THE POSSIBLE CONTROL IMPLICATIONS OF THE INFERIOR OLIVE →DEEP CEREBELLAR NUCLEI PATHWAY IN A DISTRIBUTED PLASTICITY CEREBELLAR MODEL

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MOTIVATION

The cerebellum is involved in controlling and learning smooth coordinated movements, therefore an accurate understanding of how this control engine works should have a **strong impact on the control of biomorphic robot**s.

- We have studied **the possible control implications** that the inferior olive→ deep cerebellar nuclei cell connections (IO→ DCN) may present **in a distributed-synaptic-plasticity cerebellar model** (activity conveyed by this connection seems to control plasticity at DCN synapses (Bengtsson & Hesslow 2006) (Ruigrok & Voogd 2000)).
- The Marr and Albus model hypothesized that parallel fibers (PFs) presented LTP/ LTD synaptic mechanisms so as to correlate the activity at PFs with an error signal through climbing fibers. In subsequent studies it has been demonstrated that **most of the cerebellar connections show traces of plasticity** (Hansel, Linden & DAngelo 2001).
- **We have developed a firing-rate cerebellar model** (Garrido et al. 2012) **with plasticity mechanisms** at PF→PC and at DCN synaptic inputs (from Mossy Fibers (MFs), Purkinje Cells (PCs) and IO). Therefore, we present a model where the IO→DCN pathway plays a fundamental role by refining the cerebellar learning performance.

CEREBELLAR MODEL

Our cerebellar model includes the following plasticity mechanisms:

IO-driven LTD and LTP at PF→PC connections.
IO-driven LTP and LTD at PC→DCN connections.
PC-driven LTD and LTP at MF→DCN connections.
PC-driven LTD and LTP at PC→DCN connections.

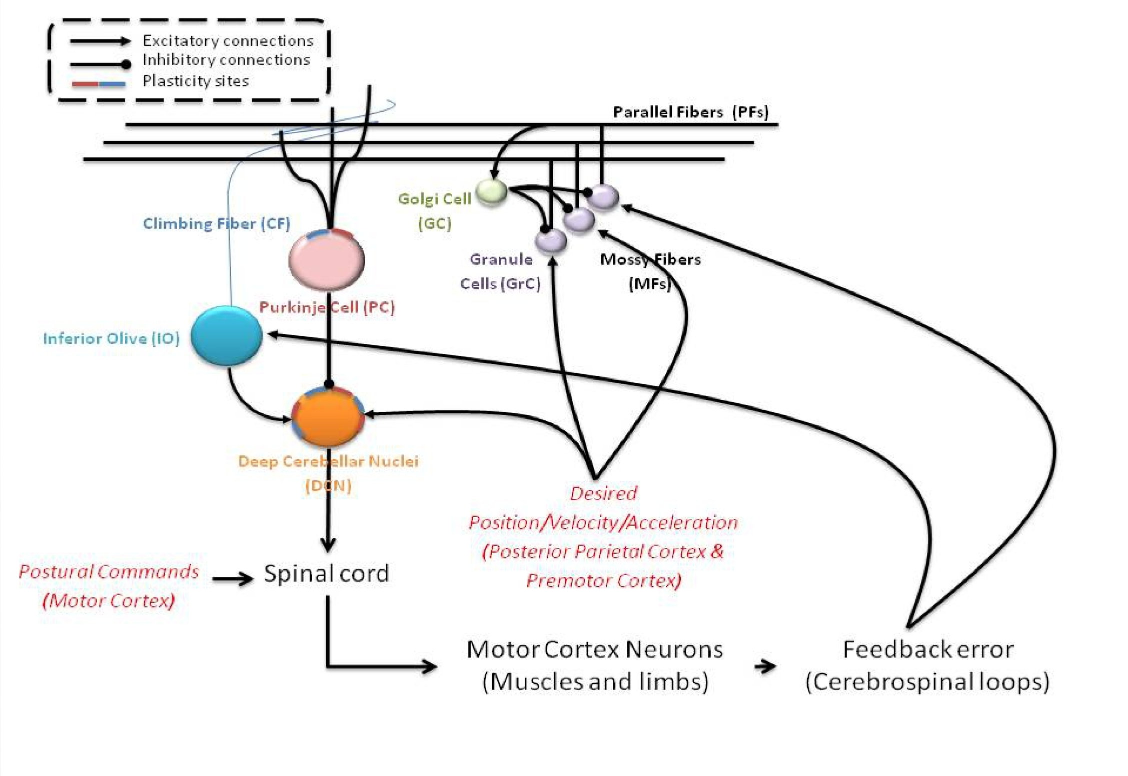
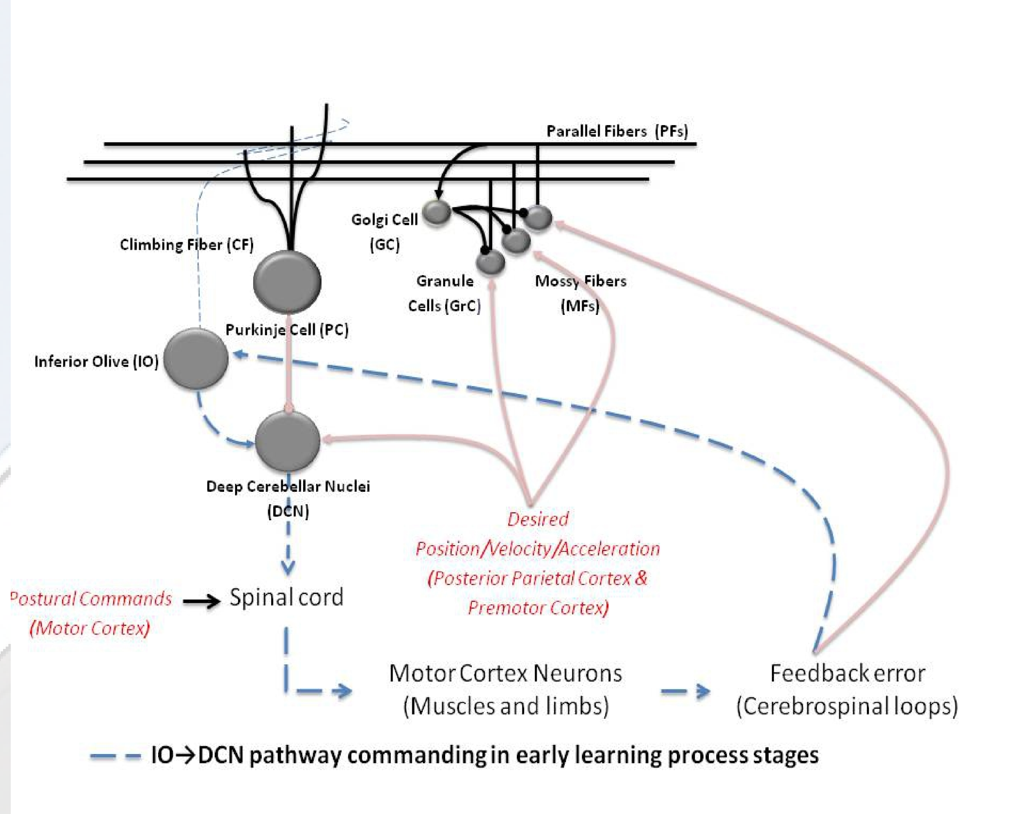
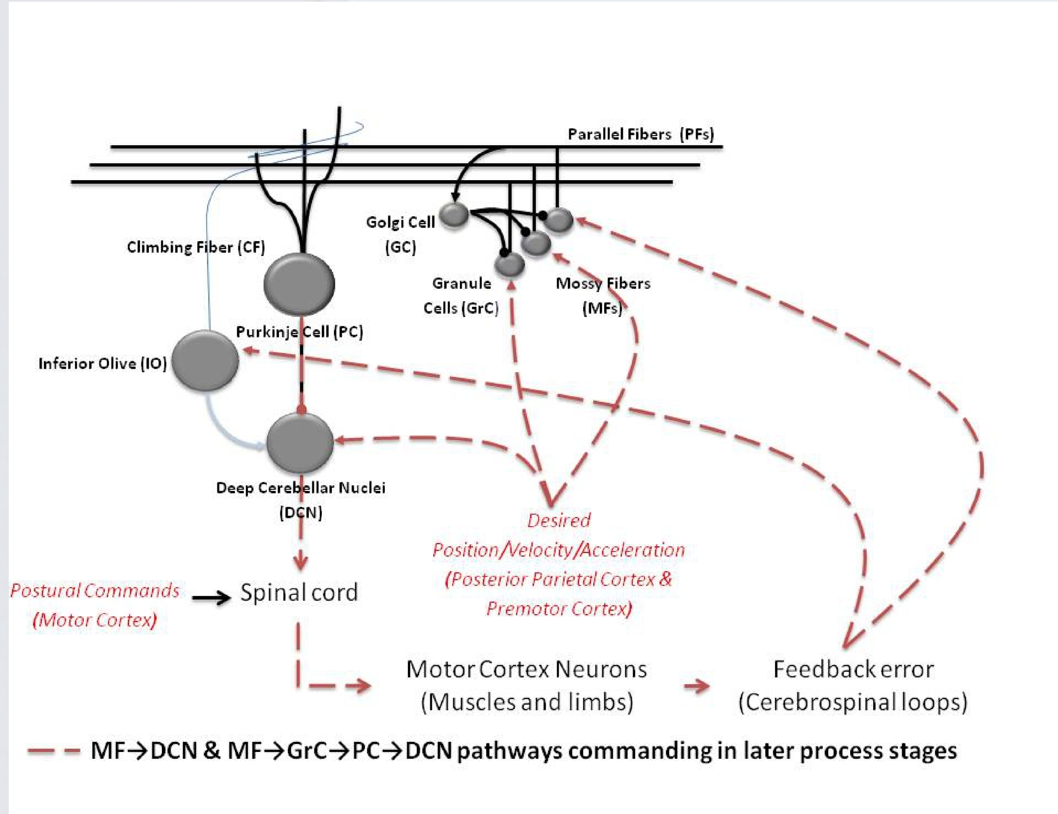


Figure 1. Cerebellar microcircuitry, main components of the cerebellar paths and plasticity sites included. The cerebellum receives proprioceptive signals through MFs. These inputs follow two different pathways: the first one reaches the DCN through the cerebellar cortex, and the second one contacts directly the DCN cells. Long-term plasticity has been represented using two colors: red indicates potentiation (LTP) and blue indicates depression (LTD).

DIFFERENT CONTROL PATHWAYS DURING LEARNING PROCESS



(A)



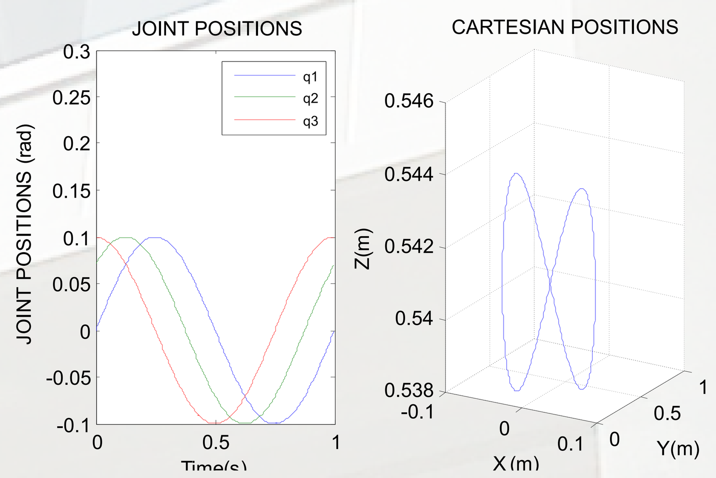
(B)

Figure 2. Effect of the presented plasticity mechanisms.
A. The feedforward control loop trough IO→DCN ensures stability during the first stage of the learning process.
B. The distributed learning process through different pathways ensures a relatively fast synaptic weight adjustment by using the PF→PC plasticity mechanism and the subsequent slow adaptation of the excitation and inhibition levels by means of the MF→DCN and PC→DCN synaptic plasticity mechanisms. These mechanisms also helps keep the PF→PC synaptic weight values in their optimum range (in our experiments, this range has been fixed to [0, 1], although other ranges could be suitable).

CONTROL ARCHITECTURE

The adaptive cerebellar module delivers corrective add-on torque values to compensate for deviations in the inverse dynamic module when manipulating an object of mismatched weight

Benchmark Trajectory to be accomplished



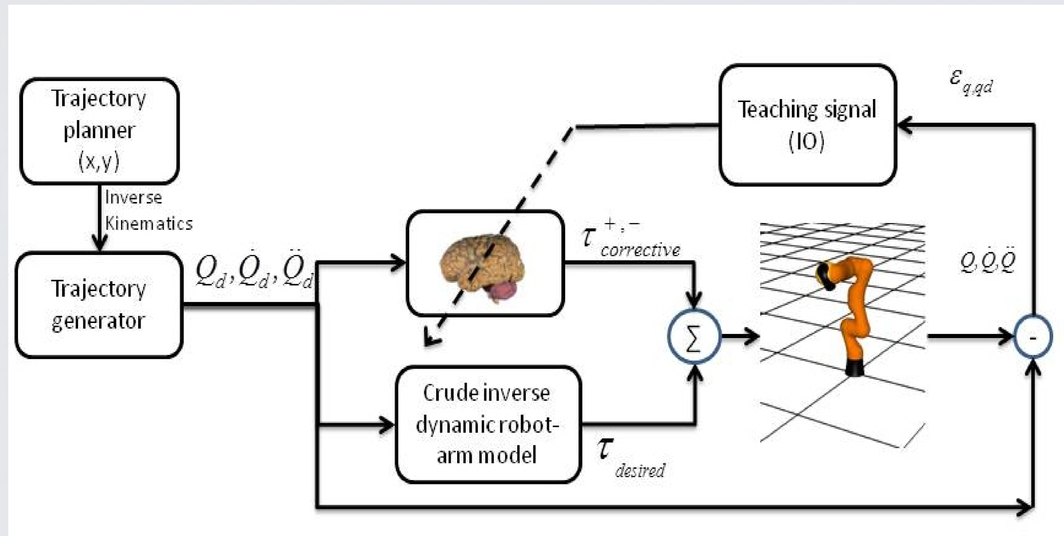


Figure 3. Light-Weight-Robot (LWR) simulator within a feed-forward control loop. The robot-plant physical characteristics can be modified to match different contexts (different contexts means that the object manipulated by the robot (payload) has different weights). This LWR robot is a 7-DOF arm composed of revolute joints. We used the first, second and fifth joint maintaining the others fixed.

RESULTS

The plasticity mechanisms that determine the synaptic strength in MF→DCN/PC→DCN/IO→DCN connections were driven by the activity from PCs which is responsible for the balance (homeostasis) between all these plasticity laws. This PC activity makes MF→ DCN and PC→ DCN synaptic strength increase while makes the IO→ DCN synaptic strength decrease. During the first learning stages the IO→ DCN corrective action predominates (Fig5.C and 5.D).Afterwards, this corrective action is gradually decreased while the corrective action provided by MF→ DCN and PC→ DCN connections is gradually increased. The transition between these two control actions is regulated by the PC activity which in turn, is working in a constant range of frequencies thanks to MF→DCN and PC→DCN connections. We obtain a system able to self-adapt by means of a distributed learning where all the learning sites are complementary working together.

FURTHER INFORMATION: If you are interested in this work or any other related information from our group, please do not hesitate to contact me at **nluque@atc.ugr.es.**

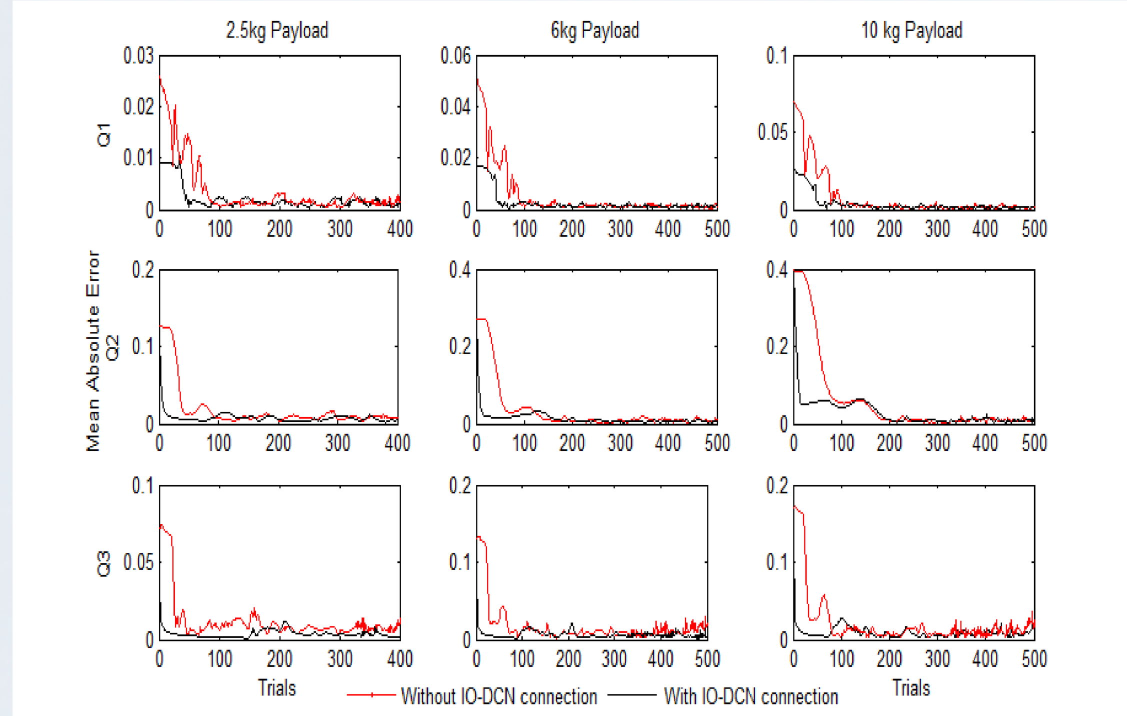


Figure 4. Comparison between the MAE evolution with/without using IO-DCN connection when manipulating different masses (2.5kg, 6kg, 10kg). The system gain has been set to manipulate up to 0.5kg. The manipulated masses are larger than expected, so the existing plasticity mechanisms at MF/PC→DCN adjust the cerebellar output to cope with these masses. The model with IO→ DCN connection supplies a proper adjustment from the beginning of the learning process

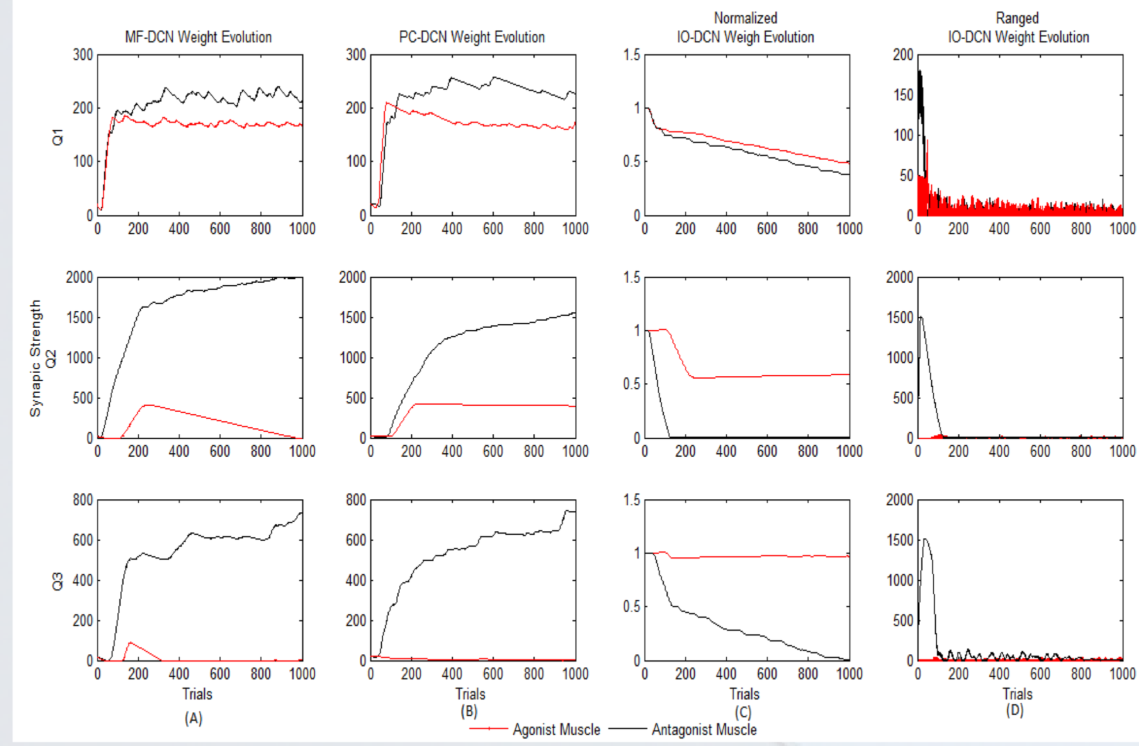


Figure 5. Synaptic weight evolution during the learning process, at IO→DCN, MF→DCN and PC→DCN connections when using a 10kg payload and initial parameters for a 0.5 kg payload setting. (A) Synaptic weight at MF→DCN. (B) Synaptic weight at PC→DCN. (C) Normalized synaptic weight at IO→DCN. (D) Synaptic weight at IO→DCN.

CONCLUSIONS

The results suggest that the cerebellar gain control is a consequence of the MF→ DCN and PC→ DCN synaptic plasticity working in balance with IO→DCN connection. Thus, this balance (homeostasis), which is implemented through different learning, enhances the cerebellar learning performance. IO→ DCN connection ensures stability in the very early learning stages, that is, while the weights of MF→DCN and PC→DCN connections have yet to stabilize. Once the learning process is finished, the IO→DCN connection effect ceases.

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