



A Modular Bio-Inspired Architecture for Motor Learning and Control of Robotics Systems

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Doctor of Philosophy
Doctoral thesis in Electrical Engineering

DTU Electrical Engineering
Department of Electrical Engineering

A Modular Bio-Inspired Architecture for Motor Learning and Control of Robotics Systems

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Summary

CLASSICAL robotic control methods struggle in overcoming the constraints and challenges of modern robotics applications. Nowadays, robots require a high level of flexibility to adaptively work in a wide range of scenarios.

Our study proposes robotic control solutions that take inspiration from the vertebrates' central nervous system (CNS) to endow robots with the necessary adaptive and predictive capabilities.

In the thesis, we first shed light on the neural mechanisms employed by the CNS to produce complex motor movements in dynamically challenging conditions. Among all the CNS regions involved in motor control, the research focuses on the cerebellum, a powerful and compact neural circuit well known for its crucial role in adaptive learning and control of complex motor behaviors.

Based on the challenges and considerations identified from the review of the literature, we propose distinct biologically inspired architectures for robotic real-time adaptive motor learning and control in unknown and disturbed environments. The cerebellar-like control schemes embed a cerebellar-like simulations model that aims to artificially reproduce the functionality, plastic learning, modularity, and morphology of the cerebellum through the combination of machine learning, artificial neural networks, and computational neuroscience techniques. The cerebellar-like control schemes mimic through engineering techniques the different theories regarding the acquisition and employment of cerebellar internal models for the control of robotic motor behavior in dynamically changing conditions.

The research merges ideas proposed by the scientific community in the last decades into a unique system that is suitable for real-time robotic applications and attempts to answer through robotics experiments various scientific assumptions regarding the cerebellar internal models theories.

The empirical results show the incredible contribution that a cerebellar-like system can incorporate whether the robotic control architecture is affected by high modeling errors, unobservable and high dimensional state and action spaces, uncertainties, sensor noise, external perturbations, and changes in the dynamics.

Even though there are many ongoing discussions regarding how the cerebellum operates, we believe that the extraordinary potential of the cerebellar-like methods can endow robots with the flexibility and dynamism that modern robotic applications require.

Resumé (Dansk)

MODERNE robotapplikationers begrænsninger og udfordringer kan være problematisk for de klassiske robotstyringsmetoder. I dag kræver robotter et højere niveau af fleksibilitet, så de kan tilpasses flere forskelligartede scenarier. Denne afhandling foreslår robotstyringsløsninger, der henter inspiration fra hvirveldyrs centralnervesystem (CNS) for at udstyre robotter med de nødvendige adaptive og forudsigelige evner. Afhandlingen afklarer først de neurale mekanismer, der anvendes af CNS til at producere komplekse motoriske bevægelser under dynamiske udfordrende forhold. Blandt alle de CNS-regioner, der er involveret i motorisk kontrol, fokuserer forskningen her på cerebellum (lillehjernen), som er et kraftfuldt og kompakt neutralt kredsløb, der er kendt for dets afgørende rolle i adaptiv læring og kontrol af kompleks motorisk adfærd.

Baseret på de udfordringer og overvejelser, der er identificeret fra gennemgangen af litteraturen, foreslår vi særskilte biologisk inspirerede arkitekturer til realtids adaptiv motorisk læring og kontrol for robotter i ukendte og forstyrrede miljøer. De cerebellar-lignende kontrolskemaer indlejrer en cerebellar-lignende simuleringsmodel, der har til formål kunstigt at reproducere funktionaliteten, plastisk indlæring, modularitet og morfologi af cerebellum gennem kombinationen af maskinlæring, kunstige neurale netværk og computertekniske neurovidenskabelige teknikker. De cerebellar-lignende kontrolskemaer efterligner gennem tekniske behandlingsmåder de forskellige teorier vedrørende erhvervelse og anvendelse af cerebellar interne modeller til kontrol af robotmotorisk adfærd under dynamisk skiftende forhold.

Denne afhandling fusionerer ideer foreslået af det videnskabelige samfund i de sidste årtier til et unikt system, der er velegnet til robotapplikationer i realtid, og forsøger gennem roboteksperimenter at besvare forskellige videnskabelige antagelser vedrørende teorierne om cerebellare interne modeller.

De empiriske resultater viser det opsigtsvækkende bidrag, som et cerebellar-lignende system kan inkorporere, selv når robotstyringsarkitekturen er påvirket af høje modelleringsfejl, ikke-observerbare og højdimensionelle tilstands- og handlingsrum, usikkerheder, sensorstøj, eksterne forstyrrelser og ændringer i dynamikken.

Selvom der er mange igangværende diskussioner om, hvordan lillehjernen, cerebellum, fungerer, er det vores overbevisning, at det ekstraordinære potentiale i de cerebellar-lignende metoder kan give robotter den fleksibilitet og dynamik, som moderne robotapplikationer kræver.

Riassunto (Italiano)

I Metodi classici per il controllo di sistemi robotici trovano difficoltà nel risolvere i vincoli e le sfide delle moderne applicazioni di robotica. Al giorno d'oggi, i robot richiedono un elevato livello di flessibilità per lavorare in modo adattativo in un'ampia gamma di scenari.

Il nostro studio propone delle soluzioni per il controllo di sistemi robotici che prendono ispirazione dal sistema nervoso centrale (SNC) dei vertebrati per dotare i robot delle necessarie capacità adattative e predittive. Nella tesi, abbiamo in primis fatto luce sui meccanismi neurali impiegati dal SNC per produrre movimenti complessi in condizioni dinamicamente impegnative. Fra tutte le regioni del SNC coinvolte nel controllo dei movimenti motori, la ricerca si concentra sul cervelletto, un influente e compatto circuito neurale noto per il suo cruciale ruolo nell'apprendimento adattativo e nel controllo di comportamenti motori complessi.

Sulla base delle sfide e delle considerazioni identificate durante la revisione della letteratura scientifica, proponiamo delle architetture di controllo robotico ispirate dai sistemi biologici con il fine di apprendere e controllare flessibilmente ed in tempo reale i movimenti robotici in condizioni ambientali sconosciute e affette da disturbi dinamici. Gli schemi di controllo proposti incorporano un modello di simulazione ispirato dal cervelletto che mira a riprodurre artificialmente la funzionalità, l'apprendimento plastico, la modularità e la morfologia del cervelletto attraverso la combinazione di tecniche di intelligenza artificiale, reti neurali artificiali e tecniche di neuroscienza computazionale. Gli schemi di controllo simil-cerebellare imitano attraverso tecniche ingegneristiche le diverse teorie riguardanti l'acquisizione e l'impiego di modelli mentali interni per il controllo del comportamento motorio robotico in condizioni che cambiano dinamicamente.

La ricerca fonde le idee proposte dalla comunità scientifica negli ultimi decenni in un sistema unico che è adatto per applicazioni robotiche in tempo reale e che tenta di rispondere attraverso esperimenti di robotica a vari presupposti scientifici riguardanti le teorie dei modelli mentali interni. I risultati empirici mostrano l'incredibile contributo che un sistema cerebellare può incorporare se l'architettura di controllo robotico è influenzata da elevati errori di modellazione, segnali non osservabili e multidimensionali, incertezze, rumore nei segnali sensoriali, perturbazioni esterne e cambiamenti nella dinamica.

Anche se ci sono molte discussioni in corso su come possa funzionare il cervelletto, riteniamo che lo straordinario potenziale dei metodi ispirati al cervelletto possa dotare i robot della flessibilità e del dinamismo richiesti dalle moderne applicazioni robotiche.

Preface

The PhD project was developed in the framework of the 10-years European project the Human Brain Project (HBP) (grant agreement No. 785907). The HBP is a H2020 FET Flagship Project which strives to accelerate the fields of neuroscience, computing, and brain-related medicine.

The Automation and Control Group at Electrical & Photonics Engineering Department at Technical University of Denmark (DTU) was partner of the Human Brain Project and was contributing in the development of new neurorobotics tools.

This thesis was prepared in the Electrical & Photonics Engineering Department at Technical University of Denmark in partial fulfillment of the requirements for acquiring the Ph.D. degree in engineering. The supervisors were:

- Professor Henrik Hautop Lund (main supervisor), Department of Electrical & Photonics Engineering, Automation and Control, DTU, Denmark
- Assistant Professor Egidio Falotico (co-supervisor), BioRobotics Institute, Scuola Superiore Sant'Anna, SSSA, Italy

The thesis consists of a summary report of the findings of the Ph.D. project and the collection of articles submitted to peer reviewed scientific journals during the project period 2018-2022.

Kongens Lyngby, 21st April 2022



Marie Claire Capolei

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Contents

Summary	i
Resumé (Dansk)	iii
Riassunto (Italiano)	v
Preface	vii
Acknowledgements	ix
Table of Contents	xi
List of Figures	xv
List of Tables	xxvi
Glossary	xxvii
Acronyms	xxxix
1 Introduction	1
Introduction	1
1.1 Motivation of the Study	2
1.2 Background of the Problem	3
1.3 Statement of the Problem	4
1.4 Scientific Objectives of the Project	5
1.5 Perspective of the Thesis	6
I Theoretical Concepts	7
I.1 Overview of the Cerebellum	11
I.1.1 Introduction	11
I.1.2 Anatomical Prospective	11

I.1.2.1 Cerebellar Microcomplexes	14
I.1.2.1.1 Molecular Layer	14
I.1.2.1.2 Purkinje Cell Layer	14
I.1.2.1.3 Granular Layer	15
I.1.2.1.4 The Afferent Fibers Systems	16
I.1.2.1.5 Deep Cerebellar Nuclei	17
I.1.3 Functional Prospective	17
I.1.4 Discussion	20
I.2 Cerebellar-like Adaptive and Predictive Control	21
I.2.1 Introduction	21
I.2.2 Cerebellar Internal Models theory	23
I.2.2.1 Inverse Internal Model	24
I.2.2.2 Forward Internal Model	25
I.2.3 State Prediction	25
I.2.4 Motor Learning	28
I.2.4.1 Direct Inverse Modeling	29
I.2.4.2 Feedback Error Learning	31
I.2.4.3 Distal Supervised Learning	35
I.2.5 Combined Internal Models	36
I.2.6 Modularity	37
I.2.7 Discussion	39
I.3 Cerebellar Models	43
I.3.1 Introduction	43
I.3.2 Top-Down Cerebellar-like Simulations Models	44
I.3.3 Bottom-Up Cerebellar-like Simulations Models	49
I.3.4 Discussion	56
Original Contribution	59
Main Research line	59
Side Projects	61
II Experimental Techniques and Results	63
II.1 Bio-inspired Control of Robotic Motor Behavior	67
II.1.1 Introduction	67
II.1.2 Biological Motor System	68
II.1.3 Bio-inspired Control of Voluntary Motor Movements	70
II.2 Cerebellar-like Simulations Model	73
II.2.1 The Role of Modularity in Motor Learning	74
II.2.2 The MCNNs Simulation Model for Real-Time Robotic Applications	75

II.2.2.1 Modularity of the MCNNs	75
II.2.2.2 The Algorithm	76
II.2.3 Discussion	82
II.3 Cerebellar-like Adaptive and Predictive Robotic Control	85
II.3.1 Introduction	85
II.3.2 From Biological to Robotic Motor Control	86
II.3.3 Cerebellar-like Control Schemes	87
II.3.3.1 Cerebellar-like Inverse Internal Model Control Scheme	87
II.3.3.2 Cerebellar-like Forward Internal Model Control Scheme	91
II.3.3.3 Cerebellar-like Tandem Internal Models Control Scheme	94
II.3.4 Discussion	97
Summary and Conclusions	101
Introduction	101
Summary of Findings	101
Future Perspectives	103
Conclusion	104
Appendices	105
Appendix A Distributed and Modular Bio-Inspired Architecture for Adaptive Motor Learning and Control	107
Appendix B A Biomimetic Control Method Increases the Adaptability of a Humanoid Robot Acting in a Dynamic Environment	113
B.1 Introduction	115
B.2 Material and methods	119
B.2.1 Robotic Plant	119
B.2.2 Motor Primitive Generator	120
B.2.3 Controller	121
B.2.3.1 Feedback Controller	121
B.2.3.2 Cerebellar-like Model	122
B.2.4 Proposed Experiments and Performance Measures	126
B.3 Results	127
B.3.1 Wrist Prosup	135
B.3.2 Wrist Yaw	136
B.3.3 Wrist Pitch	136
B.4 Discussions	136
B.4.1 Neural Basis of Feedback Control for Voluntary Movements	139
Appendix C A Cerebellar Internal Models Control Architecture for Online Sensorimotor Adaptation of a Humanoid Robot Acting in a Dynamic Environment	141

C.1	Introduction	143
C.2	Materials and Methods	145
C.2.1	Robot Plant	145
C.2.2	Planner	145
C.2.3	Controller	146
C.2.4	Cerebellar-like Network	148
C.3	Results	151
C.4	Conclusions	155

Bibliography**157**

List of Figures

I.1.1	Position of the major structures of the <i>central nervous system</i> .— Reproduced from [1]	12
I.1.2	Unfolded cerebellum showing the three functional regions with their different input-output relations, from left to right: Cerebrocerebellum, Spinocerebellum, and Vestibulocerebellum. — Reproduced from [1]	13
I.1.3	Vertical section of the cerebellar cortex showing the neural organization and the division in three layers: molecular layer, Purkinje cell layer, granular layer — Reproduced from [1]	15
I.1.4	Synaptic organization of the cerebellar micro-circuit. The circuit receives inputs from two type of afferent: <i>mossy fiber</i> (MF) (in magenta) and <i>climbing fiber</i> (Cl) (in red). The only output of the cerebellar circuit comes from the <i>deep cerebellar nuclei</i> (DCN) (in blue). The granular cells (Grs) (in pink) are the smallest and most copious cells and represent the center of cerebellar signal processing. The <i>Purkinje cell</i> (PC) (in light green) is the biggest type of cell in the circuit and constitutes the only output of the cerebellar cortex. — Reproduced from [1]	16
I.2.1	Bastian’s theory about how the cerebellum learns predictive movement control [2]. In scheme (a) , the pure feedback-dependent control or reactive control is illustrated. A change in the system dynamics appears and a reactive feed-forward motor command is processed and sent downstream to the muscles given the current sensory state. The peripheral feedback arrives with a large time delay. Thus, the feedback motor controller is not able to correct the state error. In the next movement, the same situation is iterated due to the inability of the system to learn and to adapt to changing dynamics. In scheme (b) , the mechanism of the cerebellar adaptive predictive control of movements is shown. The cerebellum learns the next movement through error-dependent adaptation mechanism. Once the model is learned, the cerebellum applies corrective prediction of the state of the motor command to update the feed-forward motor command. Dashed arrows express new or updated signals.— Reproduced from [2]	22

I.2.2	Two control architectures including (A) inverse and (B) forward internal models proposed by Miall and colleagues in 1993. In A , the inverse model processes the action necessary to move the controlled object from the sensed state to the desired state. In B , the forward model estimates the state the controlled object will reach given the sensed state and the applied action.— Reproduced from [3]	24
I.2.3	The cerebellum as Smith Predictor. The system is affected by a feed-forward delay (<i>Delay 1</i> box) and a feedback transport delay (<i>Delay 2</i> box). The models provides, first, an immediate prediction of the motor command consequences, then, a delayed copy of the prediction that match the actual feedback. — Reproduced from [3]	26
I.2.4	Cerebellar recurrent control scheme proposed by Porrill and colleagues in 2004. The forward model receive an error-related teaching signal e_i to process a goal directed learning. — Reproduced from [4]	27
I.2.5	Cerebellar recurrent control scheme proposed by Tolu and colleagues to control a robotic manipulator. The learner is constituted of two interactive modules, i.e., the forward model and the Cerebellum, that are modulated by the q, \dot{q}, \ddot{q} sensed states and the performance errors respectively (dashed magenta line). The $q^c, \dot{q}^c, \ddot{q}^c$ cerebellar contribution (bold blue line) is added to the performance error and is fed to the feedback controller. — Reproduced from [5]	28
I.2.6	Schematic of a general supervised learning system. The parameters of the learning model are adjusted by the error between the desired and the actual output.	29
I.2.7	General scheme of a direct approach for learning the inverse dynamic model. The inverse model receives as inputs the q_i sensed state of the i – <i>th</i> actuator. The parameters of the learner are adjusted given the S_i estimation error between the τ_i^{ff} feed-forward motor command and the τ_i^{inv} motor command estimated by the inverse model.	30
I.2.8	Real time dynamic robotic learning and control scheme proposed by Miller in 1990. — Reproduced from [6]	30
I.2.9	Cerebellar adaptive control loop proposed by Kawato in 1987. A cerebellar-like <i>Perceptron</i> learns the inverse-dynamics model of the controlled plant (blue box) and applies feed-forward τ_i^c torque commands (blue arrow) to correct the feedback controller action. The inverse-dynamics model gets as input only the q_i^r reference angular trajectory of each actuator, and as teaching signal the τ_i^{tot} corrected torque command (in magenta) that is sent to the corresponding actuator. — Reproduced from [7]	31
I.2.10	Cerebellar-like control scheme proposed by Tolu and colleagues to control a multi-degree of freedom robotic manipulator. The architecture take inspiration from the feedback-error learning approach proposed by [7] excepts some modification in the inputs of the learner module (ULM). The cerebellar-like system takes as input both the $Q_d, \dot{Q}_d, \ddot{Q}_d$ desired state trajectory, and the Q, \dot{Q} sensed state.— Reproduced from [8]	33

I.2.11	Cerebellar feedback-error learning proposed by Miyamoto and Kawato in 1988. The system is an optimization of the previous attempt (Figure I.2.9) [7]. A cerebellar-like neural network learns the inverse-dynamics model of the controlled plant (blue box) and applies feed-forward τ_i^c torque commands (blue arrow) to correct the feedback controller action. The scheme take its name from the S_i teaching signal of the cerebellar inverse-dynamics model that is the resulting the difference between the τ_i^{tot} total torque command and the τ_i^c torque estimated by the cerebellar model. Another major difference with respect to [7] is the cerebellar model input that includes all the \mathbf{q}^r reference angular trajectories of the actuators involved in the action.— Reproduced from [9]	34
I.2.12	Cerebellar control scheme for robotic manipulation experiments proposed by Garrido and colleagues in 2013. The cerebellar-like model learns the robot inverse model and applies feed-forward correction to the <i>Inaccurate Inverse Dynamics</i> module. The cerebellar inverse model receives as input the $Q^r, \dot{Q}^r, \ddot{Q}^r$ desired state trajectory, and the $\epsilon_{Q, \dot{Q}}$ performance error as modulating error-dependent signal.— Reproduced from [10]	35
I.2.13	Composite system for controlling a robotic arm proposed by Jordan and Rumelhart in 1992. The inverse dynamics model learns indirectly from a trained forward model. The forward model is trained by feeding the prediction error, while the inverse model is trained with the performance error.— Reproduced from [11]	36
I.2.14	Tandem internal models scheme proposed by Honda and colleagues in 2018. According to the behavioural experiments performed on patients affected by cerebellar degeneration disease, the internal models work in series and the forward model is updated before the inverse model. — Reproduced from [12]	37
I.2.15	Control scheme including multiple paired internal models proposed by Haruno, Wolpert and Kawato. The architecture is constituted of n modules, each modules is specialized on a specific motor behaviour. The module is composed of three interacting parts: a forward model, a responsibility predictor, and an inverse model. Each module is assigned to a different weight depending on its responsibility in the current action, the final motor command is given by the sum of all the weighted modules contributions.— Reproduced from [13]	38
I.2.16	Modular-RDC controller proposed by Maheri and colleagues in 2017. The cerebellar-like modular control architecture consists of n modules. Each module includes a forward and inverse internal models and adds weighted recurrent correction to the input of the feed-forward controller. A <i>Responsibility Estimator</i> module processes the a responsibility factor for each inverse model depending on the prediction error of the respective forward model. — Reproduced from [14]	40
I.3.1	Cerebellar Model Articulation Controller (CMAC) designed by Albus in 1975. The schematic is for the control of one single joint.— Reproduced from [15] .	45

I.3.2 Cerebellar Model Articulation Controller network (CMAC) proposed by Miller and colleagues in 1990. The neural network take two inputs and elaborates one output, can be interpreted as a simplified representation of the granular layer in the cerebellar cortex.— Reproduced from [6]	46
I.3.3 Cerebellar cortex neural network design by Chapeau-Blondeau and Chauvet in 1991.— Reproduced from [16]	47
I.3.4 Schematic representation of the cerebellar neural network proposed by Buonomano and Mauk in 1994. The model consists of 10^4 <i>granular cell</i> (Gr)s (in purple), 900 <i>Golgi cell</i> (GO)s (in cyan), 500 mossy fibers, and one Purkinje cell (PC). The mossy fibers and Purkinje cell (PC) are not illustrated for simplification. The shaded area and the arrow represent the regions to which the cells can synaptically be connected. The white cells are the ones receiving input from the presynaptic cell.— Reproduced from [17]	47
I.3.5 Cerebellar model architecture proposed by Barto and colleagues in 1999. The granular cells are represented by the <i>sparse expansive encoding</i> block, and receive information from the MFs mossy fibers, and the target block. The granular cells send the processed signal to the PC Purkinje cell (PC), through the PFs <i>parallel fiber</i> (PF)s. The signal in the PC is modulated by the CF climbing fibers.— Reproduced from [18]	48
I.3.6 Unit Learning Machine (ULM) proposed by Tolu and colleagues in 2012. The model consists of a LWPR non linear function approximator and a C cerebellar unit for the short term adaptation.— Reproduced from [8]	49
I.3.7 Schematic of the hybrid cerebellar model proposed by Ojeda and colleagues in 2017. The model combines the cerebellar unit proposed by [8] to a spiking neural network running on the neuromorphic hardware <i>SpiNNaker</i> (in green).— Reproduced from [19]	49
I.3.8 Large-scale computer simulations of the cerebellar model proposed by Medina in 2000. The purple layer represents the 10000 granular cells, which are connected to 900 Golgi cells (in cyan), 600 mossy fibers (in magenta), 20 Purkinje cells (in green only one is shown for simplification), and 6 deep cerebellar nuclei (NUC in blue). The network includes 300000 synapses without specific learning rules, the main focus is on the neural connectivity.— Reproduced from [20]	51
I.3.9 Anatomy of the Cerebellar-like computational model proposed by Hofstötter and colleagues in 2002. The model presents two input pathways, the CS conditioned stimulus is trasmitted through the PO pontine nucleus to the GR granular cell, the US unconditioned stimulus is conveyed to the IO inferior olivary nucleus. The DN deep cerebellar nuclei fires the CR conditioned response down to the motor system.— Reproduced from [21]	52

- I.3.10 Network structure of the "Realtime Cerebellum (RC)" proposed by Yamazaki and Igarashi in 2013. The RC includes 102400 granular cell, 1024 Golgi cell, 16 Purkinje cell, 16 basket cells, 1 inferior olivary nucleus, and 1 deep cerebellar nuclei. All the 16 PC inhibit the single DCN. One plasticity with long-term depression (LTD) and long-term potentiation (LTP) is designed at the Gr-PC innervation.— Reproduced from [22] 53
- I.3.11 Cerebellar spiking neural model proposed by Luque in 2016. The network receives the input source through 100 **MF**, modeled as leaky integrate-and-fire neurons. The granular layer consists of 2000 **GC** granular cells implemented as state generator. Each **PC** Purkinje cell receives activity from 2000 **PF** parallel fibers. The number of Purkinje cells, climbing fibers, and deep cerebellar nuclei (DCN) depends on the case of study: in case of study **A** 20,2, and 2 respectively; in case of study **B** 60, 6, and 6 respectively. In the scheme, different colors indicate signals from different input sources. The long-term potentiation (LTP) is marked with a blue arrow, while the long-term depression (LTD) with a magenta one. — Reproduced from [23] 54
- I.3.12 Cerebellar spiking neural network model employed by Richter and colleagues in 2016 to control a musculoskeletal robot. The graph in the bottom right describes how the synaptic weight at Gr-PC level changes in response to the Gr and IO activities. In the neural network from left to right: **Mof** mossy fiber, **GrC** granular cell, **InO** inferior olivary nucleus, **PuC** Purkinje cell, **DCN** deep cerebellar nuclei. — Reproduced from [24] 55
- II.1.1 General hierarchical and distributed functional architecture for controlling an intelligent and autonomous robotic system. In this example, the architecture is divided into four hierarchical levels. From top to down levels, the goal is decomposed into sub-goals and low-level actions, i.e. each task is divided into a sequence of action plans, which are transformed into motor primitives then into servo trajectories. In the horizontal partition, each level is constituted of three communicating modules: the *Sensory Processing* module acquires the data from the sensory system and extrapolates the features needed for the robotic control; the *World Modeling* module employs the features from the *Sensory Processing* module to acquire and evaluate internal models of the robot-environment system; the *Task Decomposition* module employs the models to predict and plan the actions. All the processed information are stored in a shared *Global Memory*. — Similar to [25] 68
- II.1.2 Simplified hierarchical and distributed functional architecture for the control of voluntary movements. The scheme enclose theories from different studies [26–29]. We located the cerebellum and basal ganglia in the *World Modeling* column due to their crucial roles in learning and memory functions. The role of the cerebellum in cognition is omitted. 69

- II.1.3 Proposed bio-inspired functional architecture for the control of complex robotic behaviour during the interaction with the environment. The scheme propose only the high-level connections and distribution of the bio-inspired neural circuits. The scheme follows the hierarchical and distributed organization of the NASREM model [25], the partition is here omitted for simplification and it follow the color code of Figure II.1.2. The design adheres to the guidelines from [26, 29–33]. The *Bio-Inspired Control System* control the motor behavior of a N-degree-of-freedom robotic system while it is interacting with a dynamic environment. The robot sends exteroceptive and proprioceptive sensory information to the controller sensory system. We assume that the high level goal is fixed, thus, the task level is omitted. At the *Action level*, the *Prefrontal Cortex* model divides the goal into a plan of actions. At the *Primitive Level*, the *Motor Cortex* module translates these actions into a sequence of movements that are sent down to the *Servo Level*. Here, the *brainstem* coordinates the movements, the *Reticular Spinal Tract* model modulates and adapts the low level motor movements, and the *spinal cord* executes and controls the motor commands. In the meanwhile, the *basal ganglia* learns and selects the most opportune action, and the *cerebellum* learns the internal models regarding the robot-environment dynamics to send adaptive corrections. 71
- II.2.1 High-level modular partition of the Modular Cerebellar-like Neural Networks (MCNNs). The overall simulations model is constituted of M Modular Cerebellar Circuits (MCCs) learning and storing distinct internal models. In magenta, the afferent fibers systems. — Reproduced from [34] (Appendix C) 76
- II.2.2 Schematic illustrating the modular partition of the Modular Cerebellar Circuit (MCC). Each Modular Cerebellar Circuit (MCC) is specialized in the acquisition of the $m - th$ internal model describing the motor behavior of a robotic plant with N controllable actuators. The MCC is partitioned in N sub-modules named unit learning machine (ulm). Each unit learning machine (ulm) learns the contribution of the $n - th$ robotic joint in the motor behavior. Each ulm is divided in C canonical cerebellar microcircuit (ccm), where C depends on the number of internal loops created by the climbing fiber (Cl). The cerebellar-like contribution to the motor movement of the $n - th$ actuator is the combination of the C canonical cerebellar microcircuit (ccm) outputs. The purple circles represent the granular cell (Gr) layer, we assume that some regions are specialized on a specific actuator but receives information regarding other parts of the controlled object (in magenta). — Reproduced from [34] (Appendix C) 77

- II.2.3 Canonical cerebellar circuit indicating the partition of the neurons in the ulm and canonical cerebellar microcircuit (ccm). Each ulm is specialized on the $n - th$ controllable object, while each ccm describes a specific feature of the controllable object depending on the internal loop defined by the connection with the inferior olivary nucleus (IO) (in red). The signals processed in each ccm are then combined in the deep cerebellar nuclei (DCN) that process the final cerebellar-like correction for the $n - th$ control object. — Reproduced from [34,35] (Appendix B, Appendix C) in analogy with [36] 78
- II.2.4 Schematic of the proposed Modular Cerebellar Circuit (MCC) neural networks. The mossy fiber (MF) signals (in magenta) are inputted to the granular cell (Gr)-parallel fiber (PF) system represented by the Locally Weighted Projection Regression algorithm (LWPR) algorithm (in purple). The MF projects a copy of the efference copy to the DCN (bold magenta line). This signal is also mapped by the LWPR (teaching signal). The Gr-PF output is projected to the C Purkinje cells (PC) (in green). The PC synaptic plasticity is influenced by the deep cerebellar nuclei (DCN) activity (in blue). The inferior olivary nucleus (IO) modulates the PC activity (in red). The rhombus indicates the synaptic plasticities, only shown in the first ccm for simplification. The blue boxes indicate the unit learning machine (ulm) specialized on the motor behavior of the first and $n - th$ actuators. The yellow boxes illustrate the further partition into canonical cerebellar microcircuit (ccm). — Reproduced from [34] (Appendix C) 81
- II.3.1 Main components of the proposed feed-forward cerebellar-like robotic control architecture for N controllable actuators. The robotic agent continuously interacts with an *External System* that dynamically affects the robot's motor behavior. The Agent includes: a *Trajectory Planner*; a *Controller* constituted of a poorly tuned static *Feedback Controller* and an adaptive *Cerebellar-like Inverse Model*; a physical robot plant that has N controllable actuators and their respective sensors. — Reproduced from [34,35] (Appendix B, Appendix C) 88
- II.3.2 Proposed cerebellar-like control scheme including a cerebellar-like module learning the inverse internal model of the robot-environment system. The inverse cerebellar model learns the mapping from the reference and sensed control states to the total motor command sent to the actuator (dashed magenta arrow). The learning is modulated by error-related signals (dotted red arrows). The cerebellar-like module applies feed-forward torque correction to the feedback controller output (bold blue arrow). The scheme includes noise signals affecting the sensors of the robot and the control action (bold green line). The robot continuously interacts with an external dynamic system. — Reproduced from [34,35] (Appendix B, Appendix C) 89

- II.3.3 Main components of the proposed recurrent cerebellar-like robotic control architecture for N controllable actuators. The agent continuously interacts with an *External System* that disturbs the motor behavior of the robot. The Agent consists of: a *Trajectory Planner*; a *Controller* constituted of a constant and weak *Feedback Controller* and an adaptive *Cerebellar-like forward Model*; a physical robot plant with N controllable actuators and the respective N sensors. — Reproduced from [34] (Appendix C) 92
- II.3.4 Proposed cerebellar-like control scheme including a cerebellar-like module learning the forward internal model of the robot-environment system. The forward cerebellar model learns the mapping from the τ_n^{tot} total torque command sent to all the actuators and the \mathbf{Q}^r reference states to the \dot{q}_n sense n -th motor state in term of angular velocity (dashed magenta arrow). The cerebellar action is modulated by two error-related signals (dotted red arrows), the e_n^{fb} angular velocity error and the ϵ_n^{fb} angular position error. The cerebellar-like module adds an internal feedback loop that applies \dot{q}_n^c recurrent correction to the input of the feedback controller (bold blue arrow). The scheme includes noise signals affecting the feedback controller action and the sensors of the robot (bold green lines), and the continuous interaction of the robot with an external dynamic system. — Reproduced from [34] (Appendix C) 93
- II.3.5 Main components of the proposed tandem cerebellar-like robotic control architecture for N controllable actuators. The *Agent* interacts with an *External System* that constantly disturbs the robot motor behaviour. The tandem robotic *Agent* architecture is constituted of: a *Trajectory Planner* that plans the desired movements; a *Controller* that includes a fixed *Feedback Controller* and two adaptive *Cerebellar-like Inverse Model* and *Cerebellar-like Forward Model*; a *Robotic Plant* that incorporates N controllable actuators and N sensors. The *Cerebellar-like Inverse Model* applies feed-forward torque correction to the *Feedback Controller* control action. While, the *Cerebellar-like Forward Model* adds recurrent internal loop to correct the kinematics information fed to the *Feedback Controller*. — Reproduced from [34] (Appendix C) 95
- II.3.6 Proposed tandem cerebellar-like control scheme including two cerebellar-like module learning the inverse and forward internal models of the robot-environment system. The two cerebellar-like models learn and act in tandem, i.e. the *Forward Model* is updated before the *Inverse Model*, the *Inverse Model* is modulated by the e_n^{tot} total error including the \dot{q}_n^c *Forward Model* correction, the *Forward Model* receives as inputs the τ_n^{tot} total torque commands corrected by the *Inverse Model*. The signals learned at the *Cerebellar Cortex* level are marked as dashed magenta arrows. The modulating error-related signals are indicated by dotted red arrows. The number of modulating signals in the scheme depends on the modularity of each cerebellar-like circuit. The cerebellar contributions are illustrated as bold blue arrows. The noise signals affecting the feedback controller action and the sensors of the robot are marked as bold green lines. — Reproduced from [34] 96

II.3.7	Proposed tandem cerebellar-like control architecture including the cerebellar-like simulations model scheme. – Reproduce from [34] (Appendix C)	98
II.3.8	Close-up on the connections between forward and inverse internal models in the tandem control scheme. In magenta, the mossy fibers are grouped depending on the inputs' space, i.e. A action space, G goal space, and S state space. In the proposed connection scheme, the granular layer of the inverse model learns the same A action that is sent as input to the forward model's granular layer. On the other hand, the Forward model maps the S state that is inputted to the Inverse model's learner. – Reproduce from [34] (Appendix C)	98
II.3.9	Proposed modular cerebellar-like control architecture. At the current state, no assumptions are made about how different inverse and forward internal models are combined and/or selected. In our solution, both the inverse and forward internal models correct the static control system. [34] (Appendix C)	99
A.1	The proposed bio-inspired architecture aims to solve the problem of robotic agent (in grey) adaptation during the interaction with an external system (in green). The system is modelled to control the coordination of a robotic arm during dynamical target reaching and object manipulation. The illustration shows only the high-level connections and distribution. Each building block will contains bio-inspired structures and classic control theory algorithms. The main idea, respect to the literature, is to focus on how the CNS regions internally specialize and map heterogeneous motor skills.	110
B.1	(a) The figure illustrates the main components of the functional architecture scheme and the link with the artificial robot agent and the external system. (b) The humanoid Icub holding the table-ball system in the simulation environment NRP. (c) Three controlled joints: wrist prosup ϑ_0 , wrist yaw ϑ_1 , wrist pitch ϑ_2	120
B.2	Proposed cerebellar-like circuit in analogy with [36]. (a) canonical micro-circuit. Proposed cerebellar-like neural network (b) structural partition and (c) details.	123
B.3	Functional architectures representing the proposed Experiments.	127
B.4	Angular position and velocity wrist prosup: comparison experiment I and II (a), with zoom on the angular position (c); comparison experiment I and II (b), with zoom on the angular position (d). The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment in which the cerebellar-like controller starts giving the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$).	128

- B.5 Wrist prosup experimental results. Resulting angular position error e_{ϑ_0} , comparison experiments I and II **(a)**, comparison experiments III IV **(b)**. Control input τ_0^{tot} evolution, comparison experiments I and II **(c)**, comparison experiments III IV **(d)**. Control input contributions in experiment IV comparisons between: τ_0^{tot} and τ_0^{PID} **(e)**; τ_0^{tot} and τ_0^{DCN} **(f)**. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts giving the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$). 129
- B.6 Angular position and velocity wrist yaw: comparison experiment I and II **(a)**, with zoom on the angular position **(c)**; comparison experiment I and II **(b)**, with zoom on the angular position **(d)**. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts giving the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$). 130
- B.7 Wrist yaw experimental results. Resulting angular position error e_{ϑ_1} , comparison experiments I and II **(a)**, comparison experiments III IV **(b)**. The τ_1^{tot} control input evolution, comparison experiments I and II **(c)**, comparison experiments III IV **(d)**. Control input contributions in experiment IV comparisons between: τ_1^{tot} and τ_1^{PID} **(e)**; τ_1^{tot} and τ_1^{DCN} **(f)**. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$). 131
- B.8 Angular position and velocity wrist pitch: comparison experiment I and II **(a)**, with zoom on the angular position **(c)**; comparison experiment I and II **(b)**, with zoom on the angular position **(d)**. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$). 132
- B.9 Wrist pitch experimental results. Resulting angular position error e_{ϑ_2} , comparison experiments I and II **(a)**, comparison experiments III IV **(b)**. The τ_2^{tot} control input evolution, comparison experiments I and II **(c)**, comparison experiments III IV **(d)**. Control input contributions in experiment IV comparisons between: τ_2^{tot} and τ_2^{PID} **(e)**; τ_2^{tot} and τ_2^{DCN} **(f)**. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$). 133

B.10	Comparison of the angular position MAE: (a) wrist prosup, (b) wrist yaw and (c) wrist pitch. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40\text{sec}$ or $\textit{iteration} = 10$).	134
B.11	Learning evolution of the cerebellar-like network in experiment IV: influence of the inferior olive on the PC-PF parallel fibers-Purkinje cells and IO-DCN inferior olive-Deep cerebellar nuclei connections. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area).	135
C.1	Robotic plant: a) the humanoid iCub holding the table-ball system in the Neurorobotics Platform; b) the three controlled wrist joints: 1 pronosupination, 2 yaw, 3 pitch.	146
C.2	Control architecture scheme for N actuated joints: a) main components communication, and b) controller block.	147
C.3	Canonical cerebellar circuit in analogy with [36].	149
C.4	Cerebellar-like neural network scheme: (a) structural modular partition of the inverse and forward module; (b) details of the networks.	150
C.5	Control architectures performances. The evolution of the MAE mean absolute error shows how the system is improving its tracking accuracy over the oscillations period. The plot shows the results of the 20 tests in terms of μ mean value (solid line) and 99.7% confidence interval (colored area). The vertical green line represent the moment the cerebellum starts adding contributions to the feedback loop ($k = 8$ trial).	154

List of Tables

I.1.1	Type of cells in the cerebellar cortex	18
B.1	External system features.	119
B.2	Actuated joints information: the wrist actuators (highlighted in yellow) are controlled in effort while the elbow and shoulder motors are kept to a constant angular position.	121
B.3	The mean absolute error (MAE) of the initial and final period ($T = 4$ sec). The results express the mean value μ and standard deviation σ of the 20 tests run for the four experiments.	136
C.1	Weighting kernel parameters for $[ccm_1, ccm_2]$ [10,37]: LTP long-term potentiation, LTD long-term depression, MTP potentiation modulating term, MTD depression modulating term, α decaying factor.	152
C.2	Receptive fields created by the LWPR.	153

Glossary

brainstem

The *brainstem* is a region of the central nervous system (CNS) located between the cervical spinal cord and the deep areas of the cerebral hemispheres. It has autonomic functions (regulation of the breathing, heart rate, blood pressure), motor control functions (control of balance, locomotion, posture), and it is responsible of the processing of the sensory information. xx, xxix, 11, 12, 17, 70, 71

central nervous system (CNS)

The *central nervous system* (CNS) is the part of the nervous system including primarily the brain and the spinal cord. xv, xxvii, xxxi, 1, 3, 4, 9, 11, 12, 23–25, 33, 38, 67, 68, 91, 100, 101, 104

cerebral cortex

The *cerebral cortex* is the outer neural tissue of the mammalian brain. It is associate with higher level functions, such as reasoning, consciousness, emotions, memory, and language. 11, 12, 17, 70

climbing fiber (Cl)

The *climbing fiber* (Cl) is the neural projections from the *inferior olivary nucleus* (IO) to a single Purkinje cell (PC). xv, xviii–xx, xxxi, 14, 16, 17, 41, 48, 53, 54, 56, 74, 77, 79, 83, 90, 91

deep cerebellar nuclei (DCN)

The *deep cerebellar nuclei* (DCN) are the unique output channels of the cerebellum. xv, xviii, xix, xxxi, 16, 17, 48, 51, 53, 54, 79

dendrites

The *dendrites*, or *dendrons*, are branched extensions of a nerve cell. They transmits the electrochemical stimulations from other neurons to the body of the cell. 14

Golgi cell (GO)

A *Golgi cell* is an inhibitory *interneuron* found within the granular layer of the cerebellum. It receives excitatory input from mossy fiber (MF) and parallel fiber (PF).. xviii, xxxi, 15, 45, 47, 51

granular cell (Gr)

The cerebellar *granular cells* (Gr) are the most numerous type of cells in the cerebellum. xviii, xix, xxviii, xxxi, 14, 18, 19, 45–48, 51, 52, 54, 55, 76, 78, 79

hindbrain

The *hindbrain* is one of the three major regions of the vertebrates brain and is responsible for the coordination of survival functions, such as breathing, sleep, and wakefulness. 11

inferior olivary nucleus (IO)

An *inferior olivary nucleus* (IO) is a neural structure known to coordinate signals from the spinal cord to the cerebellum. xxvii, xxxi, 17, 18, 55, 56, 74, 79

interneuron

An *interneuron*, or *association neuron*, is a neuron that transmits impulses from one neuron to another, also of different nature, such as spinal motor and sensory neurons. xxvii, 14

long-term depression (LTD)

A *long-term depression* is a reduction in the strength of neuronal synapses due to the activity of a long patterned stimulus. xxxi, 17

long-term potentiation (LTP)

A *long-term potentiation* is a process that enhance the synaptic connections between neurons through frequent activation. xxxi

mossy fiber (MF)

The *mossy fiber* (MF) is one of the main afferent neurons of the cerebellum. xv, xviii, xxvii, xxxii, 14, 16, 43, 45, 47, 48, 51, 53, 55, 76, 78

parallel fiber (PF)

The *parallel fiber* (PF) is a specialized axons of the granular cell (Gr) that ascend to the upper (molecular) layer of the cerebellar cortex. xviii, xix, xxvii, xxxii, 48, 54, 56, 76, 79

Pavlovian conditioning

The *Pavlovian conditioning*, also known as Classical conditioning, is an unconscious or automatic learning. The learning maps the relationship between an unconditioned stimulus (US) and a neutral stimulus to process a conditioned response (CR). 17, 100

Perceptron

A *Perceptron* is supervised learning algorithm. It consists of a single layer neural networks which distinguish between patterns through linear classification (binary). xvi, 31, 44, 45

Purkinje cell (PC)

The *Purkinje cell* (PC) is a large neural cell responsible of the Cerebellar Cortex Output. xv, xviii, xix, xxi, xxvii, xxxii, 14, 16, 18, 45–48, 51, 54–56, 79, 81

spike-timing-dependent plasticity (STDP)

A *spike-timing-dependent plasticity* is a biological process that adjusts the strengths of a neural connection based on the relative timing of the neuron's output signal and the input action potentials, or spikes. 53, 54

spinal cord

The *spinal cord* is a long tubular structure constituted of nervous tissue which connects the Brain to the lower back of the vertebrate body. xx, xxviii, 17, 70, 71

vestibular nuclei

The *vestibular nuclei* are a group of four sensory nuclei that are part of the extensive cranial nerve in the brainstem. 12

vestibulo-ocular reflex (VOR)

The *vestibulo-ocular reflex* (VOR) is a reflex responsible for the eye movement for the stabilization of the gaze. 12, 18

Acronyms

AMD

Autonomous Mental Development. 3

ANNs

artificial neural networks. 3

ccm

canonical cerebellar microcircuit. xx, xxi, 76–79, 81, 83

CI

climbing fiber. 14, 17, 50, 76

CNS

central nervous system. 11, 15, 19, 21, 22, 25, 28, 39, 40, 61, 65, 67, 69, 70, 72, 86, 101

DCN

deep cerebellar nuclei. xviii, xix, xxi, 15, 17, 48, 50–55, 75, 76, 78–82, 100, 102

GO

Golgi cell. xix, 52–54

Gr

granular cell. xv, xviii–xxi, 14–18, 46, 52–55, 75–77, 81

IO

inferior olivary nucleus. xviii, xix, xxi, 15, 17, 18, 48, 50–53, 55, 74–76, 78–82, 102

LTD

long-term depression. xix, 52–54

LTP

long-term potentiation. xix, 52–54

LWPR

Locally Weighted Projection Regression algorithm. xxi, 78, 79, 81–83, 103

MCC

Modular Cerebellar Circuit. xx, xxi, 75, 77, 79, 81, 83

MCNNs

Modular Cerebellar-like Neural Networks. xiii, xx, 75, 76, 82, 83

MF

mossy fiber. xix, xxi, 15–18, 52–55, 75, 76, 80, 81, 99, 100, 102

PC

Purkinje cell. xix, xxi, 14, 15, 17, 18, 43, 45, 46, 48, 50–55, 75, 76, 79–82, 100, 102

PF

parallel fiber. xxi, 14, 15, 17, 18, 45, 50, 52–54, 75, 76, 79, 81, 82, 102

ulm

unit learning machine. xx, xxi, 75–79, 81

CHAPTER 1

Introduction

THE advancement of the technologies and the larger use of robots in applications typically performed by humans increased the level of complexity and the number of constraints that robotic control systems need to satisfy. Robotic systems need to flexibly adapt in real-time to a wide range of circumstances. The enhancement of robotic adaptation would optimize the robotic performance and increase the number of robotics applications leading to minor human intervention, especially in dangerous and repetitive tasks. This adaptability comes at different levels of robotic control, from the high-level decision-making functions, to trajectory planning, until the low-level motor control.

Most classical engineering methods fail to solve the adaptation problem due to high modeling errors often caused by unmodelled nonlinearities of real-world scenarios and the lack of real-time response. Most scientists are trying to solve the adaptation problem with artificial intelligence methods. Among them, neurorobotics experts are trying to get inspiration from the central nervous system (CNS) to design bio-inspired robotic learning mechanisms and control schemes.

This thesis discusses how real-time low-level robotic adaptation can be achieved by taking inspiration from biological systems adaptive and predictive motor control. Special focus is given to the vertebrates' cerebellum, a compact neural structure of the central nervous system (CNS) that plays a crucial role in learning and execution of complex motor behavior.

We propose a cerebellar-inspired robotic solution for the real-time adaptive and predictive control of complex motor behavior in unknown and challenging environmental conditions. Our bio-inspired control architecture includes an adaptive learning module that incrementally learns through the continuous interaction within the robot and the environment, and three different control schemes for the resolution of distinct control problems, such as rejection of external disturbances, filtering of noise signals, state estimation and prediction, optimization of tracking performances.

We contribute to the state-of-the-art with a bio-inspired robotic control solution that can work in real-time without losing the unique adaptive performance of the bio-inspired cerebellar learning algorithm. The cerebellar-like simulations model test novel hypothesis regarding the modularity of the cerebellar-like circuit for robotics applications. We propose a robotic control scheme that can validate the theory regarding combined and interdependent internal models and we proved through robotics experiments the consequences of their coordination on the final motor behavior.

1.1 Motivation of the Study

The number of robotic applications is drastically thriving in all the industrial sectors. Industrial production is exponentially growing and needs to respect high pace rhythms to efficiently respond to changing consumer's needs and global competitiveness. This tendency of automatizing any industrial processes is consequentially moving human operators from all the dangerous and repetitive operations to more skilled and sophisticated tasks where human-like cognitive and practical intelligence is required.

Amazon is one of the most famous examples of how the growing mass production and use of the robotic system are strictly related. The company stated that it has been creating millions of new jobs since it started employing robots in its facilities back in 2012. The company established its robotics research and development center to investigate other robotics applications that could benefit the revenues and reduce the number of work accidents [38]. Amazon's warehouse robots operate in human-populated environments and have to cautiously handle objects of different sizes, shapes, and loads.

In the last years, the global Coronavirus pandemic has pushed the use of robots in production lines even further. In Denmark for instance, slaughterhouses are gone heavy automated and managed to not become potent infectious disease incubators as it happened in many other places around the world [39]. Robotic butchers replace humans by repetitively lifting heavy meat, using sharps tools, and working in below zero environments. Moreover, the type of objects they have to interact with and manipulate constantly change in shape, load, and viscosity.

Other growing applications see rescue robots, mostly humanoids, wheeled or quadruped robots employed as extensions of human professionals in hostile conditions that humans can not access or handle. For instance, hazardous material accidents, such as chemical, nuclear, or explosive. The need for rescue robots had a great outbreak when Japan faced a nuclear disaster in Fukushima back in 2011. That terrible event showed the world the need for dexterous robots that could stay on the frontline of hazardous work. The operative conditions include moving through rough terrains, lifting and relocating debris, and using different types of tools.

There is one specific factor that all the modern robotic applications have in common, i.e. robots work in unstructured and dynamically changing environments, often manipulating and interacting with other dynamic systems and humans. In such challenging environments, robots need to efficiently adapt the movements before being endowed with a cognitive intelligence that supports them in making decisions. High level plans can not be executed if the low-level motor control fails.

The number of robotics applications could substantially increment if the installation and integration of the robotics systems were more straightforward through adaptive and auto-recovery behaviors. Endowing robots with safely adaptive and responsive behavior would also drastically reduce the cost of all the robotic equipment (e.g. safety devices, sensors, grippers), which is usually four-five times the cost of the robot itself [40].

1.2 Background of the Problem

The robotic controller needs a model of the robotic systems and the world to perform robust and smooth motions. If the model of the robot-environment systems is uncertain, for instance, the robot manipulates an object with an unknown load, the efficiency of the classical inverse dynamics controller is no longer satisfied. To solve the adaptive motion control problem, control theorists have been formulating different control schemes to guarantee the performance of the controlled plant in terms of tracking error, stability, external disturbances, unknown dynamics, and noise signals. In general, an adaptive controller consists of two main elements,

- a module that estimates the dynamics of the system;
- a module that employs the estimation of the system to alter the controller characteristics.

Motor adaptation is a great challenge for robotics engineers because classical control methods can not fully satisfy the complexity of heterogeneous and nonlinear scenarios. Traditional adaptive control methods are based on a linearized model of the control plant and estimate a fixed number of time-varying parameters that constitute a structured mathematical model [41]. The parameters are estimated through training data. Thus, outside the linearization boundaries, the parametric controller fails due to many unpredicted factors, such as unmodeled behavior, persistent excitation issues, physical discrepancy, and over-sensitive response to high estimation error [42, 43].

In the last decades, scientists attempted in solving the robotic adaptation problem with non-parametric approaches such as artificial neural networks (ANNs) [44–49]. The integration of ANNs into the control loop of nonlinear dynamical systems proved to be advantageous for mapping high-dimensional and continuous state space systems, and reducing the repercussions of uncertainties and nonlinearities [47, 50–53]. ANNs mostly require off-line training with pre-collected data, a requirement that easily leads to failure if the robotic system is continuously interacting with an uncertain external system.

After a cautious study of brain-based systems, the Autonomous Mental Development (AMD) scientists stated that the robotic system should incrementally learn through real-time interaction with the surroundings [54, 55]. Thus, each learned skill is the result of the continuous development of the robot’s knowledge rather than the summation of off-line events [56, 57].

The *“bodies for brains”* philosophy claims that the brain needs a body to function or at least to exploit all its incredible potentialities. For instance, the newborn brain impressively grows at an extraordinary fast pace once it gets into contact with the external world, this is thanks to the incredible number of stimuli that the central nervous system receives through the body’s interaction with the external environment [58].

In 2010 during a talk, Daniel Wolpert firmly stated,

“we have a brain for one reason and one reason only and that is to produce adaptable and complex movements [59]”.

In Wolpert's opinion one can not understand the movements without a brain and can not understand the brain without the movements.

Robotics engineers embraced the brain embodiment philosophy and attempted to translate the biological principles employed by brain-based organisms into computational models and robotic systems to replace classical engineering methods.

Over the years, researchers proposed an increasing number of bio-inspired robotic solutions, from insect-like robots [60–65], snake-like robots [66–68], amphibian-like robots [69, 70], fish-like robots [71–73], octopus-like robots [74, 75], quadrupeds-like robots [76, 77], to human-like robots [78–81].

Neurorobotics scientists has been investigating how the vertebrates' central nervous system (CNS) operates to endow bio-mimetic robots with agile adaptive and predictive motor skills. Among all the neural regions of the central nervous system (CNS), there is a small and compact neural structure that plays a crucial role in adaptive and predictive motor control of movements, i.e. the cerebellum [26, 29, 82–85]. The incredibly regular and modular neural structure of the cerebellum motivated several researchers to computationally replicate it for robotic control purposes.

Several theories claim that the cerebellum learns and stores internal models mapping the relationship between the body and the environment. As an artificial adaptive controller, the cerebellum employs these internal models to reactively correct the motor control performance [3, 7, 11, 86–88]. The validation of these theories would confirm the role of the cerebellum in associative learning, force control, coordination of multi-joints movements, adaptive control, predictive timing [85, 89].

1.3 Statement of the Problem

Our study aims to devise and validate an adaptive control architecture for robotic systems interacting with an unknown dynamic environment that takes inspiration from the cerebellar adaptive control mechanisms. The robotic system has to flexibly and safely interact with the dynamic environment. Thus, the robotic agent needs to continuously learn from its interaction and adapt the motor behavior accordingly. In our study, we assume that,

- the control object is a complex robotic system with multiple degrees of freedom, N controllable rotary actuators, and N sensors;
- we have poor or no knowledge of the kinematics and dynamics models of the controlled object and the surroundings;
- the state space is not fully observable;
- the input space is continuous, time-varying, and high-dimensional;
- the robot interacts with a dynamic and unknown system;

- the robotic action is disturbed by external stochastic forces;
- the sensory feedback is affected by delays and noisy signals.

In this thesis, we focus on low-level force-based motor control. To adaptively correct the motor performance of the robotic system, the control architecture needs to include a learning module that can map in real-time the motor behavior from the observable data and apply corrections to the control action. Thus, the study is divided into two main design objectives,

- to devise and validate a cerebellar-like learning algorithm that can map and process in real-time adaptive motor response to restore the correct motor behavior in disturbed and unknown circumstances;
- to devise and validate cerebellar-like control schemes that integrate the learning algorithm to reactively process new motor skills and improve the smoothness and accuracy of the robotic motor movements.

1.4 Scientific Objectives of the Project

The main focus of the thesis is to provide an approach for developing a bio-inspired adaptive control architecture by achieving these main scientific objectives,

- to understand the principles and the key actors of biological motor control;
- to investigate the role of the cerebellum in adaptive and predictive motor control;
- to explore the structural complexity of the cerebellum;
- to analyze the cerebellar neural population and to define computational algorithms to replicate the neurons functional behavior;
- to understand the role of the cerebellar modularity in the sensorimotor mapping of complex motor behavior and to find a possible connection for the design of a modular robotic control architecture;
- to computationally model and experimentally test the processes that involve the cerebellum in the sensorial mapping during the execution of movements;
- to investigate and empirically test how the cerebellum acquires and employs internal models describing the relationship between the body and the environment and to find possible connections with robotic applications;
- to verify through robotic experiments the relationship between different internal models and how their cooperation influences the motor performance;

1.5 Perspective of the Thesis

The thesis is partitioned into two main parts, i.e. *Theoretical Concepts* (Part I) and *Experimental Techniques and Results* (Part II).

The *Theoretical Concepts* part encloses a review of the state-of-the-art and consists of three main chapters,

Chapter I.1 provides an overview of the cerebellum from an anatomical and functional perspective. We describe in detail the cerebellar micro-anatomy which we believe is pivotal for understanding how the cerebellum functions and why.

Chapter I.2 provides the literature review of the computational models developed to simulate the incredible functionalities of the cerebellum in adaptive and predictive control of motor skills. In this chapter, we particularly focus on the internal models theory and how the cerebellum is assumed to acquire and employ internal models to reactively correct the ongoing motor behavior.

Chapter I.3 provides the literature review of the cerebellar-like simulations models. We describe and compare two different types of computational modeling approaches: top-down and bottom-up.

The *Experimental Techniques and Results* part describes the methods and results employed in the thesis,

Chapter II.1 discusses the biological motor control of voluntary movements from an engineering point of view, and proposes a bio-inspired functional control architecture that could be applied for the control of robotic systems. The functional architecture collocates the cerebellum in the big picture of biological motor control where several neural regions operate independently and interdependently to perform complex motor behavior.

Chapter II.2 introduces the proposed cerebellar-like simulations model. First, we describe the structure of the bio-inspired model and the learning algorithm. Then, we discuss the empirical results and future improvements.

Chapter II.3 introduces the proposed cerebellar-like adaptive control schemes. We propose three different architectures depending on the independent or interdependent combination of cerebellar-like internal models. The chapter includes the analysis of the empirical results and a discussion regarding the generalization problem.

The thesis terminates with a *Summary and Conclusions* chapter. The chapter summarizes the findings and contributions of the presented studies and collects suggestions for future work.

The published research presented in this manuscript is collected in the *Appendix*.

Part I

Theoretical Concepts

Overview

THE first part of the thesis is dedicated to the literature regarding the cerebellum and its role in motor control. We believe that understanding the internal circuitry and functional partitions of the cerebellum is crucial to appreciate the full potentiality of this incredible central nervous system (CNS) area, and to artificially reproduce it for robotic control applications.

With this in mind, Chapter I.1 is dedicated to an extensive overview of the cerebellar anatomy and the theories regarding the role of the cerebellum in motor control.

Then, we explore in Chapter I.2 the computational models describing the role of the cerebellum in the control of motor movements with respect to the cerebellar functionalities mentioned in Chapter I.1.

In Chapter I.3, we examine the cerebellar-like simulations models proposed in the last decades by the scientific community to reproduce the cerebellar neurophysiology and neuromorphology. In particular, we analyze how the design of the simulations models can change depending on the strictness of the biological constraints rather than the reproduction of the cerebellar behavior.

CHAPTER 1.1

Overview of the Cerebellum

1.1.1 Introduction

THE cerebellum (Latin for "little brain") is the major neural structure of the vertebrates' *hindbrain* located at the back of the brain, behind the upper portion of the brainstem (Figure I.1.1). Although it represents only 10% of the total volume of the brain, it is the largest neural motor system of the central nervous system (CNS) with almost 80% of the surface area of the *cerebral cortex* [90]. The cerebellum is one of the most uniformly organized neural structures of the entire central nervous system (CNS), and it can apply similar processes to different types of signals playing an important role in both motor and cognitive functions.

The scientific community frequently stressed that a proper understanding of the modular and regular anatomy of the cerebellum and its relationship with other central nervous system (CNS) areas is necessary to properly understand the incredible functionality that this peculiar neural structure performs. According to this suggestion, the chapter first describes the cerebellar macro anatomy in terms of functional partitions (Section I.1.2), then focuses on the peculiar microphysiology that characterizes the cerebellum (Section I.1.2.1). Although the cerebellum is defined by a simple and regular structure that has been deeply experimentally investigated over the decades, its functional interpretation is still a great mystery for the scientific community. In Section I.1.3, we discuss the theories regarding the role of the cerebellum in motor activities.

1.1.2 Anatomical Prospective

The cerebellum is constituted of an outer mantle of gray matter, i.e. cerebellar cortex, and an internal white matter, locus of three deep nuclei. The nuclei represent the main output of the cerebellum, with exception of some axons located in the cerebellar cortex that transmit vestibular signals directly to the brainstem, e.g., head movements.

The cerebellum can be divided into three functional regions: the *vestibulocerebellum*, *spinocerebellum*, and *cerebrocerebellum* (Figure I.1.2).

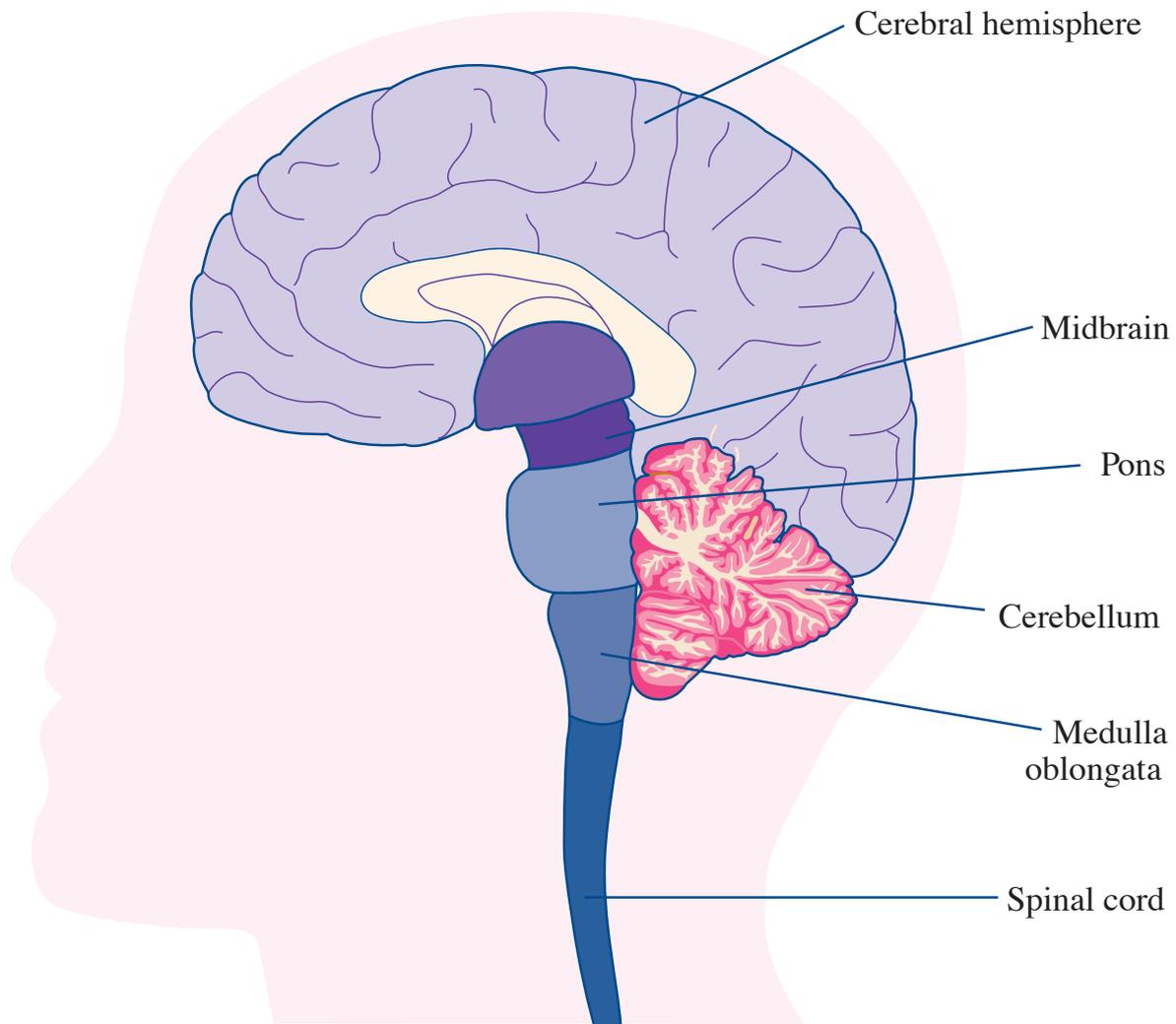


Figure I.1.1. Position of the major structures of the central nervous system (CNS).— Reproduced from [1]

The *Vestibulocerebellum* is the most primitive area of the cerebellum. It receives vestibular and visual signals, and outputs to the *vestibular nuclei*. It contributes to the control of balance, eye movements, and other vestibular reflexes, such as *vestibulo-ocular reflex* (VOR), and posture.

The *Spinocerebellum* receives and processes proprioceptive and somatosensory information from the spinal cord and projects to the brainstem and cortical regions. The Spinocerebellum governs the movements of limbs and the fine control of the digits muscles. It has also a key role in controlling body posture, balance, and orientation.

The *Cerebrocerebellum* is phylogenetically the most recent area of the cerebellum. It is highly connected to the cerebral cortex and participates in high-level functions, such as planning, execution of the movements, and cognition. This is the area of the cerebellum which is mainly involved in motor learning and predictive control [1, 91].

The structure of the cerebellar cortex is uniform and functionally branched. The

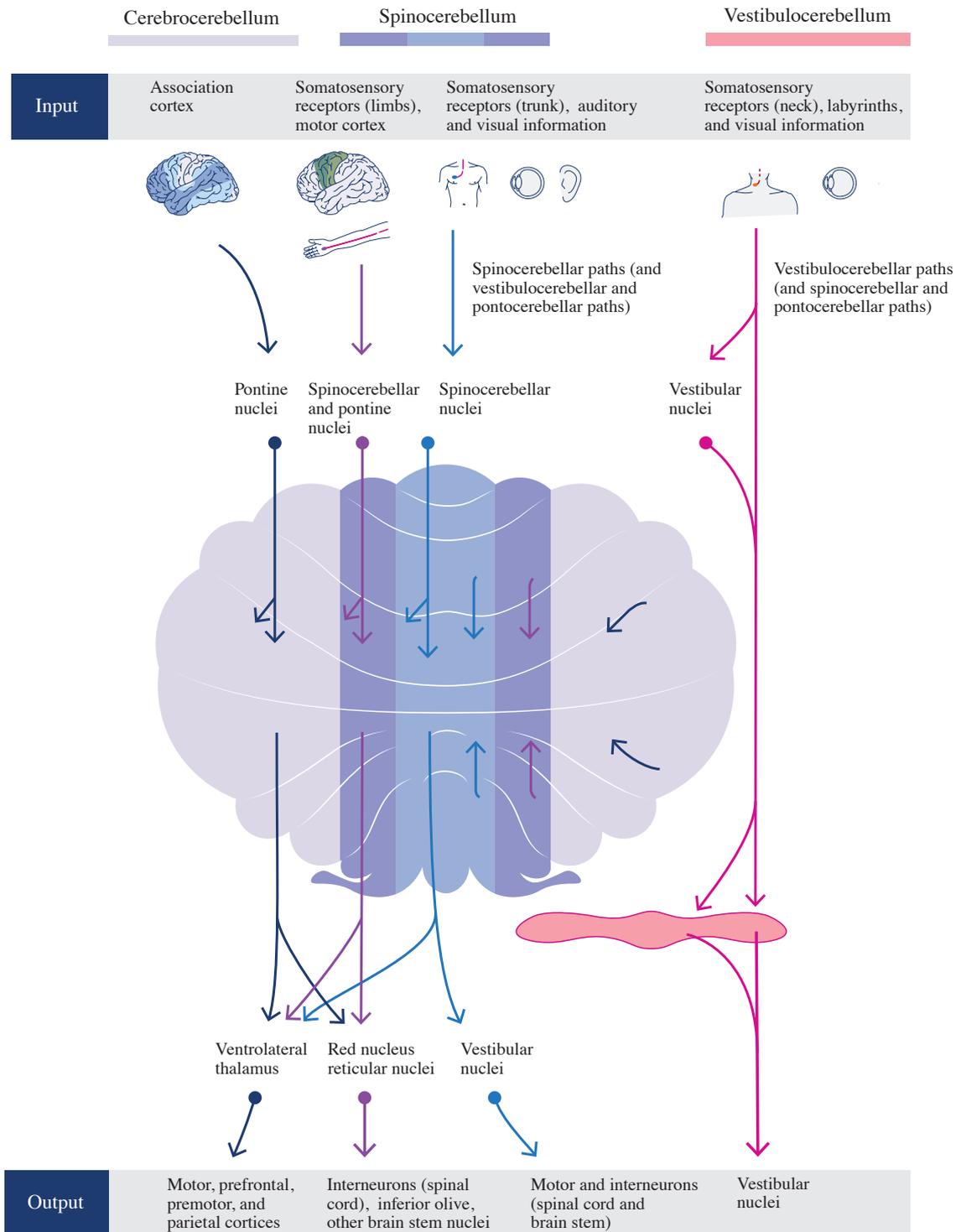


Figure I.1.2. Unfolded cerebellum showing the three functional regions with their different input-output relations, from left to right: Cerebrocerebellum, Spinocerebellum, and Vestibulocerebellum. — Reproduced from [1]

functional differentiation uniquely depends on the input-output signals that connect each area [92]. Each functional area can be further divided into numerous distinct layers that despite their individual requirements, are systematized according to common principles [93].

The parasagittal striped organization of the adult cerebellum can be divided into hundreds of independent longitudinal zones (Figure I.1.3). These longitudinal zones can be separated into cerebellar microcomplexes [92]. Each microcomplexes operates in parallel with distinct input-output connection and includes: a cortical area named microzone [94], composed by few main types of cells and connected externally through two types of distinct afferent; a nuclear area embedded deep into the white matter, consisting of few neural nuclei projecting outside the cerebellum.

I.1.2.1 Cerebellar Microcomplexes

Depending on the neural population, each cerebellar microcomplex can be further divided into a deep cerebellar nuclei (Section I.1.2.1.5), and four layers that constitute the cerebellar cortex (Figure I.1.3): molecular layer (Section I.1.2.1.1), Purkinje cell layer (Section I.1.2.1.2), and granular layer (Section I.1.2.1.3). The cerebellar microcomplex receives inputs signals from two type of excitatory afferent fibers: the mossy fiber (MF) and the climbing fiber (Cl) (Section I.1.2.1.4).

The cerebellar microcomplex can be seen as a feed-forward neural circuit. Few minor recurrent synaptic connections amplify weak neural responses and several negative feedback loops suppress any sustained signal. Thus, the cerebellar circuit does not present any reverberation.

I.1.2.1.1 Molecular Layer

The *molecular layer* is the most peripheral layer of the cerebellar cortex (Figure I.1.4). This is the center of the main signal processing happening in the cerebellum. It contains: the stellate and basket cells, that are two inhibitory interneurons; the *dendrites* of the Purkinje cells (Purkinje cells (PCs)) (Section I.1.2.1.2); and the parallel fibers (PFs), that are the axons of the granular cells (Grs) (Section I.1.2.1.3). Each PF is synaptically connected to the dendrites of few PCs, on the other hand, each PC is connected to thousand of PFs (Figure I.1.3).

I.1.2.1.2 Purkinje Cell Layer

The *Purkinje cell layer* is the only one that projects outside the cerebellar cortex and it consists of only PCs bodies. Each Purkinje cell receives a vast amount of sensory and motor information from the PFs, and a single strong modulating input through the climbing fibers (Cls). These Cls modify the synaptic connection within the PC and the

PFs depending on the supervisory instructive signal elaborated in the IO [95,96]. The PC converges the processed inputs to the DCN to control the premotor nuclei [97,98].

Recent *in vivo* experiments confirmed that the PC plays an important role in controlling the timing of particular motor domain to coordinate coherently elaborated multi-joint movements [99].

I.1.2.1.3 Granular Layer

The *granular layer* contains a large number of Grs that receive the input signals through the excitatory action of the mossy fibers (MFs), and extensively ramify towards the molecular layer where they bifurcate into PFs. Each Gr receives excitatory inputs from 3 – 4 MFs, and constitutes a closed loop with the Golgi cell (GO) (left upper part in Figure I.1.4). The Grs are the most copious neural population not only of the cerebellum (Table I.1.1) but also of the entire central nervous system [100].

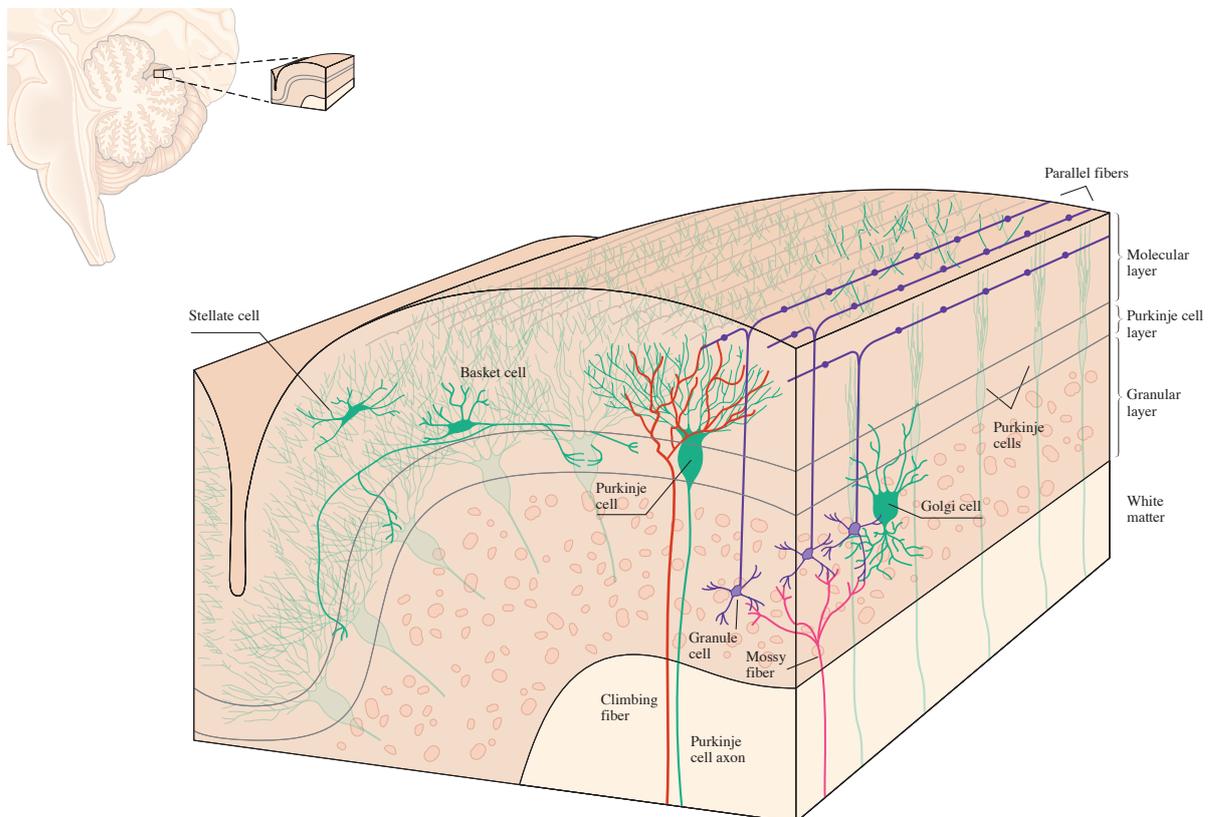


Figure I.1.3. Vertical section of the cerebellar cortex showing the neural organization and the division in three layers: molecular layer, Purkinje cell layer, granular layer — Reproduced from [1]

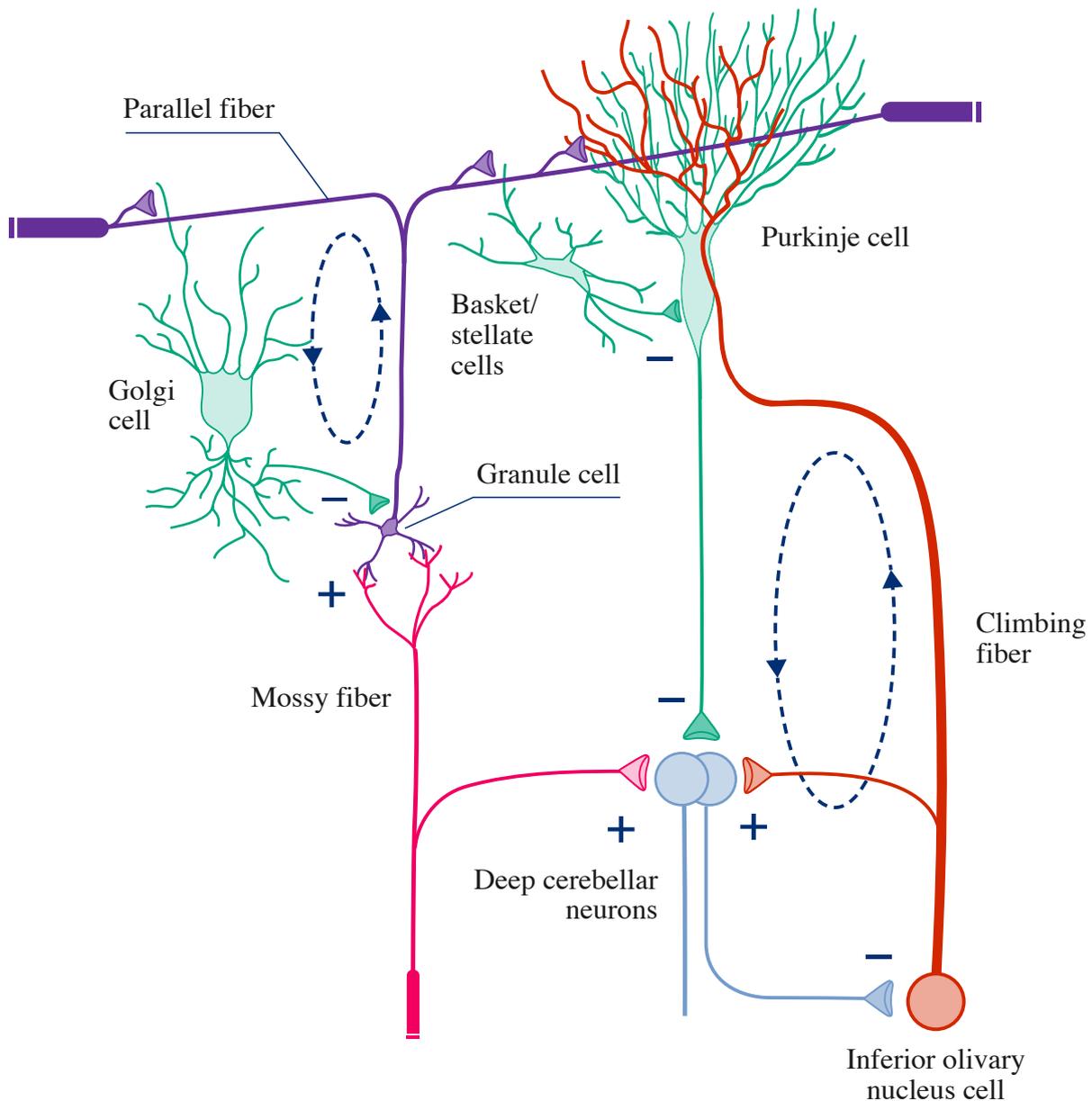


Figure I.1.4. Synaptic organization of the cerebellar micro-circuit. The circuit receives inputs from two type of afferent: mossy fiber (MF) (in magenta) and climbing fiber (Cl) (in red). The only output of the cerebellar circuit comes from the deep cerebellar nuclei (DCN) (in blue). The Grs (in pink) are the smallest and most copious cells and represent the center of cerebellar signal processing. The Purkinje cell (PC) (in light green) is the biggest type of cell in the circuit and constitutes the only output of the cerebellar cortex. — Reproduced from [1]

I.1.2.1.4 The Afferent Fibers Systems

There are two main afferent fibers in the cerebellum that are responsible for the excitatory synaptic connections with the cerebellar neurons: the mossy fibers (MFs) and the

climbing fibers (Cls).

The MFs originate from different sources, such as the brainstem and the spinal cord. The name of these fibers derives from the particular shape of their terminals that resembles the ends of fronds of club moss. The MFs convey sensory information from the cerebral cortex and the periphery of the body to the Grs and to the DCN (Figure I.1.4). The MFs-Grs arrangement is assumed to provide a powerful pattern discrimination action that could be responsible of the context learnt by each PC in response to the inferior olivary nucleus (IO) activity [95].

The Cls have origin in the inferior olivary nucleus and deliver the sensory signals from both the cerebral cortex and the periphery. Each Cl is connected to 1 – 10 PCs, while each PC is stimulated by only one single Cl. The modulating signals of the Cls together with the repeated and almost synchronised MF signals cause a *long-term depression* (LTD) in the PF-PC synapses. Scientists believe that this long-term depression (LTD) is responsible to the adaptive functionality of the cerebellar microzones [101]. The Cls also send signals to paired deep cerebellar nuclei (DCN) (Figure I.1.4). Some recent recordings have shown how the IO could possibly engage the PC during motor behaviour [99,102–104]. However, the type of information carried by the Cls has been under debate for decades. The IO results to be particularly reactive to unexpected somatosensory events, and to noxious stimuli [91]. For this reason, they could be specialized in event detection rather than carrying quantity information. Recent studies probe the role of climbing fibers in generating and evaluating predictions about the relations between somatosensory events, muscular actions, and outcome of the action [105].

I.1.2.1.5 Deep Cerebellar Nuclei

The *Deep Cerebellar Nuclei* is embedded in the white matter of the cerebellum, which is the most internal part (Figure I.1.3). The cerebellum contains in total 3 DCN, that constitute the only set of output fibers from the cerebellum: the fastigial nucleus, the interposed nucleus, and the dentate nucleus. The fastigial nucleus is related to saccadic eyes movements and to the vestibular neuronal activity. The interposed nucleus is responsible of delayed *Pavlovian conditioning* and muscle stretch reflexes of proximal limb muscles. The dentate nucleus is in charge of the initiation, planning, and control of voluntary movements. The DCN receives all the projections from each cerebellar cortex zone, including the inhibitory inputs from the PCs and the excitatory inputs from the MFs. Moreover, it is connected in a closed loop with the IO.

I.1.3 Functional Prospective

In the last decades, the research regarding cerebellar functions has increased exponentially, and numerous new hypotheses have been proposed to interpret the role of cerebellar circuitry in both motor and cognitive functions. Hereafter, we focus the discussion on

Cell	Estimated numbers in adult human	Action
Granule cell (parallel fibers)	10-100,000,000,000	Excitatory
Stellate cells	250,000,000	Inhibitory
Basket cells	90,000,000	Inhibitory
Golgi cell	20-40,000,000	Inhibitory
Purkinje cell	15,000,000	Inhibitory

Table I.1.1. Type of cells in the cerebellar cortex

the literature regarding the field of motor control which could be interesting for robotics applications.

The most validated theory claims that the cerebellum is crucial for motor learning and adaptation due to its intrinsic ability to transform the relationship between sensory input and motor outputs. According to this theory, the cerebellar action aims to optimize the resulting motor performance driven by the modulating information transmitted from the IO.

In 1969, David Marr strongly sustained that the cerebellum learns two types of motor movements: the elemental movements and the conditional reflexes.

The learned elemental movements theory affirms that each inferior olivary nucleus (IO) corresponds to a specific output, which is the elemental movement necessary to control during the execution of a more complex movement. According to this theory, every action can be represented as an ordered combination of elemental movements pattern. The role of the Purkinje cell (PC) paired to the inferior olivary nucleus (IO) is to learn the context in which each elemental movement is required and consequentially send the triggering command to perform the muscular action. In this scenario, the MFs-Grs-PC organization would perform as pattern recognition device, in particular the MFs-Grs subsystem would function as pattern separator, which is pivotal for the reliability of the PC discrimination and over-fitting. The reliability of the cerebellar cortex response is dependent on the number of active MFs, also known as the *codon*, synaptically connected to a set of granular cells, i.e codon cells.

The learned conditional reflexes theory is a type of reflex that is maintained only if a specific learned context is satisfied. According to this hypothesis, the cerebellar cortex is stabilizing a negative feedback loop activated by a set of MFs for a specific reflex learned by the IO-PC subsystem.

Neurophysiological data captured during the eye movements suggest that the cerebellum is important for calibration and stability functions, such as holding a steady gaze, vergence, smooth pursuit, and vestibulo-ocular reflex (VOR) [106, 107]. These different oculomotor functions are achieved by a reactive and online control learned through a repetitive and gradual sensorimotor adaptation process. Empirical results demonstrated that online and adaptive control of eye movement is achieved by the cerebellar cortex through the execution of inhibitory control that compensates for motor noise and environmental or internal alteration of the motor behaviour [108–112]. This inhibitory control is calibrated every time through plastic changes in the PF-PC synaptic connec-

tions.

Many research studies tried to determine the role of the cerebellum in associative learning through eyeblink conditioning experiments [113–116]. The major hypothesis foresees the cerebellum as the ideal neural area for the acquisition and storage of the motor memory trace that is crucial for the predictive and adaptive control of movements [117–119].

Behavioural studies regarding grip force control indicate that the cerebellum has a pivotal role in the predictive timing and coordination of force control when grasping and manipulating external objects [120]. Evidence shows that the cerebellum can predict the consequences of motor action whether the somatosensory feedback is too slow, and to tune the muscles' activity accordingly during the execution of voluntary movements [121].

Patients affected by cerebellar disorders are characterized by incorrect predictive motor timing of the limb movements which manifests through overshooting/undershooting, rising variability in the repetition of the behaviour, growing curvature of the trajectory, impaired timing, and febleness. The main hypothesis suggests that the kinematic parameters are the most affected by cerebellar failure [85]. Moreover, it results that these performance defects seem to be largely influenced by the gravity force and the direction of the movement [122]. These findings indicate that the cerebellum plays an important role in timing and coordination of single and multi-joints movements [123–125]. As matter of fact, the main characteristic of cerebellar ataxia is the failure in the temporal patterning of coordinated muscular movements. This failure leads to the inability of controlling the timing for rapid and reactive motor response and of coordinating dynamical interaction within the muscles [126, 127].

Three main theories regarding the cerebellum and timing received great consensus [85]:

- the representation of time is important for understanding the cerebellar action;
- the cerebellum is essential for behaviours that need real-time prediction;
- the granular cell (Gr) are fundamental for temporal coding.

The crucial role of the cerebellum in time perception and sensory processing indicates its ideal role in sensorimotor synchronization (SMS) [128, 129], i.e. reference behaviour where the action is coordinated temporally with a predictable event [85]. In this sense, the cerebellum is considered able to adapt motor behaviour in the time domain and according to predictable environmental changes [130, 131]. These hypotheses rely on the fact that the cerebellum is the only neural structure of the CNS where previously experienced complex patterns and motorsensory signals are compared and thus recognized [85].

I.1.4 Discussion

In this chapter, we described the anatomy of the cerebellum focusing on the physiological partition based on the functionality that this sophisticated neural structure performs in motor control. Then, we collected and summarized all the different opinions regarding the involvement of the cerebellum in sensorimotor control. Even though it is not clear how the cerebellum internally performs basic operations or which type of information it processes, several studies proved that the cerebellum covers important roles in a wide range of motor skills, such as associative learning, reactive and online adaptive control, predictive timing, force control and coordination of multi-joints movements, and sensorimotor synchronization. It is fascinating how this compact neural structure can perform so many distinct and important activities. More the cerebellar mysteries are unveiled, more its fascinating nature results appealing for research communities that are far from neuroscience. In the next chapter, we are going to explore how scientists tried to computationally reproduce the cerebellar operation through control and learning schemes (Chapter I.2), and the cerebellar circuits through different types of simulations models (Chapter I.3).

CHAPTER 1.2

Cerebellar-like Adaptive and Predictive Control

1.2.1 Introduction

THE cerebellum is well known to be pivotal for precise adaptive control and motor learning. For decades, scientists discussed the cerebellar functions in terms of engineering schemes for motor control and signal processing. Many studies suggested that the cerebellum functions as a sensorimotor adaptive and predictive movement controller [2, 4, 95, 96, 118, 132–135].

An adaptive controller is a signal-processing agent that transforms a set of temporally varying signals into another by decorrelating them from a teaching or error signal. Dean and Porrill summarized some general properties that recommend the cerebellum as an ideal adaptive-filter [134, 136],

- it receives a wide range of continuous time-varying signals;
- it is a signal-processing machine employed in a wide range of applications;
- its structure is easy to computationally reproduce, test, and validate;
- it contains plastic synaptic connections that can be adjusted by an error or teaching signal.

Regarding the range of practical applications, the functionality of the cerebellum strictly depends on its connection with other areas of the CNS. As matter of fact, the internal organization of the cerebellum is uniform and consists of a repetitive canonical microcircuit constituted by minor subregions each with a specific connectivity (Chapter I.1) [1, 137, 138]. Depending on the information transmitted by the teaching signal, the cerebellar application can range from sensory signal processing, to motor control, and to learning of internal models.

With "predictive controller" we refer to the feed-forward part of a movement that is projected in advance before the peripheral feedback is available.

In Figure I.2.1, Bastian and colleagues clearly illustrated how the predictive mechanism in the CNS could work [2]. Scheme (a) of Figure I.2.1 exemplifies the control of movements without cerebellar action, i.e. reactive feedback control. The controller is capable of rapidly reacting to account any important difference in the motor behaviour. However, the control action is not able to gradually correct any state error due to the peripheral feedback delay. In this scenario, the corrective action can never be optimal because it refers to a trajectory that took place in the past [2]. Behavioural studies suggest that patients affected by cerebellar damage are not able to adjust a reaching task towards a desired state, and to store any learned experience when a novel dynamics appears [139, 140].

In Figure I.2.1 scheme (b), the authors describe how the cerebellum could intervene

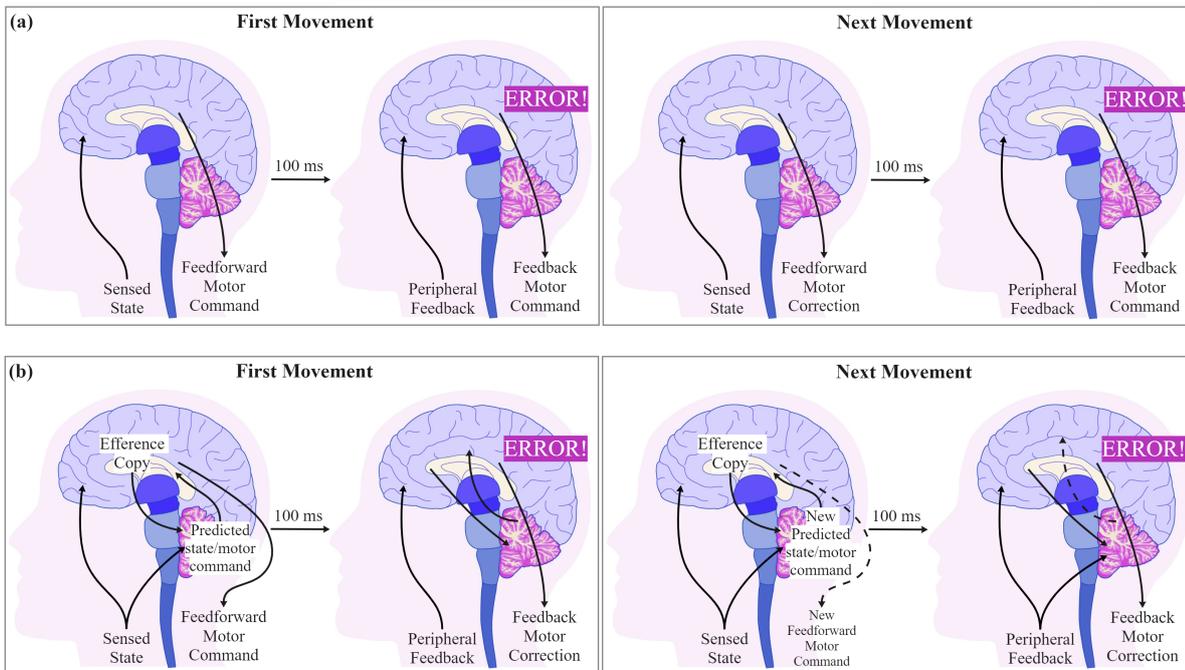


Figure I.2.1. Bastian's theory about how the cerebellum learns predictive movement control [2]. In scheme (a), the pure feedback-dependent control or reactive control is illustrated. A change in the system dynamics appears and a reactive feed-forward motor command is processed and sent downstream to the muscles given the current sensory state. The peripheral feedback arrives with a large time delay. Thus, the feedback motor controller is not able to correct the state error. In the next movement, the same situation is iterated due to the inability of the system to learn and to adapt to changing dynamics. In scheme (b), the mechanism of the cerebellar adaptive predictive control of movements is shown. The cerebellum learns the next movement through error-dependent adaptation mechanism. Once the model is learned, the cerebellum applies corrective prediction of the state of the motor command to update the feed-forward motor command. Dashed arrows express new or updated signals.— Reproduced from [2]

during the control of movements in the same changing dynamic condition. The cerebellum receives both the current sensory state and a copy of the feed-forward motor command sent to the muscle. The information is processed together with the error to learn and to predict the next motor state or command. In the next movement, the trained cerebellum sends the predicted state or motor command to correct and to update the feed-forward motor command before the peripheral feedback is available. In this manner, the system timely corrects its action towards the desired state and reduces the feedback error.

Behavioural studies on cerebellar-deficient patients are not able to suggest the type of signals the cerebellum employs to make any prediction, and which type of prediction it could make. This issue have been mainly addressed by neuroimaging, neurophysiological, and computational studies. Nowadays, there is still no consensus on how the cerebellum function, and which data it maps and stores. In particular, there is a large debate on which type of information the cerebellum employs to calibrate its learning mechanism.

In this chapter, we discuss exhaustively the computational theories regarding the cerebellar function in motor control. In particular, we explore one of the most popular theory that assumes the cerebellum as locus and generator of sensori-motor internal models (Section I.2.2): forward (Section I.2.2.2) and inverse (Section I.2.2.1) internal models. In Sections I.2.3 and I.2.4, we explore the different hypothesis regarding how the cerebellar internal models could be learned and employed by the cerebellum and the corresponding control schemes.

Thereafter, we discuss the theories related to the combinatorial action of the internal models (Section I.2.5) and the cerebellar modularity (Section I.2.6). In Section I.2.7, we wrap up the findings in a final discussion.

I.2.2 Cerebellar Internal Models theory

Many biological motor dynamics can involve both the interaction with external systems, but also the internal musculoskeletal changes due to growth or physical damage. Thus, the motor control adaptation and the continuous training of the internal and external knowledge are pivotal for the successful control of the motor apparatus.

A complete adaptive control system should be able to manage two main basic transformations: motor-to-sensory transformations, and sensory-to-motor transformations [141]. These sensori-motor representation are commonly recognized as internal models. The motor-to-sensory transformation is generally known as forward internal model, while the sensory-to-motor transformation is the inverse internal model.

The central nervous system (CNS) creates through neural circuitry these internal transformations to describe the relationship between the body and the environment [142–144]. The specialized neural circuits are equipped with adaptive learning mechanisms for the continuous generation, optimization, and prune of the internal models [145].

In 1970, Ito have been the first scientist to propose the cerebellum as ideal location for storing and maintenance of the internal models [118].

In 1995, Kawato stated that the cerebellum is the perfect candidate for this pivotal role in the control of movements for several reasons [119], such as

- the cerebellar adaptive potential, which is fundamental for the acquisition and constant update of the models;
- the wide range of sensory inputs that converge to the cerebellum;
- the ability of approximating complex dynamics.

I.2.2.1 Inverse Internal Model

A major theory claims that the central nervous system (CNS) acquires inverse dynamics models of the controlled object to perform smooth and relaxed movements by means of low mechanical stiffness [146–148]. In biological systems, the pure feedback control of rapid and coordinated movement is not achievable due to slow and small gains.

The inverse model of a dynamical system determines the inputs that is necessary to apply to the system in order to achieve a desired state. For instance in motor control, it would be the transfer function that determines how much torque is needed to reach a determine motor position [41, 149].

In diagram **A** of Figure I.2.2, the inverse model processes the necessary action that causal produces a desired state of the controlled object given the current sensed state.

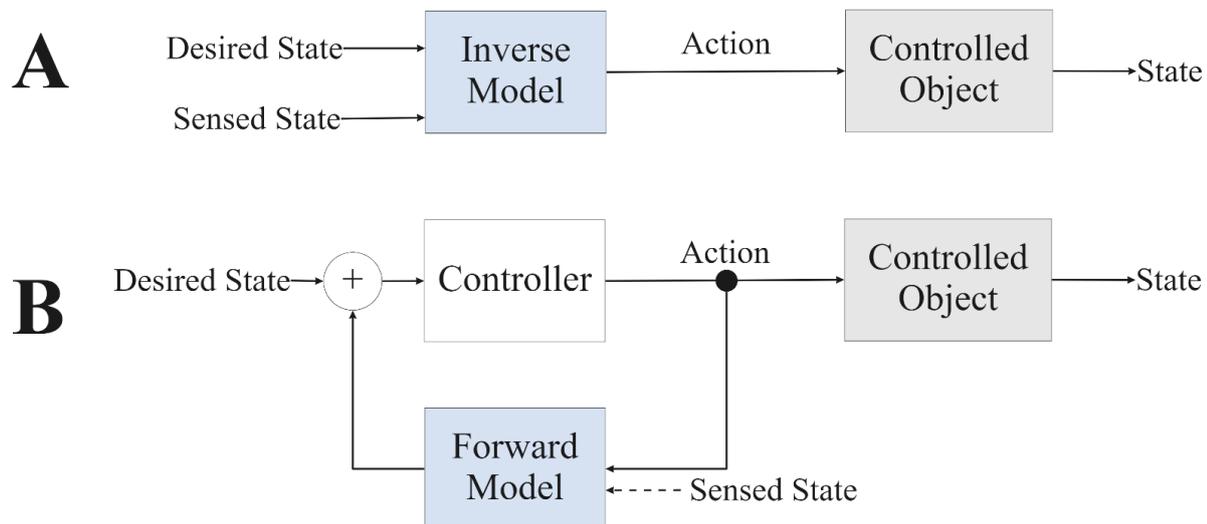


Figure I.2.2. Two control architectures including (A) inverse and (B) forward internal models proposed by Miall and colleagues in 1993. In A, the inverse model processes the action necessary to move the controlled object from the sensed state to the desired state. In B, the forward model estimates the state the controlled object will reach given the sensed state and the applied action.— Reproduced from [3]

Once the model is learned, the controlled object will ideally follow the desired trajectory that it is inputted to the model. A classic feedback controller can be seen as an approximation of the inverse model of the controlled object, because it transforms the state error into motor error [93].

There may not be a unique solution to the inverse problem due to the many-to-one mapping of the forward model. In Section I.2.4, we explore how the inverse model could be learned in a cerebellar-like motor control system, and how the non convexity of the inverse model solution could be solved.

I.2.2.2 Forward Internal Model

Many studies suggest that the peculiar communication within the cerebrum and the cerebellum forms a sort of internal feedback [150,151], which could be responsible of the creation of forward internal models within the cerebellar microzones [3,11,132,152–160].

The forward model of a dynamical system expresses the connection between the input to the system and its causal output. For instance in the central nervous system (CNS), the forward model would predict the next state of a limb in response to a motor command sent to the muscles.

In motor control scheme (diagram **B** of Figure I.2.2), the forward dynamic model is employed to estimate the next controlled object state, given the knowledge of the current sensed state and the action that is going to be applied to the object, e.g., it would be the relation within the motor command sent to the actuators system and the resulting motor movement read by the sensory system.

In 1996, Miall and Wolpert stated that forward model can be advantageous in a wide range of motor control situations, such as cancelling sensory consequences of movement or noise, supervising the learning of inverse models, overcoming time delays, state estimation, and state prediction [161]. However, it is not clear if it is a single model to perform several duties, or are distinct independent models to work in parallel [11].

In the next sections, we analyze the theories and computational models regarding how the forward model could be learn in a cerebellar-like control scheme (Section I.2.3), and how the forward model could be combined to the inverse model in the control action (Section I.2.4.3, Section I.2.6).

I.2.3 State Prediction

In 1993 in a review about how the cerebellum produces predictive representations, Miall and colleagues suggested that the cerebellum forms two type of predictive models: a forward model of the motor apparatus, and a model of the time delays of the control loop [3]. The scientists affirmed that the biological motor control of movements is affected by a wide range of delays, such as afferent delays from the receptors to the central nervous system (for instance, the significant delays caused by the visual feedback), delays due to the processing of the motor command, delays generated by the delivery of the

motor command to the muscle, and the consequential delays due to the response of the limb. These delays can provoke instability of the feedback control during the execution of fast limb movements. For this reason, they assumed that the biological motor control employs forward models to timely respond before receiving the real delayed feedback about the occurring movement, and to explore the consequences of an action before it is executed.

Miall and colleagues theory strongly relies on the speed of human movements, which is significantly higher than any visual feedback. The scientists also mentioned that the motor performance is strongly degraded if the internal model is inaccurate or not available. Thus, they believed in the existence of some kind of mechanism that incorporate model error at latter moment in the control action, as a Smith Predictor would do [162].

The Smith Predictor is a control scheme solution for long loop delay processes proposed by Smith in 1959 [162]. In Figure I.2.3, the controlled system is influenced by a $Delay_1$ feed-forward delay and a $Delay_2$ feedback transport delay. The first internal negative feedback loop includes the $plantmodel_1$ model of the plant (dashed line labeled **1**). A second positive loop is used to compare the performance of the plant with the estimated performance (dashed line labeled **2**). The second loop includes a model of the $DelayModel$ transport delay,

$$DelayModel = Delay_1 + Delay_2$$

and it is meant to match the delay of the control action with the delay in the sensor system.

In 2004, Porrill and colleagues proposed an alternative architecture for learning the forward internal model: the recurrent cerebellar architecture [4]. The authors suggested

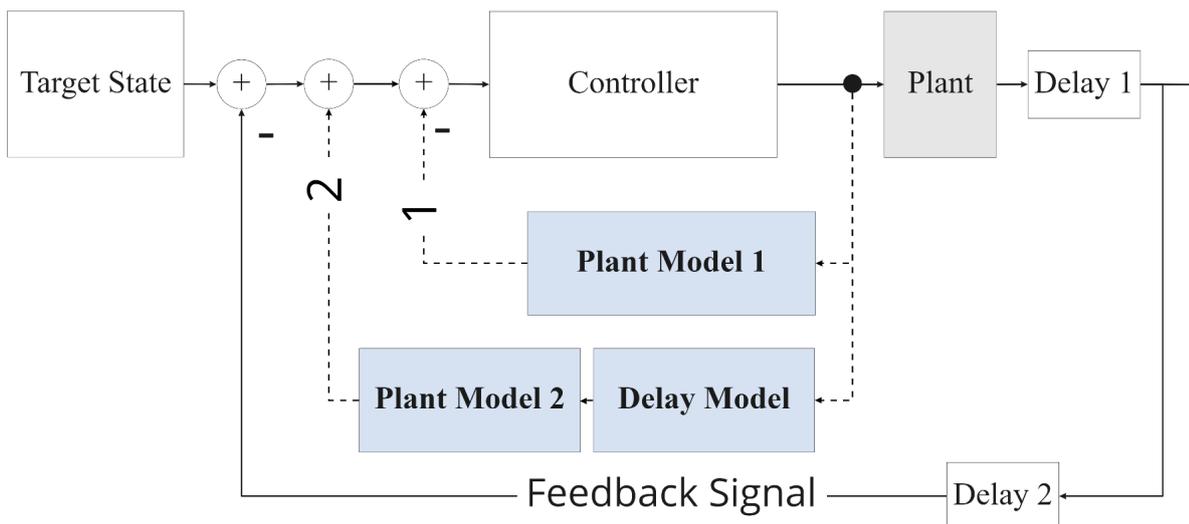


Figure I.2.3. The cerebellum as Smith Predictor. The system is affected by a feed-forward delay ($Delay_1$ box) and a feedback transport delay ($Delay_2$ box). The models provides, first, an immediate prediction of the motor command consequences, then, a delayed copy of the prediction that match the actual feedback. — Reproduced from [3]

some general connectivity requirements that a cerebellar-like scheme for learning the forward-dynamics model should observe [4, 108],

1. the input to the cerebellar-like model consists of an efference copy of the relevant motor commands;
2. the teaching signal is the model output error;
3. the error signal is computed by a comparator that subtracts the model output from the actual plant output.

In Figure I.2.4, the cerebellar-like model receives as input a copy of the τ_i motor command applied to the i -th actuator, and the e_i performance error as teaching signal. The information is processed by the cerebellar-like model which estimates the q_i^c next actuator state and adds it to the q_i^{tot} total controller input,

$$q_i^{tot} = q_i^r + q_i^c,$$

where q_i^r is the reference or desired state.

The authors affirmed that their main intention is to solve the computational difficulty of early cerebellar-like computational models [96, 163], i.e. the need of physically inaccessible information regarding the desired motor output (further discussed in Chapter I.3). Porrill and colleagues stated that the main strengths of the proposed architecture are the easiness of the implementation on high degree of freedom plant thanks to the error-related teaching signal, and the resolution of the motor compensation problem (discussed in Section I.2.4).

In 2013, Tolu and colleagues proposed a robotic control scheme based on Porrill's cerebellar recurrent architecture [4, 5]. In Figure I.2.5, the learner is constituted of two interacting parts: a forward model and a "Cerebellum" module. The forward model is modulated by the the q, \dot{q}, \ddot{q} sensed states (dashed magenta line in Figure I.2.5), and

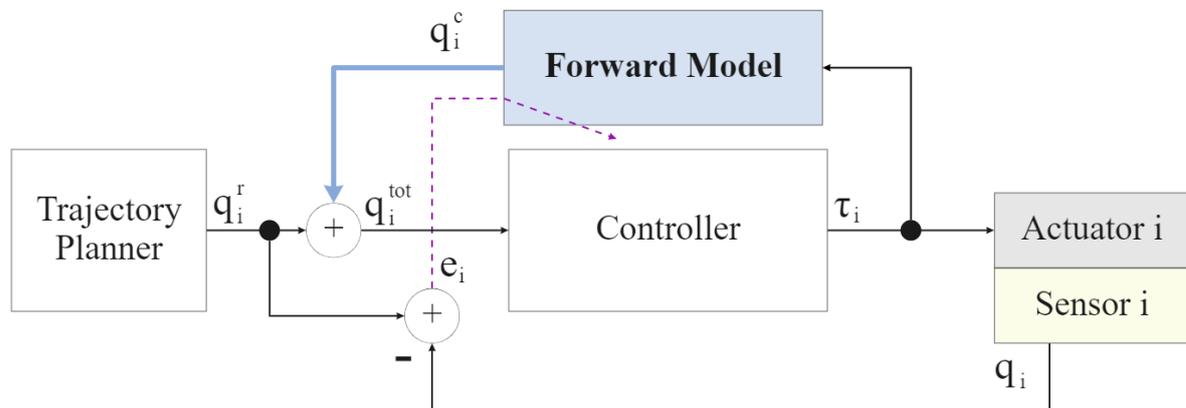


Figure I.2.4. Cerebellar recurrent control scheme proposed by Porrill and colleagues in 2004. The forward model receive an error-related teaching signal e_i to process a goal directed learning. — Reproduced from [4]

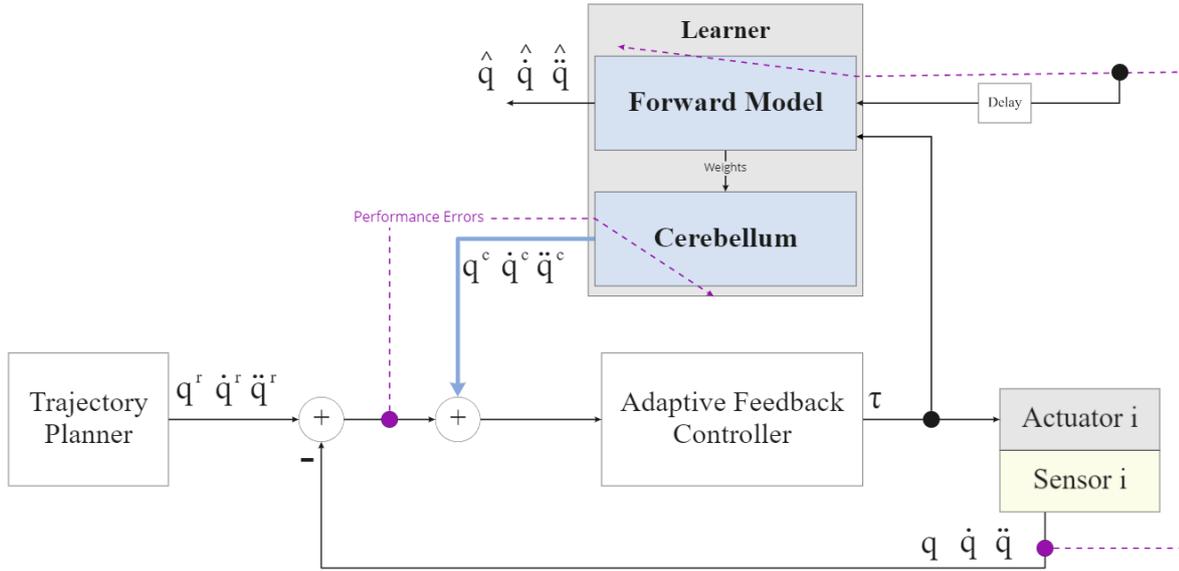


Figure I.2.5. Cerebellar recurrent control scheme proposed by Tolu and colleagues to control a robotic manipulator. The learner is constituted of two interactive modules, i.e., the forward model and the Cerebellum, that are modulated by the q, \dot{q}, \ddot{q} sensed states and the performance errors respectively (dashed magenta line). The $q^c, \dot{q}^c, \ddot{q}^c$ cerebellar contribution (bold blue line) is added to the performance error and is fed to the feedback controller. — Reproduced from [5]

takes as inputs the τ torque command sent to the actuators of the robot, and the $q(t-1), \dot{q}(t-1), \ddot{q}(t-1)$ delayed sensed states. The $\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}}$ estimated states are not directly used by the scheme, instead the cerebellar-like module employs the weights learned by the forward model to process the cerebellar corrective term. The cerebellar-like module is modulated by the performance error (dashed magenta line in Figure I.2.5). The $q^c, \dot{q}^c, \ddot{q}^c$ cerebellar contribution (bold blue line in Figure I.2.5) is added to the performance error and sent to the controller. The authors stated that the weights learned by the forward model can be compared to the granular layer activity, by enclosing a compact sensory-motor representation of the robot. The feedback controller follows an adaptive rule to compensate the friction force, and its gains are kept fix and poorly tuned.

1.2.4 Motor Learning

Motor learning generally implicates the acquisition of novel behaviour or the adaptation of an existing one. The learned behaviour changes gradually during the learning, until the desired state is reached and consequentially the learning is interrupted. Empirical results show that the CNS must necessarily employ feedback loop to indicate whether or not the body is reaching the desired behaviour [164].

In this section, we analyse three computational algorithms describing how motor movements could be potentially mapped by a cerebellar-like learner: direct inverse mod-

eling, distal supervised learning, and feedback error learning. These methods mainly differs on the data and structural connectivity they require. They are all *supervised learning* approaches, i.e., the learning parameters are modulated by the error between the desired outcome and the actual outcome of the action (Figure I.2.6) [165]).

The selection of these three supervised learning methods relies on the theory that the cerebellum is a specialized neural structure for supervised learning and its learning modules are hypothesized to be internal models modulated by error vectors [166,167].

I.2.4.1 Direct Inverse Modeling

The direct inverse modeling approach consists in a direct input-output mapping. The input-output pairs are generally provided to the supervised learning algorithm as training data in reverse order, i.e., the output of the controlled object is input to the model. In Figure I.2.7, the weight of the learner are adjusted by the S_i estimation error,

$$S_i = \tau_i^{ff} - \tau_i^{inv}$$

where τ_i^{ff} is the feed-forward motor command and τ_i^{inv} is the motor command estimated by the inverse model [168–171].

Miller widely used this approach for learning and adjusting the parameters of the cerebellar-like controller he proposed in late 1980s [6,172,172]. Miller included a cerebellar-like neural network (Section I.3.2) to learn the inverse dynamics of an industrial robotic manipulator. In Figure I.2.8, the model receives as training input the \mathbf{Q} sensed joints state,

$$\mathbf{Q} = [\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}],$$

where \mathbf{q} , $\dot{\mathbf{q}}$, and $\ddot{\mathbf{q}}$ are the sensed angular positions, angular velocities, and angular accelerations vectors, respectively, to learn the τ_0 motor command with a direct

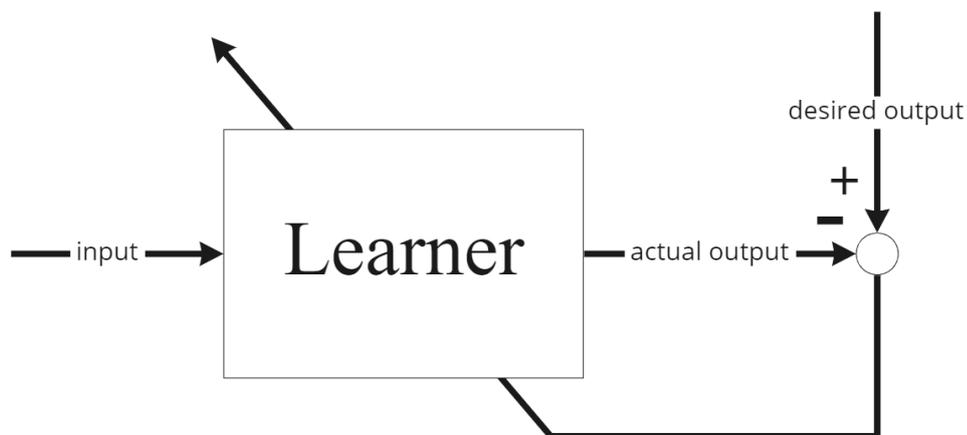


Figure I.2.6. Schematic of a general supervised learning system. The parameters of the learning model are adjusted by the error between the desired and the actual output.

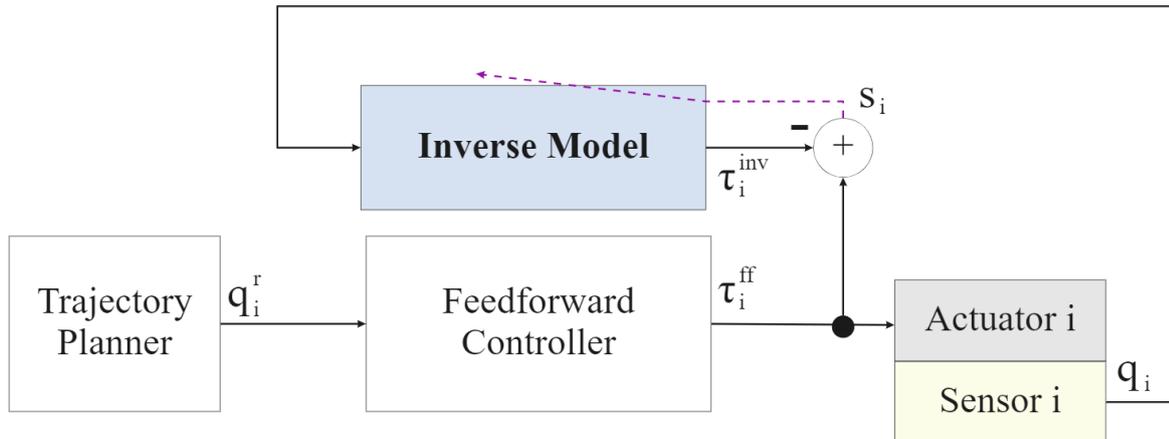


Figure I.2.7. General scheme of a direct approach for learning the inverse dynamic model. The inverse model receives as inputs the q_i sensed state of the i -th actuator. The parameters of the learner are adjusted given the S_i estimation error between the τ_i^{ff} feed-forward motor command and the τ_i^{inv} motor command estimated by the inverse model.

mapping,

$$\tau_0 = f(\mathbf{Q}),$$

where $f(\cdot)$ is the direct transformation function. The \mathbf{w} transfer function weights are adjusted by the error within the τ_0 actual motor command and the $f(\mathbf{Q})$ estimated one,

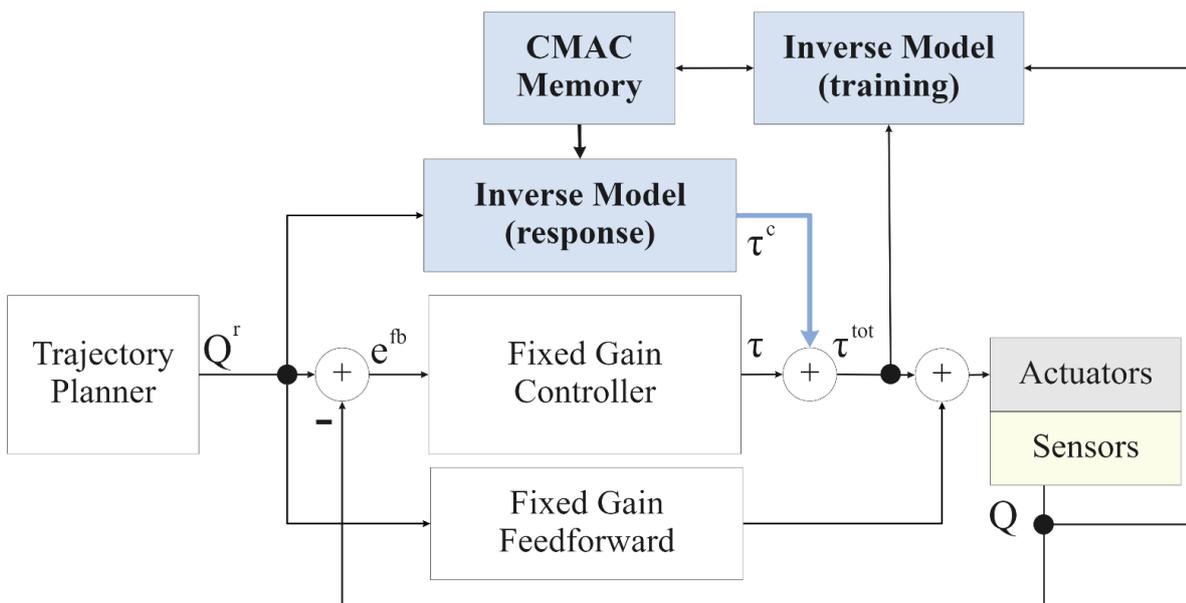


Figure I.2.8. Real time dynamic robotic learning and control scheme proposed by Miller in 1990. — Reproduced from [6]

$$d\mathbf{w} = \beta \cdot (\boldsymbol{\tau}_0 - f(\mathbf{Q})).$$

Once the model is trained, the model inputs change and the $\boldsymbol{\tau}^c$ cerebellar-like response is processed as function of the \mathbf{Q}^r reference state trajectory,

$$\boldsymbol{\tau}^c = f(\mathbf{Q}^r).$$

The experimental results shows a learning control system capable of minimizing the error within few trails. Miller stated that the performance of the overall system depends on a carefully tuned feed-forward controller due to the high sensitivity of the learning system to the controller behaviour. However once the model is learned, it does not results affected by any feed-forward controller failure.

Millers affirmed that the direct inverse modeling is not an optimal approach for learning nonlinear systems. This is due to the a singular type of redundancy that nonlinear systems present [11, 173], that lead the parameters of the adaptive controller to diverge. He added that after training the learner represented a discrete model of system nonlinearities that are not described by the fixed gain controller. One of Miller's main concern is that the system at the current state is not able to generalize over a wider range of control objectives.

I.2.4.2 Feedback Error Learning

In 1987, Kawato proposed a feed-forward control architecture that includes a cerebellar learning system for the direct acquisition of the inverse-dynamics model of a robotic manipulator [7]. The cerebellum is assumed to be a Perceptron that learns a single

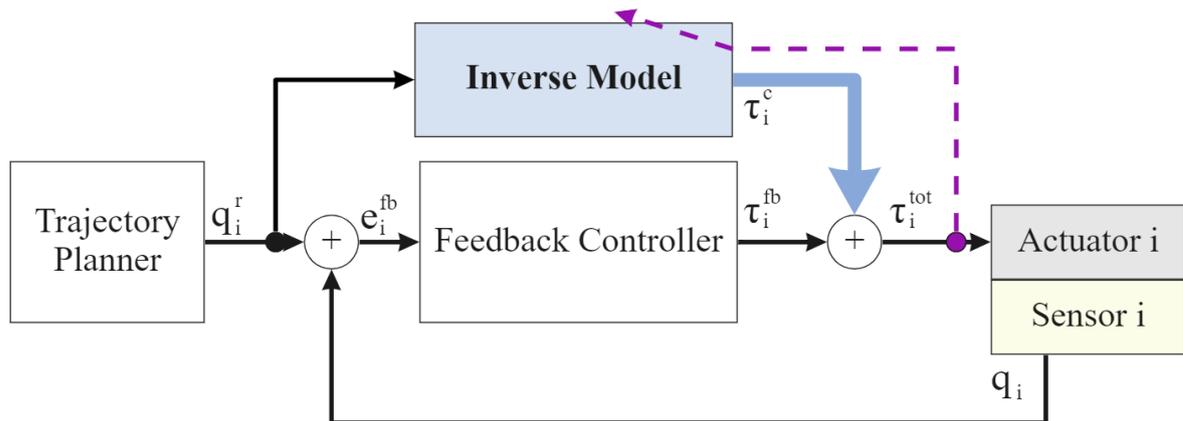


Figure I.2.9. Cerebellar adaptive control loop proposed by Kawato in 1987. A cerebellar-like Perceptron learns the inverse-dynamics model of the controlled plant (blue box) and applies feed-forward τ_i^c torque commands (blue arrow) to correct the feedback controller action. The inverse-dynamics model gets as input only the q_i^r reference angular trajectory of each actuator, and as teaching signal the τ_i^{tot} corrected torque command (in magenta) that is sent to the corresponding actuator. — Reproduced from [7]

repetitive motor pattern (further described in Section I.3.2), while it receives the q_i^r reference angular trajectory of the i -th actuator as input and the τ_i^{tot} feedback torque as teaching signal (dashed magenta line in Figure I.2.9). The cerebellar-like module applies feed-forward τ_i^c cerebellar motor contribution to the control action resulting in a τ_i^{tot} total feedback torque defined as,

$$\tau_i^{tot} = \tau_i^{fb} + \tau_i^c.$$

In the optimal case, Kawato hypothesized that the τ_i^{fb} motor torque computed by the feedback controller should converge to zero once that the inverse model has learnt the dynamics of the controlled plant, thus,

$$\tau_i^{tot} \simeq \tau_i^c.$$

The empirical tests are carried on a 3-degree-of-freedom robotic manipulator to resemble the movement of a human arm but the cerebellar-like model is omitted due to the high computational load derived from the numerical integration of many differential equations that describe the dynamics of the robot. The performance are tested with and without a poor feedback controller action. The results show that the neural model is able to learn only slow movements when the weak feedback controller is applied. Only after a learning process of 40 minutes, the system is able to react to faster movements too. Kawato claimed that the systems is able to adapt to sudden changes in the dynamics of the controlled system. Although the system performed well in learning the inverse-dynamics model, it shows great limitations due to the type of teaching signal, i.e. a wrong teaching signal makes the neural network weights diverge. This problem mainly showed up during the testing with a poor feedback controller. He assumed that the problem can be solved by slowing down the training movement.

In 2012, Tolu and colleagues applied Kawato's cerebellar-like control architecture to the real-time control of a robotic manipulator [8]. In Figure I.2.10, the control scheme includes a poorly tuned *Learning Feedback Controller* module, and a cerebellar-like adaptive inverse model that online learns and applies feed-forward correction to the feedback controller. The cerebellar-like model is modulated by the \mathbf{u}_{fb} motor command, the so-called motor error [7]. An important difference with respect to [7] is the input to the learner module, which is constituted by both the $Q_d, \dot{Q}_d, \ddot{Q}_d$ desired state trajectories, and the Q, \dot{Q} sensed states. The control architecture is tested on a simulated three degree of freedom robot arm. Tolu affirmed that the approach is suitable for accurate low gain control.

In 1988, Miyamoto and Kawato re-elaborated the previous experiments and proposed a feedback-error-learning cerebellar-like system for the trajectory control of a robotic manipulator [9]. In this design, the cerebrotocerebellum-like inverse-dynamics model receives as input signal the \mathbf{q}^r reference angular trajectories of all the actuators involved in the movement, and the S_i motor error as teaching signal (magenta arrow in Figure I.2.11). The S_i error signal is the difference between the τ_i^{tot} total torque that is sent to the controlled plant and the τ_i^c torque estimated by the cerebellar model:

$$S_i = \tau_i^{tot} - \tau_i^c. \quad (\text{I.2.1})$$

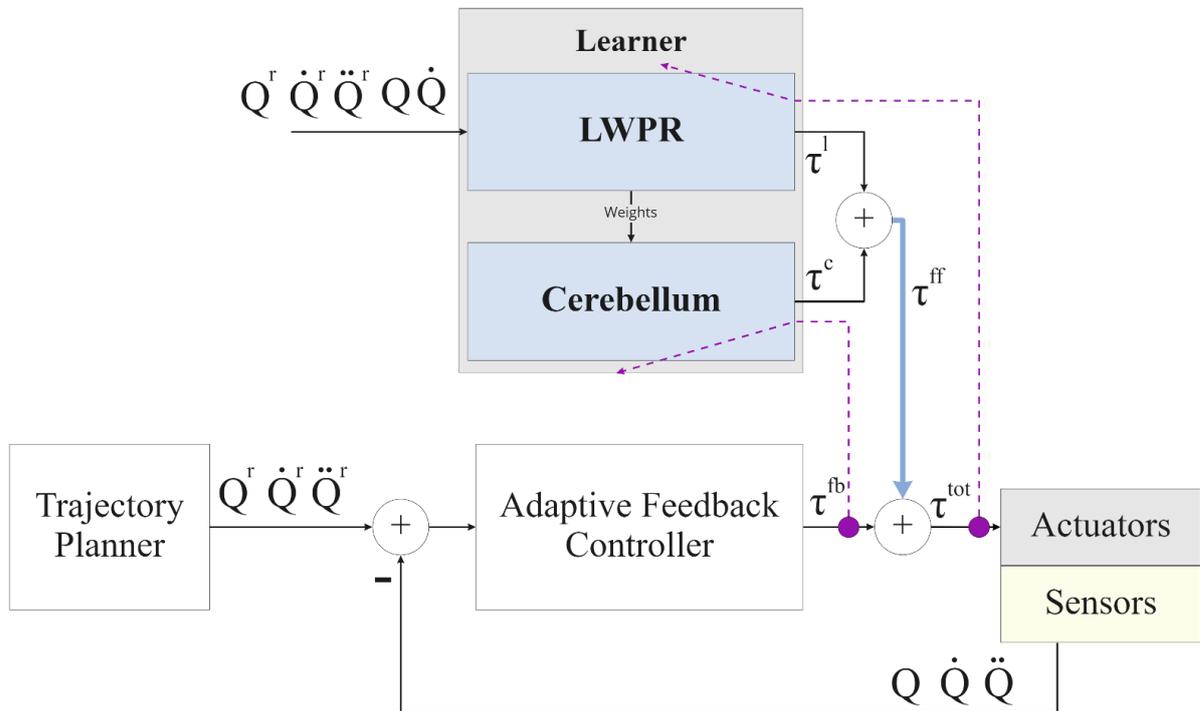


Figure I.2.10. Cerebellar-like control scheme proposed by Tolu and colleagues to control a multi-degree of freedom robotic manipulator. The architecture takes inspiration from the feedback-error learning approach proposed by [7] excepts some modification in the inputs of the learner module (ULM). The cerebellar-like system takes as input both the $Q_d, \dot{Q}_d, \ddot{Q}_d$ desired state trajectory, and the Q, \dot{Q} sensed state.— Reproduced from [8]

The researchers claimed that it is hard to imagine this type of processing happening in the central nervous system (CNS) due to the large scale connections and the difficulties in preserving the one-to-one correspondence. In the experiments, any a priori knowledge of the robot dynamics is used, and the feedback controller is exploited for the clumsy but robust control at the early stage of motor learning. The tests are similar to the previous attempt [7]. After 30 minutes of training, the empirical results show that the τ_i^{fb} decreases considerably while the τ_i^c cerebellar action increases. After training, the system is able to adapt to faster movements and dynamics changes, showing some degrees of generalization. Later in 1990, Kawato affirmed that the feedback-error learning method is a possible solution for the conversion of the error signal calculated in the task space into an error signal in the motor command space [133], and it could be a possible alternative to the distal teacher learning addressed by Jordan and Rumelhart [11]. Moreover, he mathematically proved that the feedback-error learning control scheme can be treated as a Newton-like method in functional space.

The major difference between the direct inverse modeling and feedback-error learning regards the inputs fed to the learner. The direct model is trained offline and receives as input only the sensed output from the controlled object. Once the model is learned, the model receives as inputs the desired output of the plant. For instance in Miller's control

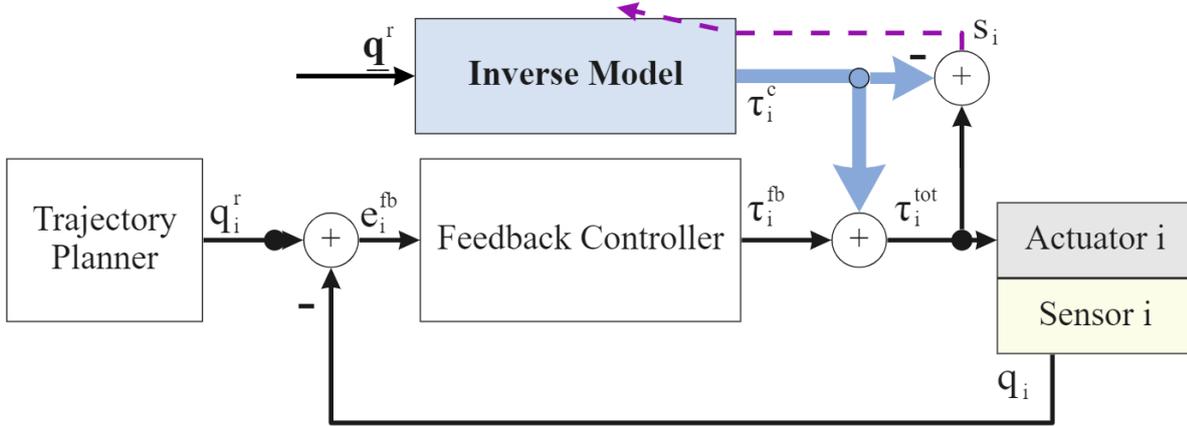


Figure I.2.11. Cerebellar feedback-error learning proposed by Miyamoto and Kawato in 1988. The system is an optimization of the previous attempt (Figure I.2.9) [7]. A cerebellar-like neural network learns the inverse-dynamics model of the controlled plant (blue box) and applies feed-forward τ_i^c torque commands (blue arrow) to correct the feedback controller action. The scheme takes its name from the S_i teaching signal of the cerebellar inverse-dynamics model that is the resulting difference between the τ_i^{tot} total torque command and the τ_i^c torque estimated by the cerebellar model. Another major difference with respect to [7] is the cerebellar model input that includes all the \mathbf{q}^r reference angular trajectories of the actuators involved in the action.— Reproduced from [9]

scheme (Figure I.2.8), the training is function of the s_0 current state,

$$\underline{V}_0 = f(s_0) , \quad (\text{I.2.2})$$

while the model response is function of the s_d desired state,

$$\underline{V}_p = f(s_d) . \quad (\text{I.2.3})$$

Instead, the feedback-error learning method learns online and employs the desired state as input to the model during both training and control. Moreover, the feedback-error learning faces another unsolved problem of direct modeling, i.e. not being goal directed [174]. This insensitivity of the model to a precise goal leads to a laborious search in the control space to find a suitable control solution. A problem that does not occur when a feedback-error learning method is employed because the feedback controller guides the model throughout a specific solution space [49].

In 2013, Garrido and colleagues proposed another control alternative suitable for robotic control and cerebellar-like spiking neural networks [10]. In Figure I.2.12, the cerebellar-like model learns the inverse model of the robotic plant and applies feed-forward motor correction to an *Inaccurate Inverse Dynamics* module. As in a feedback error-learning scheme, the cerebellum receives as input the desired joints state trajectories in terms of Q^r angular position, \dot{Q}^r angular velocity, and \ddot{Q}^r angular acceleration. The error signal employed as teaching signal of the cerebellar-like model is constituted by the $\epsilon_{Q,\dot{Q}}$ performance errors regarding angular position and angular velocity. The

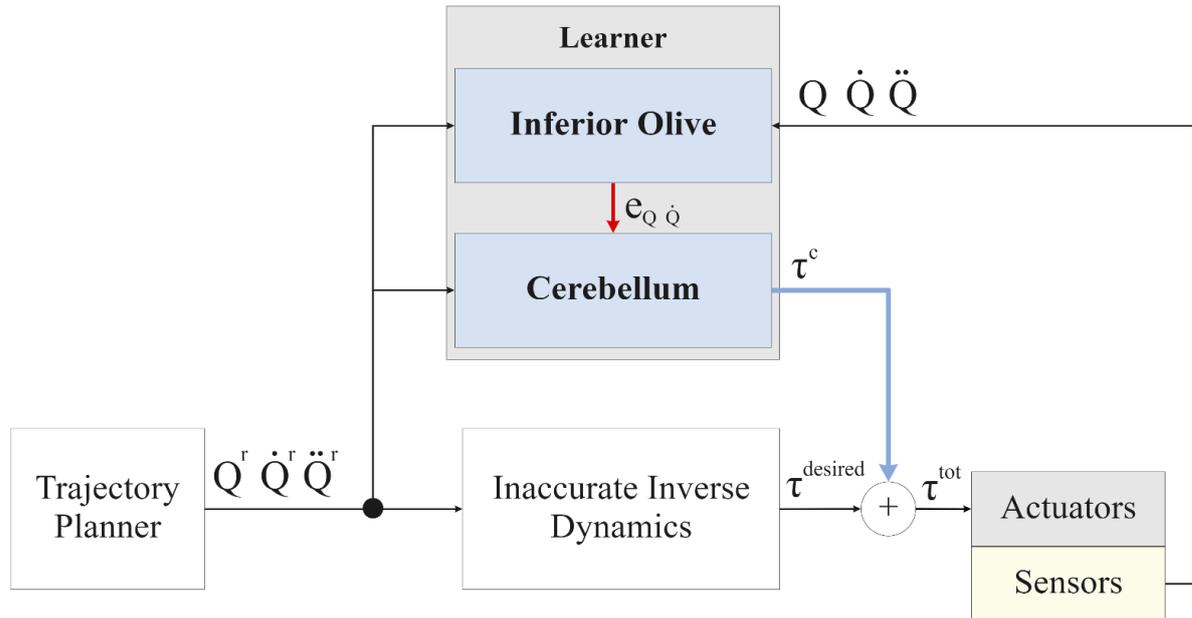


Figure I.2.12. Cerebellar control scheme for robotic manipulation experiments proposed by Garrido and colleagues in 2013. The cerebellar-like model learns the robot inverse model and applies feed-forward correction to the *Inaccurate Inverse Dynamics* module. The cerebellar inverse model receives as input the Q^r , \dot{Q}^r , \ddot{Q}^r desired state trajectory, and the $\epsilon_{Q, \dot{Q}}$ performance error as modulating error-dependent signal.— Reproduced from [10]

scientists claimed that this method avoided the distal error problem or motor error problem [4, 175]. As claimed by Porril in 2004, many experimental evidences indicates that the teaching signal in the cerebellum seems to be triggered by not predicted sensory consequences of an action, which are closer to a sensory error rather than a motor error [4, 176–179]. The architecture proposed by Garrido and colleagues have been successfully applied in further robotic experiments regarding adaptive manipulation under changing conditions [23, 37, 37].

I.2.4.3 Distal Supervised Learning

Distal supervised learning is an indirect modeling approach where the inverse model is learned indirectly through an intermediary forward model. The method was proposed as an alternative for avoiding the nonconvexity of the inverse model solution [11, 180].

In 1992, Jordan and Rumelhart proposed a general approach to employ the distal supervised learning in a control scheme [11]. In Figure I.2.13, the proposed learning and control architecture includes two interacting learning modules: a fixed forward model and an adaptive inverse dynamics model. The learning occurs in two distinct phases. In the first phase, the predictive forward model is trained. The forward model receives as training inputs the \mathbf{q} sensed plant state and the τ input to the controlled object. The weights of the forward model are modulated by the $\mathbf{q} - \hat{\mathbf{q}}$ prediction error, where

$\hat{\mathbf{q}}$ is the state predicted by the forward model. In the second phase, the learned or partially learned predictive model is employed to indirectly solve the inverse dynamics problem. The inverse model is learned by keeping the weights of the forward model fixed, and the $\mathbf{q}^r - \mathbf{q}$ performance error is employed as teaching signal, where \mathbf{q}^r is the reference state. Jordan and Rumelhart affirmed that if the forward model is inaccurate, the controller will consequentially learn an inaccurate model. However, because the composite system employs both prediction and performance errors, the controller can still improve the motor action through the actual error. They later added that the role of the forward model is to convey rough estimate of the system performance. In other words, an accurate inverse dynamics model can be learned even without an accurate forward model [11, 141].

1.2.5 Combined Internal Models

In motor learning, there is no strong evidence of the independence or interdependence of the two types of internal models, and few cases show the possible combinatorial interaction within inverse and forward internal models [181].

In 2018, Honda and colleagues developed a hybrid control scheme that includes paired

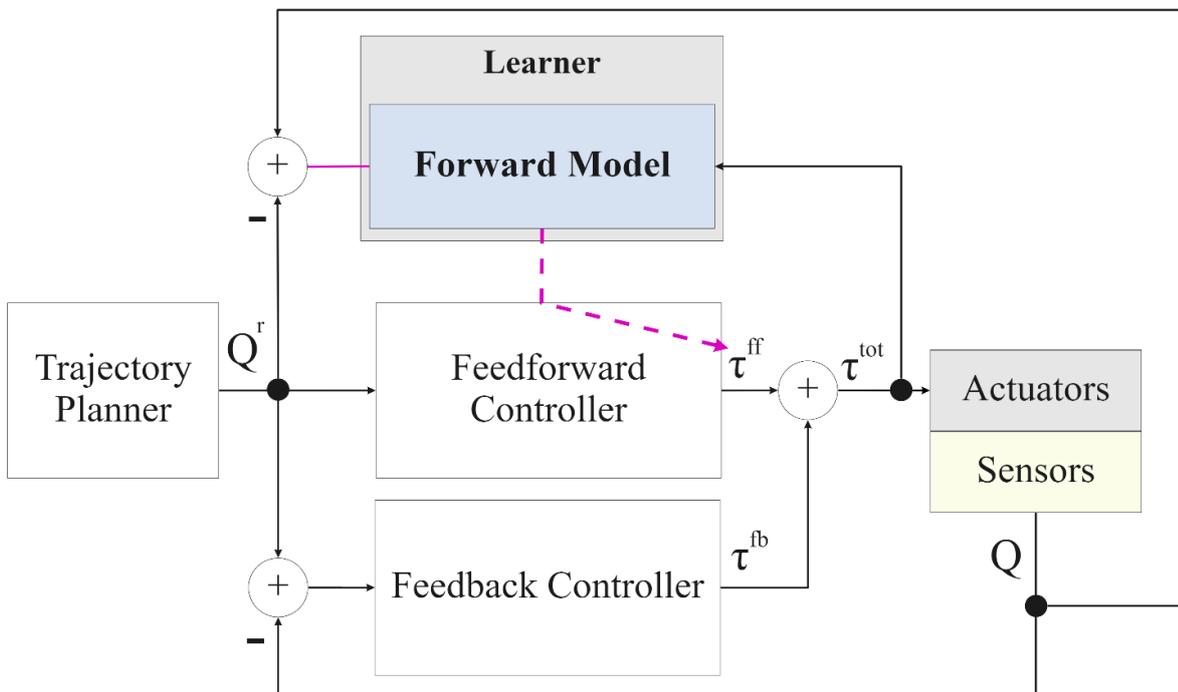


Figure I.2.13. Composite system for controlling a robotic arm proposed by Jordan and Rumelhart in 1992. The inverse dynamics model learns indirectly from a trained forward model. The forward model is trained by feeding the prediction error, while the inverse model is trained with the performance error.— Reproduced from [11]

inverse and forward models [12]. In Figure I.2.14, the forward model, the feedback controller, and the inverse model are connected in parallel. Their operations are in "tandem", i.e., the forward model is updated before the inverse model to solve the one-to-many mapping problem. The forward model provides an internal feedback loop to the controller [118], consequentially the controller is driven by both the feedback error and the forward model estimate. While the inverse model is updated by the motor error [7] and adds corrective action to the controller command. The model is experimentally validated by behavioral tests carried out by patients with cerebellar degeneration disease.

I.2.6 Modularity

There is a consensus within the scientific community regarding the possible relation between the modular structure of the cerebellar circuit and the generalization of learning. After all, it is hard to imagine a single big internal model covering a whole range of behaviors [86, 182]. According to this hypothesis, each module cannot be completely independent to generate some degree of generalization, but there should be some mechanism that regulates the learning and involvement of multiple and distinct internal models during the execution of complex motor behaviors. Some studies suggest that different internal models compete with each other in learning events that are temporally close [183, 184]. While others claim that distinct internal models could be mixed

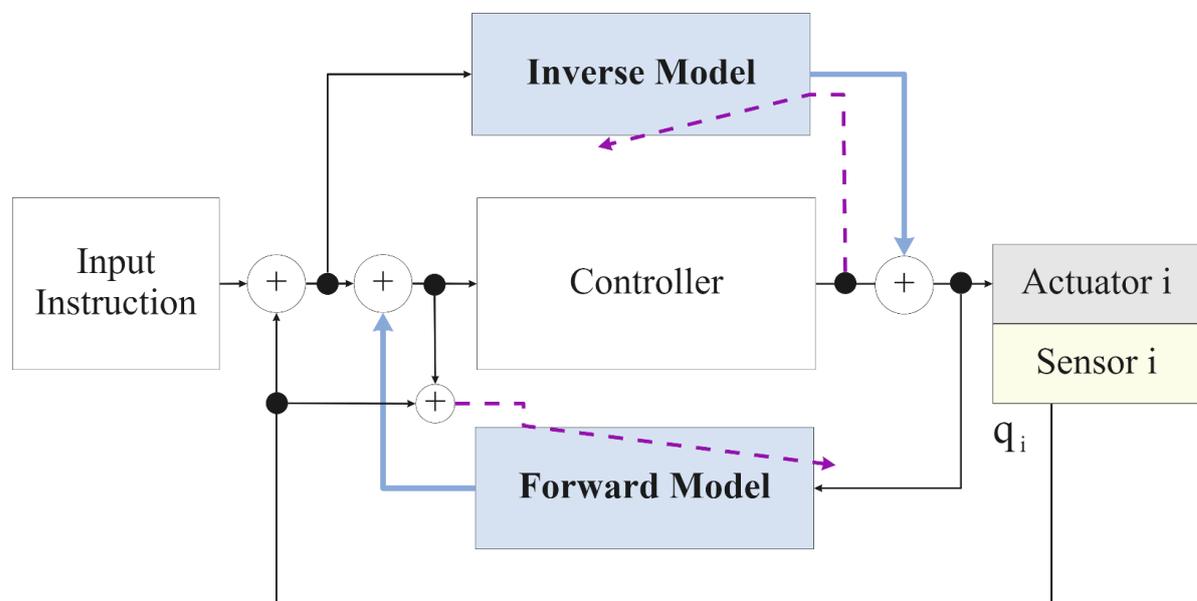


Figure I.2.14. Tandem internal models scheme proposed by Honda and colleagues in 2018. According to the behavioural experiments performed on patients affected by cerebellar degeneration disease, the internal models work in series and the forward model is updated before the inverse model. — Reproduced from [12]

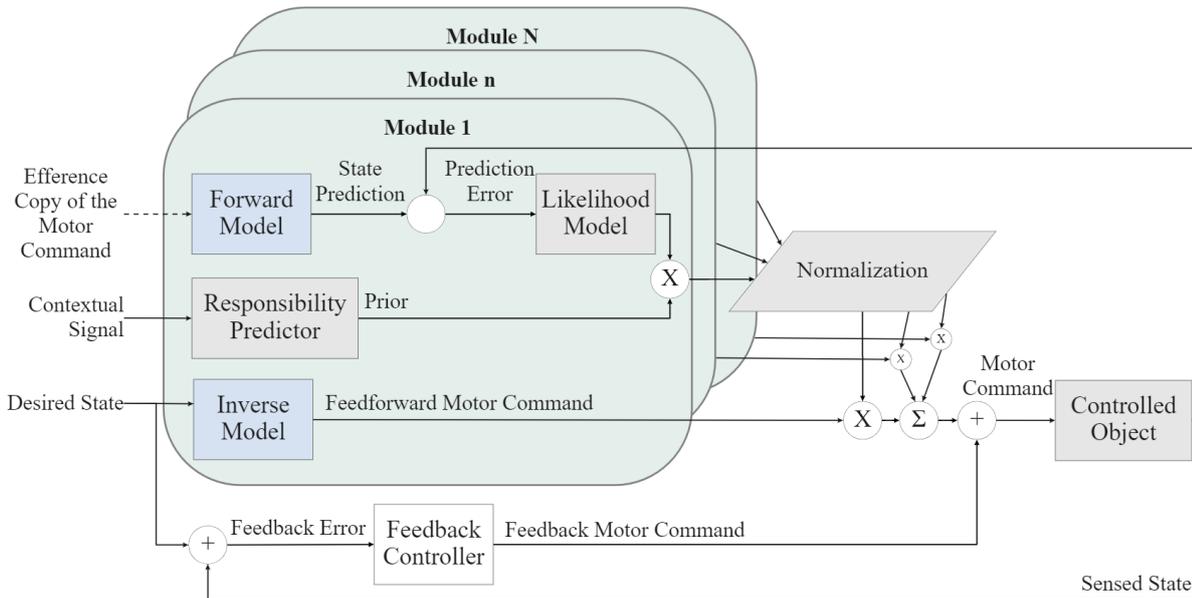


Figure I.2.15. Control scheme including multiple paired internal models proposed by Haruno, Wolpert and Kawato. The architecture is constituted of n modules, each module is specialized on a specific motor behaviour. The module is composed of three interacting parts: a forward model, a responsibility predictor, and an inverse model. Each module is assigned to a different weight depending on its responsibility in the current action, the final motor command is given by the sum of all the weighted modules contributions.— Reproduced from [13]

adaptively when required [185–187].

Based on the findings described above, Kawato and Wolpert strongly supported the hypothesis that the central nervous system (CNS) learns, maintains, and switches among multiple internal models describing the sensorimotor system and its relation with the environment [160]. They later translated this assumption into a computational model where each inverse dynamical model is tightly coupled with a corresponding predictive forward model: the Modular Selection and Identification for Control model (MOSAIC) [13, 188, 189].

The MOSAIC model has its foundation in the *mixture experts* architecture for supervised learning [182]. The *mixture experts* strategy treats the control problem as the result of a combination of multiple models specialized over local regions of the input space. In Figure I.2.15, the MOSAIC architecture combines the control command processed by n specialized modules. Each module learns the internal model of the controlled object during a specific context. The control action of each module is modulated by a "responsibility" weight that rates from 0 to 1 the level of influence of each module in the current motor behavior. Each module is constituted of three interactive parts: a paired forward and inverse dynamics models, and a responsibility predictor. The responsibility predictor processes the likelihood that each forward module is involved in the behavior of the system based on the sensory contextual cues and the prediction error, defined as the comparison of the predicted next state \hat{x} and the actual next state x . The perfor-

mance of MOSAIC is tested on a simulated arm during the manipulation of different objects. The empirical results show a model able to learn the controllers depending on their contexts. The scientists affirmed that the architecture can generalize to novel dynamics by merging the output from the learned modules. Moreover, the architecture can auto-correct online any inappropriate module selection based on inaccurate sensory feedback.

Later in 2003, the authors proposed a hierarchical architecture based on MOSAIC, the hierarchical MOSAIC (HMOSAIC), to solve the lack of hierarchical and bidirectional control of the module's activity that could facilitate the generalization of the control problem [190]. The architecture consists of several layers of MOSAIC. The layers are hierarchically connected, and the higher-level ones are employed to prioritize the selection of a lower-level module. Haruno and colleagues affirmed that this architecture could show the cerebellar involvement in higher cognitive functions and how the cerebro-cerebellar loop circuits could work. In particular, the scientists affirmed that HMOSAIC can logically describes how higher-level predictive and control models could learn abstract representations and determine the behavior of lower-level modules through a bidirectional flow of responsibility signals.

In 2017, Maheri and colleagues proposed a Modular-RDC controller to learn the control of multiple contexts and apply the most opportune cerebellar-like correction to the movement of a simple linear plant [14]. The architecture is constituted of n modules that learn and apply correction in parallel (Figure I.2.16). Each module includes inverse and forward internal models that both take as input the efferent copy of the motor command and are modulated by the performance error and the prediction error, respectively. As in MOSAIC, a *Responsibility Estimator* module continuously processes and assigns a weight to each module, i.e. a λ_i responsibility factor. The i -th responsibility factor is a function of the i -th prediction error and is employed to weight the i -th inverse model contribution to the ongoing control action. All the output of the n inverse models are combined in a weighted sum that is added to the input of a fixed linear feed-forward controller. The *Responsibility Estimator* resulted to efficiently identify and select the most appropriate controller for each learned context. The authors stated that the combination of different controllers' outputs leads to the generalization of the control problem. However, they added that although the generalization is improved with respect to the single controller case, it is not extendable outside the pre-learned range.

I.2.7 Discussion

In this chapter, we have seen how the cerebellum could be responsible for the adaptive and predictive control of movements. We are now aware that biological motor processes involve peripheral sensory feedback that runs too slowly to produce effective real-time behaviors [132, 191]. For this reason during the evolution, the CNS generated some neural mechanisms for the estimation and prediction of sensorimotor feedback to adapt and rapidly react to a wide variety of behaviors. Scientists proposed the cerebellum

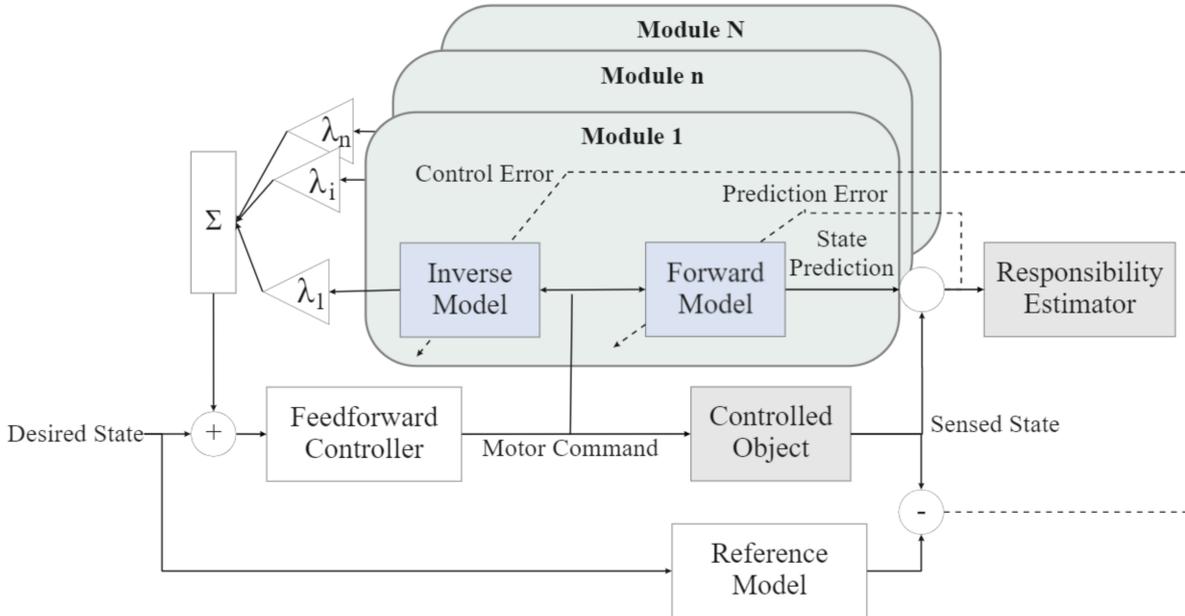


Figure I.2.16. Modular-RDC controller proposed by Maheri and colleagues in 2017. The cerebellar-like modular control architecture consists of n modules. Each module includes a forward and inverse internal models and adds weighted recurrent correction to the input of the feed-forward controller. A *Responsibility Estimator* module processes the a responsibility factor for each inverse model depending on the prediction error of the respective forward model. — Reproduced from [14]

as the location of these neural mechanisms known are internal models: inverse and forward internal models. The cerebellum learns these models by repetitions of trials. The internal models map all the motor processes and sensory dynamical information necessary to perform a motor behavior.

We explored the theories and computational models that include the use of internal models. We analyzed the multiple ways in which internal models can be used in the control scheme and their resulting functionalities. Inverse internal models result advantageous to processing predictive motor commands when the control feedback is affected by large feedback delays. To do so, the inverse internal model unconsciously transforms goals into motor commands to reach the desired state [192]. While the forward internal models can be seen as predictors of motor reactions. These types of internal models estimate the sensory consequences of an action and compensate for the sensory noise and loop delays leading to a gradually more accurate behavior [141].

The internal models are not required to be an accurate representation of the system or the external world. As suggested by Jordan and colleagues, the internal model can be seen as an initial open-loop "push" that triggers the feedback loop corrections [141]. The learning of the internal model is modulated by a performance error-like signal which enables the CNS to execute the motor action with increasing accuracy.

Direct inverse modeling is not the most efficient method to learn nonlinear system model due to the system's intrinsic redundancy [6]. Moreover, direct modeling employs

offline training that implies the change of the model inputs once the model is used by the controller. The direct learning method is not goal-directed, this factor leads to a continuous search for the solution in the control space and the consequential struggle in generalizing the control solution.

Regarding the feedback-error architecture proposed by Kawato in 1987 [7], two major concerns arise. The first one regards the difficulty of recovering a motor error signal from the sensory information which requires a good approximation of the inverse model of the plant [4]. In this regard, rapid movements resulted challenging to learn and mostly lead to weights deviation, especially when the feedback controller is poorly tuned [7]. The second concern regards the nature of the teaching signal. The type of teaching signal highly influences the performance of the learner. A wrong teaching signal leads the model weights to diverge. This problem is mainly manifested in the scheme where the teaching signal is related to a precomputed model which tends to fail when the circumstances change. Many studies suggest that the modulating signal conveyed by the climbing fiber (Cl) seems to transmit movement-related information, such as an unpredicted sensory consequence of movements that is similar to sensory error [176, 178].

The Smith predictor theory did not have much success in practical applications due to the parallel training of two distinct forward models [193]. However, Miall sustains that the employment of two different learning rates could guarantee learning stability, e.g., a slow rate for learning the feedback delay model, and a fast rate for learning the dynamic model [194].

There is no strong evidence regarding the independence or interdependence of forward and inverse internal models. However, behavioral studies suggest that these models operate in series and the forward model is most probably updated first.

The computational theories regarding the modularity of the cerebellar-like controller are still under debate. The practical application of these models on the robotic system is highly complicated due to the complexity and the large computation power needed by such computing structure. Most of the replication overly simplified the target or the controlled system itself [195].

The algorithms described in this chapter raised a strong interest within the robotics community which applied these mechanisms for the adaptive control of robotic movements. We strongly support the idea that unveiling the control mechanism of the cerebellum could help to design a robotic control scheme that can adapt and account for a wide range of motor behavior.

CHAPTER 1.3

Cerebellar Models

1.3.1 Introduction

SINCE the dawn of neuroscientific research, the cerebellar microcircuit has been a source of inspiration for theoretical and computational modeling. The true beauty of the cerebellum relies on its ability to encode different inputs to specific downstream targets by always maintaining the same regular anatomical organization and internal rules for the processing of the information. The scientific community agreed that understanding the cerebellar internal circuitry, the modularity that combines the action of the cerebellar canonical circuits, and what the cerebellum computes may greatly facilitate our knowledge of the cerebellar involvement in a large spectrum of cognitive and motor functions. Once these key principles are revealed, we may apply them to different fields, such as robotics.

In 1967, Eccles intuitively saw the cerebellum as a neural "timing" machine [196]. This brilliant intuition was immediately translated into theoretical models by Albus and Marr [95, 96], who asserted the pivotal role of the cerebellum in Motor Learning. Their proposal settled the reference point of modern computational and theoretical neuroscience.

In 1992, Tyrrell and Willshaw were the only ones that strictly adhered to Marr's model and built up a cerebellar cortex simulations model constituted of about 213.000 neural components [197]. The scientists declared that "although some of Marr's assumptions contravene neuroanatomical findings" and the system has low capacity and acts in a stochastic manner, the assumptions about the ability of the Purkinje cell (PC) in learning different patterns of activity in the mossy fibers can be confirmed.

Since Marr's and Albus' models, the advancement of neural recording and imaging technologies greatly supported a clearer analysis of the cerebellar neural structures. Neurophysiological and neuromorphological studies have been essential for optimizing the design of cerebellar simulations by incorporating more realistic details [198–203]. In this regard, the scientific community defined and supported two opposite modeling and simulation strategies: top-down and bottom-up approaches. In this chapter, we explore the differences between these two methods, and what the scientific community proposed over the decades. In Section 1.3.2, we analyze the models designed in accordance with the top-down approach that result most relevant for the topic of our dissertation. While in Section 1.3.3, we present the cerebellar-like models that are closer to the bottom-up

approach design and that have been mostly tested on robotic platforms. The chapter concludes with some final remarks in Section I.3.4.

I.3.2 Top-Down Cerebellar-like Simulations Models

The top-down modeling approach prioritizes behaviour and timing over biological constraints. The biological details of the cerebellar circuit are kept at a high level of abstraction and mostly rely on simplified mathematical models. The main research objective of this approach is to devise hypothetical mechanisms and to identify key features of the cerebellar learning paradigm [20]. While the main performance requirement is to process data in real-time to capture the predictive capabilities of the cerebellum. In this regard, Moore and Choi clearly stated the three main steps for the development of a real-time cerebellar-like computational model [204],

1. devise real-time computational models that describe as much of the known behavioral and physiological evidence as possible;
2. devise an implementation scheme that aligns features of the model with the neural circuits involved;
3. test implications of the model and its implementation in experiments.

This method have been successfully employed for practical application of the cerebellar circuit, especially in control of both industrial and bio-inspired robotic systems.

In 1975, J.S. Albus proposed a novel approach for the control of industrial manipulators: the Cerebellar Model Articulation Controller (CMAC) [15]. The CMAC has been the first model to simulate the adaptive control action and learning of the cerebellum from a high-level functional perspective. Albus claimed that classical trigonometric methods are not sufficient for modeling complex motor performance, and he believed that,

”if the fundamental principles of computation used by biological organisms were understood, it seems quite likely that an entirely new generation of manipulation control systems would be developed which would exhibit sensitivity and dexterity far beyond what is possible with present mathematical techniques” [15].

Moreover, in accordance with the top-down approach, he highlighted that bio-inspired control systems do not necessarily need to strictly model the structural characteristics of the neural substrate because it could lead to no meaningful results for robotic applications. Albus’ studies converged to the conclusion that the cerebellar circuit is analogous to a Perceptron, a single layer neural network originally designed to mimic the brain.

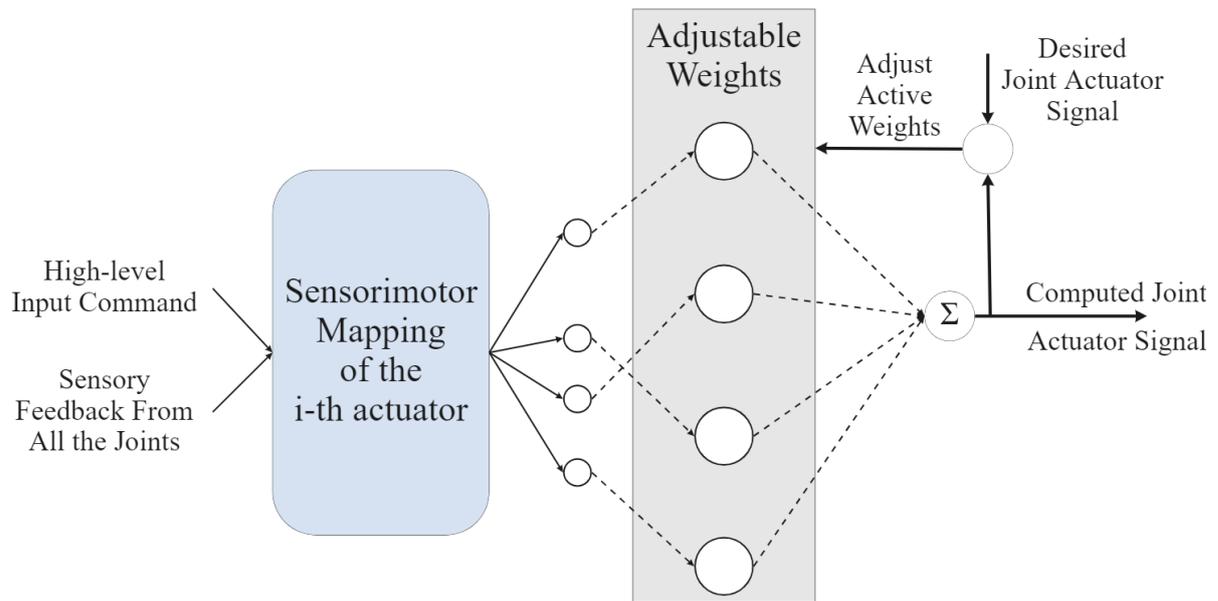


Figure I.3.1. Cerebellar Model Articulation Controller (CMAC) designed by Albus in 1975. The schematic is for the control of one single joint.— Reproduced from [15]

The cerebellar Perceptron he proposed is designed to perform static association between one set of \mathbf{S} mossy fibers input pattern and one \mathbf{A}^* output pattern on the Purkinje cell (PC) (Figure I.3.1). For many years, the CMAC model has been adopted by the scientific community as a practical alternative for learning general state space-dependent control responses [4, 135, 172, 205–208].

In the early Eighties, Miller and colleagues embraced Albus' theory and proposed a multi-layered CMAC neural network for real-time control of an industrial robot (Figure I.3.2) [6]. Miller claimed that the CMAC network can learn a large variety of nonlinear functions, hence it represents a valid alternative to back-propagation and a solution to all the possible issues that this method implies, such as laborious and time-demanding convergence, slow computation, unsuccessful incremental learning. Moreover, he claimed that although the CMAC network does not globally generalize, it shows a great advantage in high-speed hardware applications. Miller's CMAC network had great success for industrial application, where it has been mostly used to mitigate the effects of approximations errors and boost the tracking accuracy of robotic adaptive controllers [209–212].

In 1991, Chapeau-Blondeau and Chauvet proposed a neural network to reconstruct the cerebellar cortex (Figure I.3.3) [16]. Concerning the previous studies, they implemented a Golgi cell (GO)-granular cell (Gr) system to store temporal sequences of patterns, and a Perceptron layer representing the Purkinje cell (PC) layer to binary associate the temporal patterns. The model includes the excitatory or inhibitory nature of the synapses, one synaptic plasticity at the PF-PC synapses, and learning based on Hebbian rules. The Perceptron layer differs from the one proposed by Albus in the dynamic association between the input pattern and the sequence of output patterns on the Purkinje cell (PC) level.

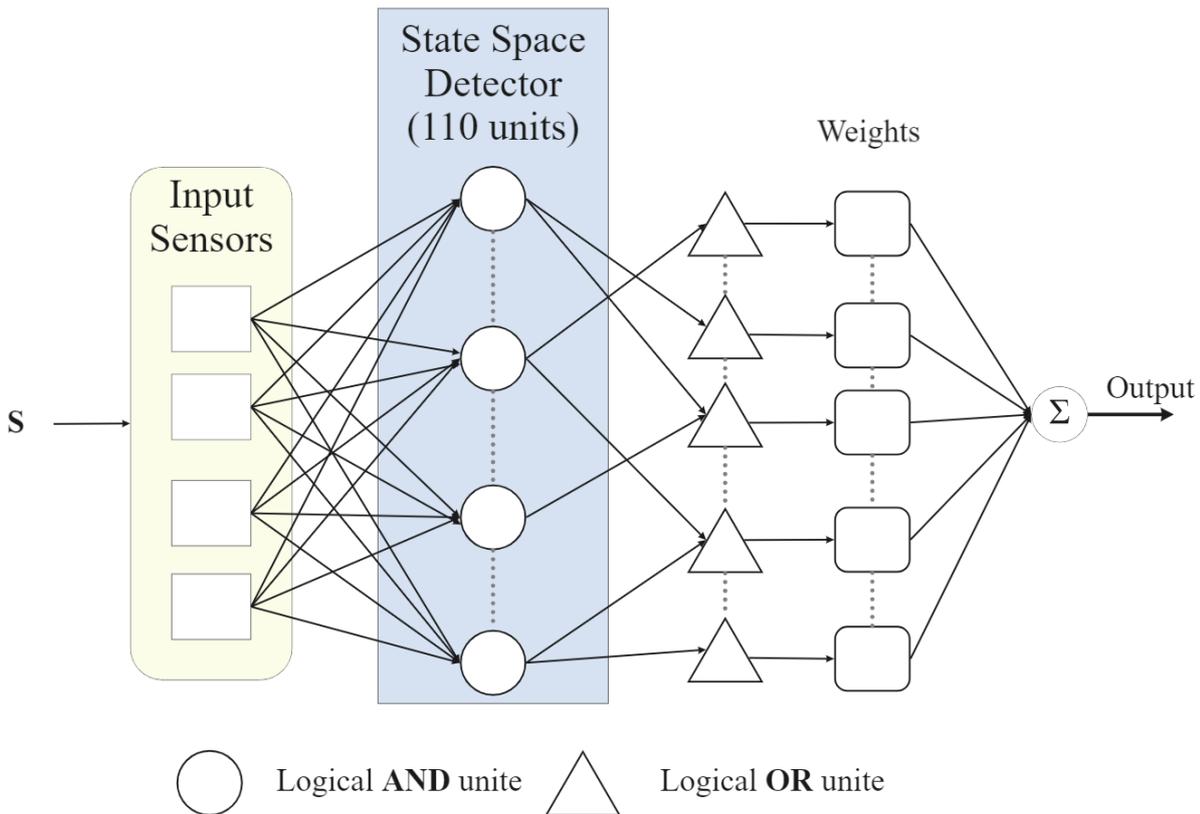


Figure I.3.2. Cerebellar Model Articulation Controller network (CMAC) proposed by Miller and colleagues in 1990. The neural network take two inputs and elaborates one output, can be interpreted as a simplified representation of the granular layer in the cerebellar cortex.— Reproduced from [6]

In 1994, Buonomano and Mauk presented a neural network model based on the synaptic organization of the cerebellum capable of generating a timed response in the order of milliseconds [17]. The model aims to qualitatively capture the basic properties of the cerebellar cortex organization (Figure I.3.4) and to demonstrate how this organization influences behavioral properties, such as timing. As proposed by Chapeau-Blondeau and Chauvet, the experiments demonstrated that the simulated granular cells activity exhibits dynamic, nonperiodic trajectories in response to periodic input and that the change in dynamic is subsequently expressed by changes in Purkinje cell (PC) activity. Buonomano affirmed that the major weakness of the model is its high sensitivity to noise. Noise signals are altered by the granular cells activity and propagate to all the networks leading to important time delays. The experiment was later tested in a large-scale simulations system leading to incredible results regarding the plasticity at the Gr-PC level (see the model proposed by Medina in Section I.3.3 [200]).

After many years studying the involvement of the cerebellum in the eyelid conditioned response, Barto and colleagues proposed a simplified model of the cerebellum for exploring the cerebellar adaptive and predictive control of one degree of freedom limb model (Figure I.3.5) [18]. The model is a reduced version of the adjustable pattern

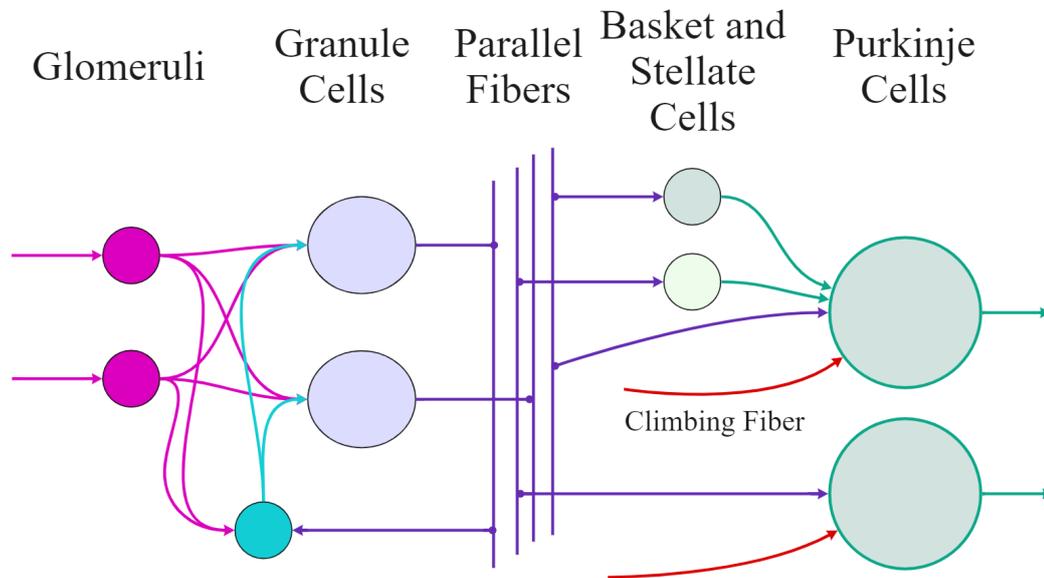


Figure I.3.3. Cerebellar cortex neural network design by Chapeau-Blondeau and Chauvet in 1991.— Reproduced from [16]

generator (APG) model developed by Berthier in 1993 [213]. The design aims to reproduce the modular anatomy of the cerebellar cortex and the downstream connection to the premotor network of the limbs. In the proposed experiment, the cerebellar model consists of only one APG module with a single Purkinje cell (PC), which is modeled as a set of nonlinear switching elements to explore the learning and control problem in a computationally feasible manner. The simplification of the APG module highly affected the processing of the motor command that instead of being the combination of multiple

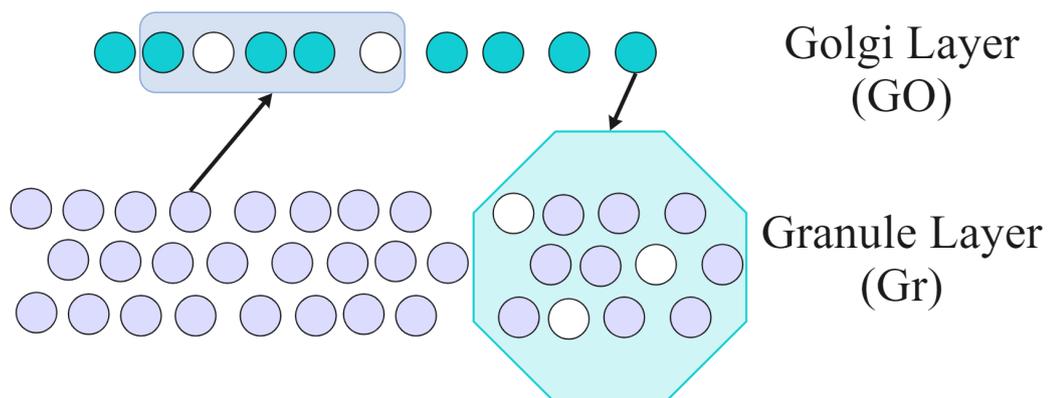


Figure I.3.4. Schematic representation of the cerebellar neural network proposed by Buonomano and Mauk in 1994. The model consists of 10^4 granular cells (in purple), 900 Golgi cells (in cyan), 500 mossy fibers, and one Purkinje cell (PC). The mossy fibers and Purkinje cell (PC) are not illustrated for simplification. The shaded area and the arrow represent the regions to which the cells can synaptically be connected. The white cells are the ones receiving input from the presynaptic cell.— Reproduced from [17]

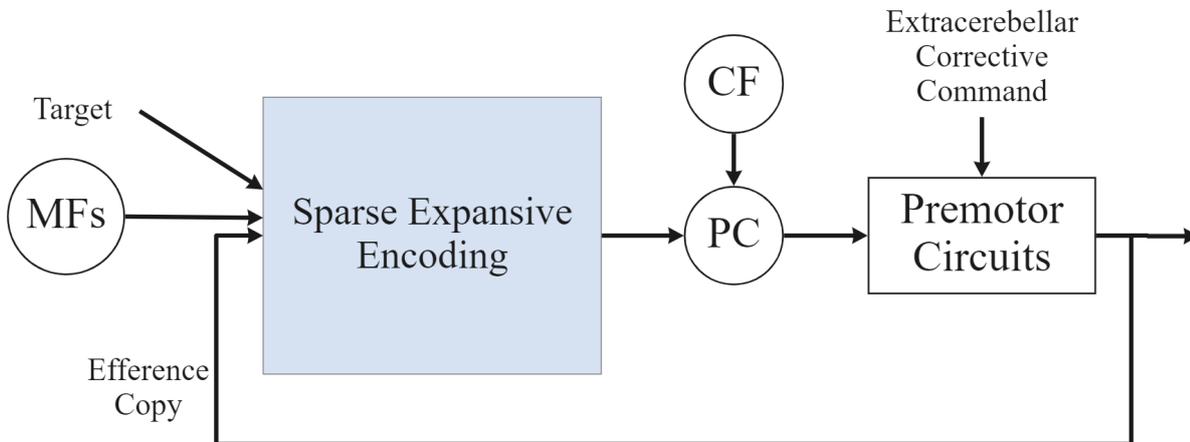


Figure I.3.5. Cerebellar model architecture proposed by Barto and colleagues in 1999. The granular cells are represented by the *sparse expansive encoding* block, and receive information from the **MFs** mossy fibers, and the target block. The granular cells send the processed signal to the **PC** Purkinje cell (PC), through the **PFs** parallel fibers. The signal in the **PC** is modulated by the **CF** climbing fibers.— Reproduced from [18]

Purkinje cells activity is the result of the decreasing activity of one cell (as seen in Chapter I.1 the PC exerts an inhibitory action on the DCN). In this regard, the model could be extended to more complex problems only through the full modular implementation of the APG model.

In 2012, Tolu and colleagues proposed a cerebellar cortex model that stood out from years of CMAC-like networks [8]. In the model design (Figure I.3.6), the granular and molecular layers is modeled with the machine learning algorithm Locally Weighted Projection Regression (LWPR) [214], while a simplified adaptive linear filter is exploited for the short term adaptation similarly to a PC-IO action (Figure I.3.6). The LWPR is a nonlinear function approximator largely used for online incremental learning of robotic systems thanks to its low computational cost [169, 215, 216]. Moreover, the LWPR can handle high dimension and redundant input data by means of an incremental version of the partial least squares regression (PLS). The application of this algorithm facilitated the testing on robots without off-line training and under different dynamics and kinematics conditions [5, 8, 217, 218].

In 2017, the cerebellar model was extended with a spiking neural network including both Purkinje cells and deep cerebellar nuclei (DCN) [19]. The cerebellar neurons are simplified to Leaky integrate-and-fire neuron model, and to speed up the computation the spiking neural network is run on the neuromorphic hardware *SpiNNaker* (Spiking Neural Network Architecture) [219]. The research group claimed that both the input representation and the learning speed of the model are optimized with this method.

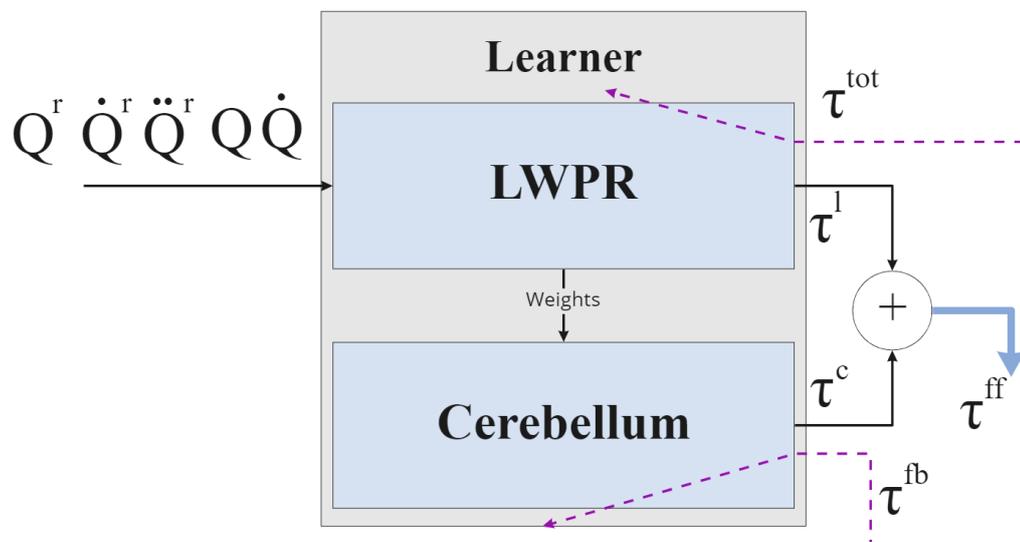


Figure I.3.6. Unit Learning Machine (ULM) proposed by Tolu and colleagues in 2012. The model consists of a **LWPR** non linear function approximator and a **C** cerebellar unit for the short term adaptation.— Reproduced from [8]

I.3.3 Bottom-Up Cerebellar-like Simulations Models

The bottom-up cerebellar modeling approach prioritizes matching the biological constraints and simulating accurately the cerebellar anatomy and physiology. These models

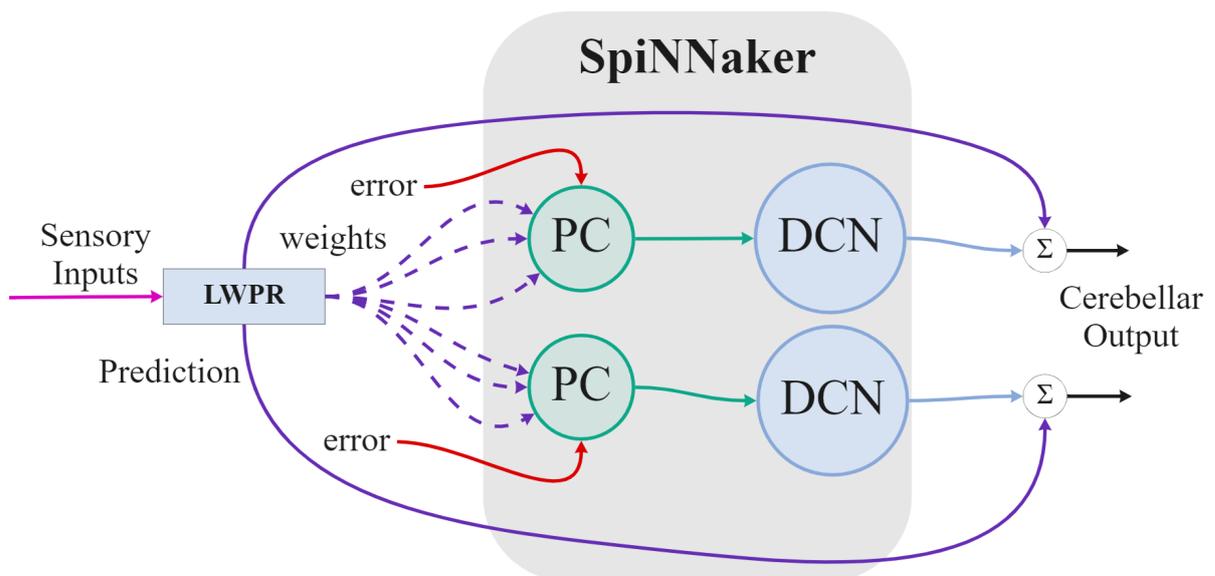


Figure I.3.7. Schematic of the hybrid cerebellar model proposed by Ojeda and colleagues in 2017. The model combines the cerebellar unit proposed by [8] to a spiking neural network running on the neuromorphic hardware *SpiNNaker* (in green).— Reproduced from [19]

are not based on assumptions about the functionality of certain cerebellar components but try to strictly adhere to the cerebellar wiring principles based on proved convergence/divergence ratios, numerical cell ratios, and connection geometry [20]. Moreover, bottom-up cerebellar models include important information about different synaptic strengths and postsynaptic responses. D'Angelo and colleagues clearly defined the main guidelines for the design and development of these "realistic" cerebellar models [36],

1. reconstruct the system through a reverse engineering process that integrates known biological features;
2. validate the model with a complex dataset that was not used to construct it;
3. analyze the performance as a real system.

The level of complexity of these models can both lead to high omission errors, as well as large and computationally intensive simulations. Hereafter, we describe some of the bottom-up models that conceptually influenced our research flow and final proposal. Most of these models have been tested on the robotic platform with great success, even though the level of simplification of both the cerebellar circuit and the robotic model is high.

In 2000, Medina and colleagues proposed large-scale computer simulations of the cerebellar eyelid conditioned response to explore how the cerebellum generates and employs temporal information (Figure I.3.8) [200]. The architecture is based on three fundamentals properties: the neurons are represented as single-compartment, leaky integrate-and-fire elements; the neurons are interconnected in ways consistent with the known numeric ratios of cells, the geometry of the projections, and the divergence/convergence ratios of connections between cell types [94, 196]; two classes of synapses are modifiable according to specific, activity-dependent plasticity rules. The experimental results show that the learning mechanism in the cerebellar cortex is mediated by differential modification of synapses that depends on their activation status before or after the conditioned stimulus action. From an empirical perspective, their simulation proved that such complex simulations of the cerebellum can adaptively learn timed responses. Moreover, Medina claims in [20] that they had to implement a more complete representation of the cerebellar synaptic conductance and condition for plasticity to generate temporally specific learning.

In 2002, Hofstötter and colleagues presented a computational model of the cerebellar microcircuit to investigate whether the plasticity mechanisms in the cerebellar cortex alone can mediate the timing of the cerebellar conditioned response (Figure I.3.9) [21]. The model includes a reduced description of the anatomical and physiological constraints of the cerebellar microcircuit to allow real-time simulations on real-world robotic platforms. The neural model assumes that: the deep cerebellar nuclei, inferior olivary nucleus, and cerebellar cortex are organized in distinct microcomplexes [220] and constitute a negative feedback loop [113]; the plasticity in the cerebellar cortex is modulated by the aforementioned negative feedback loops [221]; the learning at the PF-PC level depends on the unconditioned stimulus from the climbing fiber (Cl), and on the parallel

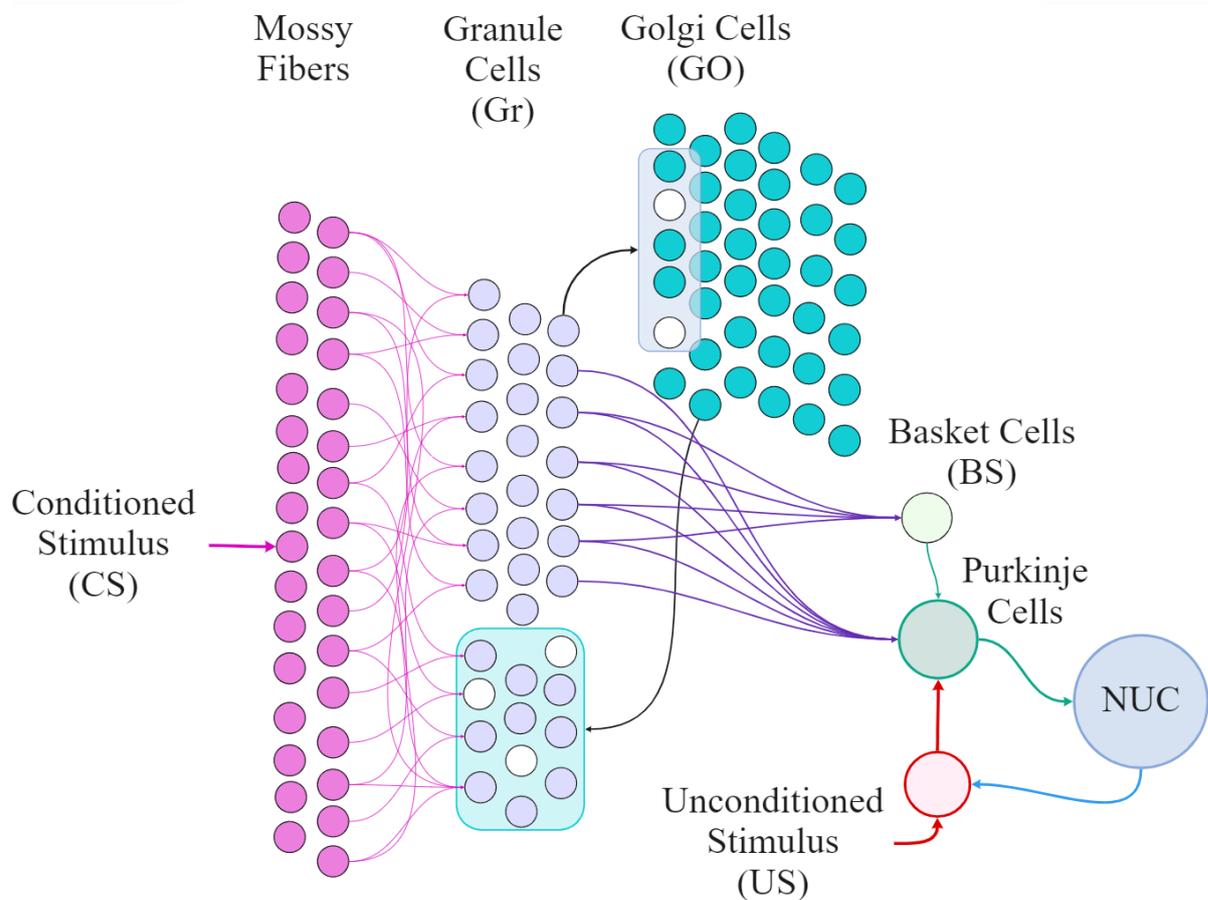


Figure I.3.8. Large-scale computer simulations of the cerebellar model proposed by Medina in 2000. The purple layer represents the 10000 granular cells, which are connected to 900 Golgi cells (in cyan), 600 mossy fibers (in magenta), 20 Purkinje cells (in green only one is shown for simplification), and 6 deep cerebellar nuclei (NUC in blue). The network includes 300000 synapses without specific learning rules, the main focus is on the neural connectivity.— Reproduced from [20]

fiber activation due to the conditioned stimulus [222, 223]; the learning of the conditioned stimulus leads to a pause of the Purkinje cell activity [20, 224]; the conditioned response is triggered by the deep cerebellar nuclei once the Purkinje cell inhibition is released [225, 226]; the Purkinje cell acts in spontaneous and conditioned modes. The neurons are modeled as integrate-and-fire neurons. The learning performances of the model are tested and analysed on a mobile robot during the execution of an obstacle avoidance task, i.e. during the interaction of the learning system with the environment. The empirical results suggest that the model can exploit the associative properties of the cerebellum leading the robot to a successful collision-free driving experience. Hofstötter claimed that in absence of the plasticity within the cerebellar nucleus, the IO-PC-DCN negative feedback loop within distinct cerebellar microcomplexes is crucial for the stabilization of the timing of the conditioned response. Moreover, there is a trade-off between

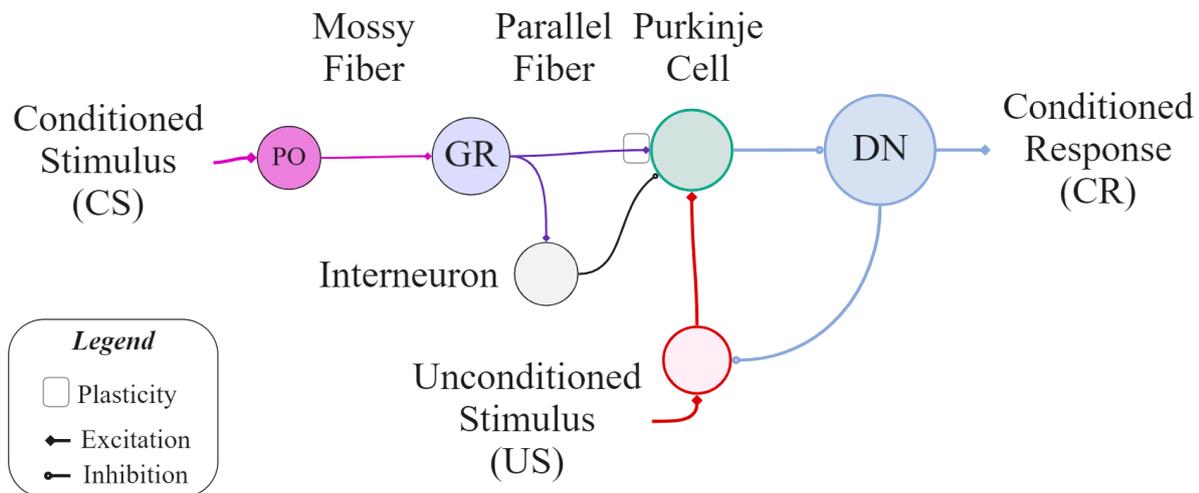


Figure I.3.9. Anatomy of the Cerebellar-like computational model proposed by Hofstötter and colleagues in 2002. The model presents two input pathways, the **CS** conditioned stimulus is transmitted through the **PO** pontine nucleus to the **GR** granular cell, the **US** unconditioned stimulus is conveyed to the **IO** inferior olivary nucleus. The **DN** deep cerebellar nuclei fires the **CR** conditioned response down to the motor system.— Reproduced from [21]

the adaptability of the circuit and the stability of its performance due to the continuous interaction of long-term potentiation (LTP) and long-term depression (LTD) during the learning.

In 2013, Yamazaki and Igarashi proposed a real-time implementation [22] of the large-scale spiking cerebellar network model they built to study the cerebellar mechanisms for simultaneous gain and timing control [227–229]. The spiking cerebellar network is constituted of more than 100000 leaky integrate-and-fire spiking neurons with realistic parameters (Figure I.3.10). Each neural connection has a constant synaptic weight empirically found in [229]. Only the synaptic plasticity within parallel fiber and Purkinje cell changes during the computer simulation following the LTP/LTD rules developed in [228, 229]. The network assumes that the inhibitory recurrent connections within Grs and Golgi cells (GOs) generate temporally-fluctuating spike patterns in response to the MFs activation [230]. The “Realtime Cerebellum (RC)” is implemented on a graphics processing unit (GPU), and it is tested on a humanoid robot to learn the proper timing for hitting a flying ball with a bat. The authors affirmed that the implementation of the cerebellar network on GPU lead to a 2-100-times speed up. Moreover, they argued that real-time simulation enables them to conduct experiments for a very long period and to investigate more on both short-term and long-term learning paradigms.

In 2016, Luque and colleagues proposed a new mechanistic cerebellar spiking model (Figure I.3.11) [23]. The spiking neural network model derives from a detailed cerebellar network proposed by Solinas and colleagues in 2010 [201], that have been later adjusted to run in real-time on robotic platforms [231–233]. Due to the incomplete knowledge, the model design assumes that: the granular cell (Gr) layer functions as a state generator following the liquid-state-machine principles [227, 234], and the plas-

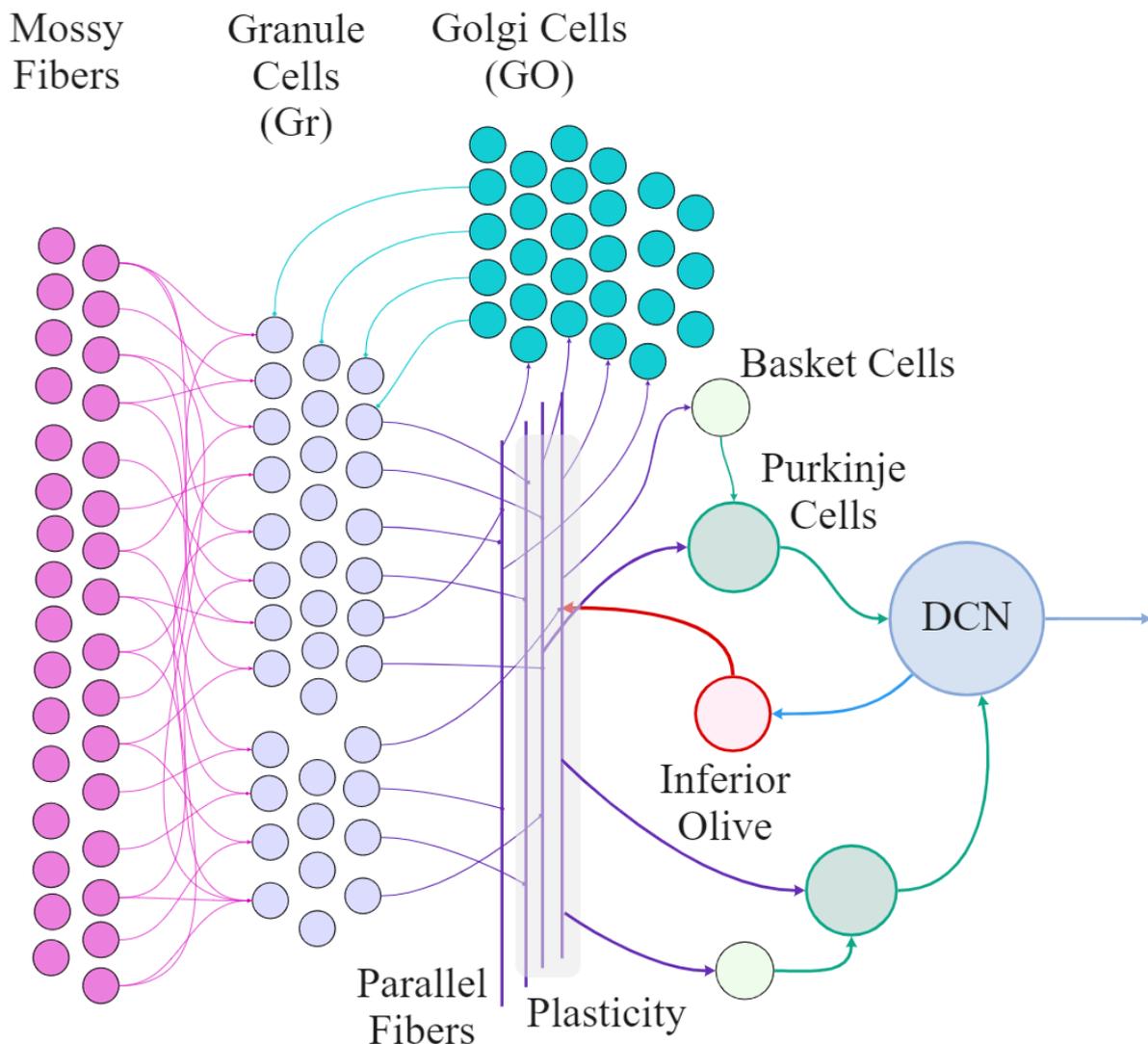


Figure I.3.10. Network structure of the "Realtime Cerebellum (RC)" proposed by Yamazaki and Igarashi in 2013. The RC includes 102400 granular cell, 1024 Golgi cell, 16 Purkinje cell, 16 basket cells, 1 inferior olivary nucleus, and 1 deep cerebellar nuclei. All the 16 PC inhibit the single DCN. One plasticity with long-term depression (LTD) and long-term potentiation (LTP) is designed at the Gr-PC innervation.— Reproduced from [22]

tivity mechanism is the one reconstructed by Solinas in 2010 [235]; the mossy fibers input layer maintains simultaneously constant firing rate and time-evolving states; the cerebellar feedback is needed to minimize the control error; the teaching signal comes only through the climbing fibers, even though there is no scientific agreement regarding the type of information conveyed by the climbing fiber (CI) [236, 237]. The cerebellar-like model includes the most complex set of *spike-timing-dependent plasticity* (STDP) mechanisms in three learning sites, such as PF-PC, MF-DCN, PC-DCN [20, 238, 239]. The spike-timing-dependent plasticity (STDP) of the deep cerebellar nuclei (DCN) is assumed to be supervised and responsible for storing Gr layer patterns that are adapted

by the teaching signal generated by the Purkinje cell (PC) [240–242]. The following sub-form of plasticity are missing: MF-Gr; GO-Gr; MF-GO. In the experiment, the cerebellar-like spiking neural network is embedded in a closed-loop control system. The study focus on the impact of the distributed cerebellar spike-timing-dependent plasticity (STDP) on learning and adaptation during the execution of robotic manipulation tasks. The empirical findings show that the cerebellar-like model can capture the self-adaptive-gain control recalibration over a broad dynamic range. Moreover, the tests suggest that the MF-DCN connection could store what is already learned at the PF-PC level, and the

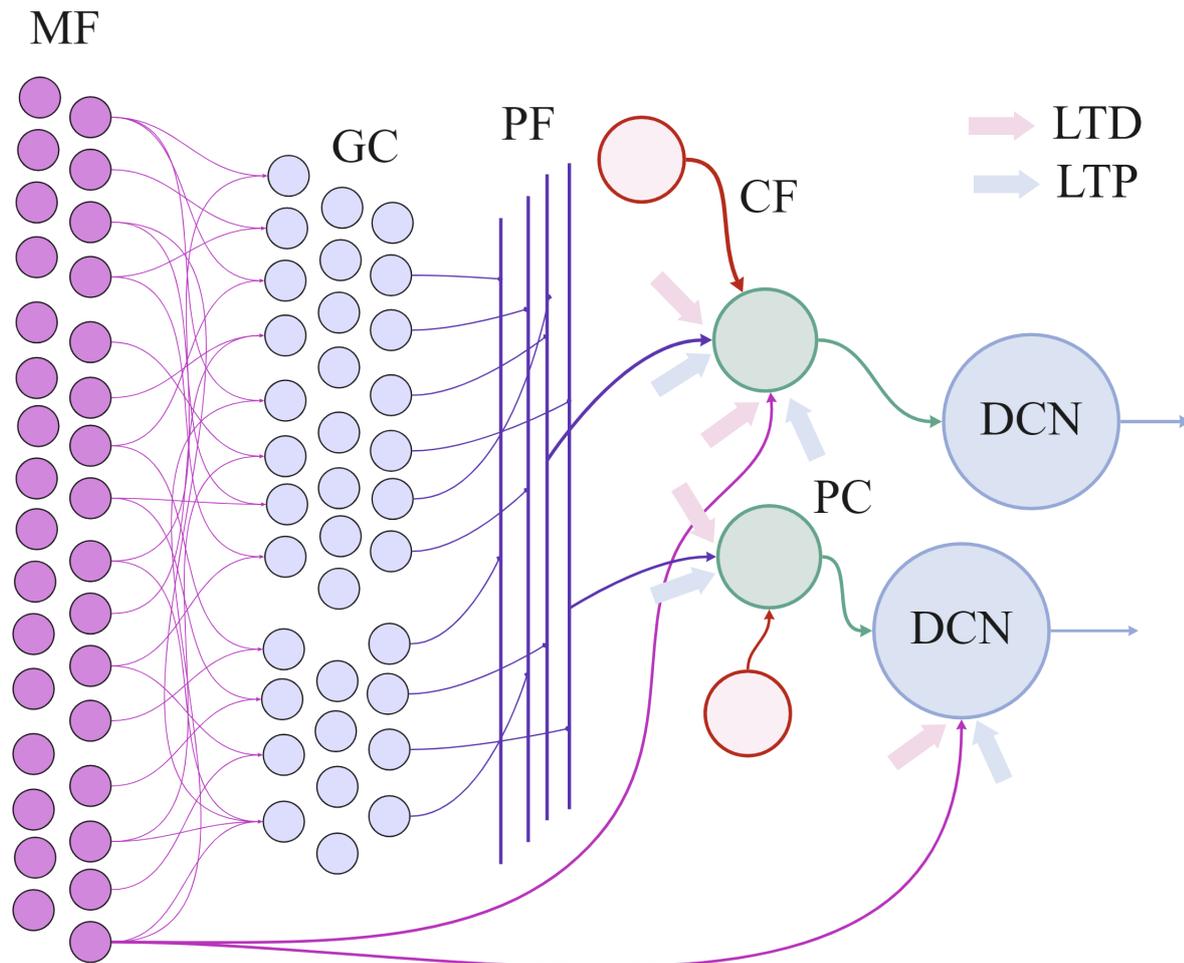


Figure I.3.11. Cerebellar spiking neural model proposed by Luque in 2016. The network receives the input source through 100 **MF**, modeled as leaky integrate-and-fire neurons. The granular layer consists of 2000 **GC** granular cells implemented as state generator. Each **PC** Purkinje cell receives activity from 2000 **PF** parallel fibers. The number of Purkinje cells, climbing fibers, and deep cerebellar nuclei (DCN) depends on the case of study: in case of study **A** 20, 2, and 2 respectively; in case of study **B** 60, 6, and 6 respectively. In the scheme, different colors indicate signals from different input sources. The long-term potentiation (LTP) is marked with a blue arrow, while the long-term depression (LTD) with a magenta one. — Reproduced from [23]

PC-DCN plasticity plays an important role in adapting the firing rate of the cerebellar output.

In late 2016, Richter and colleagues adjusted the simplified cerebellar-like model proposed by Luque in 2011 [243] to run it on the neuromorphic hardware spiNNaker [219] and to control the movement of *Myrobotics*, a musculoskeletal robotics hardware [24]. The cerebellar-like network controls two artificial muscles that move one single joint of the bio-inspired robotic arm. The neurons are designed as leaky integrate-and-fire neurons with realistic cell parameters and divergence/convergence ratios. The network consists of 32 mossy fibers, 256 granular cells, 8 Purkinje cells, and 8 inferior olivary nucleus (IO) (Figure I.3.12). Only one plasticity mechanism is implemented at the Gr-PC synapses, the learning rule is illustrated in the bottom right of Figure I.3.12. The inferior olivary nucleus (IO)s convey the teaching signal with the ϵ joint angle error. The network learns to perform antagonistic robotic muscles control in a few revolutions, and after 5 minutes of training the robot can better track the ϕ_{set} motors reference trajectories. After learning, the robot can adapt to changes in trajectory. Richter stated that the experimental setup has some limitations due to the communication within spiNNaker and the robot and to the low update rate of input and output populations. He assumed that the problem can be alleviated by using a different connector system.

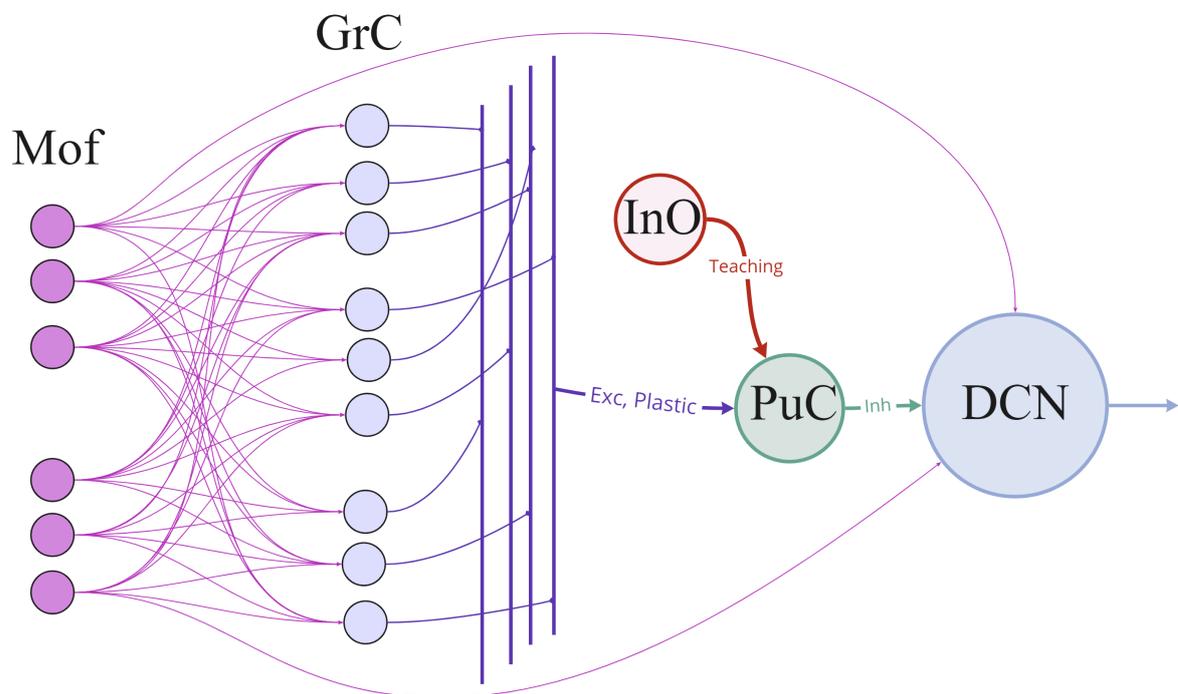


Figure I.3.12. Cerebellar spiking neural network model employed by Richter and colleagues in 2016 to control a musculoskeletal robot. The graph in the bottom right describes how the synaptic weight at Gr-PC level changes in response to the Gr and IO activities. In the neural network from left to right: **Mof** mossy fiber, **GrC** granular cell, **InO** inferior olivary nucleus, **PuC** Purkinje cell, **DCN** deep cerebellar nuclei. — Reproduced from [24]

1.3.4 Discussion

In this chapter, we explored the vast literature regarding cerebellar computational models. We focused on these simulation models that better perform in robotic testing or that explicitly confirm theoretical assumptions related to the cerebellar circuit functionality. We also find out that there exist two main contrasting methods that have been employed by the scientific community to analyze the cerebellum: top-down and bottom-up modeling approaches. These methodologies mainly differ in the level of realism they impose on the design of the model. The selection of the modeling strategy strictly depends on the final purpose of the investigation: the top-down approach results more beneficial when the main interest of the investigation is to exploit the functionality of the core cerebellar circuit; while the bottom-up approach is a perfect tool for validating hypothesis that is complex to test in-vivo experiments, and for predicting biological phenomena.

As claimed by Dean in 2010, most of the top-down cerebellar models require an in-depth revision because they neglect many cerebellar processing by focusing only on the Purkinje cell (PC), inferior olivary nucleus (IO), and parallel fiber (PF) activities. The CMAC network per se has been mostly employed as a non-linear function approximator for improving the adaptability of robotic controllers and minimizing the effects of approximation errors [209–212]. However, the level of simplification of this neural network is high concerning the whole potentiality that a cerebellar-like network could bring to the control action.

The second concern regarding the top-down modeling approaches is related to the lack of modular compartments. Modularity is one of the most important features of the cerebellum, the climbing fiber (CI) system divides the cerebellar cortex into modular micro-zones, and all these connections are plasticity-dependent making each micro-zone independent and dependent at the same time. Understanding this modularity could reveal how the cerebellum generalizes over a range of possible inputs and stores internal models.

Early bottom-up models used to fail in reproducing important behavioral properties of the cerebellum due to the lack of responsiveness, and most of the time they had to increase the level of details to get meaningful results [20]. Nowadays, the exponential improvement of computing technologies is easing the development of large-scale realistic simulation models. However, this improvement is sufficient only for the validation process of the neural network, while the analysis of the adaptation capability of the network is only possible through periodic testing over a protracted period. In this regard, the testing of these complex systems is efficient only when the model is integrated into a whole sensory-motor control system that can interact with the environment. This scenario leads to a large computational load and consequently to not affordable simulation times [36]. Many research groups are then trying to solve this problem by simplifying the model in a manner that the most important biological constraints are met [10, 23, 30, 37, 232, 237, 244]. Running large-scale realistic cerebellar models on neuromorphic hardware systems is seen as the perfect solution for resolving many of the computation and time issues. For this reason, several scientists are working on the op-

timization of these new supercomputers. D'Angelo and colleagues envisage foreseeing that complete realistic modeling of the cerebellum requires extensive cooperation within all the experts in the field [36].

Original Contribution

Main Research line

The main contribution of our research is presented in three main publications. These studies describe the design and development of the cerebellar-like simulations model and adaptive control schemes for robotics applications. The published results are enclosed in the *Appendix* of this manuscript. Paper A is a peer-reviewed abstract published in a *Frontiers Abstract Book* and presented at the *School of Brain Cells & Circuits “Camillo Golgi”*. The abstract describes the overall vision of our study and the main scientific questions we are investigating. Paper B and Paper C are open-access journal articles published in *Frontiers in Neurorobotics* and *IEEE Robotics and Automation Letters*, respectively. The studies describe the evolution of the proposed bio-inspired learning and control architecture and the empirical tests carried out on a humanoid robotic platform.

Paper A - Distributed and Modular Bio-Inspired Architecture for Adaptive Motor Learning and Control.

Capolei, Marie Claire; Falotico, Egidio; Lund, Henrik Hautop; Tolu, Silvia. School of Brain Cells & Circuits “Camillo Golgi”: The Neural Bases of Action: from cellular microcircuits to large-scale networks and modelling. Frontiers Media SA, 2018. pp. 92-97. DOI: 10.3389/978-2-88963-087-5

Resume. Autonomous robots struggle in adapting to unexpected conditions due to the lack of generalization of their control systems. We believe that designing robotic control algorithms inspired by the vertebrates’ central nervous system could endow robots with the necessary adaptive behaviors. The central nervous system is constituted of several neural structures that work independently and interdependently. We propose a robotic control architecture that mimics these neural connections from a high-level point of view. The study aims to empirically test how these neural areas cooperate in mapping and producing context-sensitive motor skills from a robotic control perspective.

Paper B - A Biomimetic Control Method Increases the Adaptability of a Humanoid Robot Acting in a Dynamic Environment.

Capolei, Marie Claire; Angelidis, Emmanouil; Falotico, Egidio; Lund, Henrik Hautop; Tolu, Silvia. In: *Frontiers in Neurorobotics*. 2019 ; Vol. 13. DOI: 10.3389/

fnbot.2019.00070

Abstract. One of the big challenges in robotics is to endow agents with autonomous and adaptive capabilities. With this purpose, we embedded a cerebellum-based control system into a humanoid robot that becomes capable of handling dynamical external and internal complexity. The cerebellum is the area of the brain that coordinates and predicts the body movements throughout the body-environment interactions. Different biologically plausible cerebellar models are available in literature and have been employed for motor learning and control of simplified objects. We built the canonical cerebellar microcircuit by combining machine learning and computational neuroscience techniques. The control system is composed of the adaptive cerebellar module and a classic control method; their combination allows a fast adaptive learning and robust control of the robotic movements when external disturbances appear. The control structure is built offline, but the dynamic parameters are learned during an online-phase training. The aforementioned adaptive control system has been tested in the Neuro-robotics Platform with the virtual humanoid robot iCub. In the experiment, the robot iCub has to balance with the hand a table with a ball running on it. In contrast with previous attempts of solving this task, the proposed neural controller resulted able to quickly adapt when the internal and external conditions change. Our bio-inspired and flexible control architecture can be applied to different robotic configurations without an excessive tuning of the parameters or customization. The cerebellum-based control system is indeed able to deal with changing dynamics and interactions with the environment. Important insights regarding the relationship between the bio-inspired control system functioning and the complexity of the task to be performed are obtained.

Paper C - A Cerebellar Internal Models Control Architecture for Online Sensorimotor Adaptation of a Humanoid Robot Acting in a Dynamic Environment.

Capolei, Marie Claire; Andersen, Nils Axel; Lund, Henrik Hautop; Falotico, Egidio; Tolu, Silvia. In: IEEE Robotics and Automation Letters. 2020 ; Vol. 5, No. 1. pp. 80-87. DOI: 10.1109/LRA.2019.2943818

Abstract. Humanoid robots are often supposed to operate in non-deterministic human environments, and as a consequence, the robust and gentle rejection of the external perturbations is extremely crucial. In this scenario, stable and accurate behavior is mostly solved through adaptive control mechanisms that learn an internal model to predict the consequences of the outgoing control signals. Evidences show that brain-based biological systems resolve this control issue by updating an appropriate internal model that is then used to direct the muscles activities. Inspired by the biological cerebellar internal models theory, that couples forward and inverse internal models into the biological motor control scheme, we propose a novel methodology to artificially replicate these learning and adaptive principles into a robotic feedback controller. The proposed cerebellar-like network combines machine learning, artificial neural network, and computational neuroscience tech-

niques to deal with all the nonlinearities and complexities that modern robotic systems could present. Although the architecture is tested on the simulated humanoid iCub, it can be applied to different robotic systems without excessive customization, thanks to its neural network-based nature. During the experiments, the robot is requested to follow repeatedly a movement while it is interacting with two external systems. Four different internal model architectures are compared and tested under different conditions. The comparison of the performances confirmed the theories about internal models combinatory action. The combination of models together with the structural and learning features of the network, resulted in a benefit to the adaptation mechanism, but also the system response to nonlinearities, noise and external forces.

Side Projects

During the Ph.D. project, we collaborated with other partners of the Human Brain Project (HBP) in parallel investigations regarding different implementations of cerebellar-like simulations models, and the cooperative role of the cerebellar-like system with other CNS models. These works are not included in the thesis to focus the dissertation only on the main cerebellar-like learning and control solution.

A Cerebellum-Inspired Learning Approach for Adaptive and Anticipatory Control.

Tolu, Silvia; Capolei, Marie Claire; Vannucci, Lorenzo; Laschi, Cecilia; Falotico, Egidio; Hernandez, Mauricio Vanegas. In: International Journal of Neural Systems. 2020 ; Vol. 30, No. 1. DOI: 10.1142/S012906571950028X

Resume. A major scientific hypothesis state that the cerebellum compensates for the peripheral feedback delays as a Smith predictor. To do so, the cerebellum employs forward internal models of the controlled plant and the delay. However, how the forward model is integrated into the control system is under debate. We propose a robotic control architecture that combines a cerebellar-like positive loop with a Smith predictor controller to endow robotic systems with accurate predictive and robust control. We test four different control architectures to compare the independent and combinatorial action of the cerebellar-like and the Smith predictor modules. The results confirm that the combination leads to the minor tuning of the control parameters, and faster adaptation.

Integration of Paired Spiking Cerebellar Models for Voluntary Movement Adaptation in a Closed-Loop Neuro-Robotic Experiment. A Simulation Study.

Corchado, Carlos; Antonietti, Alberto; Capolei, Marie Claire; Casellato, Claudia; Tolu, Silvia. Proceedings of 2019 IEEE International Conference on Cyborg and Bionic Systems and HBP Workshop. IEEE, 2020. DOI: 10.1109/CBS46900.2019.9114412

Resume. The cerebellum is pivotal for acquiring forward and inverse internal models describing the body-environment interaction. It is not clear the dependency of forward and inverse internal models. We propose a robotic control architecture that combines two cerebellar-like spiking neural networks mapping the forward and inverse internal models. The inverse cerebellar-like model applies feed-forward torque correction to the feedback controller action, while the forward cerebellar-like model adds an internal recurrent feedback loop. The control architecture is tested on a 2-degree-of-freedom modular robot. The empirical results prove that the tracking performance of the robot is optimized by 30% with respect to the no-cerebellum case.

Combining Evolutionary and Adaptive Control Strategies for Quadruped Robotic Locomotion.

Massi, Elisa; Vannucci, Lorenzo; Albanese, Ugo; Capolei, Marie Claire; Vandesompele, Alexander; Urbain, Gabriel; Maria Sabatini, Angelo; Dambre, Joni; Laschi, Cecilia; Tolu, Silvia; Falotico, Egidio. In: *Frontiers in Neurorobotics*. 2019 ; Vol. 13. DOI: 10.3389/fnbot.2019.00071

Resume. The traditional robotics control methods can not optimally perform during locomotion tasks in challenging conditions. The vertebrates' central nervous system employs specific neural structures that are the result of an evolutionary process to solve the adaptive locomotion problem in a disturbed environment. The spinal cord is the main responsible for the motion control of quadruped animals. In the spinal cord, a sort of Central Pattern Generator produces the locomotion patterns needed to perform the desired trajectory. The cerebellum seems to work in parallel with the spinal cord to learn motor behavior and provide adaptive motor corrections. In our study, we propose a bio-inspired control architecture to endow a modular robotic quadruped with adaptive locomotion. The architecture combines a Central Pattern Generator with a cerebellar-like learning and control system. We aim to understand and identify the advantage of learning the motor behavior during an evolution-inspired optimization to optimize the ongoing locomotion. In the empirical tests, we compare two bio-inspired architectures where the learning takes place during the evolutionary optimization or after that, respectively. During the experiments, the robotic dynamics and the interaction with the external system were dynamically changed to analyze the adaptive capability of the robotic system. The empirical results demonstrated that learning during the evolutionary search for locomotion trajectories produces better and more stable performances both in joint and task spaces.

Part II

Experimental Techniques and Results

Overview

THE second part of the manuscript is dedicated to the methods and results that lead to the design and development of a cerebellar-like learning and control architecture for robotics applications.

In Part I, we discovered that the cerebellum is not a stand-alone system and its action needs to be considered in relation to the fundamental cooperation it conducts with other CNS regions.

With this in mind in Chapter II.1, we describe how the cerebellum is functionally related to other neural regions and we proposed a functional control architecture to enclose these findings.

Then, Chapter II.2 and Chapter II.3 present the cerebellar-like robotic control system we developed during the Ph.D. project.

In line with Part I, the dissemination is divided into two main topics: the proposed cerebellar-like simulations model (Chapter II.2) and the cerebellar-like control schemes that integrate the simulations model (Chapter II.3).

CHAPTER II.1

Bio-inspired Control of Robotic Motor Behavior

II.1.1 Introduction

THE functional architecture for the autonomous and intelligent control of robotic systems has a distributed and hierarchical structure, i.e. it is constituted of distinct control modules located on several levels (for instance, the NASREM model in Figure II.1.1 [25]). The higher levels contribute to the logical action planning, while the lower levels are responsible for servo motor control. The modules are specialized in sensory processing, modeling of the robot-environment system, planning and executing actions. Each module shares and stores the learned information into a common database, i.e. the *Global Memory*. The components of the functional architecture communicate through data flows, the data directed towards the higher levels regard feedback information, such as sensory measurement and outcome of the executed actions, while the data directed to the lower levels communicate directives.

From an engineering point of view, we can appreciate a similar control structure in the part of the central nervous system (CNS) involved in motor behavior. Even though from an evolutionary perspective, the neural organization of the CNS is not strictly hierarchical. In Section II.1.2, we analyze the comparison within robotic functional architecture and the CNS specialized in the control of motor movements. Then in Section II.1.3, we propose the initial framework of the overall bio-inspired architecture that we aim to devise and validate for the autonomous adaptive and predictive control of complex robotic systems in challenging scenarios and we discuss the main questions we would like to address throughout the study.

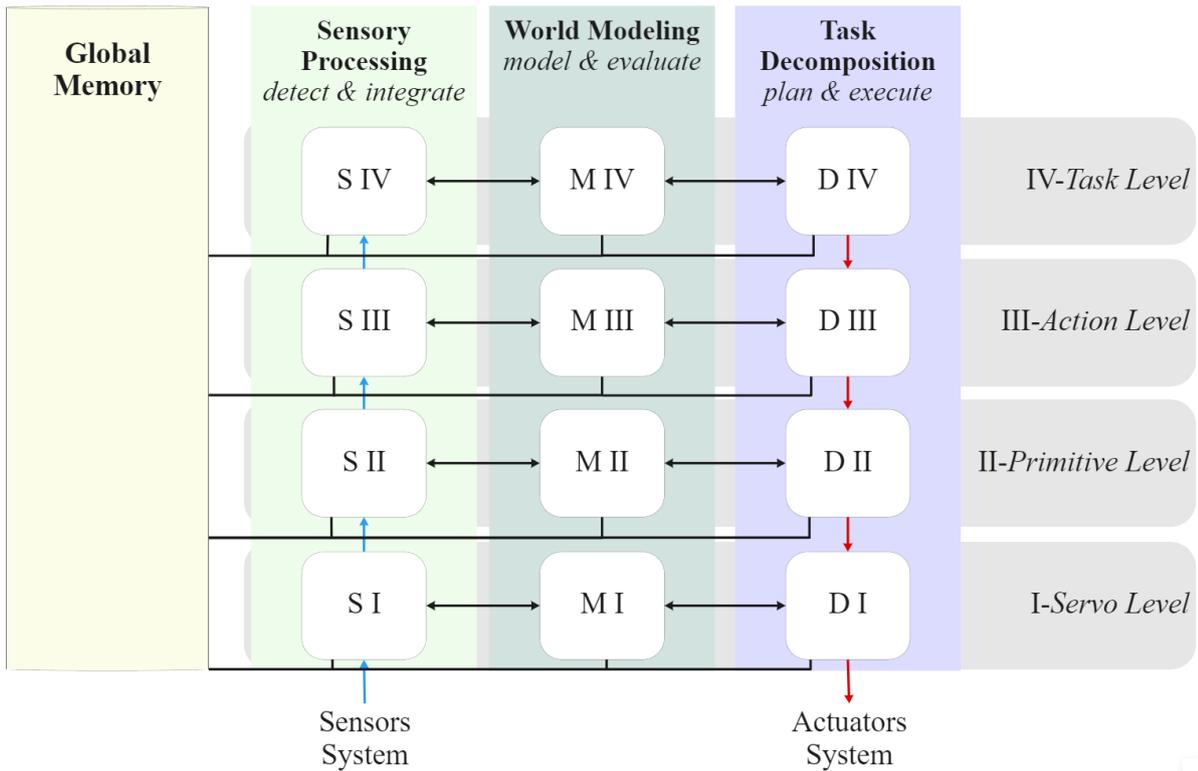


Figure II.1.1. General hierarchical and distributed functional architecture for controlling an intelligent and autonomous robotic system. In this example, the architecture is divided into four hierarchical levels. From top to down levels, the goal is decomposed into sub-goals and low-level actions, i.e. each task is divided into a sequence of action plans, which are transformed into motor primitives then into servo trajectories. In the horizontal partition, each level is constituted of three communicating modules: the *Sensory Processing* module acquires the data from the sensory system and extrapolates the features needed for the robotic control; the *World Modeling* module employs the features from the *Sensory Processing* module to acquire and evaluate internal models of the robot-environment system; the *Task Decomposition* module employs the models to predict and plan the actions. All the processed information are stored in a shared *Global Memory*. — Similar to [25]

II.1.2 Biological Motor System

The central nervous system (CNS) is well known to be a complex neural structure constituted of several regions that are functionally independent and interdependent. Each neural region addresses a distinct and essential role in the execution of complex motor behaviours.

The cerebellum is one of the most important neural structures involved in the adaptation and prediction of motor movements (Part I). In particular, the cerebellar connectivity and circuitry make the cerebellum the perfect candidate for the acquisition of internal models mapping the interaction within the body and the environment. The

cerebellum is not a stand-alone system and needs to be considered as a well-connected circuit that is part of the complex and multi-functional architecture. In this thesis, we focus only on the role of the cerebellum in low-level motor control, although, several studies proved that the cerebellum could play a crucial role in cognitive functions [83, 105, 130, 131, 192, 245–247].

During our study, it was crucial for us to understand how the cerebellum is connected to the rest of the CNS, and which neural circuits share information regarding motor control with the cerebellum. This helped us to functionally collocate the cerebellum

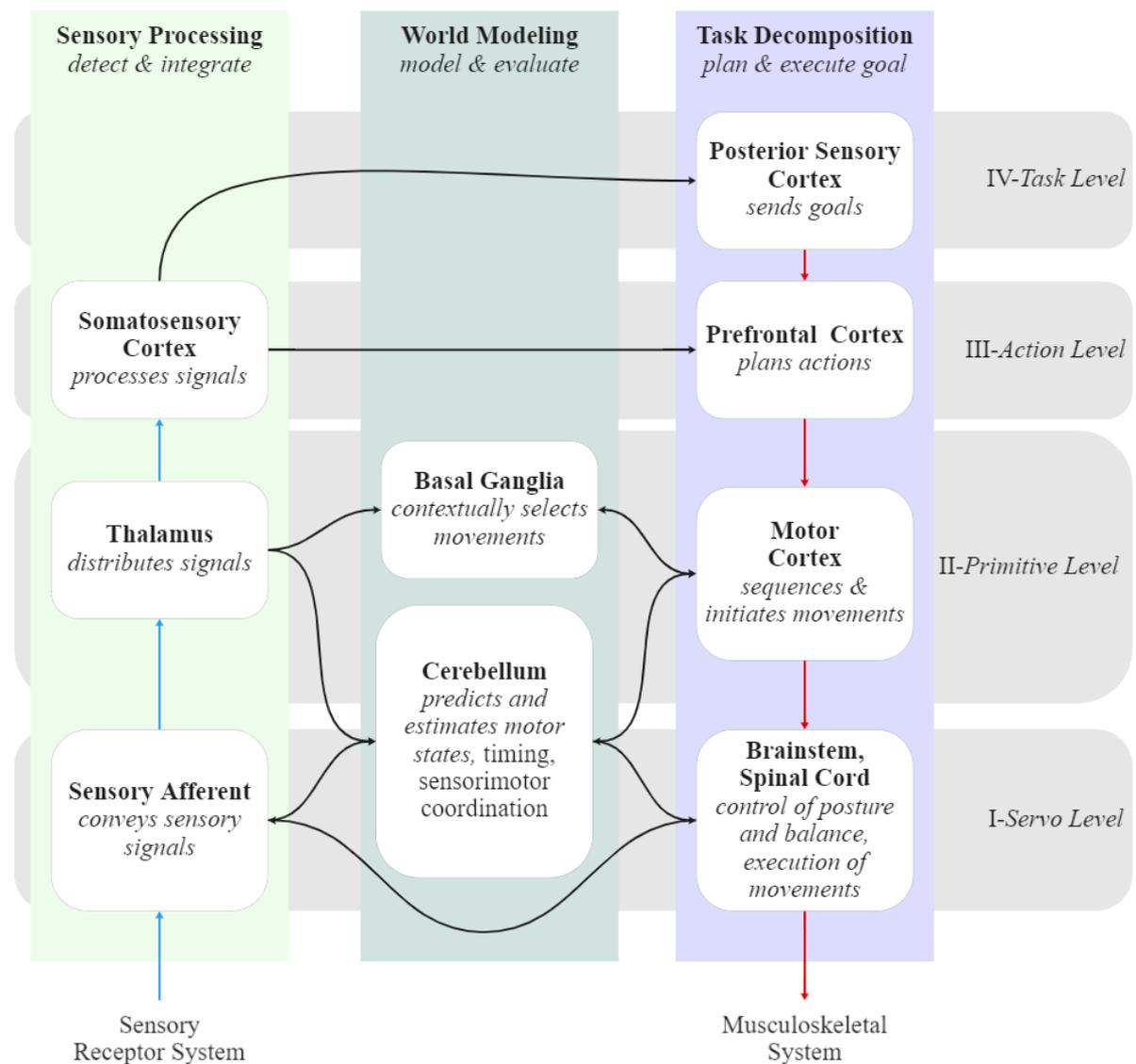


Figure II.1.2. Simplified hierarchical and distributed functional architecture for the control of voluntary movements. The scheme enclose theories from different studies [26–29]. We located the cerebellum and basal ganglia in the *World Modeling* column due to their crucial roles in learning and memory functions. The role of the cerebellum in cognition is omitted.

and make comparison with engineering schemes and consequentially make assumptions regarding the communication within the cerebellum and other CNS areas.

In Figure II.1.2, we schematized the hierarchical connections taking place in the CNS [26–29] in a functional architecture similar to the NASREM model developed for robotic control (Figure II.1.1) [25]. The cerebellum is described as a World Modeling module due to its important role in acquiring internal models mapping sensorimotor signals for a wide range of motor and cognitive functions. Similar approach is applied to the basal ganglia which conducts a pivotal role in non-declarative memory and learning [248–251].

From the review of the literature, it emerges that the cerebellum can be divided in three functional regions: the *vestibulocerebellum*, *spinocerebellum*, and *cerebrocerebellum* (described in Section I.1.2).

The cerebrocerebellum presents essential connections with the *premotor cortex*, *parietal cortex*, and the *primary motor cortex*. These neural regions are part of the cerebral cortex and are essential for high-level motor control tasks, such as planning, control, and execution of voluntary motor behavior [252]. The cerebral cortex receives somatosensory signals regarding the movements from the *sensory system* and is directly connected to some of the main CNS areas involved in motor control, such as the brainstem, the basal ganglia, and the spinal cord. The main hypothesis states that the cerebral cortex maps the relationship between sensory signals and actions patterns through unsupervised learning approach [166, 253]. Both the cerebellum and the *basal ganglia* form synaptic loops with the cerebral cortex. Recent studies proved that these loops indirectly connect the cerebellum to the basal ganglia, thus, influencing the cerebellar action [247]. The basal ganglia is well known to cover a crucial role in reinforcement learning and selection of the most pertinent motor action by the filtering of unwanted motor patterns [250, 253]. The spinocerebellum is connected to the *brainstem* through three large bundles of neurons. The brainstem functions as a coordinator of the motor signals and bridges the cerebellum with the spinal cord and the cerebrum. The *spinal cord* constitutes a fundamental sensory-motor pathway and is the main responsible for the control of voluntary movements and reflexes.

II.1.3 Bio-inspired Control of Voluntary Motor Movements

In Section II.1.2, we analyzed the biological control of movements from a functional point of view. We proposed a NASREM-like scheme for interpreting the biological motor control in a distributed and hierarchical manner that could represent a tool for future bio-inspired robotic control schemes. In our early study (Appendix A), we translated this idea into a bio-inspired control architecture that connects simulations models of the neural structures involved in the control of voluntary motor movements (Figure II.1.3). Even though, the development of such control system would take a long research process, we believe that this interconnection within different circuits is fundamental for achieving

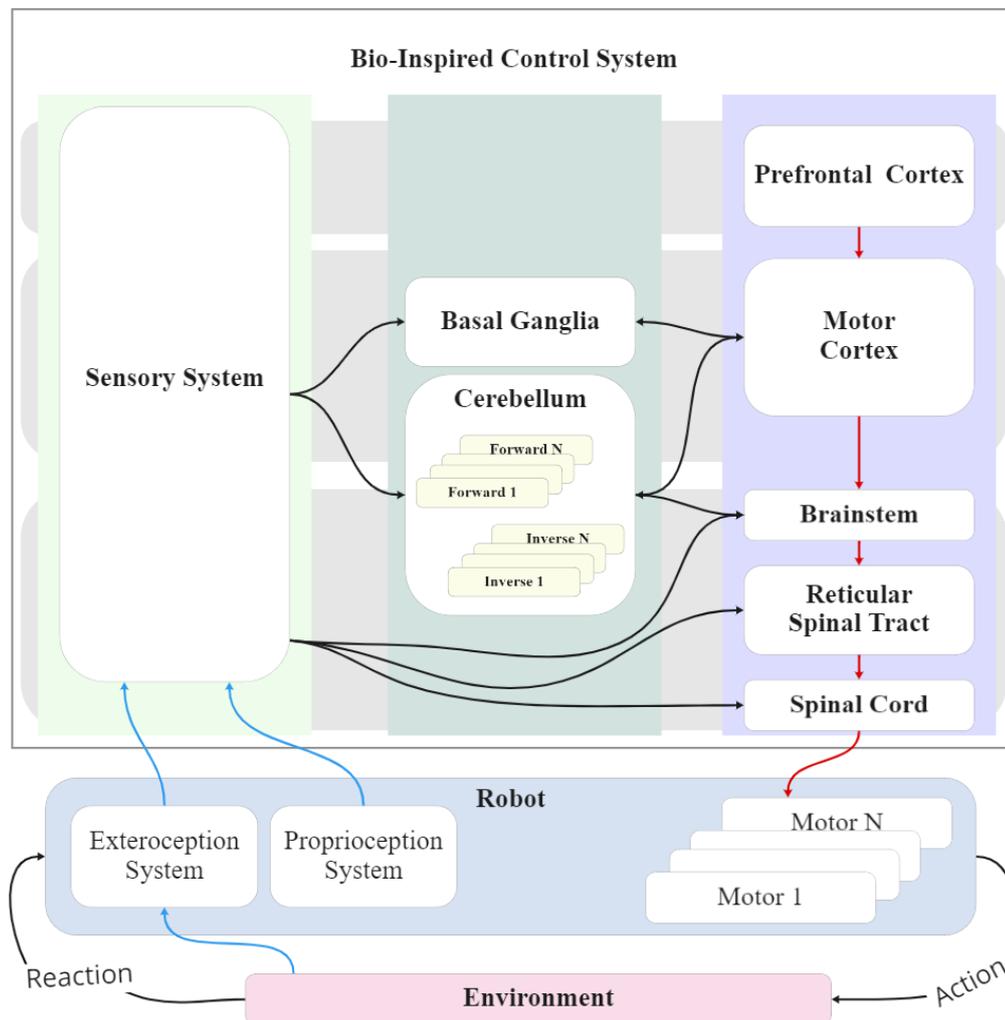


Figure II.1.3. Proposed bio-inspired functional architecture for the control of complex robotic behaviour during the interaction with the environment. The scheme propose only the high-level connections and distribution of the bio-inspired neural circuits. The scheme follows the hierarchical and distributed organization of the NASREM model [25], the partition is here omitted for simplification and it follow the color code of Figure II.1.2. The design adheres to the guidelines from [26,29–33]. The *Bio-Inspired Control System* control the motor behavior of a N-degree-of-freedom robotic system while it is interacting with a dynamic environment. The robot sends exteroceptive and proprioceptive sensory information to the controller sensory system. We assume that the high level goal is fixed, thus, the task level is omitted. At the *Action level*, the *Prefrontal Cortex* model divides the goal into a plan of actions. At the *Primitive Level*, the *Motor Cortex* module translates these actions into a sequence of movements that are sent down to the *Servo Level*. Here, the *brainstem* coordinates the movements, the *Reticular Spinal Tract* model modulates and adapts the low level motor movements, and the *spinal cord* executes and controls the motor commands. In the meanwhile, the *basal ganglia* learns and selects the most opportune action, and the *cerebellum* learns the internal models regarding the robot-environment dynamics to send adaptive corrections.

the level of generalization and adaption that robotic systems need for being employed in real-world applications. In the initial design, we assumed that the cerebellum includes several forward and inverse internal models, no assumptions are made about how these models could be paired and specialized. Moreover, the scheme does not make assumptions regarding the type of robotic signals that the bio-inspired models could share, this information is left for future investigations. With this study, we aim to understand,

- how these systems functionally cooperate?
- Which type of information the bio-inspired models could share for controlling robotics systems in challenging scenarios?
- What level of complexity we should address to both maintain the functionality of the entire system and real-time robotic control?

Concerning similar state-of-the-art attempts, our main focus is to understand how the structural modularity that characterizes the CNS can be reproduced and which contribution adds to motor learning and control of robotics system.

In this thesis, we present the research regarding the cerebellar module. The study regarding the cerebellar-like module is divided into two main research line,

- one studies the cerebellar neuromorphology and micro-level modularity and aim to devise and validate a cerebellar-like simulations model (Chapter II.2),
- the second concentrates on the modeling of the cerebellar involvement in motor functions through robotic control schemes (Chapter II.3).

CHAPTER II.2

Cerebellar-like Simulations Model

OVER the last decades, two main types of approaches have been delineated for the computational modeling of the cerebellar circuit: top-down and bottom-up approaches. In Chapter I.3, we discovered the differences between these two methods. The top-down approach focuses on the functional behavior of the cerebellar circuit. The high biological simplification makes this method the perfect candidate for real-time applications. However, the omission of most of the cerebellar time-related learning mechanisms negatively affects the adaptive performance of the simulations model. The bottom-up approach prioritizes the biological constraints to properly reconstruct the cerebellar circuit. This method significantly supported the validation of many assumptions regarding the plastic learning of the cerebellar circuit. Nevertheless, temporally specific learning is hardly achieved due to the high computational cost.

Our research purpose is to endow robots with adaptive capabilities that can support the interaction within the robot and unknown dynamic environments. To do so, the robotic control architecture needs to operate in real-time while the robot is interacting with the external system and needs to incrementally learn from the few observable sensory-motor information that is available.

In this chapter, we describe how we attempt to solve these requirements and design a cerebellar-like simulations model that could both be applied to real-time robotic applications and could observe a certain level of biological constraints to reproduce the cerebellar adaptive mechanisms. In Section II.2.1, we discuss the main research questions and assumptions that guided us during the design of the cerebellar-like simulations model. Then in Section II.2.2, we describe our solution in terms of structural design (Section II.2.2.1) and computational algorithm (Section II.2.2.2). We wrap up the research output and findings in a final discussion (Section II.2.3).

II.2.1 The Role of Modularity in Motor Learning

The most distinctive aspect of the cerebellar neuromorphology is the modular and regular partition both at macro and at the micro-levels (Chapter I.1). The cerebellum is constituted of thousands of independent canonical circuits that are located in parallel, share part of their internal loops, and map different signals. Empirical studies demonstrated that the climbing fiber (Cl)-inferior olivary nucleus (IO) systems are responsible for this neural partition, i.e. each cerebellar canonical circuit is modulated by a distinct signal. There is still a strong debate regarding the nature of the signal projected from the inferior olivary nucleus (IO). One of the most popular hypotheses claims that the IO modulating signal conveys the unpredicted sensory consequence of motor behavior which is comparable to an error-related signal [176, 178].

In Chapter I.2, we discovered that there is no strong evidence regarding the role of modularity in relation to the cerebellar action in motor control. The main hypothesis suggests that each cerebellar compartment could be the locus for the internal models acquired by the cerebellum. However, the computational models that attempted to test this theory are still under debate, and their application for robotic studies led to computationally laborious schemes that mostly lost the real-time potentiality of the cerebellum. Moreover, most of the studies regarding the modularity of the cerebellum separate the whole cerebellar circuit only in general terms, i.e. each module is constituted of a forward and an inverse internal models that describe a specific motor pattern (for instance, the MOSAIC model described in Section I.2.6 [13]). While, we believe that the modularity at the micro-level covers an important role in learning complex motor skills.

In this respect, the main dilemmas that arise when designing a cerebellar-like learning model for robotic applications regard the relationship within the cerebellar structural modularity and the mapping of motor skills, in other words,

- has the modularity of the cerebellar circuit a specific role in the extrapolation of significant information from a broad range of heterogeneous dynamical stimuli?
- How the canonical circuit is internally partitioned to map complex motor skills?
- How does the specialization of each learning unit and its reciprocal cooperation with other units influence the mapping of motor behaviour?
- How could we model the cerebellar modularity for robotics applications?
- What is the level of complexity we should address?

In the next sections, we attempt to answer these questions by merging ideas and state-of-the-art theories into a modular cerebellar simulation model that aims to reproduce the modularity of the cerebellar circuit at different levels.

II.2.2 The MCNNs Simulation Model for Real-Time Robotic Applications

In this thesis, we present the final version of the Modular Cerebellar-like Neural Networks (MCNNs) that we employed to adaptively control multi-degrees-of-freedom robotic systems acting in unknown dynamical environment. The Modular Cerebellar-like Neural Networks (MCNNs) is described in more general terms with respect to the one presented in our publications (Appendices B and C). In the model design, we attempt to answer some of the questions regarding the structural organization of the model, the neural connections, the functional role of the neural population with respect to robotics applications.

Our main design objective is to devise a cerebellar-like simulations model that can be employed for the real-time control of multi-degree-of-freedom robotic systems. For this reason, we attenuate the level of computational complexity of the model to prioritize the behavior of the cerebellar circuit over the biological constraints, similarly to the top-down cerebellar-like models presented in Section I.3.2. Thus, the model is based on assumptions regarding the functionality of the cerebellar circuitry and the biological details are modeled with simplified mathematical models.

From the review of the literature, it is clear that the adaptive capabilities of the cerebellar circuit rely on the differential modification of synapses that depends on the pre and post synaptic neural activities. Thus, the model simulates some of the biological rules regarding synaptic strength and postsynaptic response by means of four state-of-the-art bio-inspired synaptic plasticity models proposed by [10, 37]. The synaptic learning rules are placed in four learning sites: parallel fiber-Purkinje cell, Purkinje cell-deep cerebellar nuclei, inferior olivary nucleus-deep cerebellar nuclei, mossy fiber-deep cerebellar nuclei.

While to minimize the computational complexity, the dimensionality reduction and sensory-motor mapping happening at the granular cell layer level is carried out by an incremental non-linear functions approximation algorithm that has been validated for the real-time robotic control [5, 8, 169, 254].

II.2.2.1 Modularity of the MCNNs

The Modular Cerebellar-like Neural Networks (MCNNs) is partitioned in M modules, i.e. the Modular Cerebellar Circuits MCCs (green boxes in Figure II.2.1). Each MCC encodes the information related to the m -th internal model, i.e. inverse or forward internal models. The MCC learns the motor behavior of all the N controllable actuators of the robotic plant. Thus, the MCC is partitioned in sub-regions specialized on each actuator, i.e. unit learning machine (ulm) (blu box in Figure II.2.2). The ulm is further

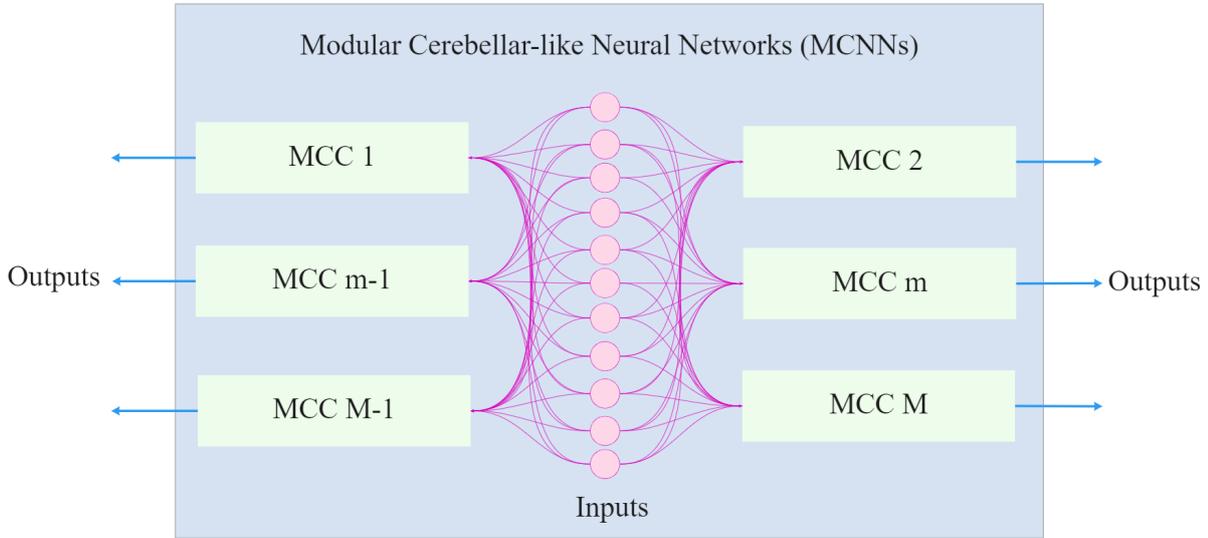


Figure II.2.1. High-level modular partition of the Modular Cerebellar-like Neural Networks (MCNNs). The overall simulations model is constituted of M Modular Cerebellar Circuits (MCCs) learning and storing distinct internal models. In magenta, the afferent fibers systems. — Reproduced from [34] (Appendix C)

divided into C specialized canonical cerebellar microcircuit (ccm). The number of ccm depends on the internal loops created by the Cl-IO system that divides the cerebellar cortex into modular micro-zones. Each ccm processes features-specific information regarding the motor performance of the n -th actuator (yellow boxes in Figure II.2.2). The signals processed by the C ccm are combined to compute the output of the n -th ulm. This output signal constitutes the cerebellar-like contribution to the motor behavior of the n -th actuator (blue output arrow in Figure II.2.2).

In Figure II.2.3, we indicate the type of neurons we included in our simulations model in analogy to the cerebellar circuit proposed in [36]. The mossy fibers (MFs) (in magenta) project time-evolving inputs to the granular cells (Grs) (in purple). The Grs performs a dimensionality reduction and sensory-motor mapping, then transmit the processed signal to the Purkinje cell (PC) (in green) through the parallel fibers (PFs). Each ccm includes one PC and the learning happening at the PF-PC is modulated by the activity of one inferior olivary nucleus (IO) (in red). The inhibitory response of the PC on the deep cerebellar nuclei (DCN) is triggered by DCN activity. The DCN output is affected by the activity of C PCs, IOs, and MFs.

II.2.2.2 The Algorithm

Hereafter, the variables x and w generally indicate the signal propagating inside the cerebellar-like networks and the weights of the networks, respectively.

Given a controlled plant with N controllable actuators, the afferent MFs convey the

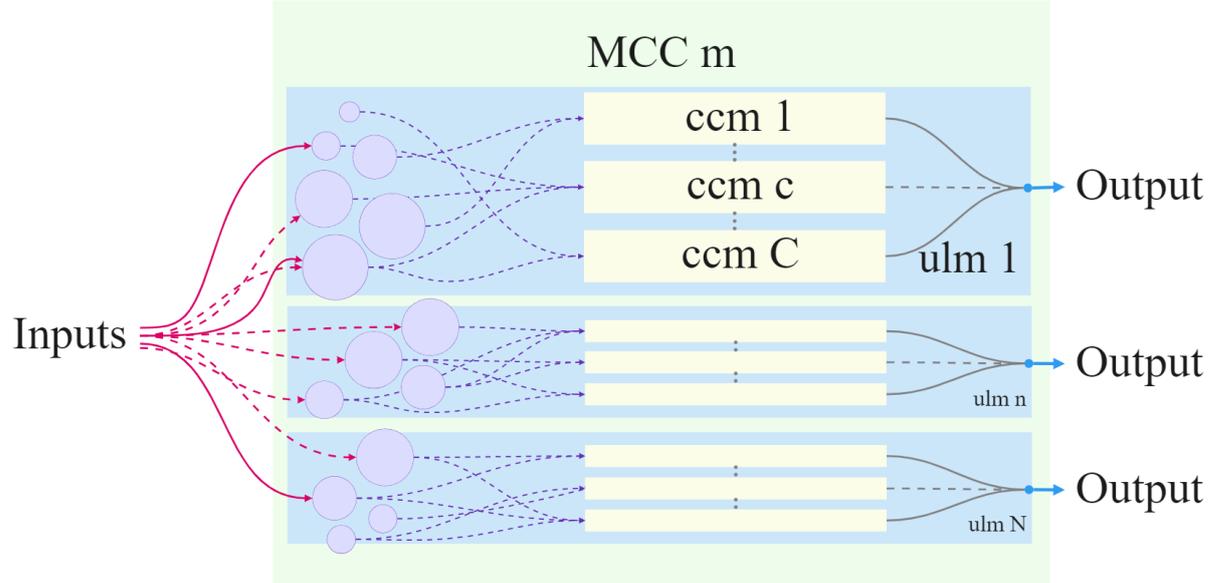


Figure II.2.2. Schematic illustrating the modular partition of the Modular Cerebellar Circuit (MCC). Each MCC is specialized in the acquisition of the $m - th$ internal model describing the motor behavior of a robotic plant with N controllable actuators. The MCC is partitioned in N sub-modules named unit learning machine (ulm). Each ulm learns the contribution of the $n - th$ robotic joint in the motor behavior. Each ulm is divided in C canonical cerebellar microcircuit (ccm), where C depends on the number of internal loops created by the climbing fiber (Cl). The cerebellar-like contribution to the motor movement of the $n - th$ actuator is the combination of the C canonical cerebellar microcircuit (ccm) outputs. The purple circles represent the granular cell (Gr) layer, we assume that some regions are specialized on a specific actuator but receives information regarding other parts of the controlled object (in magenta). — Reproduced from [34] (Appendix C)

input signals of the $m - th$ MCC (in magenta in Figure II.2.4),

$$\mathbf{MF}_{1 \times 2N}^m(t) = \begin{bmatrix} mf_1^m(t) \\ \dots \\ mf_N^m(t) \\ \dots \\ mf_{2N}^m(t) \end{bmatrix} = \begin{bmatrix} y_1^m(t) \\ \dots \\ y_N^m(t) \\ g_1^m(t) \\ \dots \\ g_N^m(t) \end{bmatrix}, \quad (\text{II.2.1})$$

where $g \in \mathbb{G}$ is the goal state belonging to the \mathbb{G} goal space, and $y \in \mathbb{Y}$ is the mapping input included in the \mathbb{Y} input space. In our solution, we generally assume that the cerebellar mapping occurs given the information from two different spaces, where one of them is always the \mathbb{G} goal space (described more in details in Chapter II.3),

$$\mathbb{Y} \times \mathbb{G} \rightarrow \mathbb{X}, \quad (\text{II.2.2})$$

where \mathbb{X} is the output space, thus, $x \in \mathbb{X}$. The \mathbb{G} goal space is included in the learning mechanism to add contextual information and to constrain the convergence of the mapping towards a desired region of the \mathbb{X} output space.

The mapping takes place in the granular cell (Gr) layer (in purple in Figure II.2.4) where the Locally Weighted Projection Regression algorithm (LWPR) [214] learns $x(t)$ given the $\mathbf{MF}_{1 \times 2N}^m(t)$ mossy fibers inputs, as proposed by Tolu and colleagues [255] to replicate the efference copy theory [256, 257].

The LWPR is a fast on-line nonlinear functions approximation algorithm suitable for the reduction of high dimensional state space systems. The algorithm employs $x(t)$ to on-line devise and train G \mathbf{Gr}_n^m local linear models,

$$\mathbf{Gr}_n^m = \begin{bmatrix} w_{n,1}^{gr,m} \\ \dots \\ w_{n,g}^{gr,m} \\ \dots \\ w_{n,G}^{gr,m} \end{bmatrix}. \quad (\text{II.2.3})$$

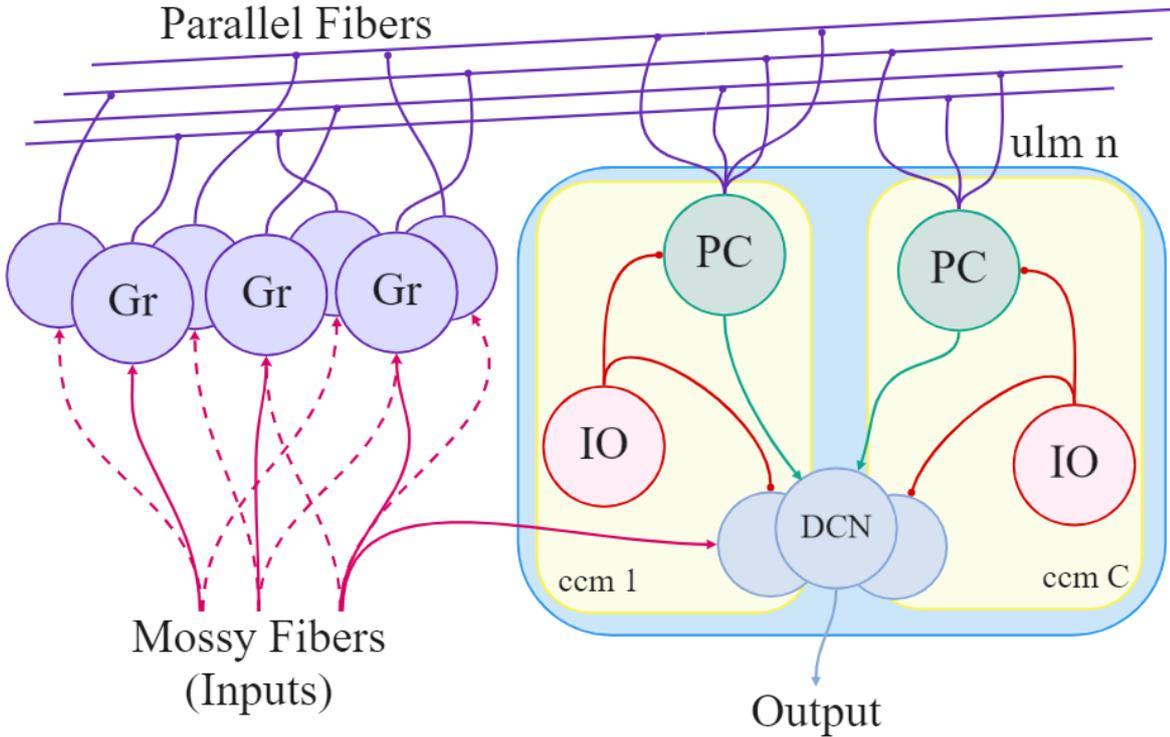


Figure II.2.3. Canonical cerebellar circuit indicating the partition of the neurons in the ulm and ccm. Each ulm is specialized on the $n - th$ controllable object, while each ccm describes a specific feature of the controllable object depending on the internal loop defined by the connection with the IO (in red). The signals processed in each ccm are then combined in the DCN that process the final cerebellar-like correction for the $n - th$ control object. — Reproduced from [34, 35] (Appendix B, Appendix C) in analogy with [36]

In our assumption, the \mathbf{Gr}_n^m represent the set of granular cells or $w_{n,g}^{gr,m}$ receptive fields employed by each MCC to learn and store the $m - th$ internal model of the $n - th$ actuator. These \mathbf{Gr}_n^m receptive fields are employed by the algorithm to compute G $\hat{x}_{n,g}^{gr,m}$ local predictions of $x(t)$.

The $\hat{x}_n^{pf,m}$ final output of the granular-molecular layer is the signal transmitted by the PFs to the PC. This signal is defined as the weighted mean of all the G $\hat{x}_{n,g}^{gr,m}$ local predictions (the complete algorithm is described by Vijayakumar and Schaal in [214]),

$$\hat{x}_n^{pf,m} = \frac{\sum_{g=1}^{g=G} w_{n,g}^{gr,m} \cdot \hat{x}_{n,g}^{gr,m}}{\sum_{g=1}^{g=G} w_{n,g}^{gr,m}}. \quad (\text{II.2.4})$$

The $\hat{x}_n^{pf,m}$ parallel fiber (PF) signal is filtered by the $w_n^{pf-pc,m}$ synaptic plasticity when entering the Purkinje cell (PC) (defined in [10]). In our application, the $w_n^{pf-pc,m}$ synaptic plasticity is modulated by error-related signals transmitted by the climbing fiber (Cl) from the inferior olivary nucleus (IO) (in red in Figure II.2.4),

$$\mathbf{io}_n^m(t) = \begin{bmatrix} io_{n,1}^m(t) \\ \dots \\ io_{n,c}^m(t) \\ \dots \\ io_{n,C}^m(t) \end{bmatrix}. \quad (\text{II.2.5})$$

the dependency of the $w_n^{pf-pc,m}$ synaptic plasticity to the IO activity is one of the main factors that endows the cerebellar circuit with adaptive capabilities [101]. In our design, the number of IO signals depends on the number of ccm, or rather on the modularity of each ulm describing the motor behaviour of the $n - th$ actuator. From the review of the literature, one of the major hypotheses claims that the climbing fibers are responsible for the internal loops inside the cerebellar circuit that specialize in the cerebellar canonical circuits.

The $x_{n,c}^{pc,m}(t)$ Purkinje cell (PC) output signal of the $m - th$ internal model is defined as the $\hat{x}_n^{pf,m}$ prediction of the LWPR (Equation (II.2.4)) modulated by the $c - th$ IO,

$$x_{n,c}^{pc,m}(t) = w_{n,c}^{pf-pc,m}(t, io_{n,c}^m) \cdot \hat{x}_n^{pf,m}(t). \quad (\text{II.2.6})$$

In contrast to the application of the LWPR proposed by [255,258], the x^{pc} PC signal is function of:

- the $\hat{x}_n^{pf,m}(t)$ LWPR prediction and not only of the LWPR weights;
- the IO conveying error-related information [167] (Equation (II.2.5));
- the w^{pf-pc} synaptic plasticity which is modulated by the IO signal.

The $x_{n,c}^{pc,m}(t)$ Purkinje cell (PC) signal transmitted to the deep cerebellar nuclei (DCN) is filtered by the $w_{n,c}^{pc-dcn,m}$ weight regarding the PC-DCN synaptic plasticity (defined in [10]), which is function of the ongoing activities of both PC and DCN,

$$x_{n,c}^{pc-dcn,m}(t) = w_{n,c}^{pc-dcn,m}(t, x_{n,c}^{pc,m}, x_n^{dcn,m}(t-1)) \cdot x_{n,c}^{pc,m}(t), \quad (\text{II.2.7})$$

where $x_n^{dcn,m}(t-1)$ is the last DCN output, i.e. the last cerebellar-like networks output.

In our networks solution, one MF projects to the DCN a copy of the $x_n(t)$ signal which is filtered by the $w_n^{mf-dcn,m}$ synaptic weight function of the PC activity (defined in [10]),

$$x_n^{mf-dcn,m}(t) = w_n^{mf-dcn,m}(t, x_n^{pc,m}) \cdot x_n(t), \quad (\text{II.2.8})$$

In our model, the closed loop within the IO and the DCN is not implemented due to the lack of computational models referring to the DCN to IO plastic connection. In the proposed network, the $x_{n,m}^{io-dcn}$ IO projection to the DCN,

$$x_{n,m}^{io-dcn}(t) = w_{n,c}^{io-dcn,m}(t, io_{n,c}^m) \cdot io_{n,c}^m(t), \quad (\text{II.2.9})$$

is filtered by the $w_{n,c}^{io-dcn,m}$ synaptic weight that is function of the IO activity (defined in [37]).

The x_n^{dcn} cerebellar-like networks output of the $m - th$ internal model is defined as (in blue in Figure II.2.4),

$$x_n^{dcn,m}(t) = k(\chi_n^{mf-dcn,m}(t) + \chi_n^{io-dcn,m}(t) - \chi_n^{pc-dcn,m}(t)), \quad (\text{II.2.10})$$

where $\chi_n^{mf-dcn,m}(t)$ is the excitatory activity of the C MFs on the DCN,

$$\chi_n^{mf-dcn,m}(t) = k(\sum_{c=1}^C x_{n,c}^{mf-dcn,m}(t)), \quad (\text{II.2.11})$$

$\chi_n^{io-dcn,m}(t)$ is the excitatory activity that the C IOs exert on the DCN,

$$\chi_n^{io-dcn,m}(t) = k(\sum_{c=1}^C x_{n,c}^{io-dcn,m}(t)), \quad (\text{II.2.12})$$

$\chi_n^{pc-dcn,m}(t)$ is the inhibitory activity that the the C PCs apply on the DCN

$$\chi_n^{pc-dcn,m}(t) = k(\sum_{c=1}^C x_{n,c}^{pc-dcn,m}(t)), \quad (\text{II.2.13})$$

and $k(\cdot)$ is a nonlinear activation function,

$$k(z) = \frac{2}{1 + e^{-2z}} - 1. \quad (\text{II.2.14})$$

In the empirical experiments, the proposed cerebellar-like simulations model efficiently performed during the real-time adaptive control of complex robotic systems in a disturbed environment. Even though the level of realism of the cerebellar model is kept quite low with respect to state-of-the art spiking neural networks, the networks can

reproduce some of the cerebellar mechanisms without losing both the adaptive behavior and the high-level of responsiveness necessary for real-time robotic application.

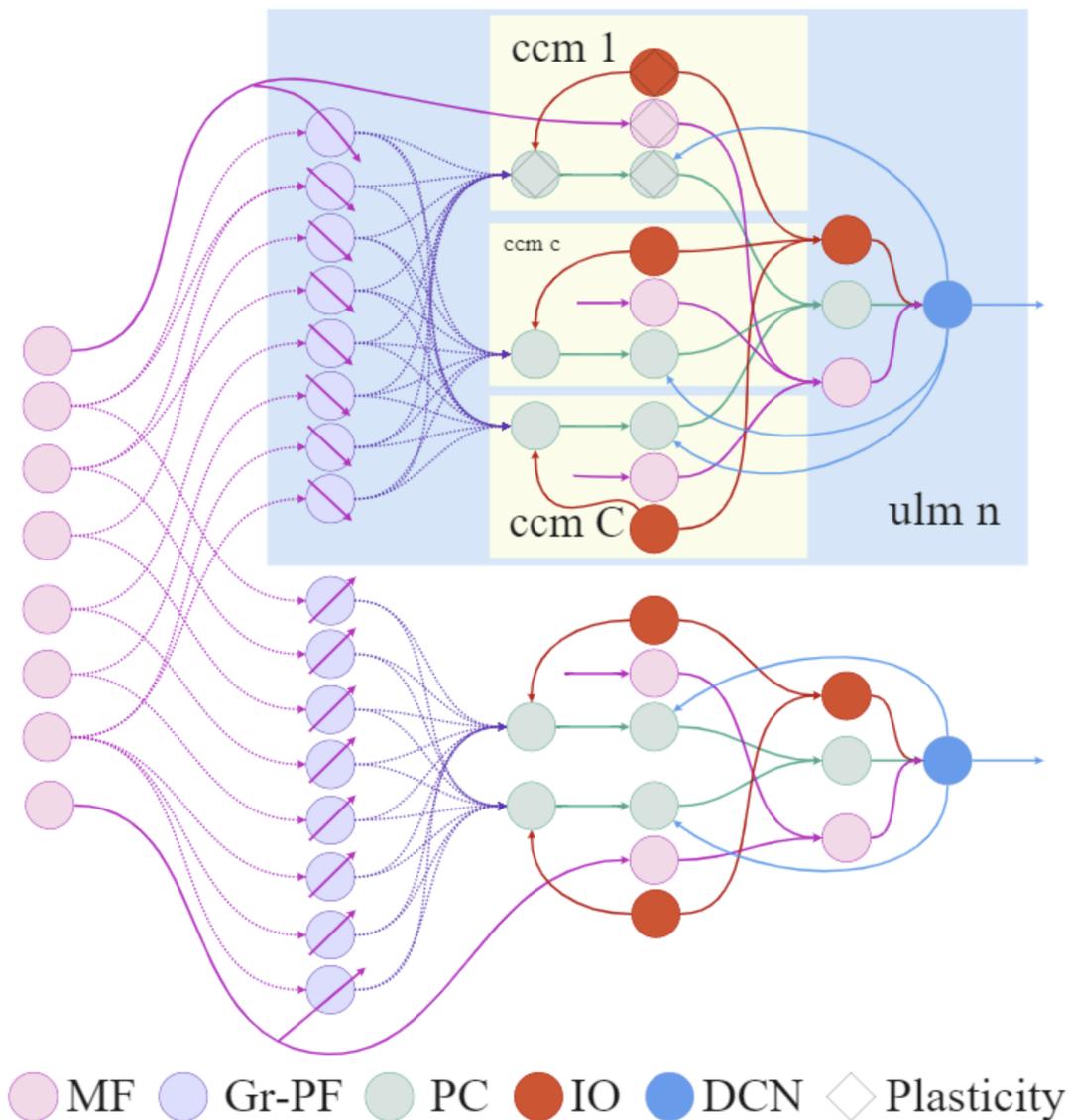


Figure II.2.4. Schematic of the proposed Modular Cerebellar Circuit (MCC) neural networks. The mossy fiber (MF) signals (in magenta) are inputted to the granular cell (Gr)-parallel fiber (PF) system represented by the LWPR algorithm (in purple). The MF projects a copy of the efference copy to the DCN (bold magenta line). This signal is also mapped by the LWPR (teaching signal). The Gr-PF output is projected to the C Purkinje cells (PC) (in green). The PC synaptic plasticity is influenced by the deep cerebellar nuclei (DCN) activity (in blue). The inferior olivary nucleus (IO) modulates the PC activity (in red). The rhombus indicates the synaptic plasticities, only shown in the first ccm for simplification. The blue boxes indicate the unit learning machine (ulm) specialized on the motor behavior of the first and n -th actuators. The yellow boxes illustrate the further partition into canonical cerebellar microcircuit (ccm). — Reproduced from [34] (Appendix C)

In the granular layer, the LWPR algorithm resulted in an effective tool for the on-line sensory-motor mapping of signals that are nonlinear, continuous, time-varying, and high-dimensional. The LWPR can manifest an unstable and jerky response when the prediction error is suddenly too high. The learning tends to drastically diverge if the instability is not controlled. This scenario can be frequent in noisy and disturbed robotic interactions due to the high variance of the signals read by the sensors. Especially in disturbed scenario, the real action performed by the robot can be very different from the predicted action due to the unpredictability of the disturbance. The stratified and modular structure of the networks empirically proved to be a robust solution for such stochastic conditions. The modularity of the circuit plays a crucial role both in mapping the motor behavior and in damping any over-reactive response.

The four bio-inspired plastic mechanisms effectively contributed to adaptively learn the robot-environment interaction. The experimental results confirmed the coupling within the controller action, the incremental learning, and the adaptive mechanism of the cerebellar-like networks (Figure B.11). The synaptic weights exhibit different behaviors in the early and post-adaptation periods. For instance, the IO-DCN plastic mechanism tends to react more in the early adaptation period while the PF-PC learning is more triggered in the post adaptation period. This is due to the different actions that the IO exerts on the DCN and the PC, respectively. To some extent, the IO is inhibiting the PC learning of the wrong action (high IO value), while exciting the DCN to trigger a corrective response.

II.2.3 Discussion

In this chapter, we presented the Modular Cerebellar-like Neural Networks (MCNNs), a bio-inspired simulations model that attempts to artificially replicate the functionality, plastic learning, circuitry, and modularity of the cerebellum. The MCNNs has been designed to,

- learn in real-time the internal models describing a controlled robotic systems motor behavior while interacting with an unknown and dynamically disturbed environment;
- reactively process an adaptive action to optimize the motor performance of the controlled robotic system.

The design mainly focuses on the applicability of the simulations model to a robotic application rather than the validation of the cerebellar neuroscientific assumptions.

The empirical findings open some interesting discussions regarding the structural modularity of the cerebellar-like computational model. In the design, we gave extra focus to how the modular partition of the neural networks could be implemented. We believe that the modular partition at the micro-level plays a pivotal role in the mapping of complex motor behavior. This division could support the extrapolation of important

kinematics and dynamics information of the ongoing motor action. As matter of fact, each sub-module is modulated by different climbing fibers and keeps track of distinct aspects that constitute the overall motor performance. Comparable state-of-the-art simulations models were applied to simplified robotic conditions that included no dynamical interaction with an external systems, thus, the learning neglected several nonlinearities that could come into place in real-life scenarios.

At the current state, our solution can not generalize over a wide range of motor behaviors. This relevant feature is under investigation, and we believe that to reach generalization the cerebellar-like circuit needs to work in parallel with other bio-inspired neural circuits, as proposed in Chapter II.1.

In a parallel project [259], we tested a simplified model of the cerebellar-like control system in combination with a central pattern generator to simulate a spinocerebellar action. Although the simplification, the empirical experiments show promising results regarding the cerebellar contribution in adaptive locomotion. We concluded that the cerebellar model needed to be optimized to be incorporated in a more complex control structure. With this purpose, we have been focusing on devising and validating the fundamentals building block of the cerebellar-like circuit, i.e. the canonical cerebellar microcircuit (ccm), then we gradually add structural complexity to the system to build the Modular Cerebellar Circuit (MCC) to store one internal model.

We are skeptical regarding the use of the LWPR for increasing the complexity of the system and finding a solution for the generalization problem. At the current state, we could not find a comparable candidate that could take charge of the mapping happening at the granular layer. In parallel experiments [260], we tested similar assumptions proposed here on cerebellar-like spiking neural networks. The learning performance is promising but the model can not work in real-time. We believe that transferring the spiking neural networks on neuromorphic hardware as *SpiNNaker* could help in reducing the large computational delays.

We did not cover the cerebellar modularity as intended by Haruno and colleagues in the MOSAIC model [13], where multiple pairs of forward and inverse internal models work in parallel and are modulated depending on their responsibility in the current motor behavior (Section I.2.6). In Chapter II.3, we further discuss this topic in relation to the findings related to motor control schemes.

At the current state, the simulation model is continuously active and learns all the ongoing motor behaviors. We are currently investigating the implementation of a mechanism that can mimic the conditioned response of the cerebellum and trigger an inhibitory mechanism when the conditioned response requirements are not satisfied. We believe that this mechanism will both constrain the learning and support the switching between distinct internal models.

In Chapter II.3, we describe how we integrated the proposed MCNNs into distinct robotic control schemes to test and validate the theories regarding the cerebellar learning and use of forward and inverse internal models for robotic applications.

CHAPTER 11.3

Cerebellar-like Adaptive and Predictive Robotic Control

11.3.1 Introduction

THE biological motor control of movements employs internal models describing the sensory-motor transformation of the body-environment system to efficiently adapt the motor response in any unknown changing scenario and to minimize the effects of sensory delays, noise signals, and disturbances (Chapter I.2).

Scientists indicate the cerebellum as the locus of the internal models and proposed diverse control schemes to validate how the cerebellum learns and employs these sensory-motor transformations.

Applying cerebellar control schemes to robotic control is not a straightforward process due to the obvious differences that characterize the biological and the robotic motor apparatus, and the lack of validation regarding the type of signals processed by the cerebellar circuit. Most of the known attempts are often run in simplified conditions and omit the complexity of robotic systems to prioritize the validation of the biological mechanisms.

In this chapter, we first discuss the scientific questions we addressed and the main challenges we faced in designing a bio-inspired robotic control solution that could satisfy our problem requirements (Section 11.3.2). Then, we present our bio-inspired solutions for the adaptive and predictive control of multi-degrees-of-freedom robotics systems in unknown and disturbed scenarios (Section 11.3.3). The chapter ends with some final remarks and discussions.

II.3.2 From Biological to Robotic Motor Control

When we consider a multi-degree-of-freedom robotic system with links connected in open loop, such as a robotic arm, the movements of each part of the robot indirectly affects the dynamics of the rest of the links. Moreover, if the robotic system interacts with an unknown external world a great number of unknown external forces impact the robotic behavior. A simple and weak static controller is not able to model and overcome all the nonlinearities that come into place. It is not feasible to hand engineer all the possible dynamics that participate in the control action especially when there is a continuous evolution of the overall dynamics.

In Chapter I.2, we discovered that the CNS learns and employs internal models describing the body and environment to overcome similar conditions and the cerebellum is the ideal candidate for this important motor function. Several engineering schemes attempted to reproduce the cerebellar involvement in adaptive and predictive motor control using internal models. However, most of the state-of-the-art architectures lack information that could lead to faster and more robust convergence of learning when employed on complex robotics structures acting in unknown and disturbed environments. With exception of a few comparable cases [23,37,37], most of the empirical tests are run on simplified models with few degrees of freedom and neglect the nonlinearities of the controlled system.

Designing the mapping mechanisms of the internal models into a robotic control scheme is not a straightforward process. One of the main challenges is understanding the type and the number of signals necessary for efficient mapping of motor behavior, especially when some important information regarding motor dynamics and kinematics are not observable.

On the other hand, testing different integration of cerebellar-like internal models into a robotic control scheme could validate the theories regarding the contribution of combined internal models in motor control. If any pairing of internal models exists,

- do the forward and inverse internal models learn from each other?
- If they learn interdependently, which model is updated first?
- Do they directly influence each other, as in the distal teacher learning approach (Section I.2.4.3)?
- If their action is coordinated, what are the consequence on the final motor behaviour?

In the next sections, we attempt to answer these questions and we propose different robotic control solutions that aim to replicate the functional role of the cerebellum and the internal models theories.

II.3.3 Cerebellar-like Control Schemes

The main task of our study is to devise and validate a robotic control architecture that can adapt in real-time to unknown conditions to improve the tracking accuracy of each robotic actuator, filter any noise signals, and reduce the effect of disturbances through force-based control action.

The design of the robotic control architecture considers these main assumptions,

- the control object is a complex robotic system with multiple degrees of freedom, N controllable rotary actuators, and N sensors;
- we have poor knowledge of the kinematics and dynamics models of the controlled object and the surroundings;
- the \mathbb{S} state space is not fully observable, especially the actual torque exerted by the motor, and the angular acceleration are not accessible;
- the \mathbb{G} goal, \mathbb{A} action and \mathbb{S} state spaces are continuous, time-varying, and high-dimensional;
- the robot interacts with a dynamic and unknown system;
- the robotic action is disturbed by external stochastic forces;
- the sensory feedback is affected by delays and noisy signals.

II.3.3.1 Cerebellar-like Inverse Internal Model Control Scheme

The scientific community agrees that the cerebellum is involved in the acquisition, storage, and employment of inverse internal models. All the cerebellar-like inverse control schemes proposed by the scientists suggest that the cerebellum employs the learned inverse model to determine the most opportune feed-forward correction to the control action.

We propose a robotic control architecture that includes a feed-forward cerebellar-like simulation model for learning, storing, and employing the inverse model describing the robot-environment interaction (Figure II.3.1). The control scheme merges different cerebellar theories and engineering methods proposed by the scientific community over the years and attempts to solve the problem's constraints stated in Section II.3.3.

In Figure II.3.1, the architecture is constituted of: a *Trajectory Planner* module which plans the next motor states; a static velocity *Feedback Controller* that processes the torque commands needed to direct the robot towards the desired configuration;

a cerebellar-like *Inverse Model* module that learns the inverse internal model of the robot-environment system and exerts adaptive corrections to the control action; a robot constituted of N controlled actuators and the corresponding N sensors; an *External System* that continuously interacts with the robot.

The N controlled robotic actuators are supposed to follow a reference trajectory transmitted by the *Trajectory Planner* module. The trajectories are defined in terms of q_n^r reference angular position of the n -th actuator,

$$q_n^r(t) = A_n \cdot \sin(2\pi f t + \varphi_n) \text{ for } n=0,\dots,N, \quad (\text{II.3.1})$$

and \dot{q}_n^r reference angular velocity,

$$\dot{q}_n^r(t) = 2\pi f A_n \cdot \cos(2\pi f t + \varphi_n) \text{ for } n=0,\dots,N, \quad (\text{II.3.2})$$

where A_n , f and φ_n are the constant trajectory amplitude, fixed temporal frequency and phase of the n -th actuator, respectively.

The *Feedback Controller* is a PID regulator with \mathbf{K} fixed gains,

$$\mathbf{K}_{1 \times N}^P = [k_1^P, \dots, k_n^P, \dots, k_N^P]$$

$$\mathbf{K}_{1 \times N}^I = [k_1^I, \dots, k_n^I, \dots, k_N^I], \quad (\text{II.3.3})$$

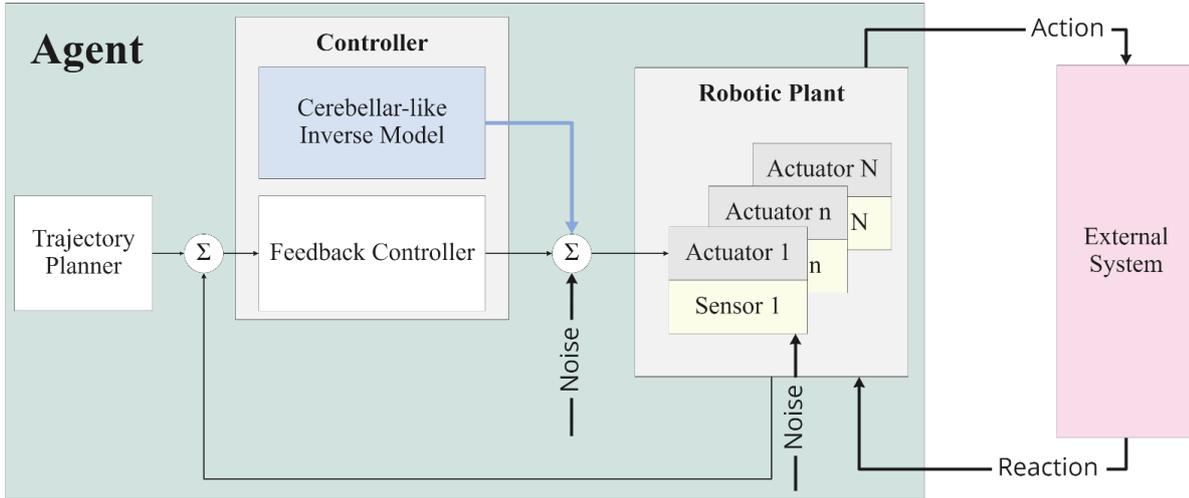


Figure II.3.1. Main components of the proposed feed-forward cerebellar-like robotic control architecture for N controllable actuators. The robotic agent continuously interacts with an *External System* that dynamically affects the robot's motor behavior. The Agent includes: a *Trajectory Planner*; a *Controller* constituted of a poorly tuned static *Feedback Controller* and an adaptive *Cerebellar-like Inverse Model*; a physical robot plant that has N controllable actuators and their respective sensors. — Reproduced from [34,35] (Appendix B, Appendix C)

$$\mathbf{K}_{1 \times N}^D = [k_1^D, \dots, k_n^D, \dots, k_N^D]$$

$$\forall k \in \mathbb{R}^+,$$

that are poorly tuned to operate in linearized conditions and exclude the interaction with the *External System*. The *Feedback Controller* receives only information regarding the e_n^{fb} angular velocity error or performance error (dotted line in Figure II.3.2),

$$e_n^{fb}(t) = \dot{q}_n^r(t) - \dot{q}_n(t), \quad (\text{II.3.4})$$

where \dot{q}_n is the sensed angular velocity, to process the τ_n^{fb} feedback torque to control the n -th actuator according to the independent joint control law,

$$\tau_n^{fb}(t) = k_n^P \cdot e_n^{fb}(t) + k_n^I \cdot \int_{t-\Delta t}^t e_n^{fb}(t') dt' + k_n^D \cdot \frac{d(e_n^{fb}(t))}{dt}. \quad (\text{II.3.5})$$

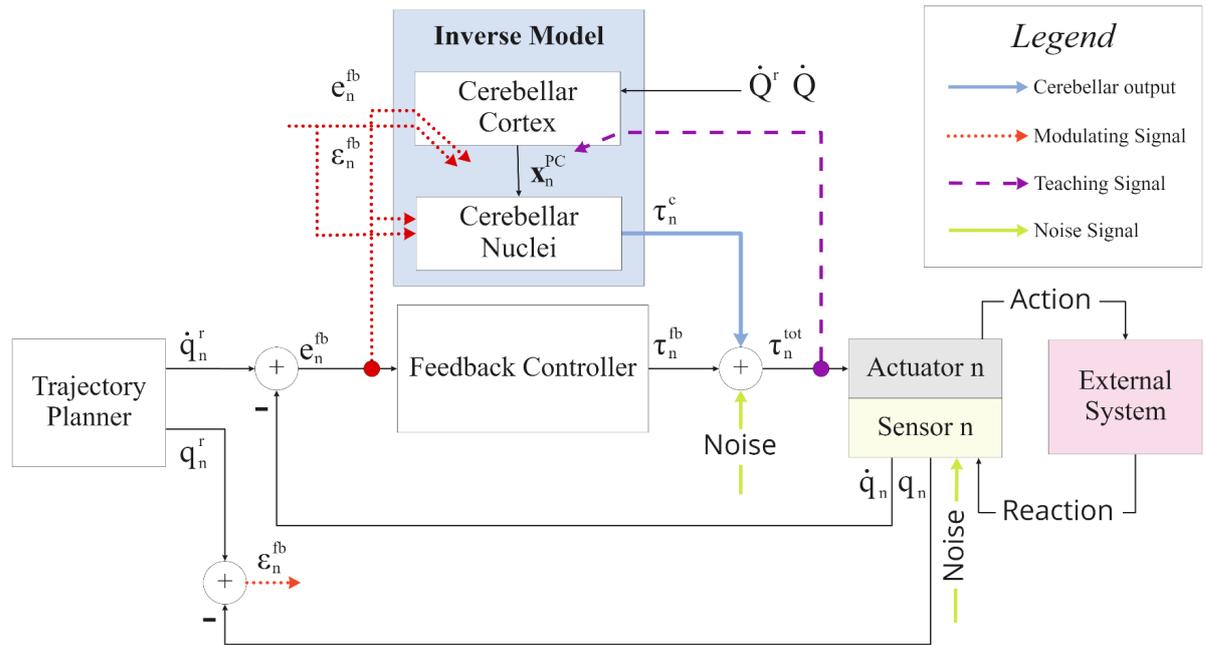


Figure II.3.2. Proposed cerebellar-like control scheme including a cerebellar-like module learning the inverse internal model of the robot-environment system. The inverse cerebellar model learns the mapping from the reference and sensed control states to the total motor command sent to the actuator (dashed magenta arrow). The learning is modulated by error-related signals (dotted red arrows). The cerebellar-like module applies feed-forward torque correction to the feedback controller output (bold blue arrow). The scheme includes noise signals affecting the sensors of the robot and the control action (bold green line). The robot continuously interacts with an external dynamic system. — Reproduced from [34, 35] (Appendix B, Appendix C)

The cerebellar-like module learns the inverse internal model of the robotic-environment system and processes the τ_n^c cerebellar feed-forward motor torque correction. Thus, the τ_n^{tot} total torque command sent to the n -th actuator is,

$$\tau_n^{tot}(t) = \tau_n^{fb}(t) + \tau_n^c(t). \quad (\text{II.3.6})$$

Similar to early Kawato's theory [7] (Chapter II.2), the *Cerebellar-like Cortex* module learns the mapping from the $\dot{\mathbf{Q}}^r$ reference angular velocities of all the actuators involved in the motor behaviour,

$$\dot{\mathbf{Q}}_{N \times 1}^r(t) = \begin{bmatrix} \dot{q}_1^r(t) \\ \dots \\ \dot{q}_n^r(t) \\ \dots \\ \dot{q}_N^r(t) \end{bmatrix} \quad \text{where } \dot{\mathbf{Q}}^r \in \mathbb{G}, \quad (\text{II.3.7})$$

and $\dot{\mathbf{Q}}$ sensed angular velocities,

$$\dot{\mathbf{Q}}_{N \times 1}(t) = \begin{bmatrix} \dot{q}_1(t) \\ \dots \\ \dot{q}_n(t) \\ \dots \\ \dot{q}_N(t) \end{bmatrix} \quad \text{where } \dot{\mathbf{Q}} \in \mathbb{S}, \quad (\text{II.3.8})$$

to the τ_n^{tot} total torque command sent to the n -th actuator,

$$\tau_n^{tot} \in \mathbb{A}_n, \quad (\text{II.3.9})$$

where,

$$\mathbb{A}_n \subset \mathbb{A}.$$

and \mathbb{G} , \mathbb{S} , and \mathbb{A} are the goal, state, and action spaces, respectively. Thus, the inverse mapping can be described as,

$$\mathbb{S} \times \mathbb{G} \rightarrow \mathbb{A}_n. \quad (\text{II.3.10})$$

The τ_n^{tot} (Equation (II.3.6)) is set as the teaching signal of the cerebellar supervised learning algorithm to learn a signal that is evolving towards the desired behavior. This evolution is possible thanks to the feed-forward τ_n^c cerebellar correction. We assume that learning the τ_n^{fb} would lead to a slow learning process which is subject to an incorrect model represented by the weak *Feedback Controller*. In this regard, the role of the modulating signal transmitted through the climbing fiber (Cl) is to calibrate the corrections concerning the ongoing demand. Thus, the learning is modulated by two error-related signals as suggested and tested by [4, 261] to solve the motor error problem and the not-observability of the actual motor commands exerted by the actuators.

The number of error-related signals depends on the modularity of the circuit, each signal refers to a specific internal loop formed by the climbing fiber (Cl). In our experiments (Appendix B, Appendix C), one signal reports the e_n^{fb} performance error (Equation (II.3.4)), which is also fed to the feedback controller; and the second signal transmits the ϵ_n^{fb} angular position error,

$$\epsilon_n^{fb}(t) = q_n^r(t) - q_n(t). \quad (\text{II.3.11})$$

The empirical results (Appendix B, Appendix C) show the adaptive and reactive action of the feed-forward cerebellar-like control which promptly anticipates the random perturbations exerted by the *External System* and progressively reduces the performance error (Figures B.10 and C.5). As hypothesized by Kawato and colleagues [7], after a first increase of the control action in the first adaptation period, the torque commands tend to decrease in the post adaptation period with the incremental learning of the inverse model (Figures B.5, B.7 and B.9 (e),(f)). We need to consider that during the overall test the *External System* keeps adding perturbations to the motor behavior, thus, the cerebellar system needs to adapt all the time to the occurring dynamics changes and the control action never strictly converges to zero.

II.3.3.2 Cerebellar-like Forward Internal Model Control Scheme

In Sections I.2.2.2 and I.2.3, we discovered the many theories suggesting the cerebellum as responsible for the internal feedback loops employed by the central nervous system (CNS) to anticipate the delayed peripheral feedback and to process the appropriate response to stabilize the ongoing motor behavior. Several studies claim that the cerebellum learns forward internal models of the object and the environment describing the relation within the action applied to the controlled object and the resulting motor movement. Scientists express this predictive role of the cerebellum in terms of a control schemes with recurrent loops, where the adaptive cerebellar-like model applies corrections to the input of a static controller.

We propose a robotic feedback control scheme that includes a cerebellar-like simulation model that learns and stores the forward model describing the robot-environment system and applies a recurrent correction to the controller input (Figure II.3.3).

The control architecture consists of: a *Trajectory Planner* module, which processes the next desired state of the robot in terms of \dot{q}_n^r reference angular velocity, and q_n^r reference angular position (Equations (II.3.1),(II.3.2)); a poorly tuned *Feedback Controller* which takes as input angular velocity-related information; a cerebellar-like module which learns the forward internal model of the robot-environment system and adds kinematic corrections into the control loop; a robotic system constituted of N actuators and the respective N sensors; an *External System* that continuously interacts with the robot dynamically affecting the robotic movements.

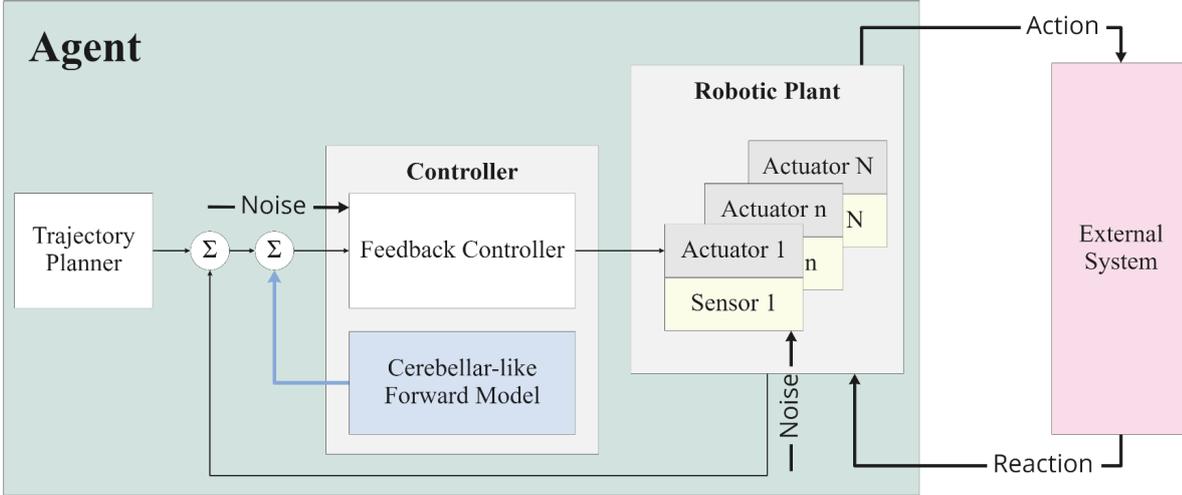


Figure II.3.3. Main components of the proposed recurrent cerebellar-like robotic control architecture for N controllable actuators. The agent continuously interacts with an *External System* that disturbs the motor behavior of the robot. The Agent consists of: a *Trajectory Planner*; a *Controller* constituted of a constant and weak *Feedback Controller* and an adaptive *Cerebellar-like forward Model*; a physical robot plant with N controllable actuators and the respective N sensors. — Reproduced from [34] (Appendix C)

As seen in Section II.3.3.1, the *Feedback Controller* is a weakly tuned PID regulator with \mathbf{K} constant gains (Equation (II.3.3)), that can poorly perform in linearized conditions without interacting with the *External System*. The *Feedback Controller* processes the e_n^{tot} total angular velocity error (Figure II.3.4),

$$e_n^{tot}(t) = e_n^{fb}(t) + \dot{q}_n^c(t), \quad (\text{II.3.12})$$

where e_n^{fb} is the angular velocity error,

$$e_n^{fb}(t) = \dot{q}_n^r(t) - \dot{q}_n(t), \quad (\text{II.3.13})$$

and \dot{q}_n^c is the cerebellar-like *Forward Model* correction, to compute the τ_n^{fb} feedback torque command sent to the n -th actuator as defined by the independent joint control law,

$$\tau_n^{fb}(t) = k_n^P \cdot e_n^{tot}(t) + k_n^I \cdot \int_{t-\Delta t}^t e_n^{tot}(t') dt' + k_n^D \cdot \frac{d(e_n^{tot}(t))}{dt}. \quad (\text{II.3.14})$$

In the *Cerebellar Cortex* of the cerebellar-like module, the \dot{q}_n causal robotic movement registered by the sensory system is mapped given the $\tau_{N \times 1}^{fb}$ total torque commands sent to the all the robotic actuators involved in the movement,

$$\boldsymbol{\tau}_{N \times 1}^{fb}(t) = \begin{bmatrix} \tau_1^{fb}(t) \\ \dots \\ \tau_n^{fb}(t) \\ \dots \\ \tau_N^{fb}(t) \end{bmatrix} \quad \text{where } \boldsymbol{\tau}^{fb} \in \mathbb{A}, \quad (\text{II.3.15})$$

where \mathbb{A} is the action space, and the $\dot{\mathbf{Q}}^r$ reference angular velocities (Equation (II.3.7)). Thus, the forward mapping can be described as,

$$\mathbb{A} \times \mathbb{G} \rightarrow \mathbb{S}_n, \quad (\text{II.3.16})$$

where,

$$\mathbb{S}_n \subset \mathbb{S},$$

and \mathbb{G} and \mathbb{S} are the goal and state spaces, respectively.

The information regarding all the actuators are sent as input to the learner to indirectly include all the disturbances that the movements of the other robotic links and

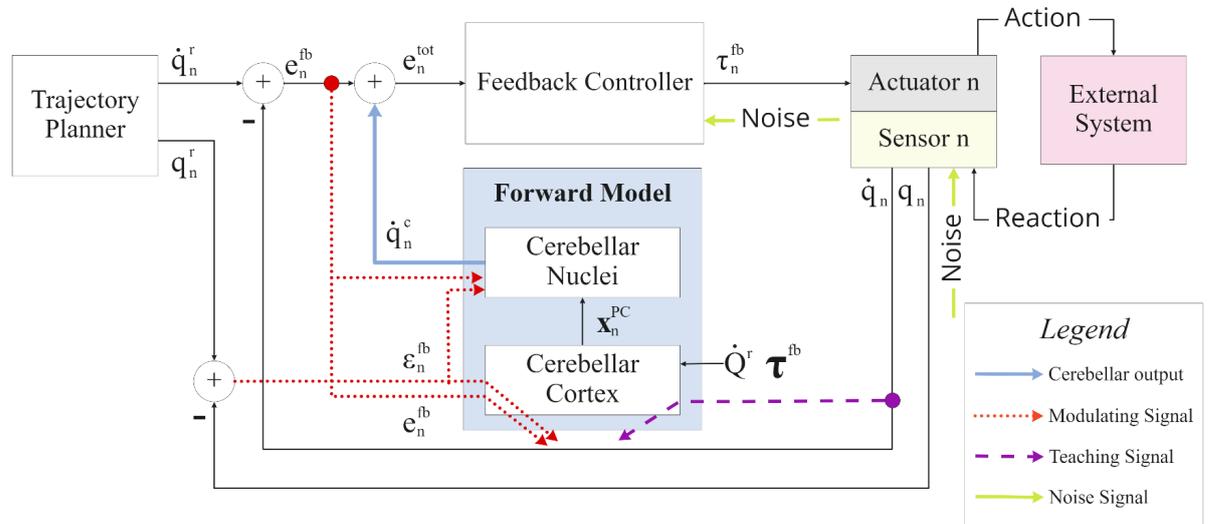


Figure II.3.4. Proposed cerebellar-like control scheme including a cerebellar-like module learning the forward internal model of the robot-environment system. The forward cerebellar model learns the mapping from the $\boldsymbol{\tau}_n^{tot}$ total torque command sent to all the actuators and the $\dot{\mathbf{Q}}^r$ reference states to the \dot{q}_n sense n -th motor state in term of angular velocity (dashed magenta arrow). The cerebellar action is modulated by two error-related signals (dotted red arrows), the e_n^{fb} angular velocity error and the e_n^{fb} angular position error. The cerebellar-like module adds an internal feedback loop that applies \dot{q}_n^c recurrent correction to the input of the feedback controller (bold blue arrow). The scheme includes noise signals affecting the feedback controller action and the sensors of the robot (bold green lines), and the continuous interaction of the robot with an external dynamic system. — Reproduced from [34] (Appendix C)

joints apply to the $n - th$ motor. We also assume that including the $\dot{\mathbf{Q}}^r$ reference angular velocities as input to the learner can add context sensitive information that could accelerate the convergence of the learning. The cerebellar-like model is modulated by two error-related signals. As mentioned in Section II.3.3.1, the number of modulating signals is strictly related to the modularity of the cerebellar circuit.

In the empirical tests (Appendix C), the first signal transmits information regarding the e_n^{fb} angular velocity error (Equation (II.3.4)), and the second signal conveys the e_n^{fb} angular position error (Equation (II.3.11)) as suggested by Porrill and colleagues [4], and tested on recurrent robotics architecture by Tolu and colleagues [5].

In Appendix C, the empirical results confirmed the crucial role of the cerebellar-like forward model in canceling the effects of sensory noise, overcoming time delays, and state prediction. As showed by Architecture **III** in Figure C.5 (cyan line), the control scheme including the cerebellar forward model results to correct the error faster than the inverse model control scheme (Architecture **II**, blue line) thanks to the reduction of the sensory delays that affect the control system. Moreover, the variance of the system response results incredibly lower in the control scheme with the forward model due to the cancellation of the noise effects (Figure C.5 Architecture **III**, cyan line). The results from the test case **B**, where extra noise is fed to the system, show that the control action seems not particularly affected by the noise signal. In particular, the variance of the second motor behavior is decreased with respect to the less noisy case. We assume that the noise signal triggers a major cerebellar corrective response in that specific case.

II.3.3.3 Cerebellar-like Tandem Internal Models Control Scheme

There is no consensus regarding the mechanisms regarding combinatorial action of the cerebellar internal models, and there is few evidence showing how these models inter-dependently operate. In our solutions, we assume that the forward and inverse models learn and act in pairs to solve the one-to-many mapping problem affecting the inverse transformation.

In Figure II.3.5, the proposed robotic architecture consists of: a *Trajectory Planner* module that processes the reference states that the robotic actuators are supposed to follow in terms of \dot{q}_n^r reference angular velocity, and q_n^r reference angular position (Equations (II.3.1),(II.3.2)); a weakly tuned angular velocity *Feedback Controller*; two cerebellar-like modules learning the forward and inverse internal model of the robot-environment system and feeding kinematics and dynamics corrections into the control loop; a robotic system constituted of N actuators and the respective N sensors; an *External System* that through its continuous interaction with the robot exerts stochastic dynamical disturbances to the robot movements.

The *Feedback Controller* module consists of a weak PID regulator with **K** constant gains (Equation (II.3.3)) tuned to function in linearized conditions not including any

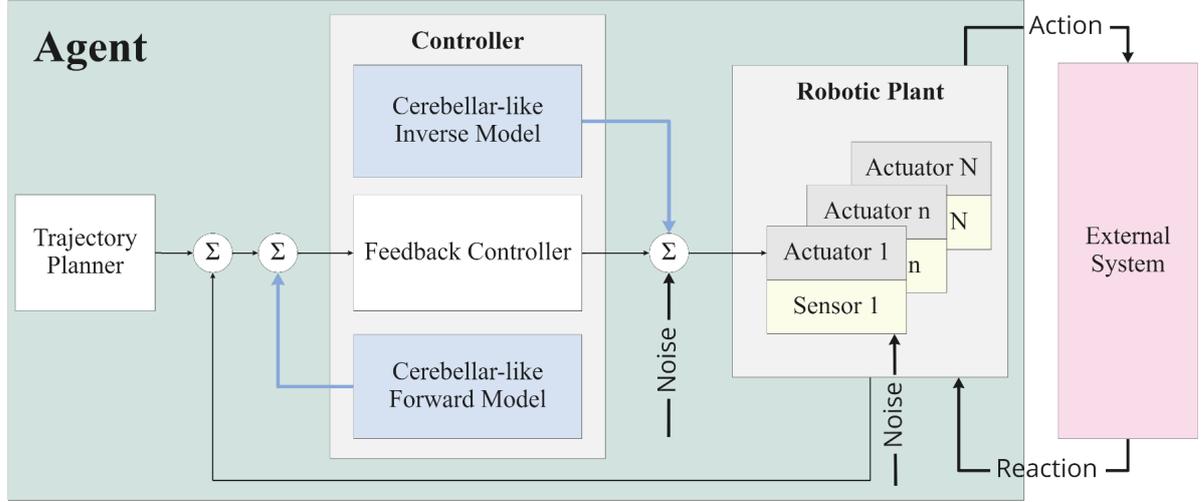


Figure II.3.5. Main components of the proposed tandem cerebellar-like robotic control architecture for N controllable actuators. The *Agent* interacts with an *External System* that constantly disturbs the robot motor behaviour. The tandem robotic *Agent* architecture is constituted of: a *Trajectory Planner* that plans the desired movements; a *Controller* that includes a fixed *Feedback Controller* and two adaptive *Cerebellar-like Inverse Model* and *Cerebellar-like Forward Model*; a *Robotic Plant* that incorporates N controllable actuators and N sensors. The *Cerebellar-like Inverse Model* applies feed-forward torque correction to the *Feedback Controller* control action. While, the *Cerebellar-like Forward Model* adds recurrent internal loop to correct the kinematics information fed to the *Feedback Controller*. — Reproduced from [34] (Appendix C)

type of noise and perturbations. The *Feedback Controller* receives as input the e_n^{tot} total angular velocity error (Figure II.3.6),

$$e_n^{tot}(t) = e_n^{fb}(t) + \dot{q}_n^c(t), \quad (\text{II.3.17})$$

where e_n^{fb} is the angular velocity error (Equation (II.3.13)) and \dot{q}_n^c is the kinematics correction processed by the *Cerebellar-like Forward Model*, to compute the τ_n^{fb} feedback torque command,

$$\tau_n^{fb}(t) = k_n^P \cdot e_n^{tot}(t) + k_n^I \cdot \int_{t-\Delta t}^t e_n^{tot}(t') dt' + k_n^D \cdot \frac{d(e_n^{tot}(t))}{dt}. \quad (\text{II.3.18})$$

The τ_n^{tot} total torque command sent to the n -th actuator,

$$\tau_n^{tot}(t) = \tau_n^{fb}(t) + \tau_n^c(t). \quad (\text{II.3.19})$$

includes both the τ_n^{fb} feedback torque command processed by the *Feedback Controller* and the τ_n^c computed by the *Cerebellar-like Inverse Model*.

The two cerebellar-like models are connected in parallel but learn and act in "tandem" as suggested by Honda and colleagues in the tandem internal models scheme [12], i.e. the forward model is updated prior to the inverse model to solve the non convexity of

the inverse model solution (Section I.2.5). However respect to [12] scheme, we suggest that:

- the e_n^{tot} total error (Equation (II.3.17)) including the *Forward Model* correction modulates the action of the *Inverse Model* instead of the e_n^{fb} performance error (Equation (II.3.13)), thus, the learning could converge faster towards a corrected solution space;
- the e_n^{fb} performance error (Equation (II.3.13)) modulates the action of the *Forward Model* [4, 5, 118];
- the *Inverse Model* learns to map the τ_n^{tot} total torque which includes both the τ_n^c and the \dot{q}_n^c inverse and *Forward Model* corrections, respectively.

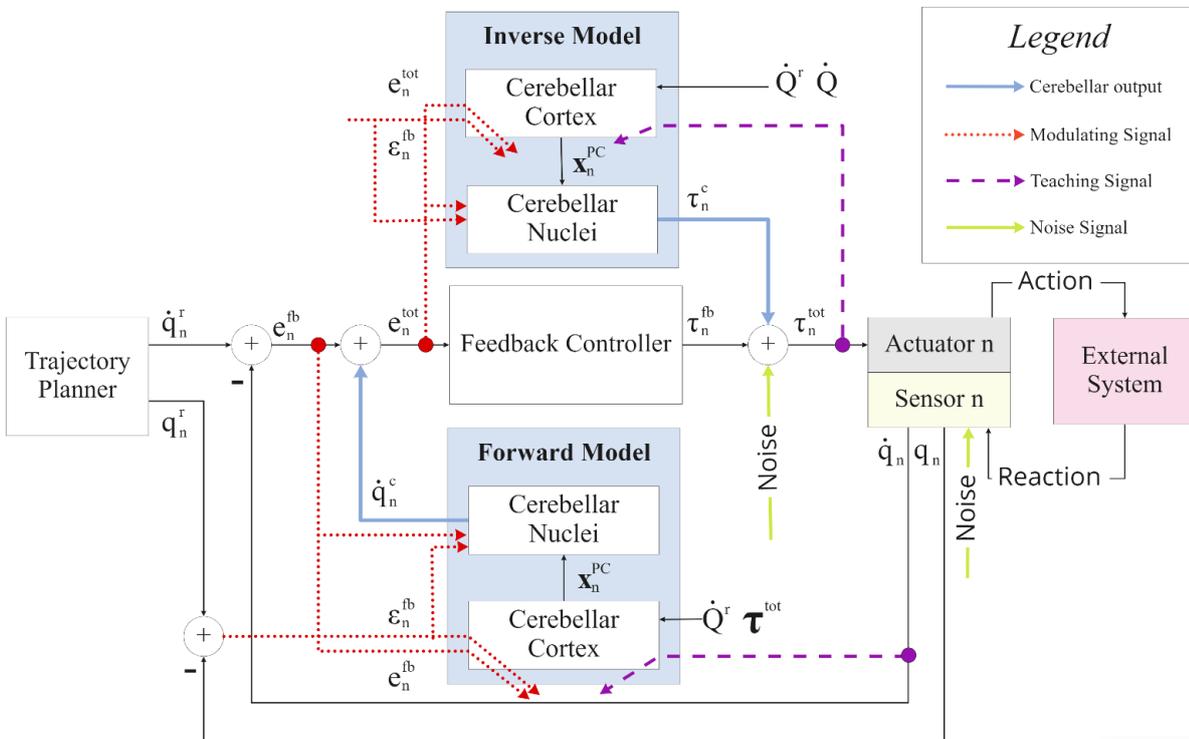


Figure II.3.6. Proposed tandem cerebellar-like control scheme including two cerebellar-like module learning the inverse and forward internal models of the robot-environment system. The two cerebellar-like models learn and act in tandem, i.e. the *Forward Model* is updated before the *Inverse Model*, the *Inverse Model* is modulated by the e_n^{tot} total error including the \dot{q}_n^c *Forward Model* correction, the *Forward Model* receives as inputs the τ_n^{tot} total torque commands corrected by the *Inverse Model*. The signals learned at the *Cerebellar Cortex* level are marked as dashed magenta arrows. The modulating error-related signals are indicated by dotted red arrows. The number of modulating signals in the scheme depends on the modularity of each cerebellar-like circuit. The cerebellar contributions are illustrated as bold blue arrows. The noise signals affecting the feedback controller action and the sensors of the robot are marked as bold green lines. — Reproduced from [34]

According to the aforementioned guidelines, the cerebellar-like *Forward Model* learns the $\dot{q}_n \in \mathbb{S}_n$ sensed angular velocity given the $\dot{\mathbf{Q}}^r \in \mathbb{G}$ desired states and the $\boldsymbol{\tau}^{tot} \in \mathbb{A}$ total torque commands of all the actuators involved in the motor behavior, thus,

$$\mathbb{A} \times \mathbb{G} \rightarrow \mathbb{S}_n, \quad (\text{II.3.20})$$

where \mathbb{A} , \mathbb{G} , and \mathbb{S}_n are the action, goal, and state spaces, respectively.

The \dot{q}_n^c correcting action of the *Forward Model* is modulated by two error-related signals: the e_n^{fb} angular velocity error (Equation (II.3.13)) and the ϵ_n^{fb} angular position error (Equation (II.3.11)).

The cerebellar-like *Inverse Model* learns the $\tau_n^{tot} \in \mathbb{A}_n$ total torque command of the n -th actuator given the $\dot{\mathbf{Q}} \in \mathbb{S}$ sensed and the $\dot{\mathbf{Q}} \in \mathbb{G}$ desired states of all the motors involved in the action, thus,

$$\mathbb{S} \times \mathbb{G} \rightarrow \mathbb{A}_n, \quad (\text{II.3.21})$$

where \mathbb{S} , \mathbb{G} , and \mathbb{A}_n are the state, goal, and action spaces, respectively.

Then, the τ_n^c *Inverse Model* correcting action is modulated by two error-related signals: the e_n^{tot} total angular velocity error (Equation (II.3.17)) and the ϵ_n^{fb} angular position error (Equation (II.3.11)).

From the empirical results, it emerges that the combination of forward and inverse internal models drastically outperforms their independent action (Appendix C). In Figure C.5, the tandem internal models architecture (Architecture **IV** in magenta) presents smaller performance error and a faster first adaptation period due to the forward model action with respect to the other control schemes. Moreover, the post adaptation period results stable and faster thanks to the rapid convergence of the inverse model. The tandem internal model scheme not only combines the contributions of the inverse and forward models, but it also increases their performances.

II.3.4 Discussion

In this chapter, we introduced our control solutions for modeling the adaptive and predictive role of the cerebellum in the control of robotic motor behaviors in unknown and disturbed scenarios. Depending on the independent or combinatorial action of the cerebellar internal models we proposed three main robotic control architectures: feed-forward, recurrent, and tandem cerebellar-like control schemes.

The first architecture includes a static feedback controller and a feed-forward cerebellar-like inverse model. The cerebellar-like inverse model resulted to be crucial in the robust rejection of dynamical disturbances and the correction of performance errors.

The second architecture consists of a static feedback controller whose control input is corrected by a recurrent cerebellar-like forward model. The cerebellar-like forward model demonstrated to be fundamental for filtering the effect of sensor noise and sensory feedback delay.

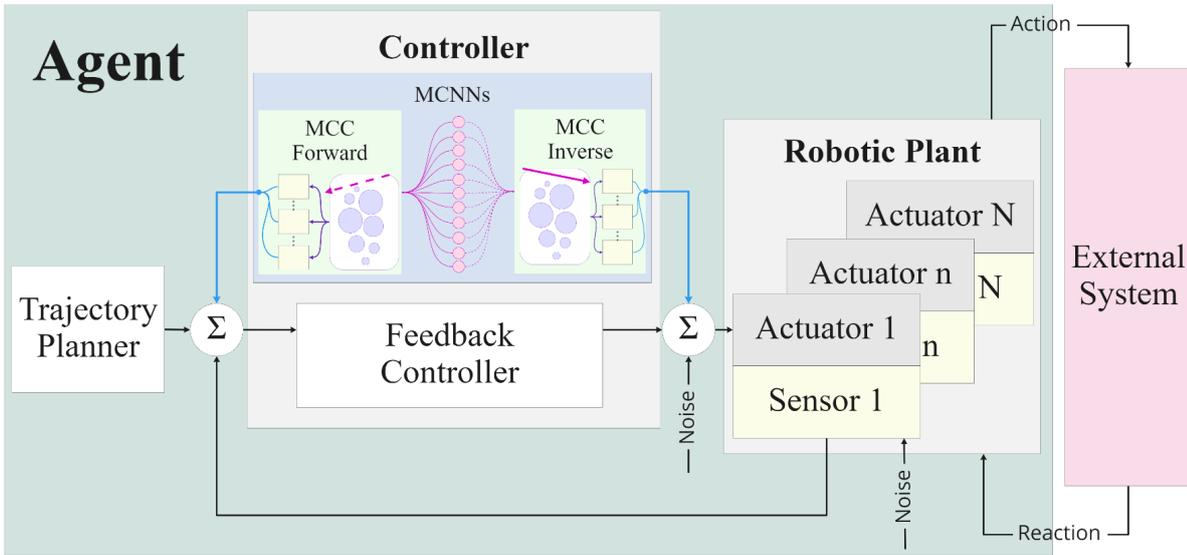


Figure II.3.7. Proposed tandem cerebellar-like control architecture including the cerebellar-like simulations model scheme. – Reproduce from [34] (Appendix C)

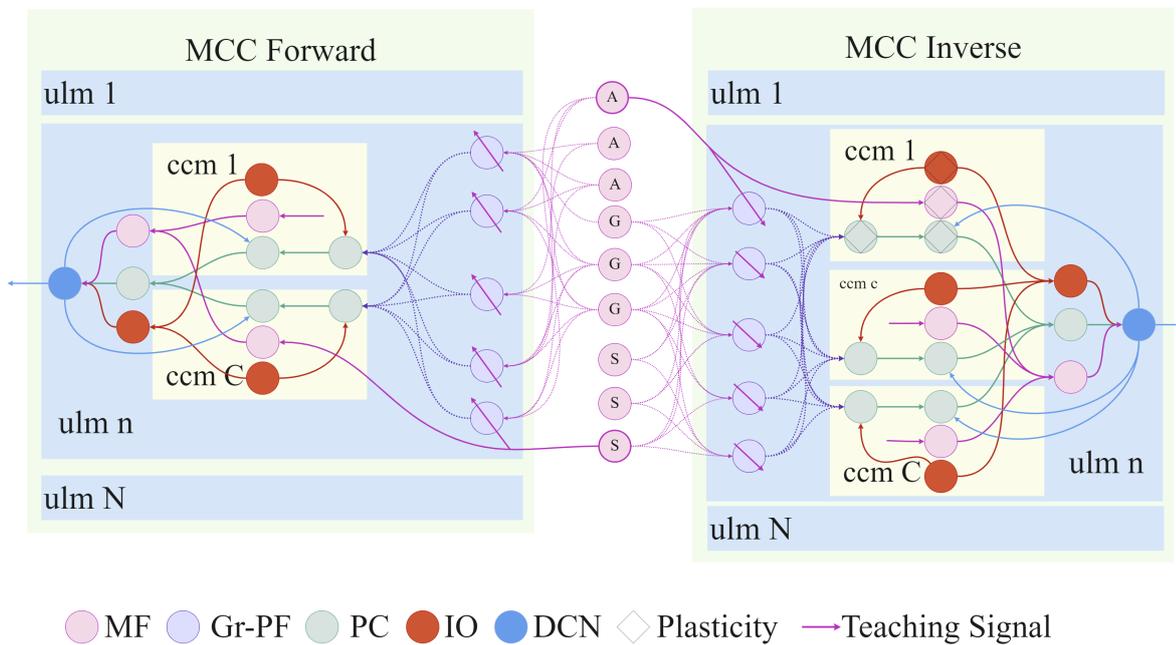


Figure II.3.8. Close-up on the connections between forward and inverse internal models in the tandem control scheme. In magenta, the mossy fibers are grouped depending on the inputs' space, i.e. **A** action space, **G** goal space, and **S** state space. In the proposed connection scheme, the granular layer of the inverse model learns the same **A** action that is sent as input to the forward model's granular layer. On the other hand, the Forward model maps the **S** state that is inputted to the Inverse model's learner. – Reproduce from [34] (Appendix C)

The last robotic architecture merges the feed-forward and recurrent cerebellar-like schemes into one. The combinations of the inverse and forward internal models' contributions incredibly outperform their independent actions leading to a fast and robust adaptive system. In Figure II.3.7, one interesting output of the internal model combination into the control scheme is the indirect connection between the two models. In the proposed experiments (Appendix C), inverse and forward models share part of their MF input signals and the granular layer maps the reciprocal input signals that are not shared (Figure II.3.8). In other words, the granular layer of the inverse model maps the $\tau_n^{tot} \in \mathbb{A}_n$ total torque command sent to the n -th actuator given the sensed states and the goal states (Equation (II.3.10)),

$$\mathbb{S} \times \mathbb{G} \rightarrow \mathbb{A}_n, \quad (\text{II.3.22})$$

the forward model employs this information to map the \dot{q}_n sensed state (Equation (II.3.16)), which is employed by the inverse transformation,

$$\mathbb{A} \times \mathbb{G} \rightarrow \mathbb{S}_n. \quad (\text{II.3.23})$$

One of the biggest challenges for the cerebellar-like control is to understand how the acquired knowledge is generalized and applied to different motor dynamics. At the current state, the proposed robotic control architectures do not include a solution for the generalization of the control problem. The generalization of the learning in the cerebellum is a complex topic which is still under debate and we are motivated to discuss further in future research.

As discussed in Chapter II.1, we believe that generalization cannot be reached if the cerebellar-like system is treated as a stand alone entity. The incredible functionality of

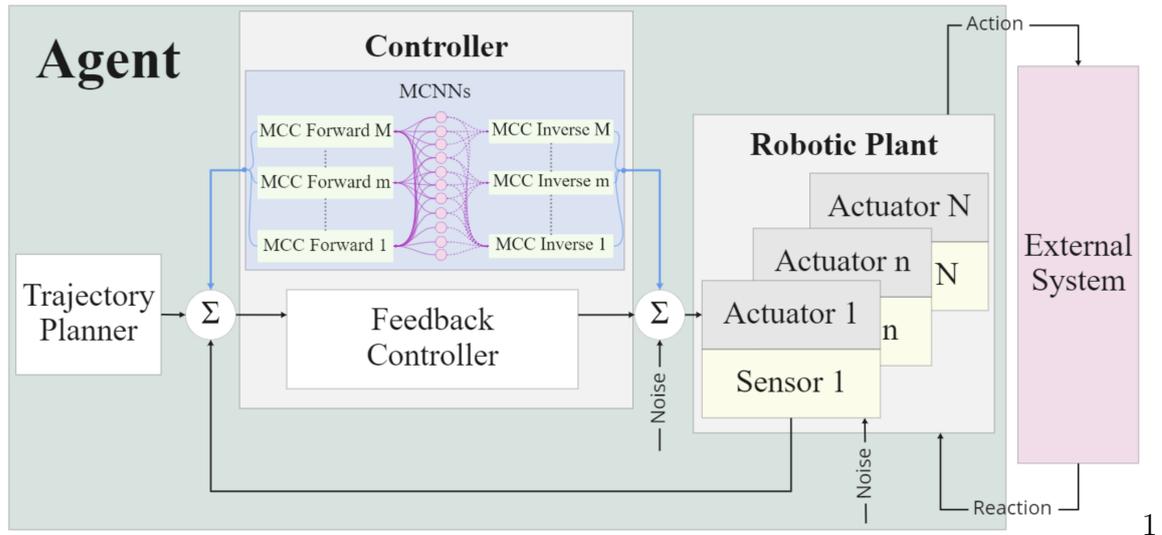


Figure II.3.9. Proposed modular cerebellar-like control architecture. At the current state, no assumptions are made about how different inverse and forward internal models are combined and/or selected. In our solution, both the inverse and forward internal models correct the static control system. [34] (Appendix C)

the cerebellum is meaningful when included in the big structure of the central nervous system (CNS), where each neural area has a pivotal independent and interdependent role.

The tandem internal models architecture has been tested only for one pair of forward-inverse internal models. In our study, we did not attempt to replicate the high-level system modularity proposed by Haruno and colleagues with the MOSAIC and HMOSAIC architectures [13,190] or by Maheri and colleagues with the Modular-RDC controller [14]. We agree that there should be a neural mechanism that triggers one cerebellar region over another, for instance a basal ganglia-like circuit. At the current state, our solution needs further investigation to reach that level of structural complexity.

Moreover, with respect to the modular architectures in the literature where only the inverse model contributes to the controller (Figures I.2.15 and I.2.16), our modular solution proposes to employ both inverse and forward models corrections into the control loop (blue arrows in Figure II.3.9). At the current state, we can not make assumptions about how different forward or inverse internal models are selected and/or combined (e.g. through the mediation of *Responsibility factors*). We believe that an answer could be found in the Pavlovian conditioning mechanism, in particular to the processes happening at the MF-DCN-PC level.

Our solution efficiently works for the low-level motor control of movement. We assume that similar mechanisms can be applied for high-level motor functions, and it would be interesting to investigate how the cerebellum employs different types of signals, including exteroceptive information.

Summary and Conclusions

Introduction

OUR project aims to find a control solution for endowing complex robotics systems with adaptive and predictive capabilities when interacting in unknown and disturbed environments. We believe that such level of flexibility can be found only in brain-based organisms. Thus, we investigated how the vertebrate's central nervous system (CNS) controls the body to produce complex motor behavior in unknown and changing scenarios. We combined all the findings in a hierarchical and functional architecture to describe how different CNS neural areas are involved in the control of voluntary movements (Chapter II.1). We discovered that among all the CNS regions, the cerebellum plays a crucial role in adaptive and predicting motor control. Thus, we focused our study on understanding how the cerebellum operates and why (Chapter I.1). We investigated how scientists attempts to model and simulate the cerebellar circuit (Chapter I.3) and its function in adaptive motor learning and control (Chapter I.2). We proposed a cerebellar-like simulations model (Chapter II.2) and distinct cerebellar-like control schemes (Chapter II.3) that could artificially replicate the incredible functionality of the cerebellum.

Summary of Findings

In this thesis, we presented several contributions regarding cerebellar-like adaptive and predictive control for robotic systems. In summary,

- we propose the general design of a hierarchical functional control architecture for the adaptive control of robotic motor behavior. The implementation of the architecture started from the cerebellum module. We believe that the generalization of the learning can be achieved only once the complete architecture is implemented due to the dependency and independence that characterize each CNS region involved in the control o voluntary movements.

- The proposed cerebellar-like simulations model merges computational neuroscience techniques with artificial intelligence methods to guarantee the adaptive learning mechanisms of the cerebellar circuit and the real-time learning and reactive response required by the considered robotic application. The cerebellar-like model includes four state-of-the-art bio-inspired synaptic plasticity models [10, 37, 235] to endow the circuit with bio-inspired adaptive learning in distinct learning sites: parallel fiber-Purkinje cell, Purkinje cell-deep cerebellar nuclei, inferior olivary nucleus-deep cerebellar nuclei, mossy fiber-deep cerebellar nuclei.
- We determine an approach to design a modular solution for applying cerebellar-like learning to robotic applications. In the design, we assume that it is important to consider the modularity of the circuit on different levels. Thus with respect to the state-of-the-art, we first focused on the design and implementation of a modular cerebellar micro-circuit (Figure II.2.2) to then gradually add complexity (Figure II.2.1).
- Concerning previous attempts, the micro-level modularity of the cerebellar circuit results in a more consistent sensorimotor mapping of the dynamics of the robotic-environment systems [259].
- The modular and stratified organization of the proposed cerebellar-like learning model results in an efficient tool for weakening any over-reactive behavior due to high prediction error at the granular-parallel fiber level and in filtering the sensory noise.
- We introduce a cerebellar-like feed-forward control scheme for the low-level control of robot behavior in real-time. The scheme merges different state-of-the-art theories [3] and cerebellar-like control models [4, 7, 8] into one that could satisfy the requirements stated in Section II.3.3. The feed-forward control scheme robustly rejects the dynamical disturbances affecting the robotic system and promptly corrects the performance errors.
- We validated the cerebellar-like recurrent control architecture proposed by Porrill and colleagues [4] on the low-level control of robotic motor movements in real-time. In this configuration, the proposed forward internal model adds an extra internal feedback loop that efficiently contrasts the effect of noise signals and sensory delays.
- We propose a robotic control architecture including both inverse and forward internal models which is based on the tandem internal model theory proposed by Honda and colleagues [12]. Concerning the state-of-the-art cerebellar-like schemes, the tandem architecture demonstrated that the internal models are not only paired but also interdependent. In the empirical experiments, the paired forward and inverse internal models show to influence their respective learning and share part of the signals they process. Moreover, their coupling combines and outperforms their independent potential.

Future Perspectives

The project has contributed to the state-of-the-art of bio-inspired robotic control with several new engineering solutions and has revealed plenty of future opportunities that need to be investigated,

- the cerebellar-like simulations model misses a mechanism to reproduce the effects of conditioned and unconditioned responses. We believe that this mechanism is needed to activate the learning of the LWPR only when specific conditions are met and to integrate the system into a more complex structure where multiple motor behaviors are learned (as in [13]).
- The LWPR is an incredible tool for mapping nonlinear systems in real-time. However, it lacks stability and can easily diverge when the prediction error is high. This can lead to over-reactive and unwanted behavior in robotic control. The proposed cerebellar-like simulations model greatly damped such unstable response, but we believe that different learning mechanisms should be investigated in the future.
- At the current state, the cerebellar-like model has been tested only for low-level motor control of multi-degrees-of-freedom robotic systems. It would be interesting to investigate how the system processes higher level information, e.g. contextual information, sequence of actions.
- In the experiments, we considered only proprioceptive sensory information from the sensors of the robot. We wonder how the cerebellum learns and employs exteroceptive information, for instance, visual information from the robot camera. In particular, does and how the cerebellar-like model elaborate information regarding the robotic end-effector and/or an external object?
- At the current state, the model can not generalize over motor behaviors that are far from the learned ones. Generalization is a topic widely discussed in the field, we believe that the key to cerebellar generalization is in its structural modularity. Thus, the investigation should focus on two research lines: one concerned with the implementation of a learning algorithm that can amplify the range of sensorimotor mapping; and one examining the role of modularity in the generalization of the learning.
- The tandem internal models architecture has been tested only for a pair of forward-inverse internal models. We wonder if the cerebellum employs different combination of coupled inverse and forward internal models and how these pairs are selected and combined.
- The hyperparameters of the cerebellar synaptic weights are static. It would be interesting to investigate an optimization algorithm that could update these parameters during the learning. The optimization would both support the general-

ization of the learning, reduce the learning speed, and increment the cerebellar adaptation.

Conclusion

In this thesis, we proposed a robotic control architecture that takes inspiration from the vertebrates' central nervous system (CNS) to endow robots with adaptive motor behavior while interacting with an unknown external system. Bio-inspired control is an incredibly interesting and promising field. Although, it encloses several challenges due to the lack of validated assumptions from neuroscientific and biological studies, we believe that it is a valuable approach for endowing robotic systems with autonomous and adaptive skills.

In our study, we explored the extraordinary potentialities of the cerebellum, an incredibly small and compact neural structure full of crucial expertise. There are plenty of theories regarding how the cerebellum works and the cerebellar involvement in motor and cognitive functions, and we tested many of these theories before reaching the current solutions.

In our cerebellar-like simulations model design, we give extra focus to the structural modularity of the neural networks to replicate the regular and modular partition of the cerebellum at different levels. This approach opens to interesting discussions regarding the role of modularity in the mapping of complex motor behavior. The empirical results proved that the approach is a robust solution for real-time incremental motor learning in disturbed conditions.

The proposed control schemes tested and validated distinct theories regarding cerebellar involvement in low-level motor control. The empirical results demonstrated the incredible role of the cerebellum in motor adaptation and state prediction, especially in disturbed and noisy conditions.

Each cerebellar-like internal model demonstrates to play a specific role at different phases during the adaptation period, and their combinatorial action merges these potentials into a complete and robust adaptive control action.

It has been astonishing to see how robots could learn and improve their performance even with simplified models of the cerebellar neural circuits.

We sustain that robotics can learn a lot from neuroscience to design novel learning and control solutions that can almost effortlessly adapt to any unstructured circumstances and we foresee a promising future for bio-inspired robotic systems.

Appendices

APPENDIX **A**

Distributed and Modular Bio-Inspired Architecture for Adaptive Motor Learning and Control

Distributed and Modular Bio-Inspired Architecture for Adaptive Motor Learning and Control

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Recent studies have demonstrated that autonomous robots can outperform the task they are programmed for, but are limited in their ability to adapt to unexpected situations [262]. This limitation is due to the lack of generalization, i.e., the robot can not transfer knowledge across multiple situations. Even the application of modern artificial intelligence (AI) techniques does not support a robust generalization when the range of probable inputs is infinite [263–266]. As a matter of fact, AI methods can interpolate knowledge but not extrapolate it, i.e., they can adapt on new, unseen data that are within the bounds of their experience, but not on data that are outside the bounds. So far, robots have been mostly treated as stand-alone systems in a vacuum, while the real world is more complex and includes continuous interaction with external entities. Accordingly, the design of a generalized robotic controller is not trivial, in particular when the dynamical condition are unknown.

From the observation of nature, it is possible to deduct the level of competence that animals have when interacting with the environment. The study and understanding of the central nervous system (CNS), which is the main responsible of the body complex movements [267] during the interaction with the environment [268], may give new insights about the artificial replication of the animals' interactive and adaptive behaviour. As a matter of fact, the CNS is constituted by different regions which role, relation and distribution are important for the optimal execution of complex tasks (see [29] for a review).

This investigation has its foundation in the Human Brain Project (HBP) [269], which is trying to achieve a more clear understanding of the brain's capabilities. Here, we propose the initial design of a distributed and modular bio-inspired control architecture that aims to artificially replicate the CNS areas involved in planning and executing voluntary movements (Fig.A.1).

The distribution of the architecture is based on the "*divide and conquer*" concept, where the whole system is decomposed into separated and specialized components. The modularity refers to the independence of each component and its interdependence to the other structures of the architecture. The malfunctioning of each module only affects its contribution to the system and not to the operating state of the other modules. The design of the architecture is specific for gross motor skills involved in the coordination of a robotic arm during the interaction with an external system, such as dynamical target reaching and object manipulation. The control system will be tested mainly on virtual robots in the physical simulation environment offered by the Neurorobotics Platform (NRP) [270]. The NRP not only includes a variety of robot and environments, but also a detailed physics simulator. The architecture follows the guidelines from different studies [26, 29–33] and includes CNS regions such as the brain stem (action regulation), the cerebellum (motor adaptation), the spinal cord (motor pattern generation), the basal ganglia (action selection), and the motor cortex (Initiation, planning, procedure of motion). The CNS areas will be modelled combining classical control and robotics methods together with bio-inspired AI techniques.

This study does not only aim to artificially mimic the connectivity and functionality of the CNS (as seen in previous studies [271–273]), but to also analyze, with practical evidence, how different brain regions map context-sensitive motor skills as proposed by Wolpert and Kawato [189]. This is because we believe that the modularity of each brain region is fundamental for the extrapolation of valuable information from heterogeneous dynamical stimuli. This extrapolation could facilitate the motor prediction and adaptation in changing or unknown conditions.

Among these CNS regions, it is well known the pivotal role of the cerebellum in motor learning and adaptation [274–277]. Several robots have been already endowed with cerebellar-like control architectures with promising results [5, 8, 217, 261, 278]. However, these studies mostly focused on the functionality of a specific CNS region, keeping the contribution and dependency with other brain structures neglectable. Moreover, the experiments were run in simplified conditions with marginal dynamics, absent interaction with the environment, and relative goal, i.e., goal not related to an external reference or exteroceptive sensors.

Our investigation will firstly focus on the cerebellum. The way the cerebellum maps and processes the sensory information in relation to the execution of complex dynamical tasks is not totally clear. We assume that an answer could be found in the regular and modular structure of the cerebellum, where distinct functional units can be observed [279]. In 2006, Ito claimed that in each unit a forward or an inverse internal model is captured for representing the relation between action and outcome [137]. In addition to Ito's internal models theory, there is also evidence that the human cerebellum can be modelled by a combination of both inverse and forward internal models [189].

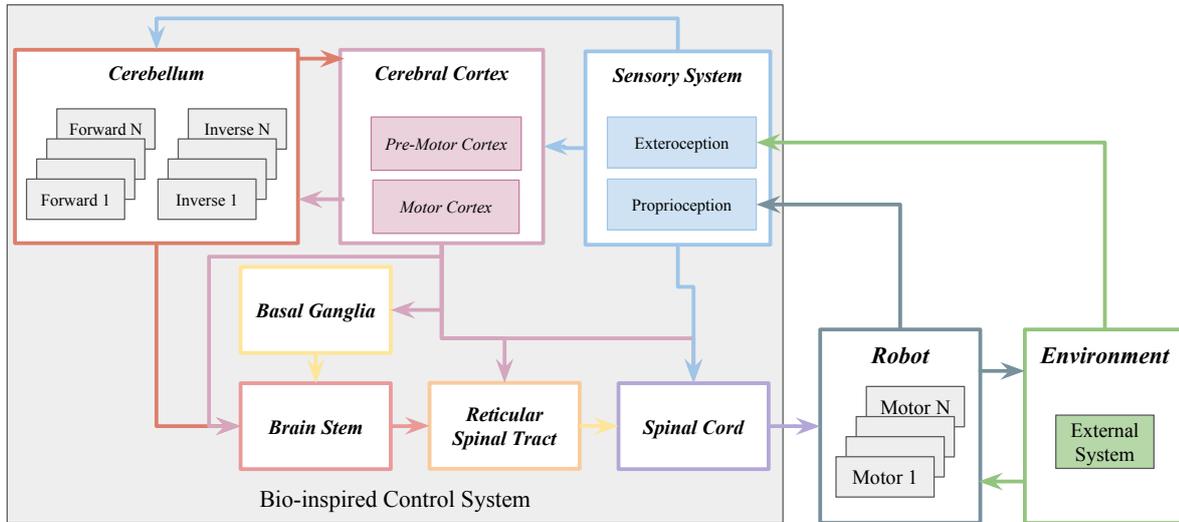


Figure A.1. The proposed bio-inspired architecture aims to solve the problem of robotic agent (in grey) adaptation during the interaction with an external system (in green). The system is modelled to control the coordination of a robotic arm during dynamical target reaching and object manipulation. The illustration shows only the high-level connections and distribution. Each building block will contain bio-inspired structures and classic control theory algorithms. The main idea, respect to the literature, is to focus on how the CNS regions internally specialize and map heterogeneous motor skills.

Nonetheless, this mixed model has not widely been used in robotic control in particular when the characteristics of the robot and/or the environment change. The secondary aspect to be investigated is the reciprocal interaction between the cerebellum and other CNS areas [26]. The cerebellum will be integrated in the distributed architecture shown in Fig.A.1.

Starting from the theory that the cerebellum is decoupled into sub-units, we are going to analyze how the specialization of each unit and their cooperation influences the mapping of heterogeneous dynamical information onto motor skills. From this analysis, we expect to comprehend how the malfunctioning of a specific unit can influence the final corrective action of the cerebellum. At the same time, this could help to understand which feature is not mapped correctly inside the internal model and consequentially correct this lack. Thereafter, from a macro-level perspective, we will investigate how the learned experience is exchanged and utilized across different CNS regions for planning and executing context-related motor commands. This study could give new guidelines for modelling a more robust and distributed robotic control architecture. As matter of fact, the CNS demonstrated that the malfunctioning of one system component does not preclude the operating state of the whole architecture, which is a beneficial aspect for modern autonomous robot. On the other hand, the application of neuro-scientific assumptions on practical experiments could give a feedback and open new lines of research.

To conclude, the outcome of the present investigation will provide the state-of-the-

art for more complex bio-inspired control architectures for neuro-robots that learn from experiences under varying dynamical conditions.

Acknowledgments

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APPENDIX B

A Biomimetic Control Method Increases the Adaptability of a Humanoid Robot Acting in a Dynamic Environment

A Biomimetic Control Method Increases the Adaptability of a Humanoid Robot Acting in a Dynamic Environment

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abstract

One of the big challenges in robotics is to endow agents with autonomous and adaptive capabilities. With this purpose, we embedded a cerebellum-based control system into a humanoid robot that becomes capable of handling dynamical external and internal complexity. The cerebellum is the area of the brain that coordinates and predicts the body movements throughout the body-environment interactions. Different biologically plausible cerebellar models are available in literature and have been employed for motor learning and control of simplified objects. We built the canonical cerebellar microcircuit by combining machine learning and computational neuroscience techniques. The control system is composed of the adaptive cerebellar module and a classic control method; their combination allows a fast adaptive learning and robust control of the robotic movements when external disturbances appear. The control structure is built offline, but the dynamic parameters are learned during an online-phase training. The aforementioned adaptive control system has been tested in the Neuro-robotics Platform with the virtual humanoid robot iCub. In the experiment, the robot iCub has to balance with the hand

a table with a ball running on it. In contrast with previous attempts of solving this task, the proposed neural controller resulted able to quickly adapt when the internal and external conditions change. Our bio-inspired and flexible control architecture can be applied to different robotic configurations without an excessive tuning of the parameters or customization. The cerebellum-based control system is indeed able to deal with changing dynamics and interactions with the environment. Important insights regarding the relationship between the bio-inspired control system functioning and the complexity of the task to be performed are obtained.

B.1 Introduction

Controlling a robotic system that operates in an uncertain environment can be a difficult task if the analytical model of the system is not accurate. Models are the most essential tools in robotic control [280], however, modeling errors are frequently inevitable in complex robots, for instance humanoids and soft robots. Such redundant modern robots are mechanically complex and often interacts with unstructured dynamical environments [171, 281]. Traditional hand-crafted models and standard physics-based modeling techniques do not sufficiently take into account all the unknown nonlinearities and complexities that these system present. This lack consequentially leads to a reduced tracking accuracy or, in the worst case, to unstable null-space behavior.

Modern autonomous and cognitive robots are requested to adapt not only the decisions but also the forces exerted in any varying condition and environment. The selected movement can not be executed properly if the robot does not adjust the forces according to the changing dynamics. Because of this, modern learning control methods should automatically generate model based on sensor data streams, so that the robot is not a closed entity, but a system that interacts and evolves through the interaction with a dynamic environment.

In this paper, we intend to design an adaptive learning algorithm to control the movements of a complex nonlinear dynamical system. In particular, we assume that: the Jacobian poorly describes the actual system; the robot interacts with one or more unmodeled external objects; the sensor-actuator system is distributed and not all the states are observable or can be describe with parametric function designed off-line; the action/state space is continuous and high-dimensional. The control system should solve the inverse dynamics control problem of a multiple-joint robotic system affected by static and dynamic external disturbances during the execution of a repeated task. The controller is envisioned to reduce the tracking accuracy of each actuator through force-based control input.

In early days of adaptive self-tuning control, models were learned by fitting open parameters of predefined parametric models [41, 282–284]. Although this method had great success in system identification and adaptive control techniques [285], the estimation of the open parameters can lead to several problems, such as: slow adaptation; unmodeled behaviour and persistent excitation issue [42]; inconsistency of the estimated

physical parameters [43]; unstable reaction to high estimation error. In recent years, non-parametric approach has been shown to be an efficient tool in the resolution and prevention of the aforementioned problems thanks to the adaptation of the model to the data complexity [45], and several methods have been proposed [46], such as neural networks [47], and statistical methods [48, 49, 286].

In the eighties, Narendra's research group at Yale University exploited the adaptability of artificial neural networks (ANNs) to identify and control nonlinear dynamical systems [50, 287–289]. Their experiments showed that the versatility of the ANNs resulted beneficial for controlling the different behaviors that characterize complex dynamical systems. Although the robustness of the classic parametric method in most of the control scenarios, ANNs were largely used in adaptive control to overcome uncertainties, unmodeled nonlinearities and to handle more complex state space systems [47, 51–53, 290, 291]. As matter of fact, the non-linear components and the layered structure that distinguish the ANNs facilitate the mapping and constrain the effects of nonlinearities. Furthermore, the on-line adjustment of the parameters respect to the input-output relationship without any strict structural parameterization results advantageous for adapting to time-dependent changes.

In the Nighties thanks to the extended application of ANNs in robotics, Juyang Weng introduced the Autonomous Mental Development approach (AMD) to artificial intelligence [54, 292]. Weng theories were mainly inspired by how the biological systems efficiently calibrate their movements under internal and environmental changes. Accordingly to AMD the robot have to be embodied in the environment, and its processing is not preprogrammed but is the result of the continuous and real-time interaction within the two systems [293–295]. Respect to classic parametric approaches, the developing artificial agent creates and adapts models describing itself and its relation with the environment rather than learning and estimating parameters of a mathematical model built off-line. These theories found large application for high level cognition tasks (see [55] for a review) but were also applied to low level control in visually-guided robots [56, 57, 296].

With the aim of mimicking artificially the motor efficiency of the biological system, James S. Albus proposed a neural network-based learning algorithm for robotic controller based on theories of central nervous system (CNS) structure and function: the "cerebellar model articulation controller", commonly known as CMAC module [297]. Several studies in literature demonstrated that, the anatomy and physiology of the cerebellum is suitable for the acquisition, development, storage and use of the internal models describing the interaction within body and environment [87]. Moreover, the cerebellum is composed by separated regions which functionality relies both on the internal structure of the circuit and on the connection with other CNS areas [26, 29]: each region receives both the desired movements from the cortex and the sensory information from tendons, joints and muscles spindles and elaborates a signal that corrects whereas other CNS region are lacking. As matter of fact, subjects affected by cerebellum damage often present motor deficit, such as uncoordinated and ballistic multiple-joint movements [245]. For this reason in the last decades, scientists tried to explain the roles of the cerebellum in motor control, especially its contribution to sensory acquisition and timing and its involvement in the prediction of the sensory consequences of action. Moreover, this adaptive control

nature motivated several researchers towards a deeper understanding of the cerebellum for robotics application.

Two main research lines born since Marr and Albus proposed the first artificial cerebellum-like network as pattern-classifier for controlling a robotic manipulator [95, 297]: the first research line focuses on purely industrial application and has as major representative W. Thomas Miller; the second research line, mainly represented by Mitsuo Kawato, deep-rooted in neuroscience and kept investigating on the biological evidence of the cerebellum structure and functionalities in relation to other CNS areas [7, 86].

Miller applied the CMAC module in a closed loop vision-based controller to solve the forward mapping with direct modelling [298]. Although the advantages, such as the rapid algorithmic computation based on least-mean-square training and the fast incremental learning, this approach lack of generalization and is sensitive to noise and large error [6]. Over the years, researchers have been focusing on solving these drawbacks and the CMAC module has been mostly used as non-linear function approximator to boost the tracking accuracy of the adaptive controller and mitigate the effects of the approximation errors [209–212]. Although the promising results obtained by these applications of the CMAC network, this industrial research line did not completely exploit the overall capabilities and components of the cerebellum. It is worthy to note that the CMAC module mimic the cerebellar circuit only at the granular-purkinje level, for this reason only the mapping and classification functionalities are exploited.

The neuroscientific research line has been investigating mainly on the layered structure of the cerebellar circuit proposing several synaptic plasticity models [23, 37, 233, 244, 299, 300], network models [16, 101, 136, 227, 301, 302], adaptive linear filter model [18, 135, 303], and combination of both [255, 258]. These cerebellar-like models were embedded into bio-inspired control architectures to analyze how the cerebellum adjusts the output of the descending motor system of the brain during the generation of movements [7, 274], and how it predicts the action, minimizes the sensory discrepancy and cancels the noise [208, 304]. The experiments regarded the generation of voluntary movements with both simulated and real robots, e.g. eye blinking classical conditioning [233], vestibulo-ocular task [232], the gaze stabilization [305], and perturbed arm reaching task operating in closed-loop [10, 23, 254, 258]. From the analysis of the literature, it then emerged that research groups have treated the robots as stand-alone systems without interactions with the environment, while the real world is more complex and every external interaction counts. It is worth mentioning that the previous works have been employed for motor learning and control of simplified objects.

In this paper we present a robotic control architecture to overcome modeling error and to constrain the effects of uncertainties and external disturbances. The proposed controller is composed of a static component based on a classic feedback control methods, and of an adaptive decentralized neural network that mimic the functionality and morphology of the cerebellar circuit. The cerebellar-like module add feed-forward corrective torque to the feedback controller action [9, 94]. A non-parametric nonlinear function approximation algorithm have been employed to map on-line and to reduce the high dimensional and redundant input space. The algorithm creates the internal model describing the interaction within system and environment. This model is kept

under development throughout the execution of the task. The neural network mimic the composition of the cerebellar microcircuit. The layered structure of the network constrains the effects of nonlinearities and external perturbations. The network weights are based on non-linear and multidimensional learning rules that mimic the cerebellar synaptic plasticities [10, 37].

This manuscript extends the previous works under three main aspects: 1. cerebellar-like network topology and input data; 2. feedback control-input; 3. dynamic control under external changing conditions. With the aim at giving more insights into the capacity of the cerebellum of generating control terms in the framework of accurate control tasks, the following research questions come naturally to mind: can a control system be generalized to control robotic agents by endowing them with adaptive capabilities? Can accurate and smooth actions in a dynamic environment be performed by the extrapolation of valuable sensory-motor information from heterogeneous dynamical stimuli? Does this sensory-motor information extrapolation facilitate the motor prediction and adaptation in changing conditions? The tests were carried out in the Neuro-robotics Platform [270] with the virtual humanoid robot iCub. The robot arm has to follow a planned movement overcoming the disturbances provoked by a table attached to the hand and a ball running on it. A similar example was solved by employing a conventional control law together with computer vision techniques [306, 307]. However, this approach assumes a fixed robot morphology defined and described before running the experiment, and there is no run-time adaptation to the “biological changes” as we see in human beings. Balancing a table with a ball running on it is a relevant example of how humans learn to calibrate, coordinate and adapt their movements, hence, we investigate how robots can achieve this task following the biological approach. [308] also followed the biological approach; they tackled the problem taking into account the dynamics of the system, four different forces are found by means of a liquid state machine and applied in four different points of the table to achieve the balancing task. A supervised learning rule is used for the training step, which concludes that after 2500 seconds no further improvement of the performance is obtained.

Hence, the main advantages of our model are: the low amount of (sometimes implausible) prior information for the control, a fast reactive robotic control system, an on-line self-adaptive learning system. Thanks to these features the robot can perform a determinate physical task and adapt to changing conditions. In conclusion, this approach introduces a fast and flexible control architecture that can be applied to different robotic platforms without any/excessive customization.

In the first section that follows, we present the control architecture, the adopted cerebellar-like model and the description of the method. In the second section, we report the experimental setup as well as the results of the comparison study of four control system approaches including the respective analysis. Finally, we will discuss the main findings of the study correlating them to previous literature.

B.2 Material and methods

In this section, we present our bio-inspired approach to solve the problem of controlling the right arm of the ICub humanoid robot despite the occurrence of an external perturbation. The experiment consists of a simulated humanoid robot that executes a requested movement using three controlled joints of the right arm. During the simulation, a ball is launched on the table that is attached to the robot's right hand; the ball is free to roll on the table, as illustrated in Figure B.1(b). The movements of the ball are provoked by the shaking of the robot arm and consequentially of the table. The key information about the external system components (e.g. the ball and table) are reported in Table B.1.

The proposed control architecture (Figure B.1(a)) is composed of three main building blocks: the *robotic plant*, which is the physical structure (Section B.2.1); the *motor primitive generator*, which is responsible of the trajectory generation (Section B.2.2); the *controller*, which elaborates the torque commands to move each motor to the desired set point (Section B.2.3).

	Mass [Kg]	Volume [m ³]	Static friction coefficient	Dynamic friction coefficient
Ball	0.01	6.54×10^{-5}	0.02	0.01
Table top	0.1	9×10^{-4}	0.01	0.01

Table B.1. External system features.

B.2.1 Robotic Plant

The ICub humanoid robot is 104cm tall and it is equipped with a large variety of sensors (such as gyroscopes, accelerometers, F/T sensors, encoders, two digital cameras) and 53 actuated joints that move the waist, head, eyes, legs, arms, and hands. During the experimental tests, eight revolute joints of the right arm were actuated: four joints were kept constant to maintain the arm up (e.g. elbow, shoulder roll, shoulder yaw and shoulder pitch), and three joints were controlled in effort by the proposed control system (namely wrist prosup, wrist yaw and wrist pitch). The axis orientation of the controlled actuators are illustrated in Figure B.1(c). Additional information about the actuated joints are reported in Table B.2. In this work, we used the encoder to only read the state of the controlled joints (e.g. angular position and velocity) and save it in the process variables,

$$\mathbf{Q}_{N \times 1}^c(t) = \begin{bmatrix} \vartheta_{c,0}(t) \\ \dots \\ \vartheta_{c,N}(t) \end{bmatrix} \quad \text{where } N = 2, \quad (\text{B.1})$$

$$\dot{\mathbf{Q}}_{N \times 1}^c(t) = \begin{bmatrix} \dot{\vartheta}_{c,0}(t) \\ \dots \\ \dot{\vartheta}_{c,N}(t) \end{bmatrix} \quad \text{where } N = 2, \quad (\text{B.2})$$

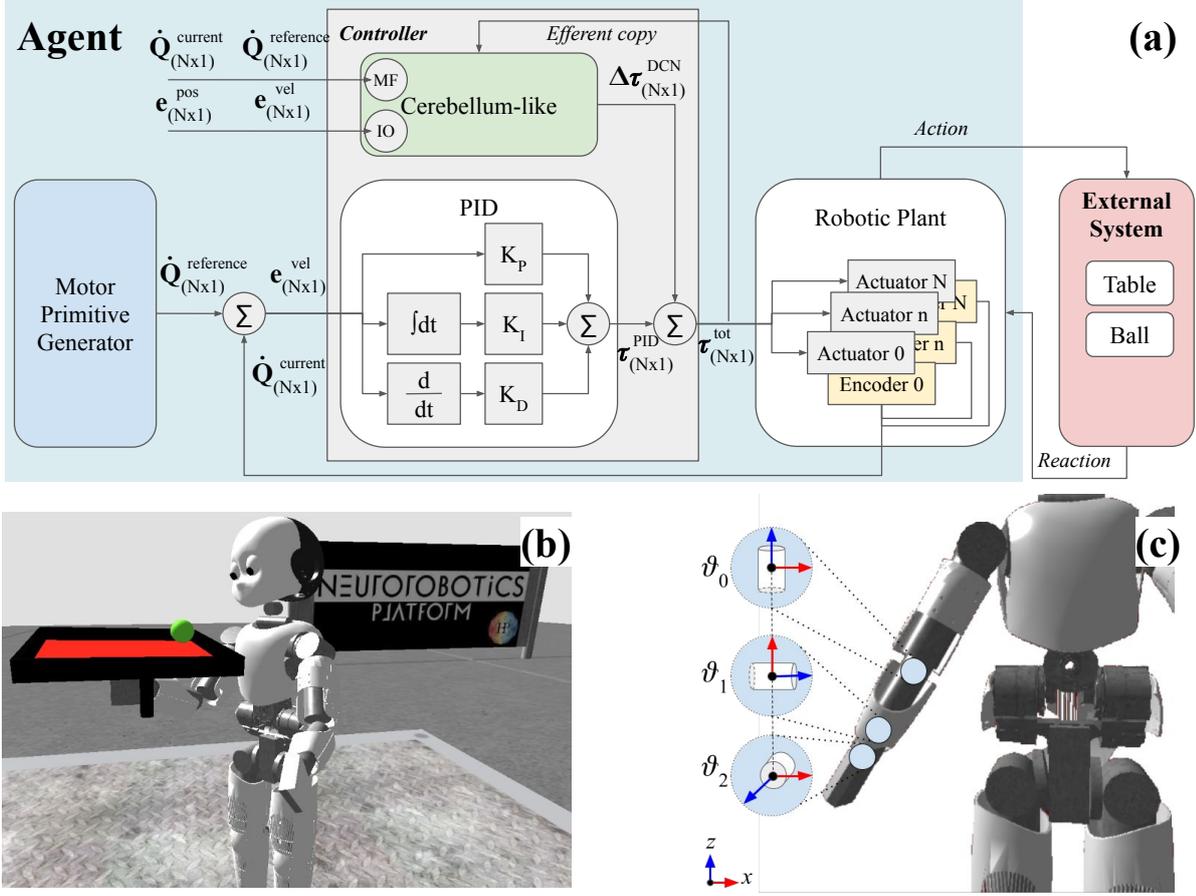


Figure B.1. (a) The figure illustrates the main components of the functional architecture scheme and the link with the artificial robot agent and the external system. (b) The humanoid Icub holding the table-ball system in the simulation environment NRP. (c) Three controlled joints: wrist propup ϑ_0 , wrist yaw ϑ_1 , wrist pitch ϑ_2 .

B.2.2 Motor Primitive Generator

The motor primitive generator plans the trajectory for each actuated joint and communicates the reference value to the control system at each time step. The reference angular position and velocity of each joint are defined as oscillators with fixed amplitude, natural frequency and phase,

$$\mathbf{Q}_{N \times 1}^r(t) = \begin{bmatrix} \vartheta_{r,0}(t) \\ \dots \\ \vartheta_{r,N}(t) \end{bmatrix} = \begin{bmatrix} A_0 \cdot \sin(2\pi ft + \varphi_0) \\ \dots \\ A_N \cdot \sin(2\pi ft + \varphi_N) \end{bmatrix}, \quad (\text{B.3})$$

$$\dot{\mathbf{Q}}_{N \times 1}^r(t) = \begin{bmatrix} \dot{\vartheta}_{r,0}(t) \\ \dots \\ \dot{\vartheta}_{r,N}(t) \end{bmatrix} = \begin{bmatrix} 2\pi f A_0 \cdot \cos(2\pi ft + \varphi_0) \\ \dots \\ 2\pi f A_N \cdot \cos(2\pi ft + \varphi_N) \end{bmatrix}, \quad (\text{B.4})$$

	Min ϑ [rad]	Max ϑ [rad]	Max $\dot{\vartheta}$ [rad · sec ⁻¹]	Control	Value
wrist prosup $n = 0$	-0.8726	0.8726	100	effort	controlled variable
wrist yaw $n = 1$	-0.4363	0.4363	100	effort	controlled variable
wrist pitch $n = 2$	-1.1344	0.1745	100	effort	controlled variable
elbow	0.0959	1.8500	100	position	constant = 1.14 [rad]
shoulder roll	0.0000	2.80649	100	position	constant = 0.1 [rad]
shoulder yaw	-0.645772	1.74533	100	position	constant = -0.1 [rad]
shoulder pitch	-1.65806	0.0872665	100	position	constant = -0.9 [rad]

Table B.2. Actuated joints information: the wrist actuators (highlighted in yellow) are controlled in effort while the elbow and shoulder motors are kept to a constant angular position.

where $N = 2$. The temporal frequency is $f = 0.25\text{Hz}$, while the oscillations \mathbf{A} amplitude and φ phase of each joint are set to:

$$\mathbf{A}_{1 \times N} = [A_0, A_1, A_2] = [0.1727, 0.1363, 0.0345] \text{ rad}$$

$$\varphi_{1 \times N} = [\varphi_0, \varphi_1, \varphi_2] = [0.5\pi, 0.5\pi, 0.0] \text{ rad.}$$

B.2.3 Controller

The *controller* block (Figure B.1(a)) is composed of a static component based on classic control methods (Section B.2.3.1), and of an adaptive decentralized block representing the bio-inspired regulator, i.e. the cerebellar-like circuit (Section B.2.3.2). Both sub-blocks receive information about the $\mathbf{Q}^c, \dot{\mathbf{Q}}^c$ process variables measured from the encoders located in the *robotic plant* (Equations B.1-B.2), and the $\mathbf{Q}^r, \dot{\mathbf{Q}}^r$ reference trajectory signals from the *motor primitive generator* (Equations B.3-B.4). The controller directly sends the τ^{tot} total control input to the robot servo controller which actuates the joints for $\delta t = 0.5\text{sec}$. The τ^{tot} total control input is expressed as the result of a feed-forward compensation (as the AFEL architecture proposed by [255]),

$$\tau_{N \times 1}^{tot} = \begin{bmatrix} \tau_0^{tot} \\ \dots \\ \tau_N^{tot} \end{bmatrix} = \begin{bmatrix} \tau_0^{PID} + \Delta\tau_0^{DCN} \\ \dots \\ \tau_N^{PID} + \Delta\tau_N^{DCN} \end{bmatrix}, \quad (\text{B.5})$$

τ^{tot} where τ_n^{PID} and $\Delta\tau_n^{DCN}$ (where $n = 0, \dots, N$) are the contributions from the static and the adaptive bio-inspired controller respectively.

B.2.3.1 Feedback Controller

The static control system refers to the classic feedback control scheme with PID regulator. It is defined static due to its time-constant control terms. The closed-loop system continuously computes the $\mathbf{e}_{\dot{\vartheta}_n}$ angular velocity error of each joint as the difference

between the $\dot{\vartheta}_{r,n}$ reference (Equation B.4) and the $\dot{\vartheta}_{c,n}$ process variable (Equation B.2),

$$\mathbf{e}_{N \times 1}^{vel} = \begin{bmatrix} e_{\dot{\vartheta}_0} \\ \dots \\ e_{\dot{\vartheta}_N} \end{bmatrix} = \begin{bmatrix} \dot{\vartheta}_{r,0} - \dot{\vartheta}_{c,0} \\ \dots \\ \dot{\vartheta}_{r,N} - \dot{\vartheta}_{c,N} \end{bmatrix}. \quad (\text{B.6})$$

The $\mathbf{e}_{\dot{\vartheta}_n}$ error (where $n = 0, \dots, N$) is used to apply correction to each controlled joint in terms of effort,

$$\boldsymbol{\tau}_{N \times 1}^{PID} = [\tau_0^{PID}, \dots, \tau_N^{PID}]^T, \quad (\text{B.7})$$

according to the independent joint control law expressed as

$$\tau_n^{PID}(t) = K_{P,n} \cdot e_{\dot{\vartheta}_n} + K_{I,n} \cdot \int_{t-\Delta t}^t e_{\dot{\vartheta}_n}(t') dt' + K_{D,n} \cdot \frac{d\dot{\vartheta}_n(t)}{dt} \quad \text{for } n = 0, \dots, N, \quad (\text{B.8})$$

where the integration time window is $\Delta t = 10$ samples. The regulator is tuned to weakly operate in a linearized condition which excludes the presence and disturbance of the ball, hence the proportional, integrative and derivative terms are static and set respectively to,

$$\begin{aligned} \mathbf{K}_P &= [K_{P,0}, K_{P,1}, K_{P,2}] = [2.9000, 2.3000, 2.3500] \\ \mathbf{K}_I &= [K_{I,0}, K_{I,1}, K_{I,2}] = [1.9400, 1.9000, 1.9000] \\ \mathbf{K}_D &= [K_{D,0}, K_{D,1}, K_{D,2}] = [0.0050, 0.0001, 0.0004]. \end{aligned}$$

B.2.3.2 Cerebellar-like Model

The proposed cerebellar-like network has been designed to solve robotic problems (Figure B.2). In particular, the sensory input and the corrective action in output refer to entities regarding the actuated motors, such as motor angular position, velocity or effort. Electrophysiological evidence about the encoding of movement kinematics has been found at all levels of the cerebellum; for example, in this review, [309] reported that the mossy fibers (MF) inputs encode the position, direction, and velocity of limb movements. Moreover, many hypotheses suggest that the cerebellum directly contributes to the motor command required to produce a movement. In our model, the input-output relationship is based on the previous suggestions and the signal propagation throughout the cerebellar network layers is in accordance with the robotic control application. The main design concept is that the signal propagating inside the circuit have the same dimension of the $\Delta\tau^{DCN}$ output signal from the Deep Cerebellar Nuclei (DCN). The propagated signal is modulated inside the network by other signals that are correlated with the intrinsic features of the controlled plant, such as position and velocity terms, in order to have a complete description of the state.

The neural network structure is divided into separated modules (Figure B.2(b)), or namely *Unit Learning Machine* (uml) [255, 258]. Assuming that the robot plant is composed by N controllable object, then each uml is specialized on the n-th controlled

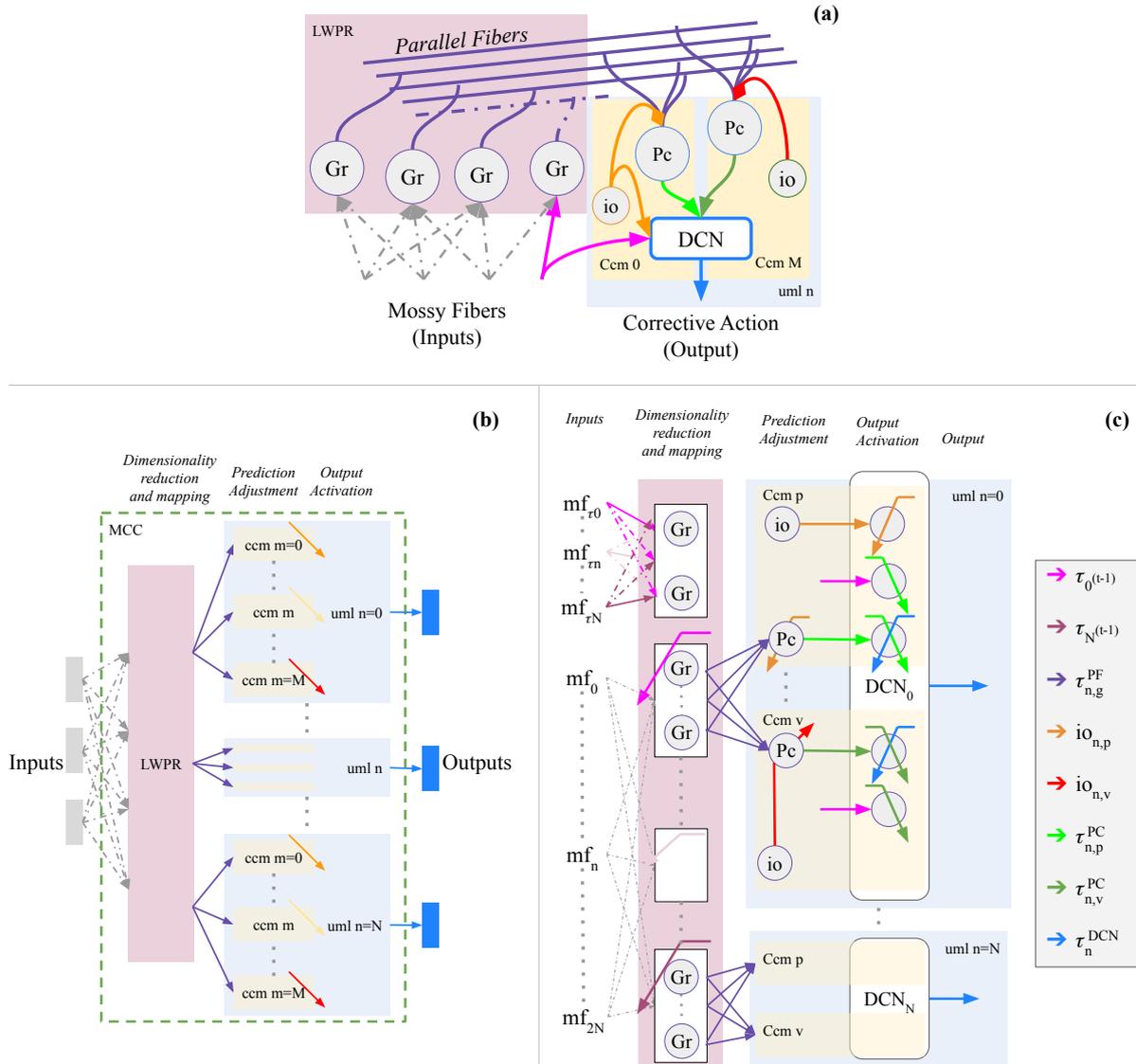


Figure B.2. Proposed cerebellar-like circuit in analogy with [36]. **(a)** canonical micro-circuit. Proposed cerebellar-like neural network **(b)** structural partition and **(c)** details.

object (where $n = 0, \dots, N$), or rather the DCN output of the uml will be the cerebellar contribution for the specific object. The uml itself is separated into M sub-modules which represent the *canonical cerebellar microcircuit* (ccm). Each ccm is specialized with respect to a specific feature describing the behavior of the n -th controlled object. The overall $umls$ and other structures, that are dedicated to the dimensionality reduction and mapping of the sensory information, compose together the *Modular Cerebellar Circuit* (MCC).

In the proposed experiment, the canonical cerebellar microcircuits (ccm) of each controlled object are specialized in p position and in v velocity. In details, the Purkinje layer of each n -th uml presents a pair of Purkinje cells (PC) (Figure B.2(c)), specialized

in position $Pc_{n,p}$ and velocity $Pc_{n,v}$ respectively through different climbing fibers ($io_{n,p}$, and $io_{n,v}$). Moreover, the bio-inspired controller receives the same sensory information of the feedback controller (Section B.2.3.1), but it is intended to correct the e_{ϑ_n} angular position error, whereas the PID corrects the $e_{\dot{\vartheta}_n}$ angular velocity error. This is solved through the connection inferior olive-deep cerebellar nuclei (IO-DCN), which conveys information about the angular position error. An additional aspect, the inferior olive signals differs from Kawato's feedback error learning theory [133] and our previous experiments [255, 258], because the Jacobian does not correctly approximate the system, therefore the required conditions are not satisfied and it is not efficient to compare the motor signals.

The mossy fibers transmit the information about the current and reference state of the controlled joints in terms of angular velocity to the granular cells (Gr),

$$\mathbf{MF}_{2N \times 1}(t) = \begin{bmatrix} mf_0(t) \\ \dots \\ mf_{2N}(t) \end{bmatrix} = \begin{bmatrix} \dot{\mathbf{Q}}_{N \times 1}^r(t) \\ \dot{\mathbf{Q}}_{N \times 1}^c(t) \end{bmatrix} = \begin{bmatrix} \dot{\vartheta}_{r,0}(t) \\ \dots \\ \dot{\vartheta}_{r,N}(t) \\ \dot{\vartheta}_{c,0}(t) \\ \dots \\ \dot{\vartheta}_{c,N}(t) \end{bmatrix}. \quad (\text{B.9})$$

The granular layer-parallel fibers network is the circuit area committed to the mapping of the mossy fibers signals and to the prediction of the next output given the current sensory input [95, 96]. As in our previous works [255, 258], we artificially represented this network with the Locally Weighted Projection Regression algorithm (LWPR) [214]. The LWPR resulted an efficient method for the fast on-line approximation of non-linear functions in high dimensional spaces. Given the $\mathbf{MF}(t)$ mossy fibers input vector (Equation B.9), the LWPR creates G local linear models that in our scheme represent the Gr_g granular cells (for $g = 0, \dots, G$). Each linear model employs the $\mathbf{MF}(t)$ to make a $\hat{\tau}_{n,g}^{gr}$ prediction of the control input $\tau_n^{tot}(t-1)$ (where $n=1, \dots, N$). The total output of the granular-parallel fibers network is the weighted mean of all the linear models specialized in velocity,

$$\hat{\tau}_n^{PF}(t) = \frac{\sum_{g=1}^{g=G} w_{n,g}^{gr}(t) \cdot \hat{\tau}_{n,g}^{gr}(t)}{\sum_{g=1}^{g=G} w_{n,g}^{gr}(t)} \quad \text{for } n = 1, \dots, N, \quad (\text{B.10})$$

where $w_{n,g}^{gr}$ and $\hat{\tau}_{n,g}^{gr}$ are defined in [214].

In our scheme, there are two Purkinje cells per controlled joint $Pc_{n,p}$ and $Pc_{n,v}$ (where $n = 0, \dots, N$). The $w_{n,p}^{pf-pc}$ synapses connecting the parallel fibers and the $Pc_{n,p}$ (PF-PC connection) [10], are modulated by the the $io_{n,p}$ inferior olive (IO) signal,

$$io_{n,p}(t) = \tilde{e}_{\vartheta_n}(t), \quad (\text{B.11})$$

that transmits the information about the \tilde{e}_{ϑ_n} normalized angular position error of the n -th joint,

$$e_{\vartheta_n}(t) = \vartheta_{r,n}(t) - \vartheta_{c,n}(t), \quad (\text{B.12})$$

¹ w^{pf-pc} weighting kernel parameters: $LTD_{max} = 10^{-3}$, $LTP_{max} = 10^{-3}$, $\alpha = 170$.

while the $w_{n,v}^{pf-pc}$ ¹ synaptic strengths between the parallel fibers and the $PC_{n,v}$, are modulated by the $io_{n,v}$ inferior olive signal,

$$io_{n,v}(t) = \tilde{e}_{\dot{j}_n}(t), \quad (\text{B.13})$$

that transmits the information about the $\tilde{e}_{\dot{j}_n}$ normalized angular velocity error of the n -th joint (Equation B.6). The $w^{pf-pc}(t, io_0(t))$ weighting kernel tends to support the control actions that lead to an error lower than a specific threshold e^{thresh} ,

$$\mathbf{e}_{\vartheta}^{thresh,pc} = \begin{bmatrix} e_{\vartheta_0}^{thresh,pc} \\ \dots \\ e_{\vartheta_N}^{thresh,pc} \end{bmatrix} = \begin{bmatrix} w_{0,p}^{pf-pc}(t, io_0^p(t) = 0) \cdot \max(e_{\vartheta_0}) \\ \dots \\ w_{N,p}^{pf-pc}(t, io_{N,p}(t) = 0) \cdot \max(e_{\vartheta_N}) \end{bmatrix} = \begin{bmatrix} 0.012 \\ 0.008 \\ 0.002 \end{bmatrix} [\text{rad}], \quad (\text{B.14})$$

$$\mathbf{e}_{\dot{\vartheta}}^{thresh,pc} = \begin{bmatrix} e_{\dot{\vartheta}_0}^{thresh,pc} \\ \dots \\ e_{\dot{\vartheta}_N}^{thresh,pc} \end{bmatrix} = \begin{bmatrix} w_{0,v}^{pf-pc}(t, io_0^v(t) = 0) \cdot \max(e_{\dot{\vartheta}_0}) \\ \dots \\ w_{N,v}^{pf-pc}(t, io_{N,v}(t) = 0) \cdot \max(e_{\dot{\vartheta}_N}) \end{bmatrix} = \begin{bmatrix} 0.012 \\ 0.008 \\ 0.002 \end{bmatrix} [\text{rad} \cdot \text{sec}^{-1}]. \quad (\text{B.15})$$

Respect to our previous work [255, 258] the output signals of the Purkinje cells are directly function of the $\hat{\tau}_n^{PF}(t)$ prediction instead of the $w_{n,g}^{gr}$ weights,

$$\tau_{n,p}^{PC}(t) = w_{n,p}^{pf-pc}(t, io_{n,p}(t)) \cdot \hat{\tau}_n^{PF}(t) \quad (\text{B.16})$$

$$\tau_{n,v}^{PC}(t) = w_{n,v}^{pf-pc}(t, io_{n,v}(t)) \cdot \hat{\tau}_n^{PF}(t). \quad (\text{B.17})$$

Afterwards, the $\tau_{n,p}^{PC}(t)$ $\tau_{n,v}^{PC}(t)$ Purkinje cells signals are scaled by the synaptic weights $w_{n,p}^{pc-dcn}$ and $w_{n,v}^{pc-dcn}$ ² [10], that are modulated by the Purkinje cells and the deep cerebellar nuclei activities (PC-DCN),

$$w_{n,p}^{pc-dcn} = f(t, \tau_{n,p}^{PC}(t), \Delta\tau_n^{DCN}(t-1)), \quad (\text{B.18})$$

$$w_{n,v}^{pc-dcn} = f(t, \tau_{n,v}^{PC}(t), \Delta\tau_n^{DCN}(t-1)). \quad (\text{B.19})$$

resulting in the input signals,

$$\tau_{n,p}^{PC-DCN}(t) = w_{n,p}^{pc-dcn} \cdot \tau_{n,p}^{PC}(t) \quad (\text{B.20})$$

$$\tau_{n,v}^{PC-DCN}(t) = w_{n,v}^{pc-dcn} \cdot \tau_{n,v}^{PC}(t). \quad (\text{B.21})$$

In addition, the deep cerebellar nuclei receives the input signals $\tau_{n,p}^{MF-DCN}$, $\tau_{n,v}^{MF-DCN}$ from the mossy fibers and $\tau_{n,p}^{IO-DCN}$ from the inferior olive. In our proposed circuit, the mossy fibers connected to the deep cerebellar nuclei (MF-DCN) conveys the information about the $\tau_n^{tot}(t-1)$ last control input sent to each controlled joint (Equation B.5). This input is scaled by the synaptic weights $w_{n,p}^{mf-dcn}$ and $w_{n,v}^{mf-dcn}$ ³ [10], modulated by the respective n -th Purkinje cells activities,

$$\tau_{n,p}^{MF-DCN}(t) = w_{n,p}^{mf-dcn}(t, \tau_{n,p}^{PC}(t)) \cdot \tau_n^{tot}(t-1), \quad (\text{B.22})$$

² $w_{n,p}^{pc-dcn}$ weighting kernel parameters: $LTD_{max} = 10^{-4}$, $LTP_{max} = 10^{-4}$, $\alpha = 2$.

³ $w_{n,v}^{mf-dcn}$ weighting kernel parameters: $LTD_{max} = 10^{-4}$, $LTP_{max} = 10^{-4}$, $\alpha = 2$.

$$\tau_{n,v}^{MF-DCN}(t) = w_{n,v}^{mf-dcn}(t, \tau_{n,v}^{PC}(t)) \cdot \tau_n^{tot}(t-1). \quad (\text{B.23})$$

The $\tau_{n,p}^{IO-DCN}$ inferior olive contribution in the deep cerebellar nuclei (IO-DCN) is given by the $io_{n,p}$ (Equation B.11), which is modulated by the $w_{n,p}^{io-dcn}$ ⁴ synaptic weight [37],

$$\tau_{n,p}^{IO-DCN} = w_{n,p}^{io-dcn}(t, io_{n,p}(t)) \cdot io_{n,p}(t). \quad (\text{B.24})$$

The final $\Delta\tau_n^{DCN}$ cerebellar corrective term is the result of the τ_n^{MF-DCN} modulated control input subtracted by the τ_n^{PC-DCN} prediction modulated by the current error together with the $\tau_{n,p}^{IO-DCN}$ modulated contribution of the error itself,

$$\Delta\tau_n^{DCN} = (\tau_{n,p}^{MF-DCN} + \tau_{n,v}^{MF-DCN}) - (\tau_{n,p}^{PC-DCN} + \tau_{n,v}^{PC-DCN}) + \tau_{n,p}^{IO-DCN}, \quad (\text{B.25})$$

or rather,

$$\Delta\tau_n^{DCN} = (\tau_n(\vartheta_n, \tau^{tot}) + \tau_n(\dot{\vartheta}_n, \tau^{tot})) - (\hat{\tau}_n^{tot}(e_{\vartheta_n}) + \hat{\tau}_n^{tot}(e_{\dot{\vartheta}})) + \tau_n(e_{\vartheta_n}).$$

B.2.4 Proposed Experiments and Performance Measures

The proposed control scheme has been applied in four different experiments with the aim at analyzing the advantages of the bio-inspired controller in presence of dynamical disturbances. In details, the four experiments differ from the presence of the ball and the cerebellar-like controller contribution (Figure B.3):

- **Experiment I:** control input without both cerebellum contribution and ball disturbance,

$$\tau^{tot} = \tau^{PID} \quad (\text{no ball}); \quad (\text{B.26})$$

- **Experiment II:** control input with cerebellum contribution, without ball disturbance,

$$\tau^{tot} = \tau^{PID} + \Delta\tau^{DCN} \quad (\text{no ball}); \quad (\text{B.27})$$

- **Experiment III:** control input without cerebellum contribution, with ball disturbance,

$$\tau^{tot} = \tau^{PID} \quad (\text{ball}); \quad (\text{B.28})$$

- **Experiment IV:** control input with both cerebellum contribution and ball disturbance,

$$\tau^{tot} = \tau^{PID} + \Delta\tau^{DCN} \quad (\text{ball}). \quad (\text{B.29})$$

⁴ $w_{n,p}^{io-dcn}$ weighting kernel parameters: $MTD_{max} = -10^{-4}$, $MTP_{max} = -10^{-5}$, $\alpha = 100$.

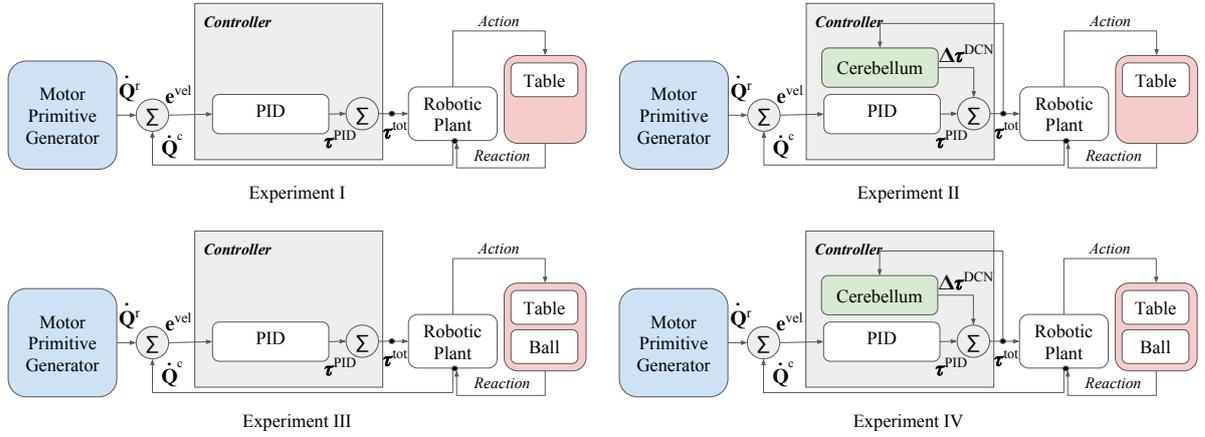


Figure B.3. Functional architectures representing the proposed Experiments.

The performance of each experiment will be measured by analysis of the *mean absolute error* (MAE) evolution computed for the angular position error of each controlled joint (Equation B.12),

$$mae_{\vartheta_n}(k) = \frac{\sum_{i=t}^{t+T} |e_{\vartheta_n}(i)|}{T} \quad \text{for } n = 0, \dots, N. \quad (\text{B.30})$$

The MAE is computed for every trajectory period $T = 8$ sec (Equation B.3).

B.3 Results

The software describing the system is based on the ROS [310] messaging architecture and is integrated in the Neurorobotics Platform (NRP) [270]. The NRP is a simulation environment based on ROS and Gazebo [311] which includes a variety of robots, environments and a detailed physics simulator. The three wrist motors are controlled in effort through the Gazebo service *ApplyJointEffort*, while the elbow and the three shoulder motors are controlled in position through their specific ROS topic. The sensory information from the encoders are received with a sampling frequency of $f_{\text{sampl}} = 50$ Hz. The computer used for the test has the *Ubuntu 16.04* Operating system (OS type 64 – bit), the Intel Core™ *i7 – 7700HQ* CPU@2.80GHz \times 8 processor, and the *GeForce GTX 1050/PCIe/SSE2* graphics card.

Each experiment was performed 20 times with a total duration of about 3 min. The recorded data was saved in .csv files and processed for the analysis. The results are expressed as mean value of the 20 tests, and σ standard deviation or 95% confidence interval. In each experiment, the cerebellar-like circuit is activated after $t = 40$ sec (or 10th iteration), which is the moment all the actuated joints reach a stable configuration (included the shoulder joints and the elbow). In experiments II and IV, the ball is launched on the table after $t = 5$ sec (purple vertical line in the figures).

The comparison of the 4 experiments for each controlled joint are presented separately in 3 parts. In each part, we analyze the joint states, i.e. $\vartheta_{c,n}(t)$ angular position and $\dot{\vartheta}_{c,n}(t)$ velocity (Figures B.4,B.6,B.8), respect to the control action (Figures B.5,B.7,B.9). Moreover, we compared the mean absolute error MAE to measure the performance of the different cases (as reported in Table B.3 and illustrated in Figure B.10).

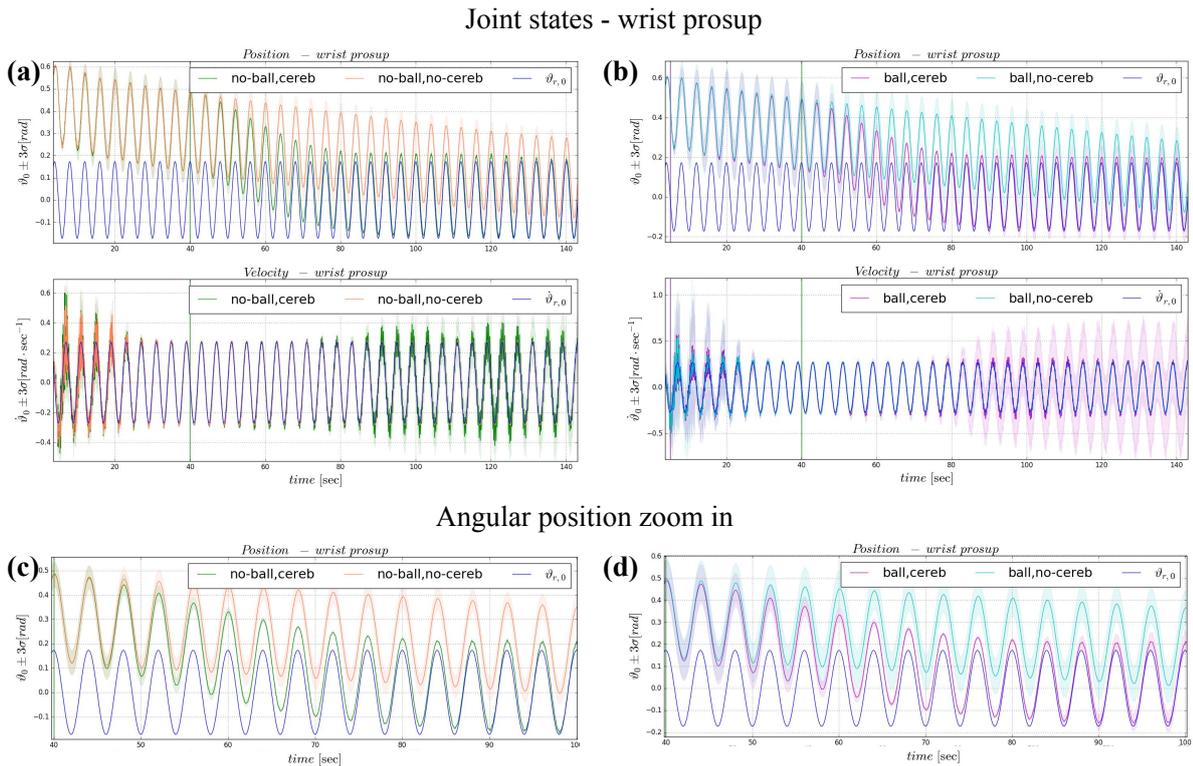


Figure B.4. Angular position and velocity wrist prosup: comparison experiment I and II (a), with zoom on the angular position (c); comparison experiment I and II (b), with zoom on the angular position (d). The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment in which the cerebellar-like controller starts giving the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$).

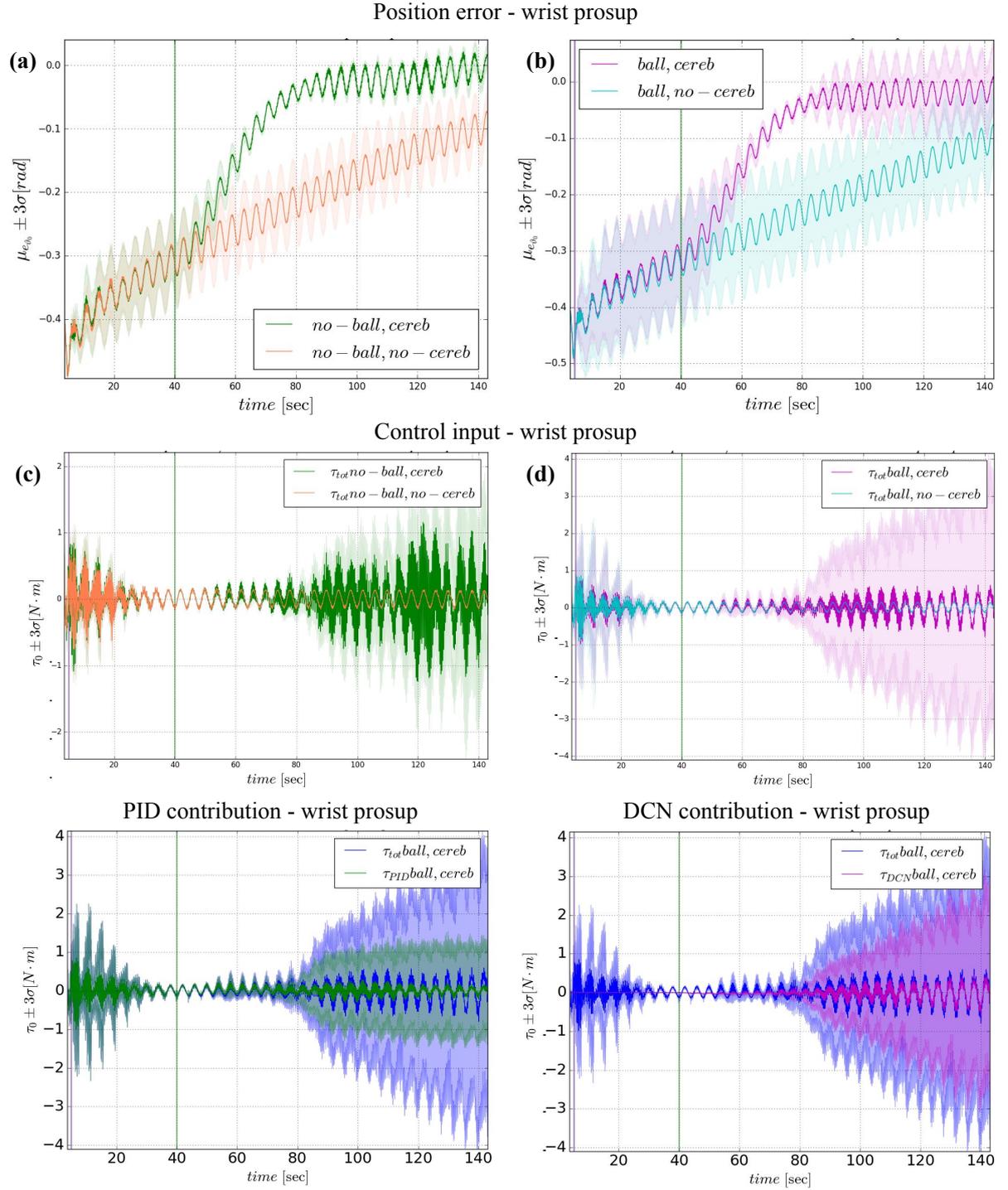


Figure B.5. Wrist prosup experimental results. Resulting angular position error e_{θ_0} , comparison experiments I and II (a), comparison experiments III IV (b). Control input τ_0^{tot} evolution, comparison experiments I and II (c), comparison experiments III IV (d). Control input contributions in experiment IV comparisons between: τ_0^{tot} and τ_0^{PID} (e); τ_0^{tot} and τ_0^{DCN} (f). The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts giving the corrective action ($t = 40$ sec). The vertical purple line indicates the instant the ball is launched on the table ($t = 5$ sec).

Joint states - wrist yaw

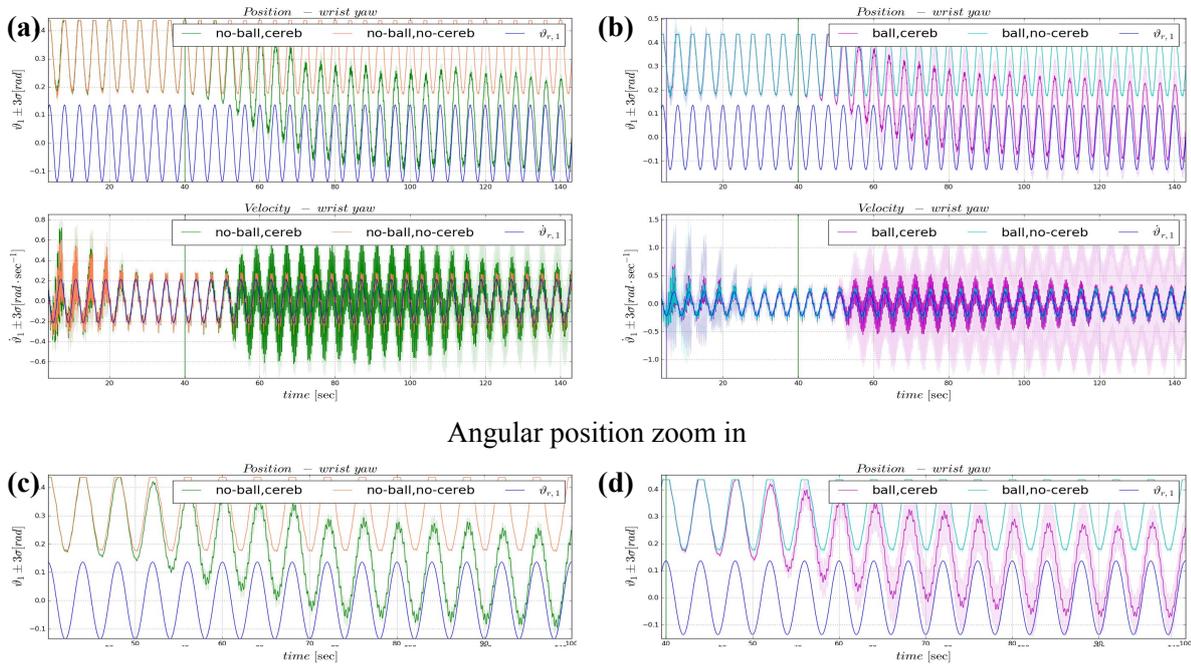


Figure B.6. Angular position and velocity wrist yaw: comparison experiment I and II (a), with zoom on the angular position (c); comparison experiment I and II (b), with zoom on the angular position (d). The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts giving the corrective action ($t = 40$ sec). The vertical purple line indicates the instant the ball is launched on the table ($t = 5$ sec).

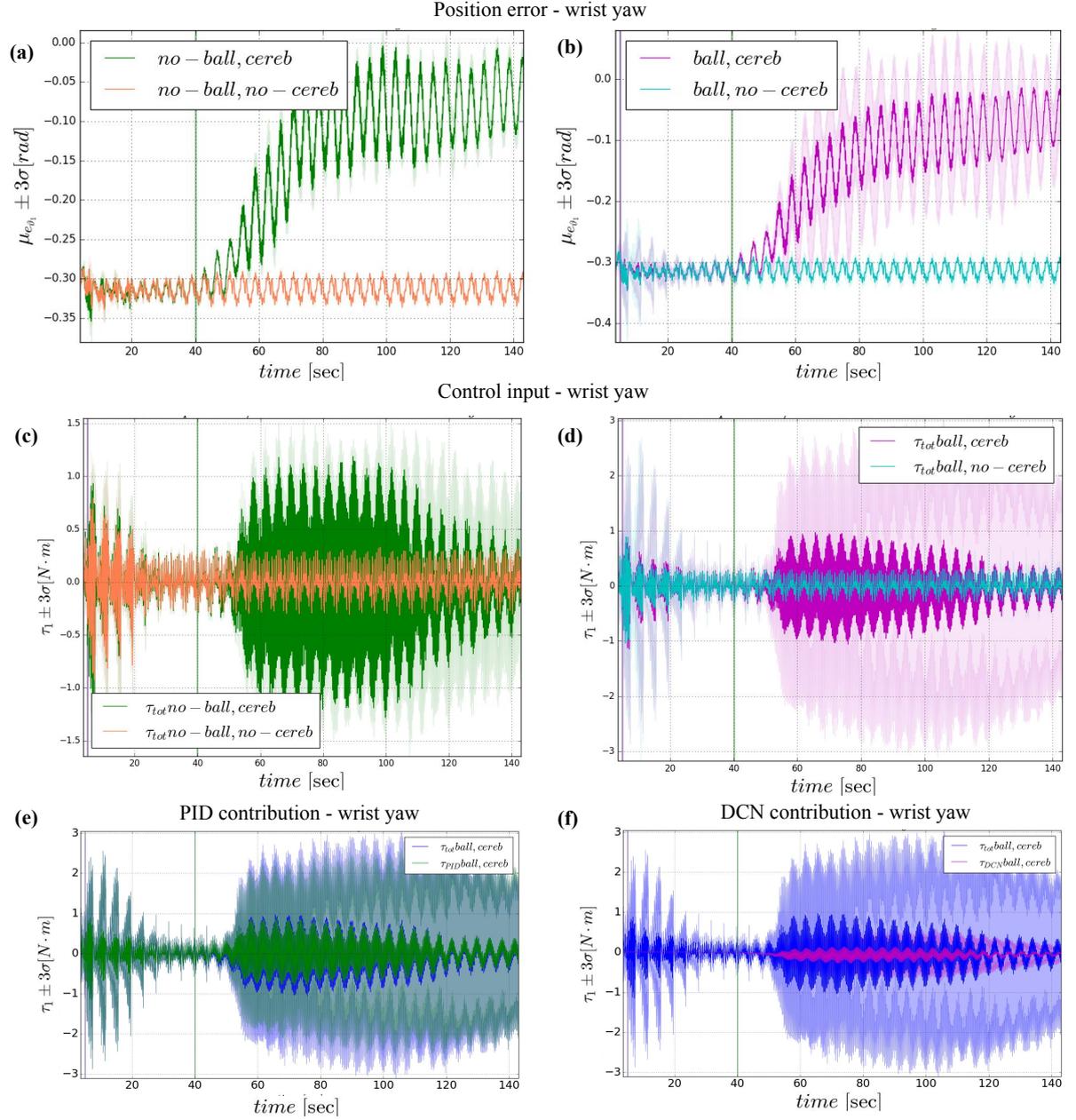
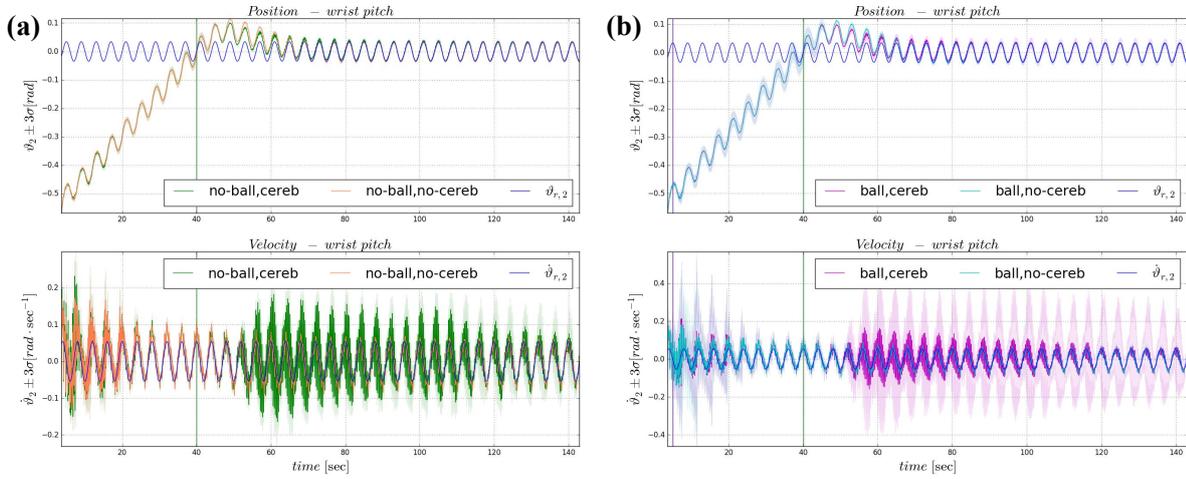


Figure B.7. Wrist yaw experimental results. Resulting angular position error e_{θ_1} , comparison experiments I and II (a), comparison experiments III IV (b). The τ_1^{tot} control input evolution, comparison experiments I and II (c), comparison experiments III IV (d). Control input contributions in experiment IV comparisons between: τ_1^{tot} and τ_1^{PID} (e); τ_1^{tot} and τ_1^{DCN} (f). The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$).

Joint states - wrist pitch



Angular position zoom in

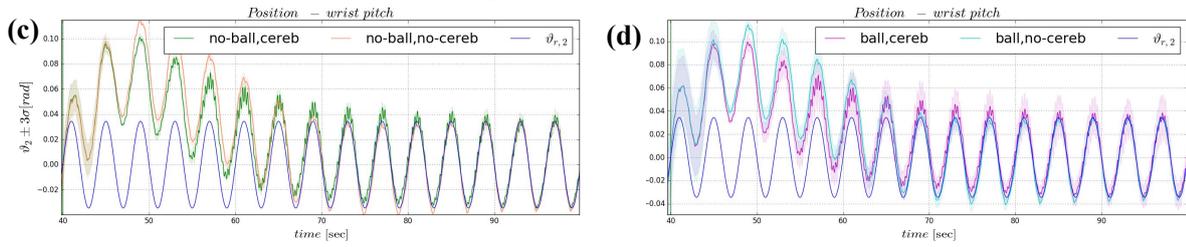


Figure B.8. Angular position and velocity wrist pitch: comparison experiment I and II (a), with zoom on the angular position (c); comparison experiment I and II (b), with zoom on the angular position (d). The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40$ sec). The vertical purple line indicates the instant the ball is launched on the table ($t = 5$ sec).

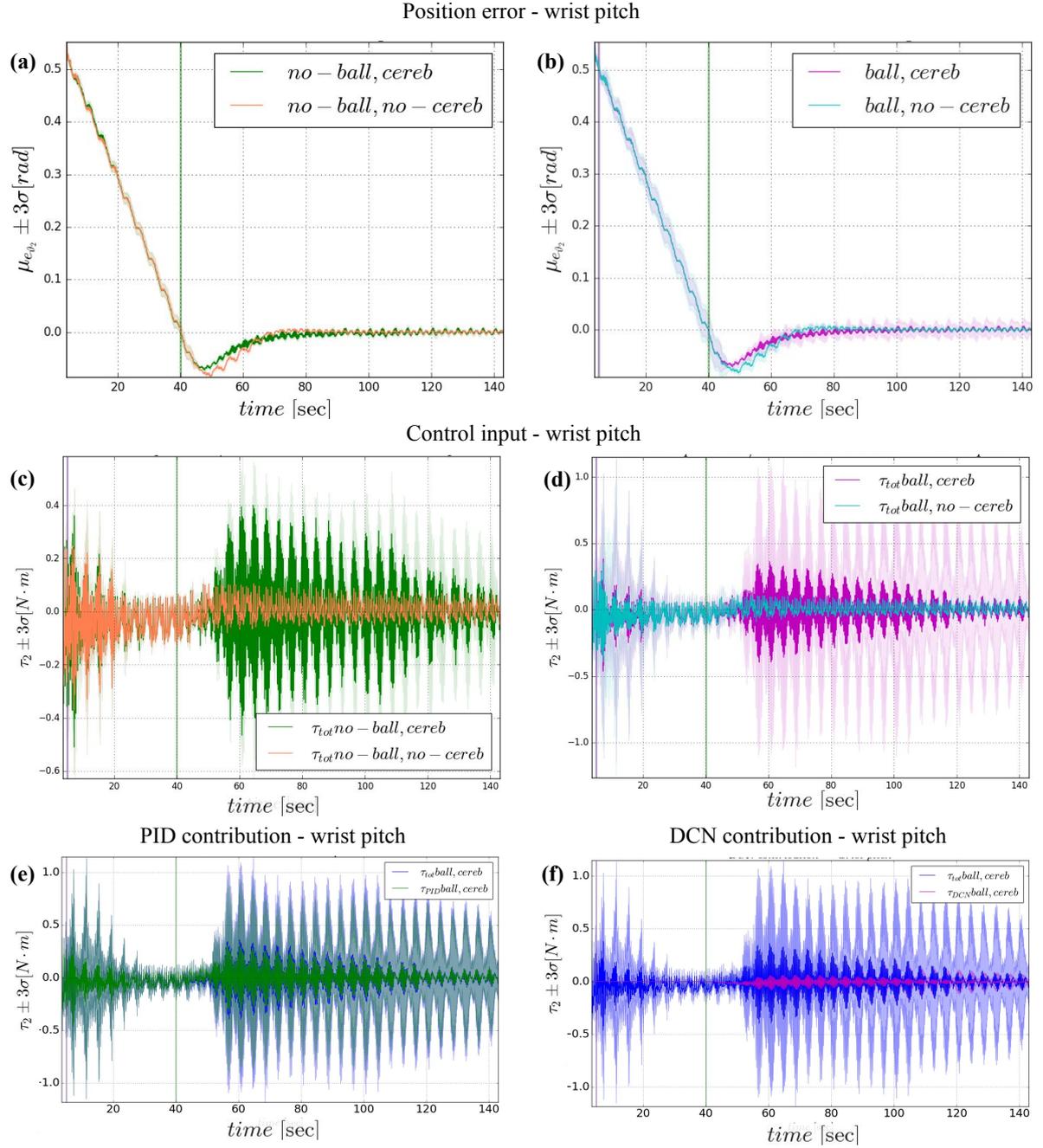


Figure B.9. Wrist pitch experimental results. Resulting angular position error e_{θ_2} , comparison experiments I and II (a), comparison experiments III IV (b). The τ_2^{tot} control input evolution, comparison experiments I and II (c), comparison experiments III IV (d). Control input contributions in experiment IV comparisons between: τ_2^{tot} and τ_2^{PID} (e); τ_2^{tot} and τ_2^{DCN} (f). The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40\text{sec}$). The vertical purple line indicates the instant the ball is launched on the table ($t = 5\text{sec}$).

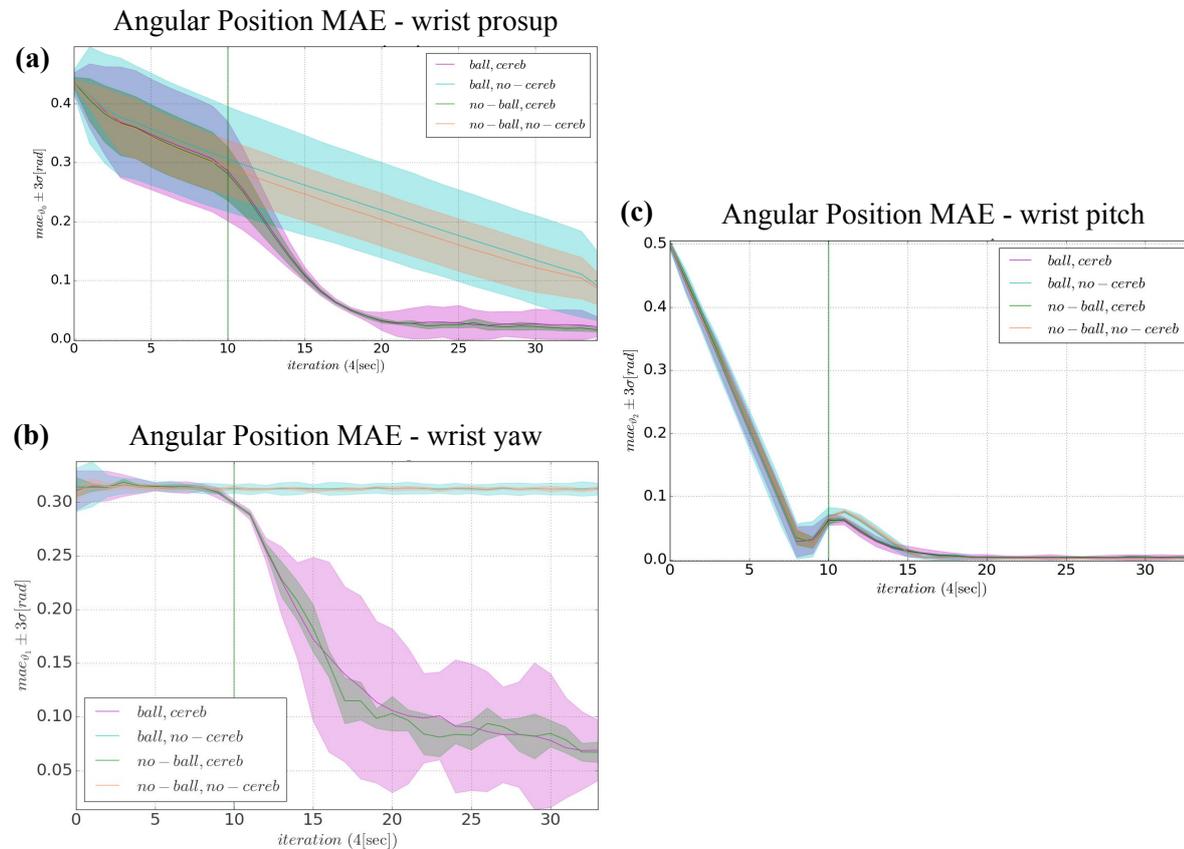


Figure B.10. Comparison of the angular position MAE: (a) wrist prosup, (b) wrist yaw and (c) wrist pitch. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area). The vertical green line indicates the moment the cerebellar-like controller starts providing the corrective action ($t = 40\text{sec}$ or $\text{iteration} = 10$).

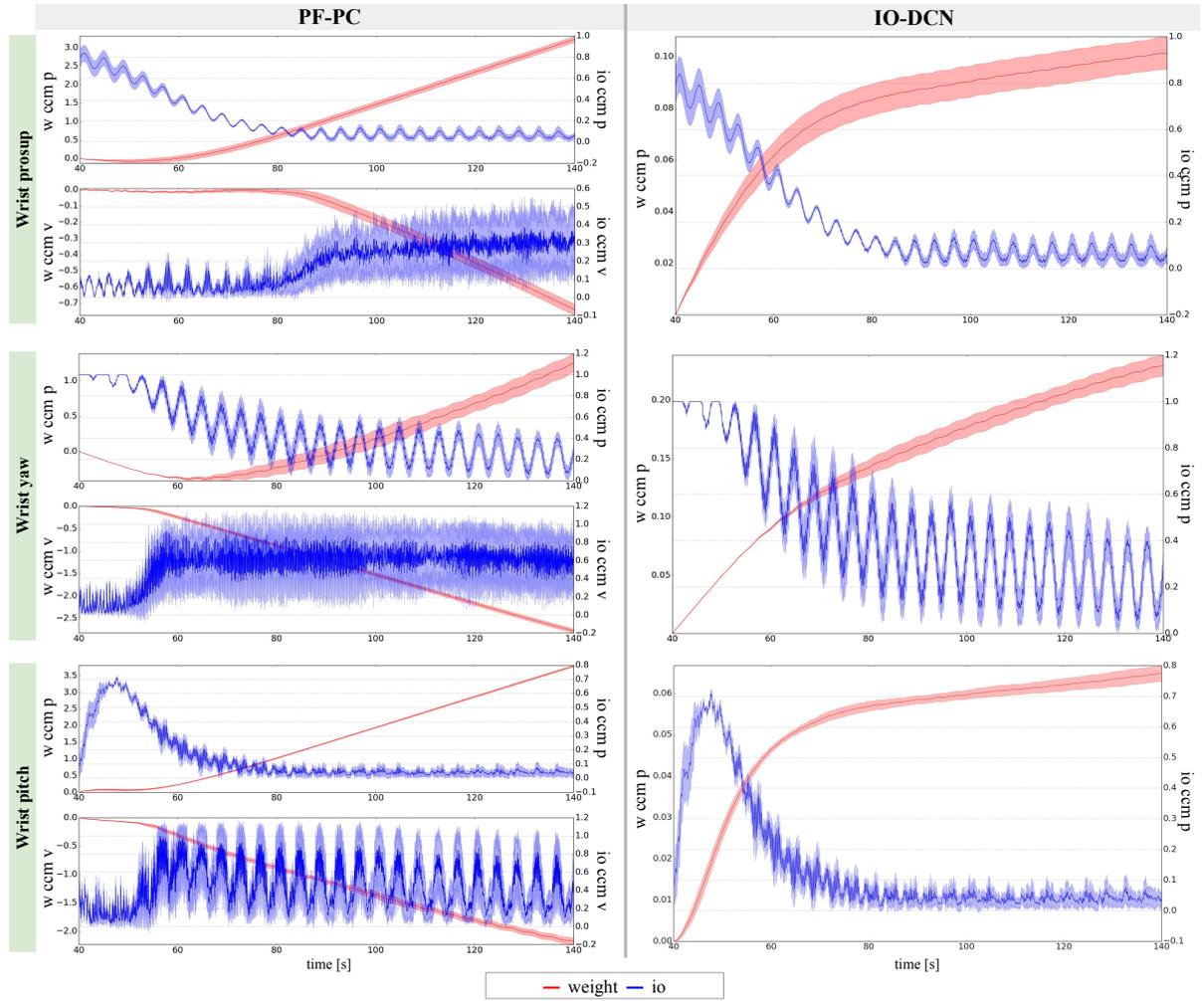


Figure B.11. Learning evolution of the cerebellar-like network in experiment IV: influence of the inferior olive on the PC-PF parallel fibers-Purkinje cells and IO-DCN inferior olive-Deep cerebellar nuclei connections. The plots show the results of the 20 tests in terms of mean value (solid line) and 95% confidence interval (colored area).

B.3.1 Wrist Prosup

In the details of Figures B.4(a),(b), the corrective action of the cerebellar-like circuit (Experiments II,IV) leads $\vartheta_{c,0}$ faster to the desired trajectory $\vartheta_{r,0}$ with respect to the case without corrections (Experiments I,III). $\vartheta_{c,0}(t)$ starts getting closer to the desired position in about one period $T = 4$ sec after the activation of the cerebellum (Figure B.4(c),(d)). In Figures B.5(a),(b) it is evident how the angular position error e_{ϑ_0} drops when the cerebellum action grows (Figure B.5(c),(d)). In particular, the mean absolute error drastically decreased by the 95% and 94% in experiment II and IV respectively, while it only decreased by the 74% and 73% in Experiment I and III (Figure B.10(a), the numerical results are reported in Table B.3). The main difference be-

tween experiments with and without ball is the σ standard deviation. In the final period, the experiments with the ball present a larger standard deviation which is 30% (without cerebellum) and 19% (with cerebellum) respect to the NO ball-case.

B.3.2 Wrist Yaw

The wrist yaw joint is the most affected by the cerebellum action. In Figure B.6, it is evident how with only the PID contribution $\vartheta_{c,1}(t)$ presents a constant and large offset with respect to $\vartheta_{r,1}(t)$. As soon as the cerebellum contribution $\Delta\tau_1^{DCN}$ grows (around the 50 sec, Figure B.7(c),(d)) the error descends (Figure B.7(a),(b)). The mean absolute error decreases by the 78% in experiment II and IV, while it only drops 1% in experiments I and III (Figure B.10(b)). In the last period, the experiments with the ball have a standard deviation 30 – 33% larger than the NO ball-cases.

B.3.3 Wrist Pitch

On the other hand, the wrist pitch gains from the cerebellar action only when the error is larger than $e_{\vartheta_2}^{thresh}$, which is around 40 – 60 sec (Figure B.8), taking into account that the cerebellum is started at $t = 40$ sec. The $\Delta\tau_1^{DCN}$ gets more silent (Figure B.9(c),(d),(e)) when the angular position error is small (Figure B.9(a),(b)). In Figure B.10(c) is more evident how the cerebellum accelerates the corrective action between iteration 10 and 15 where the MAE with the cerebellum (experiment II) is 17% lower respect to experiment I (in experiment IV the MAE is 16% lower respect to experiment III).

		ball				no ball			
		cerebellum		no cerebellum		cerebellum		no cerebellum	
		initial	final	initial	final	initial	final	initial	final
mae_{ϑ_0} [rad]	μ	0.4136	0.0241	0.4148	0.1104	0.4068	0.0188	0.4136	0.1037
	σ	0.0181	0.0085	0.0273	0.0242	0.0120	0.0017	0.0319	0.0075
mae_{ϑ_1} [rad]	μ	0.3148	0.0689	0.3168	0.3123	0.3139	0.0671	0.3172	0.3130
	σ	0.0048	0.0093	0.0070	0.0018	0.0012	0.0031	0.0016	0.0005
mae_{ϑ_2} [rad]	μ	0.4380	0.0042	0.4395	0.0019	0.4437	0.0037	0.4401	0.0020
	σ	0.0045	0.0012	0.0063	0.0001	0.0026	0.0003	0.0013	2.9177e-05

Table B.3. The mean absolute error (MAE) of the initial and final period ($T = 4$ sec). The results express the mean value μ and standard deviation σ of the 20 tests run for the four experiments.

B.4 Discussions

In this work, a bio-mimetic control scheme is presented in the framework of a robotic task, in which simultaneous control of the object dynamics and of the internal force exerted by

the robot arm to follow a trajectory with the object attached to it is required. To address multi-joint corrective responses, we induced and combined three-joint wrist motions. Thus adaptation skills are required especially to deal with an external perturbation acting on the robot-object system. The main observation is that plastic mechanisms given by a feed-forward cerebellum-like controller effectively contribute to the learning of the dynamics model of the robot arm-object system and to the adaptive corrections in terms of torque commands applied to the joints. These cerebellar torque contributions, together with feedback (PID) torque outcome, allow the progressive error reduction by incorporating distributed synaptic plasticity based on the feedback from the actual movement.

The results about the three controlled joints showed a fast reactive control in the test cases when the cerebellum-like model is active, which is even more evident when the ball (random perturbation) is present as shown in Figures B.4, B.6, B.8**(b)**,**(d)**. An incremental velocity control input is then provided to the controller of the system to deal with the perturbation. The purpose of considering a heterogeneous stochastic dynamical stimuli (board and ball) was to test and examine the activation of incremental learning and adaptation of the cerebellum-like controller and at the same time to confirm its coupling with the feedback control inputs. Previous studies have shown that the feedback processes are omnipresent in voluntary motor actions [312] and rapid corrective responses occur even for very small disturbances that approach the natural variability of limb motion. In human beings, these corrections commonly require increases in muscle activity generated i.e. by applied loads [313]. By analogy, a similar effect can be noticed at joint-level in our system. In the experimental situation, the joints that are more influenced by the limb dynamics (wrist prosup and yaw joints) under the effect of the table and ball increase their control input activity as represented in **Figures** B.5, B.7**(c)**,**(d)**, while the wrist pitch joint has a much more reduced activity B.9**(c)**,**(d)** compared to the previous two joints. This phenomena is also reflected in the control input provided by the cerebellum-like model. The bigger the position error is at the beginning of the simulation with only the PID control case (experiments I and III) the more effective the cerebellar-like corrections are (experiments II and IV) as shown in **Figures** B.5, B.7, B.9**(a)**,**(b)**. It should be noted that for the wrist pitch joint the PID controller leads to approx. 0.0 (rad) MAE around 40 sec from the beginning of the simulation. However, among all the joints, the fundamental role of the cerebellum in motor control is confirmed by its anticipatory response for decreasing the error as it is appreciated in **Figures** B.10. The control system achieved these result by creating up to 9 *Gr* receptive fields per uml at the granular level (or rather LWPR). In **Figure** B.11, it is possible to appreciate how the IO inferior olive signals (in blue) of each ccm promptly influence the synaptic weights (in red) between the PF parallel fibers and the PC Purkinje cells (left column), and the contribution of the inferior olive itself on the the DCN Deep Cerebellar nuclei corrective action (right column). In the IO-DCN connection details, the synaptic weights rapidly increment in the first tract around 40 – 60 sec where the error is higher and then keep increasing slowly for the final adjustments. On the other hand, the PF-PC connection tends to not over-react at the beginning of the simulation around 40 – 60 sec, while it strengthen when the error decline. We assume that this

opposite influence of the IO on the synaptic weights makes possible the filtering and the dumping of any external disturbances or high error.

This control model proposes a plausible explanation on how control feedback is used by the central nervous system (CNS) to correct for intrinsic as well as external sources of disturbances. Furthermore, the bio-mimetic model represents a plausible control scheme for voluntary movements that can be generalized to control robotic agents without mayor tuning of the parameters. Our controller with distributed plasticity allows efficient adjustment of the corrective signal regardless of the dynamic features of the robot arm and of the way the added perturbations affect the dynamics of the arm plant involved. According to this, the controller (cerebellum-like and PID) is adaptable by providing adjustable torque commands among the joints to overcome external dynamic and stochastic perturbations and to have a both fast and precise movement. This replies to our question about if the sensory-motor information extrapolation made by the cerebellum-like facilitates motor prediction and adaptation in changing conditions. It should be noted that the adaptation mechanism adopted here is not constrained to any specific plant or testing framework, and could therefore be extrapolated to other common testing paradigms.

[36] illustrated in their paper the schematic representation of how the core cerebellar microcircuit is wired inside the whole brain. The proposed cerebellar-like model has been designed in analogy with it. In contrast with [10], [232], [233], the proposed model encodes the movement kinematics at the mossy fibers level [309], and presents a coupling at the Purkinje layer for velocity and position terms representation. Likewise, the synaptic strengths at PC-DCN level as well the synaptic strengths at IO-DCN level are modulated by signals related to position or velocity. The mossy fibers are connected to the DCN and to some granular cells to convey the efference copy or motor command information. The IO cells are devoted to teaching signal error transmission in terms of position and velocity errors. The teaching errors modulate the synaptic strengths at PF-PC and IO-DCN levels.

[314] postulated that high dimensionality problem (high-dimensional sensory-motor inputs vs low training data) is accomplished by the cerebellum by regulating the synchronous firing activities of the inferior olive (IO) neurons. Though the implementation of coupling mechanisms at the inferior olive cells would be an interesting work to have a better explanation on multiple joint control. This extension could also provide additional insights into the internal connectivity of the cerebellar microcomplex. Further investigation will be possible in the future of how specific properties of the cells, of the network topology and synaptic adaptation mechanisms complement each other in the bio-inspired architecture.

B.4.1 Neural Basis of Feedback Control for Voluntary Movements

Feedback control of movement is essential to guarantee movement success especially to compensate for perturbation arising from the interaction with the external world. Different brain areas (primary motor cortex, primary somatosensory cortex, cerebellum, supplementary motor area, etc.) are involved during a voluntary movement and cooperate in many levels of hierarchy. Feedback control theory might be the key for understanding how the previous areas plan and control the movement hierarchically. By using control terminology, during the voluntary movement of a limb, the primary motor cortex acts as a controller, and the limb connected to neuronal circuits becomes the controlled object.

The cerebellum learns and provides the internal models that reproduce the inverse or direct dynamics of the body part. Thanks to the cerebellar internal model learning, the primary motor cortex performs the control without an external feedback [246]. By our simulations, we suggest that such behaviour can be confirmed. Indeed, the cerebellar-like contributions drive the feedback controller towards better accuracy and precision of the movement. In the future, a visual feedback input will be considered to probe the sophistication of feedback control processing and cerebellar-like learning consolidation.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

MCC, ST conceived and designed the experiments, analyzed the data, and wrote the paper. MCC implemented the architecture and performed the experiments. EA contributed to materials and analysis tools. HHL and EF reviewed the paper.

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Supplemental Data

Data Availability Statement

The raw data supporting the conclusions of this manuscript will be made available by the authors, without undue reservation, to any qualified researcher.

APPENDIX C

A Cerebellar Internal Models Control Architecture for Online Sensorimotor Adaptation of a Humanoid Robot Acting in a Dynamic Environment

A Cerebellar Internal Models Control Architecture for Online Sensorimotor Adaptation of a Humanoid Robot Acting in a Dynamic Environment

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abstract

Humanoid robots are often supposed to operate in non-deterministic human environments, and as a consequence, the robust and gentle rejection of the external perturbations is extremely crucial. In this scenario, stable and accurate behavior is mostly solved through adaptive control mechanisms that learn an internal model to predict the consequences of the outgoing control signals. Evidences show that brain-based biological systems resolve this control issue by updating an appropriate internal model that is then used to direct the muscles activities. Inspired by the biological cerebellar internal models theory, that couples forward and inverse internal models into the biological motor control scheme, we propose a novel methodology to artificially replicate these learning and adaptive principles into a robotic feedback controller. The proposed cerebellar-like network combines machine learning, artificial neural network, and computational neuroscience techniques to deal with all the nonlinearities and complexities that modern robotic systems could present. Although the architecture is tested on the simulated humanoid iCub, it can be applied to different robotic systems without excessive customization, thanks to its neural network-based nature. During the experiments, the robot is requested to follow repeatedly a movement while it is interacting with two

external systems. Four different internal model architectures are compared and tested under different conditions. The comparison of the performances confirmed the theories about internal models combinatory action. The combination of models together with the structural and learning features of the network, resulted in a benefit to the adaptation mechanism, but also the system response to nonlinearities, noise and external forces.

C.1 Introduction

Modern robots are often mechanically complex, and are embedded in unstructured non-deterministic environments [281]. The accurate and stable motor control of such systems is often challenging due to the unreliability of the hand engineered modeling strategies, which are too strict to describe all the complexities and nonlinearities.

In this manuscript, we propose an online learning and control algorithm to dynamically adapt the movements of a robotic system acting in an uncertain non-deterministic environment. In the design process, we assumed that: the Jacobian poorly describes the actual robotic condition; one or more unmodeled external objects interfere with the movement; the state space system is multivariable and not fully observable; the action/state space is continuous and high-dimensional. In this view, the controller should improve the tracking accuracy of each actuator, and minimize the effects of noise through force-based control input.

Traditionally, uncertain systems were learned by estimating open parameters of structured mathematical models [41]. Although this approach has been used for several years in system identification and adaptive control, fitting the parameters of fixed structure with training data can lead to different drawbacks, such as: physical inconsistency [43]; unmodeled behavior; persistent excitation issues [42]; and unstable reaction to high estimation error.

In the last decades, due to the advancement in artificial intelligence, a large number of non-parametric approaches have been proposed to solve the aforementioned problems [44–49]. For instance, the introduction of artificial neural networks (ANNs) into nonlinear dynamical systems adaptive control were advantageous for reducing the effects of nonlinearities and uncertainties, and for handling high dimensional and continuous state space systems [47, 50–53]. Although the structural versatility that distinguishes ANNs, the continuous interaction within the robotic system and the non-deterministic environment can be constrained by the off-line training of the neural network.

The Autonomous Mental Development (AMD) theorists claim that robots should learn and evolve their processing through real-time interaction with the environment [54, 55]. In this view, model learning is not seen anymore as a summation of off-line learned experiences but as an online development of the current knowledge of the system [56, 57]. These theories have their foundation in studies of biological systems, such as humans, especially infants. The advanced mechanisms exploited by biological systems to explore their relation with the surroundings, and control their own movements, motivated several scientists towards a better understanding of the biological motor control.

James S. Albus was the first person to propose a robotic control architecture enhanced by an artificial neural network based on evidence of the central nervous system (CNS): the "cerebellar model articulation controller" (CMAC) [15]. The CMAC module was mainly inspired by the David Marr's theory [95] that depicts the cerebellum, a neural structure located at the back of the brain, as "language translator between data in the cerebrum, and command sequences needed by the muscles" [96].

In the last decades, several scientists have been attracted by the fascinating mechanisms and functional roles of the cerebellum in motor and cognitive tasks [26, 29, 82–85]. Among all the hypotheses, the scientific community is highly supporting the involvement of the cerebellum in the acquisition and maintenance of the internal models, mapping the correlation within the body and the environment [3, 86–88], i.e., forward and inverse models [7, 11]. If confirmed, these assumptions would explain several complex mechanisms underlying the neural control of movements [89].

The inverse model elaborates the motor command that leads the system from the current state to a desired one [315]. Its contribution enables fast and coordinated limb movements, that are not achievable with pure feedback control, due to the biological system dynamics [7]. Evidences show that some of the motor deficits caused by cerebellar dysfunction, e.g., quick ballistic limbs movements and impaired muscle coordination [316], are due to the lack of feed forward contribution in motor control, or rather the neural control loop is affected by slow reaction time and sensory delay [89]. Although it is controversial [317, 318], scientists argued that integrating the efference copy signal of the delayed sensory feedback could overcome these CNS transmission problems [256]. Different prototypes of cerebellar control architecture based on the inverse model theory has been proposed, such as: adaptive filter models [18, 133]; spiking neural networks [10, 23]; combination of parametric adaptive control and machine learning techniques [218, 255].

The forward model describes the causal relationship between the outgoing motor command and system state. This model results beneficial to predict those state transitions that are not directly accessible [161]. Electrophysiological studies [319, 320], computational theories [3, 86], imaging and lesion data [304, 321] suggest that the forward model could explain pivotal cerebellar functions, such as error correction and learning. Moreover, robotics experiments proved that the forward model could play an important role in action prediction, sensory discrepancy minimization, and noise cancellation [208, 258].

Inspired by the theory of coupled internal models [12, 181, 189, 231, 322, 323], we propose a novel methodology to replicate and exploit artificially the cerebellar internal models learning and corrective action. In particular, we designed a neural network that, through the combination of machine learning, artificial neural network, and computational neuroscience techniques, replicates the functionality, learning, modularity, and morphology of the cerebellar-circuit. This bio-mimetic network is embedded in a feedback robotic control architecture, and is intended to minimize modeling errors and to constrain the effects of noise, uncertainties, and external disturbances. The network weights are defined by non-linear and multidimensional learning functions that mimic the cerebellar synaptic plasticities, as proposed by [10, 37]. The manuscript presents the comparison of four adaptive control architectures based on the cerebellar internal models theories. The control system is tested on the virtual humanoid robot iCub [324] embed-

ded in the Neurorobotics Platform (Fig.C.1.a) [270,325]. The architectures performance are evaluated under different noise and external perturbation conditions. The study confirmed that the forward and inverse internal model coupling shows improved performance respect to the independent internal models action. Moreover, the biologically plausible weighting kernel together with the layered structure of the cerebellar networks resulted beneficial to constrains the effects of external perturbations and nonlinearities.

The structure of the paper is as follows: in section C.2 we describe the overall control architecture, giving special focus to the cerebellar-like component; in section C.3, the experimental set up and results are presented. The manuscript concludes with the discussion of the main findings in comparison with the literature and future directions.

C.2 Materials and Methods

The robotic system, or rather *Agent* (Fig.C.2.a), consists of: a *Planner*, which generates the $\mathbf{Q}_{N \times 1}^r, \dot{\mathbf{Q}}_{N \times 1}^r$ reference motors angular positions and velocities (where N is the number of controlled joints), that are sent to the controller; the *Controller*, which elaborates the $\tau_{N \times 1}^{tot}$ torque commands needed to move the actuators to the $\mathbf{Q}_{N \times 1}^r, \dot{\mathbf{Q}}_{N \times 1}^r$ desired states; the *Robotic Plant*, which includes the actuators and the proprioceptive sensors employed to read the \mathbf{Q} and $\dot{\mathbf{Q}}$ actual angular positions and velocities respectively. The *Agent* interacts with two external systems, which in this manuscript are represented by a table and a rolling ball (Fig.C.1.a).

C.2.1 Robot Plant

The humanoid iCub is a 53 degree of freedom (dof) robotic system equipped with several type of sensors, such as: encoders, accelerometers, gyroscopes, F/T sensors, digital cameras. For the sake of simplicity, the overall system actuates seven motors of the right arm: four motors are kept constant to keep the arm upwards (i.e. elbow, shoulder roll, shoulder yaw and shoulder pitch), and $N = 3$ motors are controlled by the proposed controller (namely wrist pronosupination, wrist yaw and wrist pitch, Fig.C.1.b). The n -th actual motor state is read by the encoders and saved in the $q_n \in \mathbf{Q}_{N \times 1}$ angular position and $\dot{q}_n \in \dot{\mathbf{Q}}_{N \times 1}$ angular velocity process variables.

C.2.2 Planner

The *Planner* plans the $q_n^r \in \mathbf{Q}_{N \times 1}^r, \dot{q}_n^r \in \dot{\mathbf{Q}}_{N \times 1}^r$ reference trajectories, or rather it generates oscillator movements,

$$q_n^r = A_n \cdot \sin(2\pi ft + \varphi_n) , \quad (\text{C.1})$$

$$\dot{q}_n^r = 2\pi f A_n \cdot \cos(2\pi ft + \varphi_n) , \quad (\text{C.2})$$

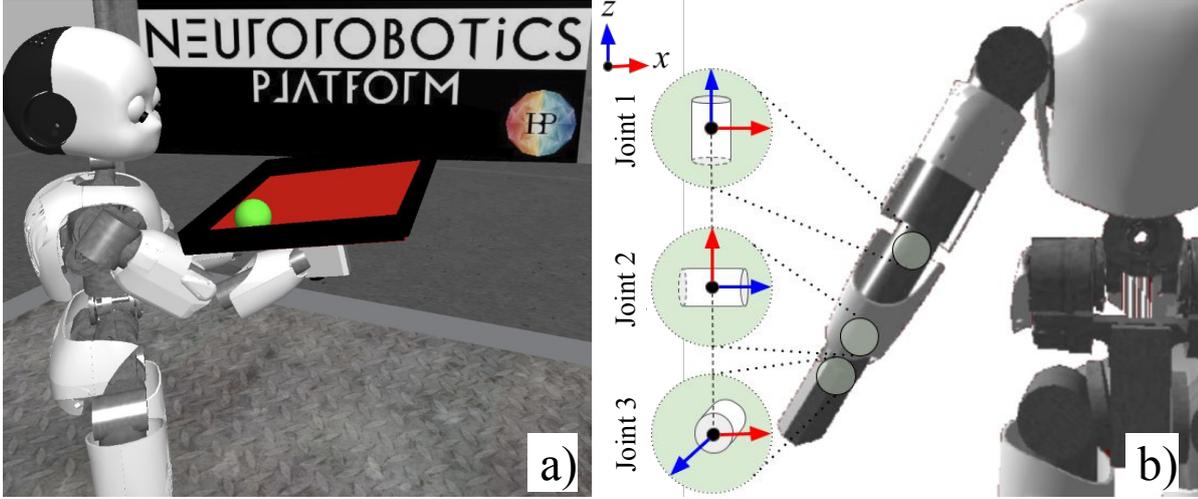


Figure C.1. Robotic plant: **a)** the humanoid iCub holding the table-ball system in the Neurobotics Platform; **b)** the three controlled wrist joints: **1** pronosupination, **2** yaw, **3** pitch.

with fixed temporal frequency $f = 0.25\text{Hz}$, A_n amplitude and φ_n phase,

$$\mathbf{A}_{1 \times N} = [A_1, A_2, A_3] = [0.1727, 0.1363, 0.0345] \text{ rad}$$

$$\boldsymbol{\varphi}_{1 \times N} = [\varphi_1, \varphi_2, \varphi_3] = [0.5\pi, 0.5\pi, 0.0] \text{ rad.}$$

C.2.3 Controller

The *Controller* once received the $\mathbf{Q}, \dot{\mathbf{Q}}$ actual robot states computes the $\tau_n^{tot} \in \boldsymbol{\tau}_{N \times 1}^{tot}$ torque command to move each actuator to the q_n^r, \dot{q}_n^r desired state. This subsystem is constituted by a static module based on classical control methods, and by two decentralized cerebellar-like neural networks (section C.2.4): inverse and forward models (blue boxes Fig.C.2.b). The inverse cerebellar-like module adds $\Delta\tau_n^c \in \boldsymbol{\Delta\tau}_{N \times 1}^c$ feed-forward corrective torque command to the $\tau_n^{fb} \in \boldsymbol{\tau}_{N \times 1}^{fb}$ feedback controller motor input [9, 94], while the forward module applies $\Delta\dot{q}_n^c \in \boldsymbol{\Delta\dot{q}}^c$ state-specific adjustment to the feedback loop [323, 326, 327]. In this initial design, the forward model corrective term is narrowed to the angular velocity, which is the feedback controller input.

In the details of Fig.C.2.b, the closed-loop computes the $e_n^{fb} \in \mathbf{e}_{N \times 1}^{fb}$ feedback angular velocity error of the n -th motor,

$$e_n^{fb} = \dot{q}_n^r - \dot{q}_n. \quad (\text{C.3})$$

This quantity is corrected by the forward cerebellar-like module which predicts the consequence of the outgoing motor command and adds $\Delta\dot{q}_n^c$ contribution to minimize the e_n^{fb} feedback error. The \mathbf{e}^{tot} total error,

$$e_n^{tot} = e_n^{fb} + \Delta\dot{q}_n^c, \quad (\text{C.4})$$

it is then employed by both the feedback controller to compute the feedback torque command τ_n^{fb} , according to the *proportional-integrative-derivative* (PID) independent joint control law, and by the inverse cerebellar-like model to compute the corrective torque $\Delta\tau_n^c \in \Delta\tau_{N \times 1}^c$, that minimizes both the \mathbf{e}^{tot} and the $\epsilon_n \in \epsilon$ angular position error,

$$\epsilon_n = q_n^r - q_n. \quad (\text{C.5})$$

The total control input sent to the motors is the result of a feed-forward compensa-

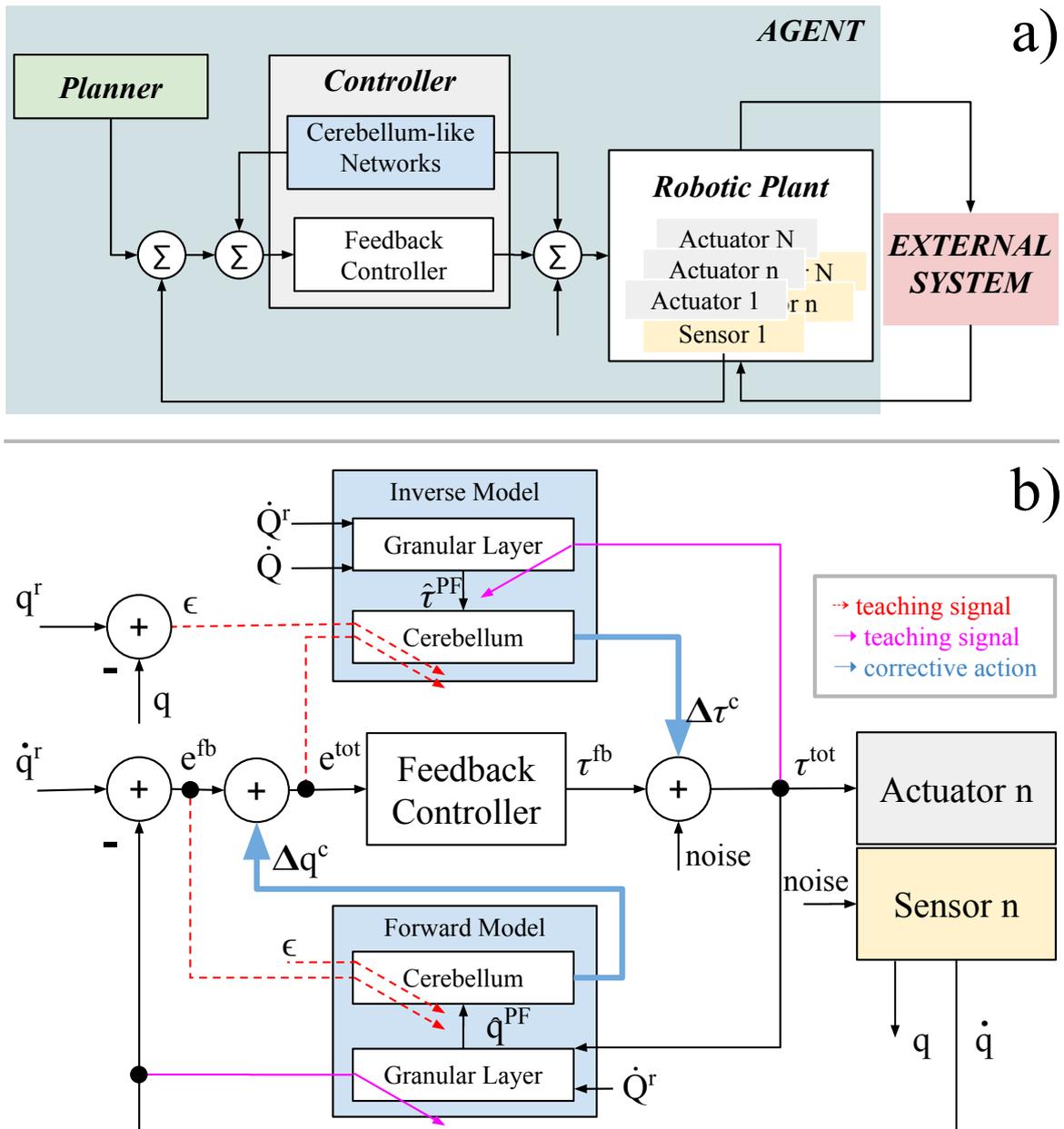


Figure C.2. Control architecture scheme for N actuated joints: **a)** main components communication, and **b)** controller block.

tion [133],

$$\boldsymbol{\tau}^{tot} = \boldsymbol{\tau}^{fb} + \boldsymbol{\Delta}\boldsymbol{\tau}^c . \quad (\text{C.6})$$

On a final note, the PID regulator \mathbf{K} gains are tuned to weakly operate in linearized conditions which exclude the disturbance of the ball and sensory noise,

$$\begin{aligned} \mathbf{K}^P &= [K_1^P, K_2^P, K_3^P] = [2.9000, 2.3000, 2.3500] \\ \mathbf{K}^I &= [K_1^I, K_2^I, K_3^I] = [1.9400, 1.9000, 1.9000] \\ \mathbf{K}^D &= [K_1^D, K_2^D, K_3^D] = [0.0050, 0.0001, 0.0004] . \end{aligned}$$

C.2.4 Cerebellar-like Network

The cerebellum is constituted of several micro-zones that plausibly correspond to the minimal *ulm unit learning machine* (Fig.C.3) [94]. Each *ulm* presents similar internal micro-circuitry, but it differs from the others in terms of external connectivity. There are two main type of axons that connect each *ulm* to the outside: the mf *mossy fibers* (in magenta Fig.C.3), which project signals regarding the position, velocity and direction of the limbs movements [309]; the *climbing fibers* (in red), that project from the io *inferior olive nucleus* the signal encoding the error [179, 319]. These axons transmits the information to two main groups of cells: the Gr *granule cells*, that in Marr's opinion encode combinations of mossy fibers inputs [95]; the pc *Purkinje cells* (in green Fig.C.3), that modulated by the inferior olive axon and excited by the pf *parallel fibers* (in violet) projecting from the granule cells, they influence the activity of the dcn *deep cerebellar nuclei* (in blue). The dcn is inhibited by the pc and excited by both the io and mf, and it is responsible for the final processing of the signal that is sent outside the cerebellar circuit.

In the proposed model (Fig.C.4.a), each *ulm* (light blue box) processes the information of the n -th controlled object (where $n=1, \dots, N$). Accordingly, the dcn of the n -th *ulm* outputs the $\Delta\dot{q}_n^c$ and $\Delta\tau_n^c$ cerebellar corrections. Each *ulm* is divided into M sub-modules representing the ccm *canonical cerebellar microcircuit* (yellow boxes in Fig.C.4.a). Each ccm encodes kinematic and/or dynamic features of the n -th controlled object, such as angular position and velocity. The N *ulm* together compose the MCC *Modular Cerebellar Circuit* mapping the inverse and forward models of the robotic system (green boxes in Fig.C.4.a).

Hereafter for the sake of simplicity, the variable x generally recalls the signals \dot{q}_n and τ_n propagating inside the two separated networks, and w generally recalls the specific network weight. The mossy fibers of the inverse MCC transmit information about the actual and reference angular velocity of all the controlled joints,

$$\begin{aligned} \mathbf{MF}_{2N \times 1}^{inv} &= [mf_1^{inv}, \dots, mf_{2N}^{inv}]^T = \\ &= [\dot{q}_1^r, \dots, \dot{q}_N^r, \dot{q}_1, \dots, \dot{q}_N]^T , \end{aligned} \quad (\text{C.7})$$

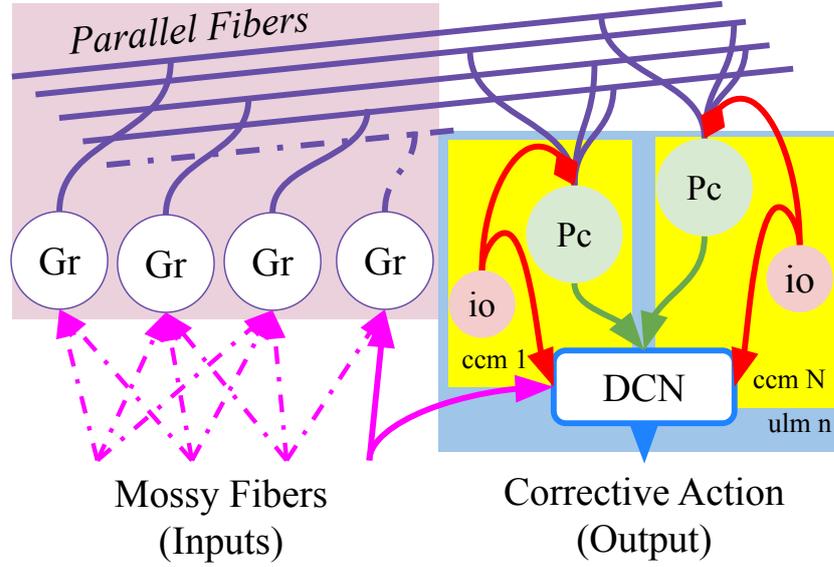


Figure C.3. Canonical cerebellar circuit in analogy with [36].

while the mossy fibers of the forward MCC project the signal encoding the reference angular velocities and the latest control inputs (C.6),

$$\begin{aligned} \mathbf{MF}_{2N \times 1}^{f_{rw}} &= [m f_1^{f_{rw}}, \dots, m f_{2N}^{f_{rw}}]^T = \\ &= [\dot{q}_1^r, \dots, \dot{q}_N^r, \tau_1^{tot}(t-1), \dots, \tau_N^{tot}(t-1)]^T. \end{aligned} \quad (\text{C.8})$$

The mossy fibers signals are then mapped and exploited to predict the τ^{tot} control input (inverse MCC) and \dot{q} system state (forward MCC). As proposed by [255], the granule layer is represented by the Locally Weighted Projection Regression algorithm (LWPR) [214]. The LWPR is a fast on-line nonlinear function approximation algorithm suitable for the reduction of high dimensional state space system. To replicate the efference copy theory [256,257], the LWPR uses a copy of the outgoing τ^{tot} (inverse MCC) and actual \dot{q} (forward MCC) as modulatory signals (in cyan Fig.C.4) to create and train on-line G local linear models, or rather Gr_g granule cells (where $g=1, \dots, G$). These models are employed by the algorithm to make $\hat{\tau}_{n,g}^{gr}$, $\hat{q}_{n,g}^{gr}$ local predictions of the control input (inverse MCC) and angular velocity (forward MCC) respectively. The final output of the granular-parallel fibers layer (in violet Fig.C.4.b) is the weighted mean of all the linear models (refer to [214] for the complete set of formulas),

$$\hat{x}_n^{pf} = \frac{\sum_{g=1}^{g=G} w_{n,g}^{gr} \cdot \hat{x}_{n,g}^{gr}}{\sum_{g=1}^{g=G} w_{n,g}^{gr}}. \quad (\text{C.9})$$

The w^{pf-pc} [10] synaptic strengths of the pf-pc parallel fibers-Purkinje cells connections (Table C.1) is modulated by the io inferior olive transmitting the error signals (C.3,C.4,C.5) (in red Fig.C.4.b),

$$\mathbf{io}_n^{inv} = [io_{n,1}^{inv}, io_{n,2}^{inv}]^T = [\epsilon_n, e_n^{tot}]^T, \quad (\text{C.10})$$

of the error signal; the inferior olive transmits the angular position and velocity error instead of the τ^{fb} [167].

The pc signal transmitted to the dcn (in green Fig.C.4.b) is scaled by the $w_{n,m}^{pc-dcn}$ synaptic weight [10], which is function of both the pc and dcn activities,

$$x_{n,m}^{pc-dcn} = w_{n,m}^{pc-dcn}(t, x_{n,m}^{pc}, \Delta x_n^c) \cdot x_{n,m}^{pc}. \quad (\text{C.13})$$

In the proposed scheme, the mossy fibers (in magenta Fig.C.4.b) project to the dcn deep cerebellar nuclei a copy of the τ_n^{tot} outgoing control input (C.6) (inverse MCC) and the \dot{q}_n actual angular velocity (forward MCC). The mf contribution to the dcn activity is highly influenced by the pc Purkinje cells [10],

$$x_{n,m}^{mf-dcn} = w_{n,m}^{mf-dcn}(t, x_{n,m}^{pc}) \cdot x_n, \quad (\text{C.14})$$

while the strength of the inferior olive input to the deep cerebellar nuclei is determined by the io itself [237],

$$x_{n,m}^{io-dcn} = w_{n,m}^{io-dcn}(t, io_{n,m}) \cdot io_{n,m}. \quad (\text{C.15})$$

The final corrective action of each cerebellar-like network (in blue Fig.C.4.b) is function of the excitatory activity of mossy fibers and inferior olive, and the inhibitory action of the Purkinje cells,

$$\Delta x_n^c = +k\left(k\left(\sum_{m=1}^M x_{n,m}^{mf-dcn}\right) + k\left(\sum_{m=1}^M x_{n,m}^{io-dcn}\right) + \right. \\ \left. -k\left(\sum_{m=1}^M x_{n,m}^{pc-dcn}\right)\right), \quad (\text{C.16})$$

where the nonlinear activation function $k(y)$ is defined as,

$$k(y) = \frac{2}{1 + e^{-2y}} - 1. \quad (\text{C.17})$$

C.3 Results

Four architectures that differ in terms of internal models contributions are compared: (I) feedback controller; (II) feedback controller combined with inverse cerebellar-like network; (III) feedback controller combined with forward cerebellar-like network; (IV) feedback controller combined with inverse and forward cerebellar-like networks. Each architecture has been tested in the presence of table-ball disturbances (case A), and extra uniformly distributed noise $\mathcal{U}(-0.1, 0.1)$ added to the process variables read by the sensors (case B). Hereafter, we use the notation "architecture number+A/B" (for instance IIA) to recall a specific test.

Table C.1. Weighting kernel parameters for $[ccm_1, ccm_2]$ [10,37]: LTP long-term potentiation, LTD long-term depression, MTP potentiation modulating term, MTD depression modulating term, α decaying factor.

PF-PC						PC-DCN						
n	Forward			Inverse			Forward			Inverse		
	LTP	LTD	α	LTP	LTD	α	LTP	LTD	α	LTP	LTD	α
1	$[10^{-2}, 10^{-3.3}]$	$[10^{-2}, 10^{-3.3}]$	[800, 170]	$[10^{-2}, 10^{-3}]$	$[10^{-2}, 10^{-3}]$	[300, 70]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]
2	$[10^{-2}, 10^{-3.3}]$	$[10^{-2}, 10^{-3.3}]$	[800, 170]	$[10^{-2}, 10^{-3}]$	$[10^{-2}, 10^{-3}]$	[300, 70]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]
3	$[10^{-2}, 10^{-1}]$	$[10^{-2}, 10^{-1}]$	[800, 170]	$[10^{-2}, 10^{-3}]$	$[10^{-2}, 10^{-3}]$	[500, 70]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]
IO-DCN						MF-DCN						
n	Forward			Inverse			Forward			Inverse		
	MTP	MTD	α	MTP	MTD	α	LTP	LTD	α	LTP	LTD	α
1	$[10^{-3}, 10^{-4}]$	$[10^{-4}, 10^{-5}]$	[1000, 100]	$[10^{-3}, 10^{-4}]$	$[10^{-4}, 10^{-5}]$	[100, 100]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]
2	$[10^{-3}, 10^{-3}]$	$[10^{-4}, 10^{-4}]$	[600, 100]	$[10^{-3}, 10^{-3}]$	$[10^{-4}, 10^{-4}]$	[100, 200]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]
3	$[10^{-4}, 10^{-4}]$	$[10^{-5}, 10^{-5}]$	[300, 1000]	$[10^{-4}, 10^{-4}]$	$[10^{-5}, 10^{-5}]$	[500, 200]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]	$[10^{-4}, 10^{-4}]$	$[10^{-4}, 10^{-4}]$	[2, 2]

The software is based on the ROS messaging framework [310] integrated in the Gazebo-based simulation environment Neurorobotics Platform (NRP) [270]. The three wrist joints are controlled in effort through the Gazebo service *ApplyJointEffort*. The encoders information are sampled at $f_{samp} = 50$ Hz. The computer used for the test has the *Ubuntu* 16.04 Operating system (OS type 64-bit), the Intel CoreTM i7-7700HQ CPU@2.80GHz \times 8 processor, and the *GeForce GTX 1050/PCIe/SSE2* graphics card. The tests are performed 20 times per experiment. Due to the stochastic nature of the experiments, the recorded data are expressed as μ mean value and σ standard deviation of the 20 tests. The oscillation (C.1,C.2) period is $T = 4$ sec which corresponds to one k trial, or rather iteration. The ball is launched from above when the table is parallel to the floor (1st trial). Due to some simulator problems that cause initial jerky movements of the robot, the cerebellar-like networks initiate the learning after the 5th trial, and are enabled to send correction after 2 more trials. This procedure is generally not necessary and is tailored to the simulator. The paper focuses on the angular position tracking performances of each experiment, which are measured in terms of MAE *mean absolute error* evolution computed for the ϵ_n angular position error of each joint,

$$mae_{q_n}(k) = \frac{\sum_{i=t}^{t+T} |e_{q_n}(i)|}{T} \quad \text{for } n = 0, \dots, N. \quad (\text{C.18})$$

Fig.C.5 reports the MAE evolution obtained for the three controlled joint during the 20 tests. From the analysis, the **IV** architecture (in magenta) resulted to correct larger errors faster with respect to the two networks used independently. This reactive behavior also appears in the **III** scheme (in cyan), but it is highly boosted in **IV** by the feed forward correction of the inverse model, thanks to the reduction of the loop delays affecting the feedback controller. Although the feedback controller is highly perturbed by the propagation of noise in the system (**IB** in green Fig. C.5), the biomimetic architectures do not present evident consequences. In particular, thanks to the forward model action, architectures **III** and **IV** robustly reduce the effect of noise as suggested by [208].

In about 5 trials, architecture **IV** rapidly corrects the feedback controller performance leading to an extra drop of 12% (joint 1) and 90% (joint 2) with respect to architecture **I** (in green). Moreover, architecture **IV** is the only one able to correct rapidly the

deviation of joint 3 between trials 8 and 15. It is worthwhile to mention that the feedback controller of the first joint is highly affected by the table weight, which slowly leads the joint towards the correct reference.

As we expected, the number of Gr granule cells of each *ulm* (LWPR receptive fields) created during the test case **B** are larger respect to the not noisy test (Table C.2), especially for architecture **III** and **IV** that resulted to act more robustly against noise. Moreover, We believe that the large numerical difference between the Gr of the two MCC is due to the update of the forward MCC before the inverse MCC that solve the one-to-many mapping issue of the inverse model [12].

Table C.2. Receptive fields created by the LWPR.

Architecture	II		III		IV	
Case	A	B	A	B	A	B
Inverse MCC	8	14	-	-	11	16
Forward MCC	-	-	78	146	436	510

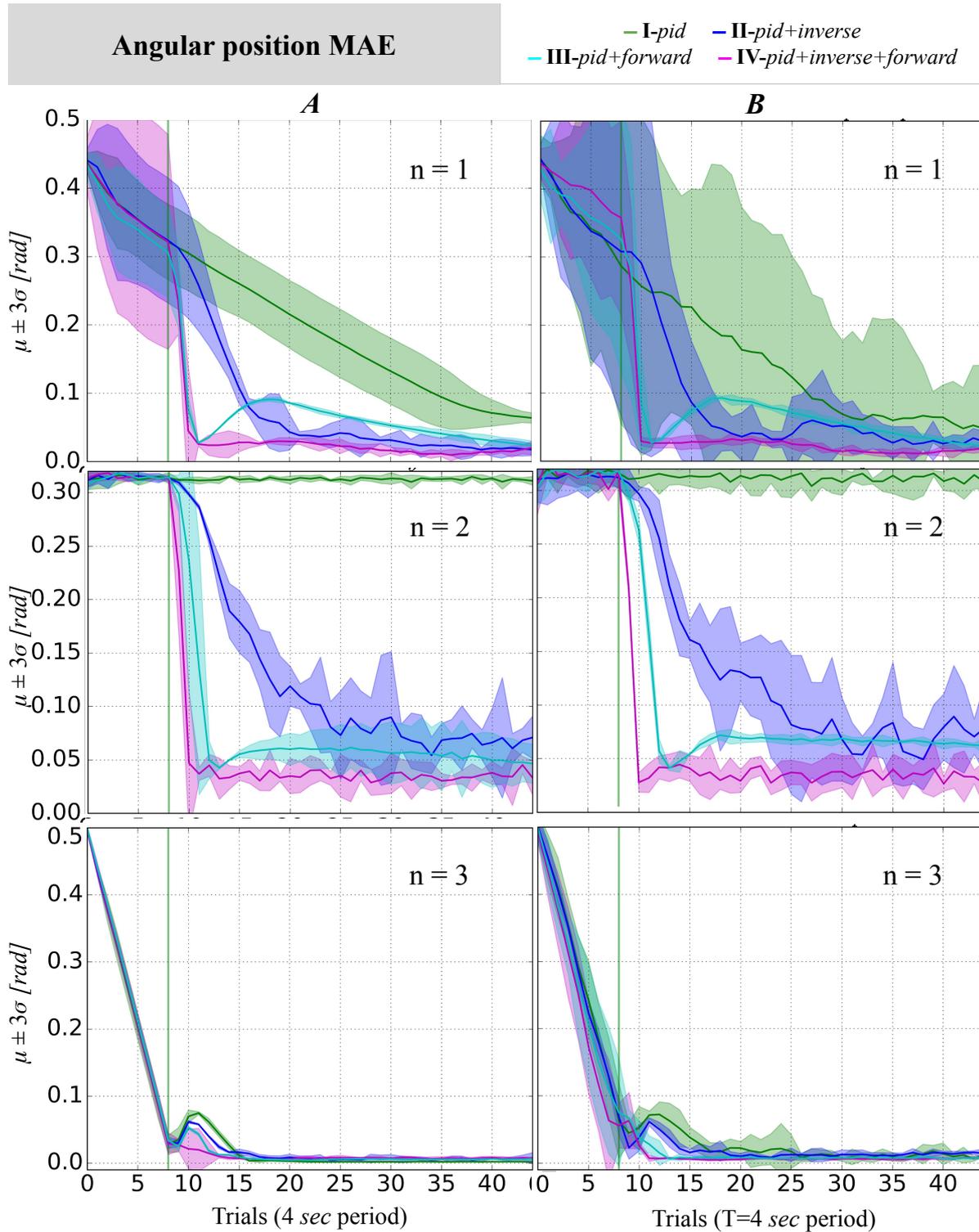


Figure C.5. Control architectures performances. The evolution of the MAE mean absolute error shows how the system is improving its tracking accuracy over the oscillations period. The plot shows the results of the 20 tests in terms of μ mean value (solid line) and 99.7% confidence interval (colored area). The vertical green line represent the moment the cerebellum starts adding contributions to the feedback loop ($k = 8$ trial).

C.4 Conclusions

Thus far, we have presented, tested, and compared four control architectures based on a versatile and real-time modeling structure that replicates the cerebellar internal models individual and combinatorial theories. In particular, we introduced a novel bio-mimetic learning and control cerebellar network that combines computational neuroscience, machine learning, and artificial neural network methods. The biomimetic controllers are tested on a humanoid robot acting in a perturbed non-deterministic environment.

The experiments confirmed the theories about the internal model independent and combinatorial contribution. In particular, the forward model resulted to act rapidly and efficiently against any noise and external perturbation in the early adaptation period, while the inverse model highly boosted the feedback controller action through the adaptive feed forward compensation that helped to reduce tracking error and loop delays in the post adaptation period. Finally, the combination of the internal models into a feedback control scheme merged the models strengths and guaranteed improved tracking accuracy, adaptation, high robustness to perturbations and filtering of noise.

In the details of the biomimetic neural network, the granule cells-parallel fibers layers are artificially interpreted with the LWPR. The algorithm has been employed differently with respect to the past experiments [255, 328], both in terms of input, training, and output signals (the details are listed in Section C.2). The algorithm resulted an efficient tool for the online mapping of high dimensional input space, and prediction of complex non-linear functions. Although high estimation errors can lead the LWPR to jerky prediction, the stratified structure of the network and the application of non-linear functions largely damped any over-reactive behaviors.

Most of the artificial cerebellar model do not employ biologically plausible learning and frequently miss the dcn deep cerebellar nuclei layer [208, 255, 298]. In the proposed model, the learning rules that iteratively update the network weights are based on synaptic plasticities derived from computational neuroscience studies [10, 37]. At some extend, this learning approach makes the network conceptually closer to the spiking models presented in the literature [10, 231, 232] but still not comparable due to the different codification of the signals propagating inside the networks. Moreover with respect to [231], we embedded the networks into a feedback control scheme where the MCCs are combined in a "tandem model" [12], in order to solve the one-to-many mapping problem affecting the inverse model. Although the high number of synaptic plasticities includes a large number of learning parameters, the network does not required excessive tuning, and no adjustment were necessary between experiments: the tuning resulted to work robustly even in highly noisy conditions (experiments **B**). For the scope of this manuscript, we did not focus on the optimal tuning, but we believe, as in most neural network case, that a modeling algorithm could help assetting the best combination of parameters. An additional difference with respect to the literature, is the internal modularity of each *uml* unit learning machine, which is divided in specialized compartment encoding kinematics or dynamical features. This modular and layered structure of the network significantly reduced the effects of nonlinearities, sensor noise, high feedback and prediction (LWPR)

errors.

Despite the novelties with respect to past models, at the current state the cerebellar network can not generalize all the possible conditions. The model itself replicate only a small component of a wider and modular structure that is under investigation. The biological cerebellum is composed by a large number of canonical circuits working in parallel. It is not clear how different circuits operate together towards a more general and complete learning and control action, but it is our intention to analyze these motor dynamics employing the proposed component as main building block. Moreover, the cerebellum is just one of the central nervous system area involved into the neural control of movements. We believe that the full exploitation of the cerebellar potentialities is only possible if the circuit collaborates with other generalized and biological plausible control structures.

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