it is not able to apply dangerous forces and can absorb energy.





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In this paper, we emulated the learning strategy followed by biological systems to control low-gain compliant robotic platforms in the presence of sensorimotor pathways with delays of hundreds of millisecond. To do this, we studied how a cerebellum model can abstract dynamics models of the robotic platform to facilitate control by predicting and correcting errors in the motor space.

#### **2. Cerebellum Model**

Previous modelling of the cerebellum contribution in movement learning includes the modeling of smooth pursuit eye movements [\(Kettner et al., 1997\). I](#page--1-0)n this work, the cerebellar nuclei cells were not implemented in their model, and analog units, not spiking neurons were used. [Schweighofer et al. \(1998a\)](#page--1-0) proposed a cerebellum model learning the inverse dynamics of a two-link six-muscle arm system. The parallel fiber-Purkinje cell (PF-PC) long-term depression (LTD) was biologically inspired, but not the long-term potentiation (LTP), which was implemented as a weights normalization process. Moreover, learning was performed over short trials only (less than 500 ms) and not continuously as in our contribution.

A few cerebellar models for eyelid conditioning have used spiking neurons (e.g. [Medina and Mauk, 1999; Hofstötter et al., 2002\).](#page--1-0) Learning was based on spikes coincidences between neurons, but



Fig. 1. Cerebellum model diagram. Inputs about the movement (desired arm state and target information) were sent (upward arrow) to the two layers of mossy fibers (MF): distance to the target and its absolute position in the experimental field ( $d_{\text{targ}}(t)$  and  $\theta_{\text{targ}}$ ) as well as desired positions ( $\theta$ ) and speeds ( $\dot{\theta}$ ) of the shoulder (s) and elbow (e) joints along the trajectory. These desired states were obtained from a crude inverse kinematic model (see [Fig. 9\),](#page--1-0) representing motor cortex and other motor areas. The mossy fibers projected to two layers of granule cells (GR, 1000 neurons per layer) and to 16 deep cerebellar nuclei (DCN) cells. The 32 Purkinje cells (PC), 16 DCN cells and 32 inferior olive (IO) neurons were divided along 4 functional zones (inspired from cerebellar microzone organisation), one for each of the actuators, agonist or antagonist, of the elbow and shoulder joints. The PC received excitatory inputs from all the desired joint state-related GR (ascending axons that maintain the cells in a state of excitability) and from all parallel fibers PF with a connection probability of  $p_{PC-PF} = 0.8$ . They also received an afferent from the IO in a one-to-one scheme. In turn, the DCN cells received inhibitory connections from two PCs of the same microzone. The teaching signal was processed by the IO cells (downward arrow, top) (see [Fig. 9\).](#page--1-0) At the output of the cerebellum (downward arrow, bottom), the DCN firing rates were interpreted as predictive positive (+) and negative (−) torque corrections (τ) for the shoulder (s) and elbow (e) joints. The numbers in brackets indicate the number of cells per layer and per zone.

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