

A microscopic image of neural fibers, likely from the cerebellum, showing a complex network of branching structures. The fibers are rendered in shades of blue and green, with some appearing more prominent and detailed than others. The background is a dark, deep blue.

# *Understanding Computational Models of Cerebellum Using Robots*

Master Thesis

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Technische Universiteit Delft



# UNDERSTANDING COMPUTATIONAL MODELS OF CEREBELLUM USING ROBOTS

MASTER THESIS

by

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# PREFACE

Curiosity about how humans function and what makes us special on this planet has drawn me towards research on the BRAIN. At the beginning of my masters program I approached Prof. Jonker to discuss some of the ideas I had on human vision system and the brain. With his typical excitement for science and technology he quickly introduced me to Ir. K.N. McGuire, who was then working on a cerebellum inspired robot vision set-up. After interacting with her the idea of working on such a topic was highly exciting. I imagined the thesis work would help me answer my own questions about the brain and human life in general.

After completing the plethora of courses and assignments at TU-Delft, I went away for my Internship on computer vision at Paris. Working on computer vision and seeing its current status, the fact that humans and other animals can do so much with vision and brain got me more excited about starting the thesis. Beginning on an ambitious research goal was highly exciting and challenging. Since I did not have much background about neuroscience I had to start from the basics to help me avoid making false assumptions. The problem statement at the beginning was being re iterated as and when we realized it was more complex than we imagined. Literature study helped me formulate my research question and divide it into sub goals to work with. The most difficult part was to remember the variety of tongue twisting names the nuclei and brain regions are given. But then they became familiar over time. Moving onto the implementation phase, I used the robot head, model built by PhD student Xin Wang and also used by K.N. McGuire for her thesis. Their work on the interface of the system and McGuire's simulation model of the robot were extremely useful and made it easy for me to focus on the main goal without having to build everything from scratch.

After doing what I have described through out this report, it was a truly humbling journey to realize the complexity that lies within ourselves. It has fascinated me enough to extend this journey by taking up a PhD to study more about the brain. Before the reader continues to reading the report, I request a few more minutes so that I can thank the people who are responsible for making this happen.

I would like begin with Prof. Jonker, when ever I was lost in the complexity of the work and felt small he cheered me up staying exited and curious about even the smallest observations. His expertise from building computer chips truly added a new dimension during our discussions on how the silicon chips are similar to computational architecture in the brain. My secondary supervisor Cagatay Soyer was a great joy to work with. All our discussions on the cerebellum are how humans think and act are truly cherish-able moments for life. Apart from the academic support one needs emotional support as well to stick to a problem for long time. My grand parents, mother, father, sister have truly sacrificed a lot from their lives to help me do what I want. My friend Sagar who has been a replacement for me in family back at home is something I owe him forever. I never believed digital systems could get people closer but thanks to FaceTime and Skype I stayed in touch with Meghana and Chaitra who supported me all along. But I had a family in Delft too, which is one of the best things I take back home from here. Thanks to Radesh for silently supporting me and making sure I eat on time to have the energy to work. I thank Apeksha, Arjun, Ashwathi, Giri, Kashmir, Kiran, Prasobh, Preethi and Rahul (Names are arranged alphabetically!) for believing in and supporting me. I dedicate this work to all the great music that kept me awake during the nights and day while working.

*S. Tata Ramalingasetty  
Delft, January 2013*



# ABSTRACT

Robotics has evolved since its inception and has found major applications in industries. With recent demand for medical and social robots, they are required to be flexible, compliant and adaptable. Today's robots are far from performing smooth, fine co-ordinated movements that are required to be used in the fields mentioned above. Primates seem to be excellent at such tasks, especially humans who perform complex tasks in dynamic environments and the credit is attributed to the complex brain structures and bio-mechanical design. In particular, cerebellum is understood to be involved specifically in fine co-ordinated movement control. But the understanding of computations that are responsible for this functionality has seen no consensus yet. One reason for this is the number of theories that exist to explain the functionality. This work focuses on reviewing existing theories and models to come up with testable model cases in a control scenario. To understand the principles behind cerebellum two different control scenarios are developed. One a control engineering approach to control the position of a DC motor and second a biological control scenario of vestibulo-ocular reflex (VOR) for image stabilization. For testing these a biologically realistic firing rate neuron model is used. For the implementation of VOR a robot head with stereo cameras is used. The purpose of VOR is to reduce image blur in the cameras. And cerebellum is known to be the adaptable block of this reflex. At the end of this work from the engineering control scenario it was observed that cerebellum as forward model adds stability to the system. And in the case of VOR the cerebellum was able to adapt the gains when subjected to disturbances.

**Keywords :** VOR, optical flow, firing rate model, forward model.



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## ABBREVIATIONS

<b>Ab</b>	Abducens Nuclei
<b>AER</b>	Address Event Representation
<b>ANN</b>	Artificial Neural Networks
<b>AVOR</b>	Angular Vestibulo Ocular Reflex
<b>Ba</b>	Basket Cells
<b>CF</b>	Climbing Fiber
<b>DCN</b>	Deep Cerebellar Nuclei
<b>FMME</b>	Forward Model Motor Error
<b>FMSE</b>	Forward Model Sensory Error
<b>GoC</b>	Golgi Cell
<b>GrC</b>	Granule Cell
<b>IMME</b>	Inverse Model Motor Error
<b>IMSE</b>	Inverse Model Sensory Error
<b>LTD</b>	Long Term Depression
<b>LTP</b>	Long Term Potentiation
<b>Ivor</b>	Linear Vestibulo Ocular Reflex
<b>MF</b>	Mossy Fiber
<b>MPT</b>	Model Parameter Tuning
<b>MVN</b>	Medial Vestibular Nuclei
<b>NN</b>	Neural Networks
<b>OKR</b>	Opto Kinetic Reflex
<b>OM</b>	Oculomotor Nuclei
<b>PC</b>	Purkinje Cell
<b>PF</b>	Parallel Fiber
<b>PID</b>	Proportional-Integral-Derivative
<b>RMSE</b>	Root Mean Square Error
<b>SCC</b>	Semi Circular Canal
<b>VN</b>	Vestibular Nuclei
<b>VPN</b>	Vestibular Pause Nuclei



# 1

## INTRODUCTION

"Stay Hungry Stay Foolish"

---

— Steve Jobs

**H**umans baffle themselves and others some times by their intricate motor control, be it in sports, art or survival. This fine motor control has evolved over thousands of years and today human brain is so adaptable that new, complicated motions can be mastered within few years. In the current era of robots, there is a rising interest in making robots replace mundane tasks taken up by humans everyday. For example tasks like picking and placing an object on a conveyor built now has been replaced by robot arms. The next step is it to improve robots to do more complex tasks. There are many challenges for robots to achieve this. Some of the major ones facing the robot community today are :

- Multi Joint Coordinated Control
- Control Loop delays
- Sensory Fusion
- Adaptability

The above challenges are constantly tackled by researchers but when one looks at humans or other vertebrates species immediately it can be observed that all of the above mentioned problems are already solved by them. Neuro-motor control along with body bio-mechanics is what makes it possible to achieve fine, co-ordinated movements in all the vertebrates. This observation though not new has drawn significant interest in the recent years. More attempts are made to understand how the brain is able to perform these complex computations in the most efficient manner.

Brain studies have helped us understand the blocks or regions involved during motor control. But the hierarchy in brain is so complex that it has been challenging to explain the working principles of each module separately. Lesions to brain centers causes loss of a particular function and by comparing the changes with a normal specie one can attribute the lost functionality to be the role of that particular brain region. This method allows neuroscientists to map different brain regions to various functions which when summed up can produce complex activities. This approach not only works for higher brain regions but can also be done for micro-functionality of a particular brain region. Figure 1.1 shows the work of (Schoch, 2008) where different sub-regions of the cerebellum are mapped to their corresponding functionality loss using MRI scanning techniques. Though there are distinct regions responsible for each

functionality it should be kept in mind that it only means that particular region is most prominently responsible but not solely. Different brain regions interact with each other and share tasks introducing a lot of redundancy in the system to avoid failures.

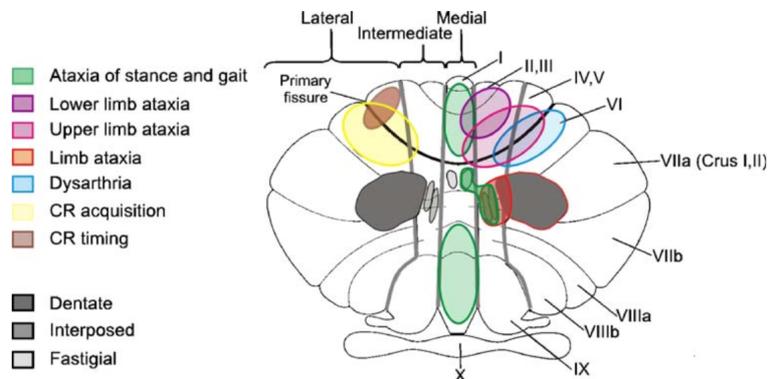


Figure 1.1: Cerebellum regions attributed to their corresponding functionality losses (Schoch, 2008)

By knowing specific brain regions responsible for each task robotics community has tried to focus on several regions to be studied. One of them is cerebellum. Before discussing the role and functionality of the cerebellum in movement control, first an over view of the motor control in central nervous system is done.

## 1.1. MOTOR CONTROL IN CENTRAL NERVOUS SYSTEM

Figure 1.2 shows a simplified version of the main blocks/regions involved in the central nervous system for movement control.

- Musco-skeletal system forms the final end effector that interacts with the environment.
- It is actuated by muscles which are controlled by the lower motor neurons present in spinal cord. Almost all control of the muscle has to be through the lower motor neurons present in the spinal cord. There are few exceptions to this where higher regions directly control the muscle. Spinal cord is also responsible for the two reflexes, stretch and tendon reflex.
- Next higher level is the brain stem. Brain stem is mostly involved in involuntary actions such as breathing. It is also involved in gating sensory information that arises from the stimuli and prevents excess information flowing into the brain.
- Cerebellum and Basal Ganglia form the side loops of the motor control. They are not directly involved in producing movements but only in improving them. Lesion to these regions does not paralyze some one but instead causes instability and difficulty in movements. Cerebellum is involved in fine movements, coordination and timing between movements and tuning of other elementary reflexes such VOR and in turn playing a crucial role in balance and stability.
- As with the cerebellum basal ganglia only modulates the descending motor actions. Lesion studies have shown that it is involved in action selection, movement modulation and eye movements. Since it is reward center of the brain there are theories that it is involved in higher level decision making as well.
- The intermediate entity in the brain is Thalamus. It is the data center of the brain as it receives information almost all brain regions and other brain regions can subscribe to relevant information.

An important role of the thalamus is to decide what to pay attention to among all the information flowing in (Peters and Van der Smagt, 2002).

- The final or the highest center for motor is the motor cortex and association cortex. These are involved in higher brain functions such as decision making, choosing actions and relevant movements. This structure still remains as a mystery to neuroscience in deciphering its functionality (Peters and Van der Smagt, 2002).

One thing that can be noticed immediately from the list is that multiple regions in the brain have similar roles. This has always been a problem in studying any individual region exclusively. Trying to look at the whole system at once is currently a very difficult task. Of all the regions discussed above, Cerebellum is a good candidate to study. The role of cerebellum is something robots today lack and find challenging. Understanding how it functions would have tremendous impact on how robots work. Also to neuroscience it would be very beneficial to understand other brain regions. Since it is at the lower level of the control center and only acts as a side loop, it is easier to isolate it and study while abstracting the functions of higher brain regions using conventional engineering techniques. By carefully choosing the right motor movement it is possible to even eliminate the involvement of spinal cord in the circuit. Cerebellum's neuronal anatomy described in chapter 2 shows that it has one of the simplest and homogeneous neuronal circuitry. All these reasons have attracted researchers from a long time to study the cerebellum.

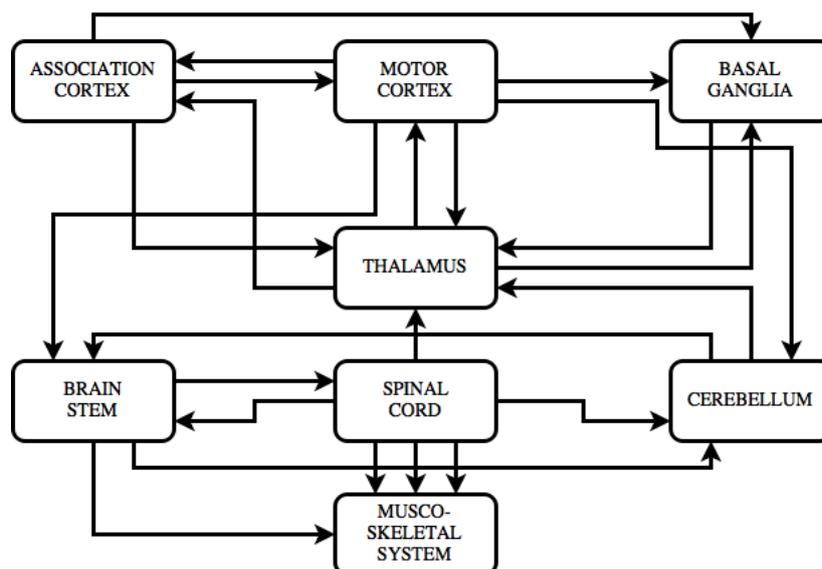


Figure 1.2: Central nervous system involved in motor control

So then why is there no theory on how the cerebellum works. Well the problem is that currently there are so many theories about the cerebellum that there is consensus on one. Difficulty in performing tests and measurements on brain has limited the progress and understanding the computational models of the cerebellum. Cerebellum's involvement in a wide range of tasks has made it more difficult to come up with an unified theory that can explain all its workings. But there are also some road blocks in neuroscience itself which are hindering its progress. (Markram, 2013) describes seven main challenges and in section 1.2 few that are relevant for the work are discussed.

## 1.2. CHALLENGES IN NEUROSCIENCE

Four challenges the neuroscience currently faces are discussed below. Each of these challenges are addressed in this thesis work while also keeping the bigger picture of understanding the cerebellum's computational models in mind. More details on the research goals are discussed in section 1.3.

- **Change the way Neuroscience is done** : For progress of Neuroscience it is to time work like other big fields in science like physics, astronomy and more. Meaning large collaborative initiatives need to be encouraged, open source data sharing and exchange of knowledge should be primary principles of Neuroscience research. (Markram, 2013) states "We have spent too much time waiting for a new Einstein to unify our field" expressing that it is about time people move from small isolated labs to large research groups that take cohesive decisions on important problems at hand.
- **Predictive Neuroscience** : Approach of studying individual neurons or even synaptic pathways as they are may be impossible for the astronomical number of neurons and synaptic pathways in a brain. Instead research should be towards building predictive models that capture the workings of certain aspects of brain.
- **Simulating the Brain** : Due to increasing fear in the public on the methods of Neuroscience techniques to understand the brain, step ahead would be to build a simulation model of the brain. This way one can conduct experiments in a repeatable manner and have no ethical constraints that exist now. Simulation not only involves Neuroscience community but other areas like hardware and software needed to do these computations.
- **From the Brain to Brain-Inspired Technology** : "The human brain is the world's most sophisticated information processing machine, yet it operates on computational principles that seem to be completely different from those of conventional computing technology" (Markram, 2013). This challenge can be treated as the one that describes the aim of the thesis. The ability of the brain to adapt to dynamic environments and learn tasks in short span of time makes it highly interesting to understand its workings and implement similar principles in technologies that better serve humans and other species.

## 1.3. RESEARCH GOALS

The main research goal of this master thesis can be formulated as, "*To understand the principles of cerebellum's involvement in movement control by implementing a realistic simulation to be tested on a robot head*". The objective can be broken into sub-goals to have a more organized approach at building up the thesis. Objectives are broken in the same way this thesis was conducted,

- To understand the existing theories on cerebellum's movement control functionality and draw conclusions on why there is no consensus yet.
- Implement a realistic cerebellum model that is free from any assumptions on its functionalities to start with.
- Test the cerebellum model in simple control scenarios to understand and criticize few existing theories.
- Set-up a robot environment which mimics a biological system that involves the cerebellums functionality.

Each of these are discussed a bit more in detail now. The first goal is to existing theories of the cerebellum. There is abundance of literature related to cerebellum and its role in movement control. Often this is misleading and can contradictory to each other. In this work one of the primary goal is to synthesize relevant information from the existing literature and represent it in a unambiguous way.

Once there is some understanding on the cerebellum's theories to explain its functionality, the next goal is to implement a simulation model of the cerebellum. This model is required to be as close to the real cerebellum as possible so that results from the simulation can be extended to biological counterpart with high confidence. The simulation model also needs to be computationally efficient so that it can be used in the next steps of this research.

The third goal of the thesis was aimed at testing the simulation model created in the previous step with the existing theories of cerebellum's role in control loop for a simple mechanical system. This would allow to critically review if a particular role is possible by the cerebellum and under what situations this can and cannot work.

The final goal of the thesis is to use a biological scenario to where in the cerebellum is know to play an important role is set-up and then with the simulation model and the robot set-up the environment is studied and conclusions are drawn on the possibilities of cerebellum's role and its computational mechanisms.

## 1.4. REPORT ORGANIZATION

This section describes how the complete thesis is organized so that the reader can skip to the his/her chapter of interest if it requires no prior reading. The organization also follows the same flow as that of the research goals outlined in section 1.3. Chapter 2 focuses on the first objective of the thesis. At first the anatomy of cerebellum is discussed which are important and relevant further chapters of the thesis. The anatomy is reviews the existing understanding of each cell and its role in the cerebellum. It is then extended to how learning is accomplished in the cerebellum. Finally an overview of all the existing theories on cerebellum are discussed and the chapter ends with proposing different possibilities of using the cerebellum as internal model in a control scenario.

Chapter 3 begins with various methods to look at the cerebellum to create a simulation model. Then focus is on firing models and how they can be used to construct an computationally efficient cerebellum model. More details on the steps involved in constructing a biologically realistic model is given. The chapter concludes with the discussion on implementation of learning rules for real time adaptation of the model.

Chapter 4 focuses on the goal of implementing a biologically realistic scenario to test the cerebellum model. The chapter begins with description on Vestibulo-Ocular Reflex and how the three neuronal arc involved in VOR is implemented using transfer functions. Then the chapter turns towards the practical hardware, robot head used for testing and framework responsible interfacing software, actuators and sensors.

Using the scenarios created in the previous chapters, both engineering control approach (PID) and biological control case (VOR) are subjected to various tests in chapter 5. The chapter also discusses the various parameters and metrics used to evaluate the performance of the cerebellum during control action. The results of all the described experiments are shown and commented upon.

Chapter 6 finally summarizes the whole work in the beginning and then discusses each of the goals taken up more critically and why particular choices were made to proceed further during the research. Also a section focuses on explaining the results obtained in the experiments chapter and reviews possible roles the cerebellum might be playing. Finally all the work is stitched together and a consensus on the work done is described. Since it is just the beginning of understanding the cerebellum model, final part of the chapter is dedicated to lay down the path for future research to be carried out.



# 2

## ANATOMY AND THEORIES OF CEREBELLUM

"When the solution is simple, God is answering."

---

— Albert Einstein

**C**erebellum has been a topic of interest for several decades now in the field of Neuroscience. Aristotle coined the name cerebellum which means "The Little Brain" in Latin. The naming is appropriate for two reasons, one it contains more than half of the total brain cells (Herculano-Houzel, 2010) and two it is involved functions ranging from voluntary and involuntary movement control to higher cognitive processing (D'Angelo and Casali, 2012). Unlike other brain regions, Cerebellum has received more attention due to its minimal and homogeneous neuronal architecture. With all the attention and research for decades unfortunately there is still no consensus on the role, functionality and information processing techniques of the cerebellum. Fortunately the anatomy of cerebellum is well understood and documented. In section 2.1 of the chapter a brief introduction to the cerebellum anatomy and functional organization is discussed. Learning is what makes the brain capable of adapting to dynamic environments, in section 2.2 the learning rules that exist in the cerebellum are discussed. In section 2.3 theories on the existing roles and models of the cerebellum are discussed with critical review on their relevancy in explaining the cerebellum's working. Using the theory from section 2.3, section 2.4 outlines the 5 possible models the cerebellum could be performing as and a simple control scenario to test them.

### 2.1. CEREBELLUM ANATOMY AND ORGANIZATION

Cerebellum has been studied and organized at various levels. Two ways of dividing cerebellum and relevant for understanding future chapters are discussed in this section.

1. Regional organization
2. Layer organization
3. Cell organization

#### 2.1.1. REGIONAL ORGANIZATION

On regional level the cerebellum can be organized into three major regions:

### VESTIBULOCEREBELLUM

This part of the cerebellum receives information from vestibular and visual centers of the brain to regulate balance and eye movements. This is the oldest part of the cerebellum that is seen in all vertebrates. Lesions in this part of the cerebellum can lead to several deficits in motor control. A few examples for vestibulocerebellum deficit are nystagmus, smooth pursuit, strabismus, oscillopsia and VOR (Hotson, 1984). In figure 2.2<sup>1</sup> the circuits connecting the part of cerebellum to the only external nuclei, vestibular nuclei is shown. Cerebellum receives vestibular information and projects back to the same nuclei forming a closed loop modification of vestibular nuclei.

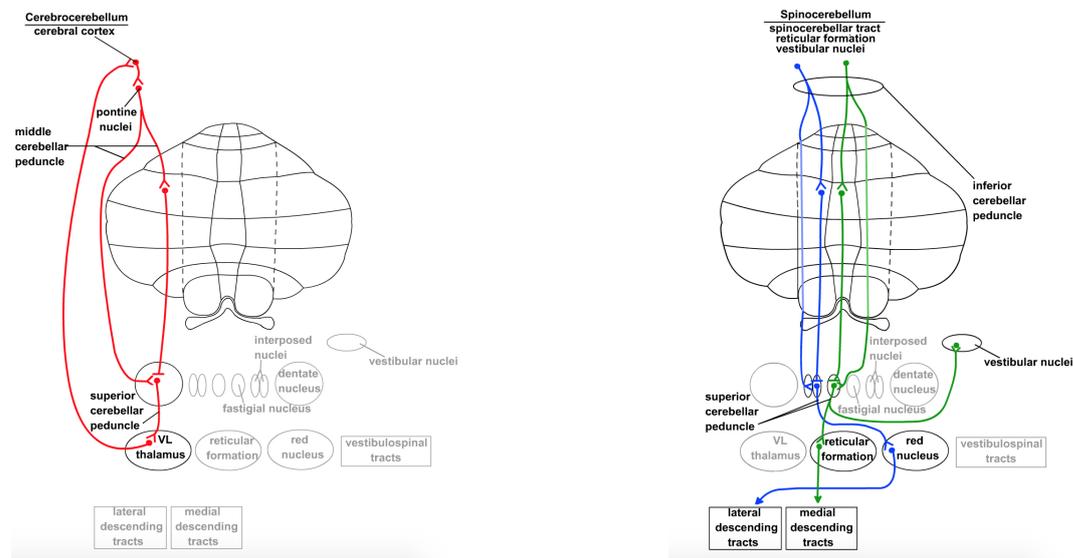
### SPINOCEREBELLUM

This part of the cerebellum receives proprioceptive, visual and auditory information from the spinocerebellar tract. The outputs innervate rubrospinal, vestibulospinal and reticulospinal tracts and is responsible for regulation of body and limb movements and integration of sensory and motor commands to produce adaptive coordinated movements. Spinocerebellum is believed to have at least two maps of the body (Edition, 2004). Most prominent effects seen due to spinocerebellum lesion are in coordination of gait, lack of co-ordination in hand movements, speech and eye movements. Figure 2.1b shows the tracts connecting different parts of the brain to cerebellum. There are two separate distinct tracts that flow through this region of the cerebellum.

### CEREBRO-CEREBELLUM

This is the newest and largest region of the cerebellum, receiving information from cerebral cortex and is involved in movement planning and cognitive functions. Large connections to the cerebral cortex are found through the pontine nucleus. The connections from this regions project to the thalamus and then back to the cerebral cortex. Since this region receives higher level goal oriented information from the cerebral cortex, one of its functions could be to predict the necessary movement information. This information is passed back to the motor cortex via thalamus and then to the lower motor neurons via brain stem and the spinal cord.

The structural connectivity of the above cerebellum regions to other brain region are shown in figure 2.1



(a) Cerebrocerebellum

(b) Spinocerebellum

Figure 2.1: Regional organization of cerebellum based in its connectivity

<sup>1</sup> Imagesource : <http://neuroscience.uth.tmc.edu/s3/chapter05.html>

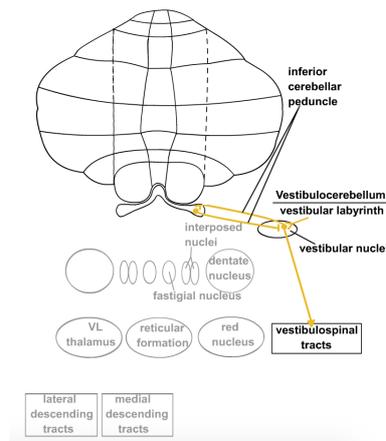


Figure 2.2: Vestibulocerebellum

### 2.1.2. LAYER ORGANIZATION

On a cellular level cerebellum has a highly regular structure, this uniform organization of cell structures makes it fairly easy to study the cerebellum at a cellular level. The cerebellar cortex is again sub-divided into 3 main groups based on their cell composition :

1. **Granule Layer** : This is the inner most layer of the cerebellar cortex and contains granule cells and mossy fiber axons.
2. **Purkinje Layer** : This is the middle layer and contains the purkinje cells, the only source of output to the deeper nuclei that connects to brain stem and the thalamus.
3. **Molecular Layer** : The outer most layer contains the basket and stellate cells along with axons from granule cells.

### 2.1.3. CELL ORGANIZATION

One of the most interesting features of the cerebellum's anatomy is its homogeneous cellular architecture through out. All the regions discussed in section 2.1 have the same cellular architecture but involved in different functional roles. This has lead to a consensus that this unified architecture must have a common information processing technique and based on its inputs it performs different roles. Thus it has become challenging to explain how a wide range of functions can be encapsulated in a single architecture. In chapter 3 some theories which have tried to explain the possible workings of this architecture are briefly discussed.

There are 5 major cells that are considered to be important for all the processing happening inside the cerebellum. fig. 2.3 shows the cellular architecture and the layer division based on the cells.

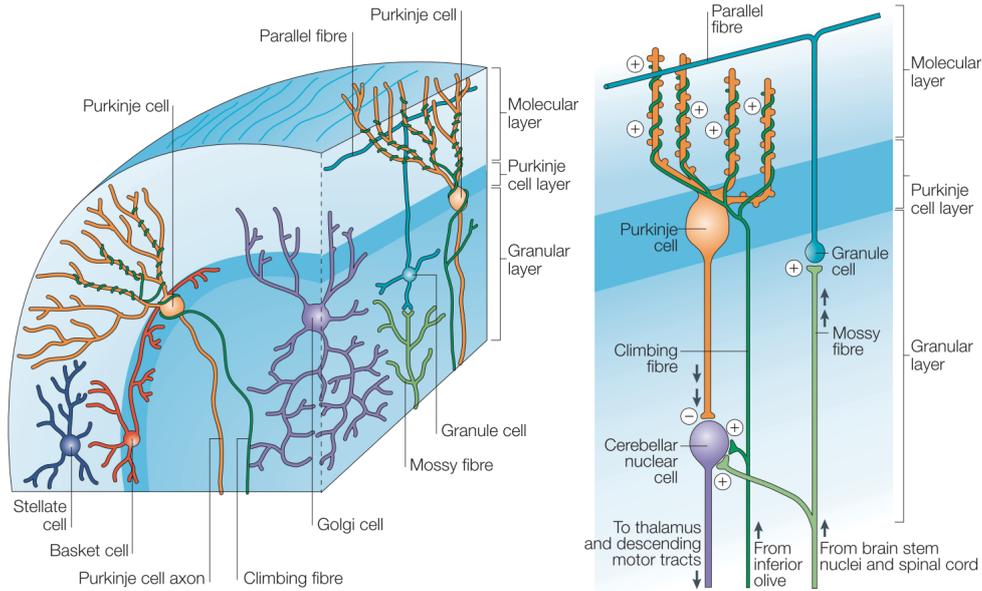


Figure 2.3: Cellular and micro structure of the cerebellum (Apps and Garwicz, 2005)

1. **Mossy Fibers (MF):** These form the major source of input to the cerebellum. As seen in the regional organization section, cerebellum receives information from several other brain regions. Mossy fibers carry visual and auditory, somatosensory, proprioception, efference motor commands, higher goal commands. Mossy fibers terminate forming excitatory synapses at the Granule cells (GrC) in the granule layer, Golgi (GoC) cells and the Deep Cerebellar Nucleus (DCN).
2. **Granular Cells (GrC) :** GrCs are small in size and are the most frequently found cells in the cerebellar cortex (Peters and Van der Smagt, 2002). Their small size is what makes the cerebellum contain more than half of the brain cells. They have a unique cell structure with four dendrite and two axons that project to the molecular layer and form parallel fibers that innervate the purkinje cell dendrites in the molecular layer. Parallel fibers are perpendicular to the purkinje cell dendrites allowing them to synapse with thousands of purkinje cells.
3. **Climbing Fibers (CF):** CF's are the secondary source of inputs that flow into the cerebellum. In most cases it is seen that CF's carry signals that are responsible for learning in the cerebellum (Línera and Gil, 2011) (Rasmussen *et al.*, 2008) (Ito, 2006) (Tabata *et al.*, 2002). In other words CF's carry the error signals. CF's originate from various nuclei in inferior olive. However it is still unclear how the errors are represented. The dispute is mainly between error being represented in sensor domain or motor command domain. In the following section it will be seen that for learning to happen, if the cerebellum works as a forward model the errors need to be in sensory domain and errors need to be in motor command domain for learning an inverse model.
4. **Purkinje Cells (PC):** PCs are the largest of the cells present in the cerebellum and belong to the purkinje layer, their dendrites form synapses with the parallel fibers. PC's also receive signals from the mossy fibers. As seen in figure fig. 2.3 PC axons are the only source of output from the cerebellum before reaching the deep cerebellar nuclei that project other parts of the brain. PC's projection to the deep cerebellar nuclei is inhibitory. The synapse between PC and Parallel fibers is mostly accepted to be the major site of learning. Learning happens through Long Term Potentiation and Long Term Depression. PCs are most famous for their two distinct spike patterns.

- (a) *Simple Spikes* : These are spike trains produced by PCs at a frequency of 17-150Hz that occur mostly when PCs are activated by parallel fibers.
  - (b) *Complex Spikes* : These are spikes produced at lower frequency of 1-3Hz with a long initial burst followed by a small amplitude higher frequency burst of spikes. Complex spikes are produced by Climbing fibers from the Inferior olive. Though every PC is innervated with just 1-10 climbing fibers, the synapse is so strong that it suppresses the activity of parallel fibers and produces complex spikes.
5. **Golgi Cells (GoC)**: GoC's are inhibitory inter-neurons that regulate the activity of GrC's by forming both feed-forward and feed back connections. GoC's receive excitatory input from mossy fibers (feed-forward) and another excitatory input from the output of GrC's(feed back).
  6. **Basket Cells (Ba)**: Apart from the above mentioned major cells in the cerebellum there are few other less commonly found but responsible cells. In fact there are still more cells to be discovered in the cerebellum. Basket cells are inhibitory inter-neurons that innervate PC's to regulate its activity.

## 2.2. LEARNING IN CEREBELLUM

Of all the brain regions cerebellum is considered to be highly plastic due to its involvement in learning new motor tasks and constantly adapting to errors. Experiments like the prism adaptation test show that cerebellum is responsible in learning new motor tasks (Baizer *et al.*, 1999). But there is evidence that learning is not isolated to cerebellum but involves other cortical structures as well (Menzies *et al.*, 2010). In either case lesion studies show that cerebellum deficit patients have degraded their ability to learn a new task. Experiments have shown that after learning a new task even if the cerebellum is removed/suppressed the learning still appears to be present (Robinson, 1976). This shows that there is transfer of learning from cerebellum to other structures (Menzies *et al.*, 2010).

As described in the previous section, main learning site of plasticity in the cerebellum is at the synapses between PF and PC. This plasticity has been identified to be governed by two main processes namely (Ito, 2001; Albus, 1971; Marr, 1969)

- Long Term Depression (LTD) : LTD is the process where the efficacy between the PF-PC synapses reduce over time. It is governed by the activity of climbing fiber originating in the inferior olive. LTD occurs only when there is a simultaneous activity of the climbing fibers and the parallel fibers. During LTD purkinje cells produce complex spikes but they are not strong enough to drive other neuronal circuits
- Long Term Potentiation (LTP) : LTP is the reverse of LTD that is the efficacy between the PF-PC synapses increase over time when there is no correlation between the climbing fiber and parallel fiber activity.

The above two learning process are not specific to cerebellum but they exist in other brain regions too. There is more evidence now that the site of plasticity is not solely limited to PF-PC synapses but indeed in other cerebellum locations as well. Though most the work ever since then has accepted that these are the sites of plasticity for several tasks, there are evidences that apart from PF-PC plasticity there exists zones of learning in the granular layer, molecular layer and at Deep cerebellar nuclei (D'Angelo *et al.*, 2016). (Anastasio, 2001) proposed a learning algorithm that does not use climbing fiber as error signals that modulate the PF-PC synapses but instead use them as a synchronization pulse for learning. These evidences show that even at the cellular level cerebellum is yet to be fully understood. Most researchers agree to the fact that cerebellum's working is largely dependent on the task and it causes confusion when results from different tasks are compared for a common understanding. (D'Angelo and

Casali, 2012) state that cerebellum operates as a general purpose architecture whose output and computations depends on context and the loop in which it operates with other brain regions.

### 2.3. THEORIES ON ROLE AND FUNCTION OF CEREBELLUM

After understanding basic components that make up the cerebellum the next step is to extend these to understand the functionality of the whole cerebellum in control context. Functions of the cerebellum are primarily understood due to lesions. In (Riku, 1995) authors mapped different regions of the cerebellum to various losses motor control and timing related activities.

The processing of Cerebellum can be formulated in simple terms as "mapping a set of time dependent input signals into another set of time dependent output signals". In the past attempts to explain the action of Cerebellum has many. The theory that stuck for longest is that of cerebellum consisting an internal model. Original proposed by (Ito, 1970), the fact that brain along with the spinal cord is able to perform complex tasks involving large number of joints and muscles at high speeds calls for an internal model that can generate commands in a feed-forward mode to avoid delays due to sensory feed backs. Currently the debate is between two types of models that might exist in the cerebellum. One being that cerebellum learns the inverse dynamics model of the control objective under supervised learning conditions and then uses this model to produce motor commands. The inverse model hypothesis has its own drawbacks that it requires a error signal in motor commands to train the cerebellum but if the motor error are a priori then there is no requirement of an inverse model in the first case. However these challenges have been solved from a control engineering perspective but finding physiological evidences of these in the brain has been challenging (Wolpert *et al.*, 1998). The other alternative for an internal model is that the cerebellum acts as a forward model, that is it based on the current motor commands and past sensory information it can predict the consequences or future sensory states which would arise because of the current motor action. This prediction allows the brain to avoid waiting for the sensory feedback to correct itself. (Miall and Wolpert, 1996) discuss on why there is a need for a forward model in the brain and why cerebellum could be a possible site for this more in detail.

Based on the models discussed above chapter 3 discusses implementations that are based on them. Apart from the above mentioned models there are other less accepted theories in the literature as well. One of them is the multiple forward and inverse model, (Wolpert and Kawato, 1998) proposed a possibility that cerebellum could be a possible site that contains pairs of forward and inverse models of different movement related tasks. New tasks can be formed by a combination of these modules. This theory has not received support from neuroscience studies and has not been tested in simulations as well. Another proposal is that cerebellum acts as a general processing unit which adapts its role based on the inputs and tasks (D'Angelo and Casali, 2012).

No theory has seen full support or can be completely denied. Most of the proposals have evidence supporting their claims but it is hard to extend the results to a generalized theory that can explain all other experiments. One of the main challenges is the difficulty in measuring neuronal activity from different brain regions. The studies are also often restricted to specific species and works have shown that there are differences in the way each individual species brain works and results cannot be often extrapolated to other species. (Markram, 2013) extends these challenges in neuroscience that are few of the reasons why there is consensus in the theory on cerebellum.

Assuming that cerebellum contains an internal model is very important for simulation studies. Simulations do not include all brain regions in detail and often abstracted to simpler blocks which capture only its top level functionality. Therefore one needs to decide where and how the inputs and outputs of the cerebellum connect in a given control. Depending on these choices the role of cerebellum would be either as a forward or inverse model. One may argue that if one knows the inputs and outputs of a block then why not conclude if it is a forward/inverse model, unfortunately understanding how neurons encode information is yet another unclear area in neuroscience. This has raised difficulties in correlating

neural activity to engineering dimensional quantities such as position, velocities and forces.

## 2.4. CEREBELLUM IN SIMPLE CONTROL SCENARIO

In this section the possibilities of using above discussed cerebellum models in a control scenario is discussed. From lesion studies it has been understood that a deficit in cerebellum's functionality does not lead to complete loss of motor control but only deteriorates the performance and timing of movements. This can be extended to an assumption in simulations that there exists a primary control loop in the system that is less-adaptable and limited in performance under stable conditions. This allows the system to be controlled even without the cerebellum. This loop can be extended to be the motor cortex of the brain. In simulation model a classical Proportional-Integral-Derivative (PID) feedback control approach that is simple and most widely used in control application is the primary control loop. PID control is a three parameter feedback error dependent module. The governing equation that transforms the error into appropriate corrective motor actions ( $u$ ) is given in 2.1, the time dependent error signals are transformed to Laplace domain.

$$u = K_p * e(s) + K_d * s * e(s) + K_i \frac{e(s)}{s} \quad (2.1)$$

Where,

- $K_p$  - Proportional gain
- $K_d$  - Derivative gain
- $K_i$  - Integral gain

The control experiments are performed on a simple mechanical systems. An electric dc motor for position control. More details on the system are discussed in chapter 5. Control scheme without the cerebellum is shown in fig. 2.4.

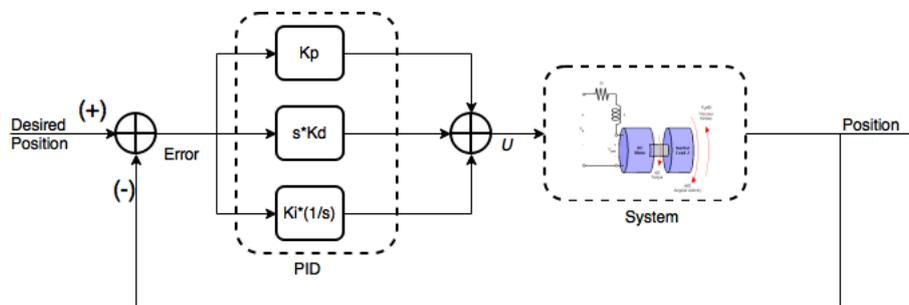


Figure 2.4: PID feedback control with mass spring damper system

There are two major ways in which the cerebellum can influence the control loop. One is to modulate the sensory information that arrives through the feedback or to modulate the motor commands generated by the PID control block. The former is the forward model case where the cerebellum learns to modulate the sensory information and the latter is the inverse model case where it learns to modulate the motor commands produced by the PID block. The above models can be further subdivided based on their learning signals. Research has shown that cerebellum learns under supervision of a learning signal via the climbing fiber. But there has been difficulty in understanding what errors the climbing fibers actually encode. Two possibilities are, error signals can be either in sensory domain or in motor command domain. Though there is little evidence supporting that cerebellum learns via motor errors since if motor errors were already known there is indeed no necessity for correction. The final other possibility that

could be the role of cerebellum is system parameter tuning. It is clear that cerebellum does not directly influence motor actions but does it via other brain regions that are responsible for motor control. This could mean that cerebellum tunes other brain centers to produce appropriate motor actions to reduce the error it receives. This is also in accordance to the multiple plasticity site theory that learning is indeed transferred to other brain centers over time. This extended to the simple control loop can be seen as the cerebellum influencing the PID parameters in order to achieve the required dynamics. The five possibilities can be now enumerated :

- Forward Model Sensory Error (*FMSE*)

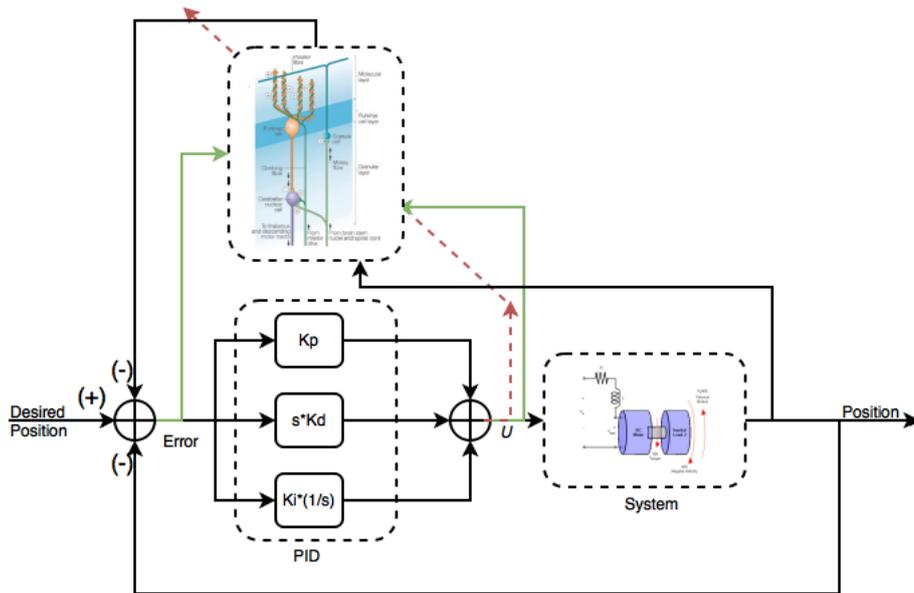


Figure 2.5: PID Control with cerebellum modulating sensory information based on motor error

- Forward Model Motor Error (*FMME*)

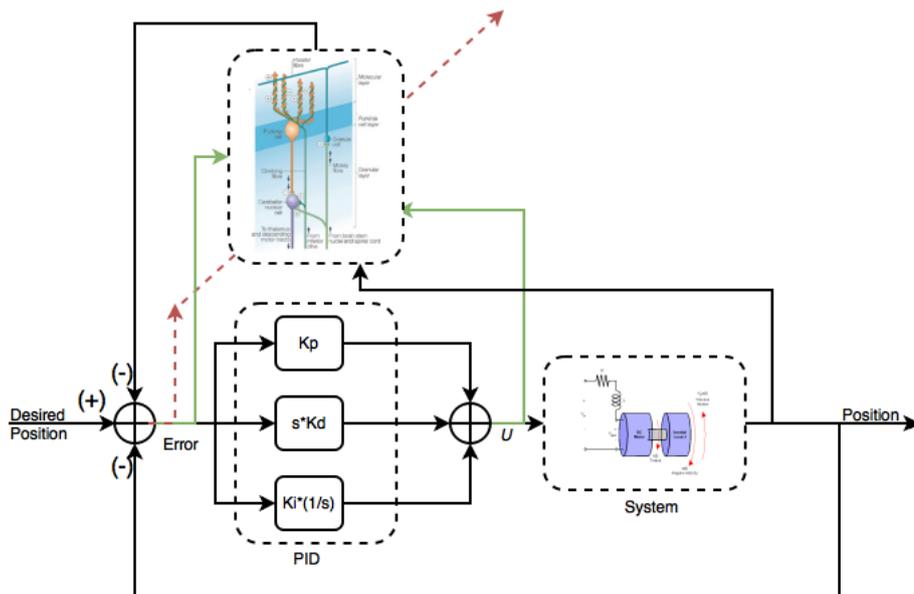


Figure 2.6: PID Control with cerebellum modulating sensory information based on sensory error

- Inverse Model Sensory Error (*IMSE*)

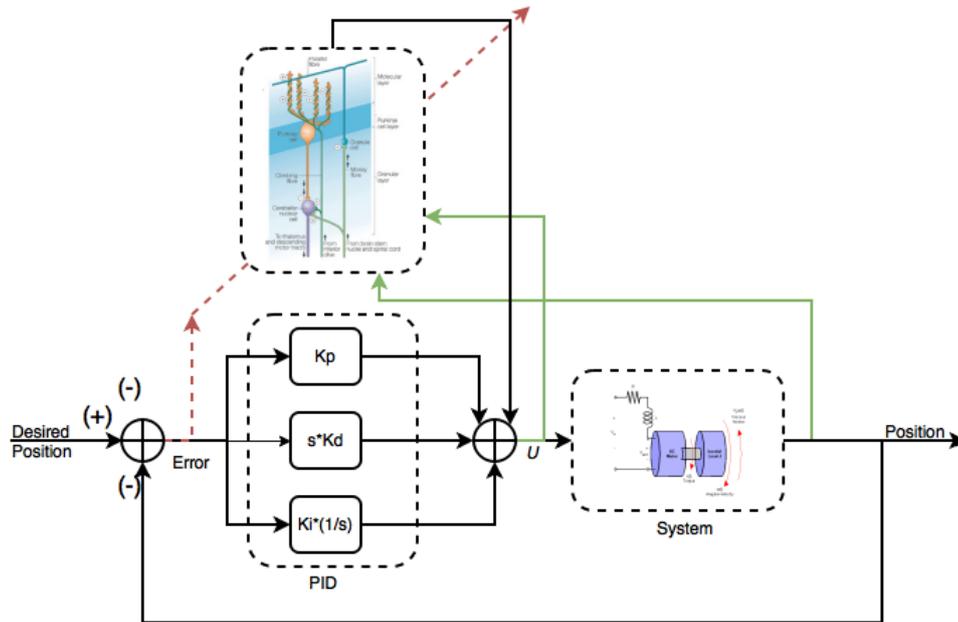


Figure 2.7: PID Control with cerebellum modulating motor command based on sensory error

- Inverse Model Motor Error (*IMME*)

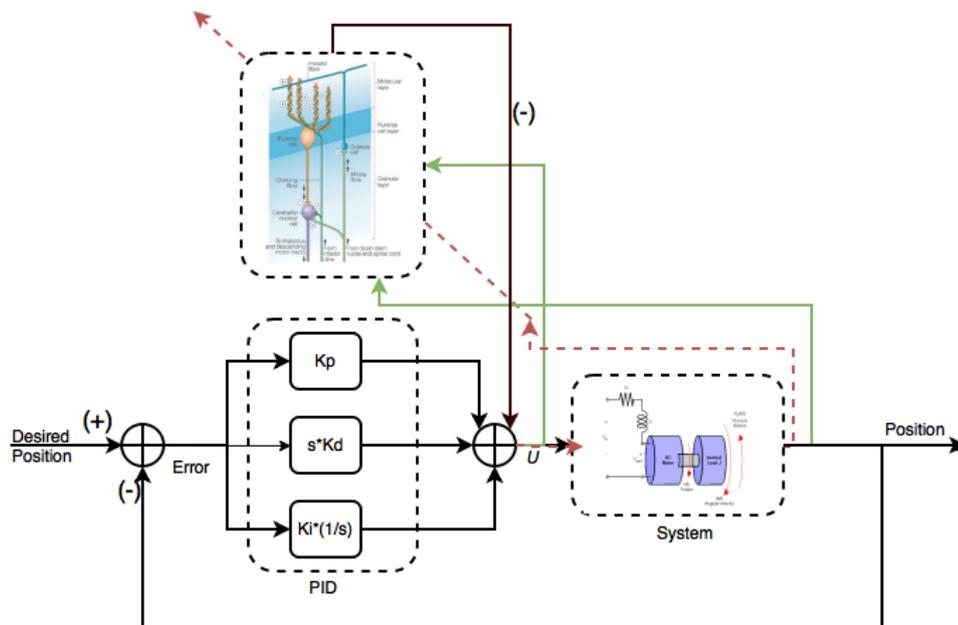


Figure 2.8: PID Control with cerebellum modulating motor command based on motor error

- Model Parameter Tuning (*MPT*)

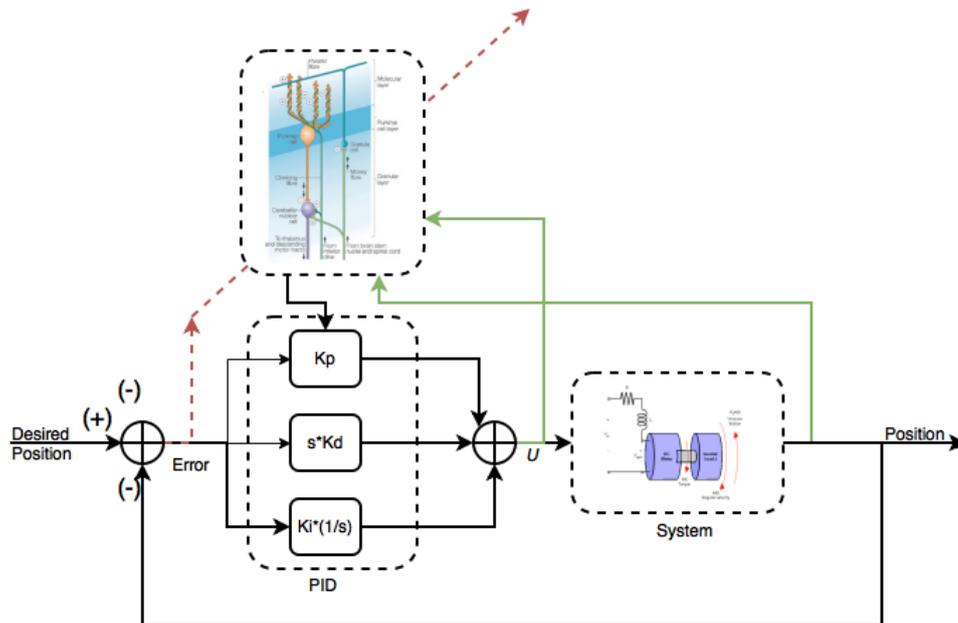


Figure 2.9: PID Control with cerebellum tuning the control parameters

For each of the above shown possibilities, response and performance of the circuit is evaluated in chapter 5. Evaluating multiple models under one control scenario allows one to comment on different model principles with more confidence.

### Summary

1. Anatomy of the cerebellum is discussed at macro and micro level.
2. Different regions of the cerebellum are involved in exclusive functions of the body.
3. Cellular organization in the cerebellum and roles of each cell/fibers are discussed.
4. Learning mechanisms involved in the cerebellum and new proposals that there are multiple sites of plasticity to be considered for understanding the cerebellum.
5. Based on the basic anatomy existing theories explaining the functionality of cerebellum.
6. Internal model theory is the most famous one that has received excessive testing and studies.
7. Mainly two types of internal model possibilities :
  - Forward Model theory
  - Inverse Model theory
8. Forward model theory has been receiving more support from neuroscience studies.
9. Reflections on difficulties in finding a consensus for the role of cerebellum.
10. PID based control loop for simulating the role of cerebellum
11. Outlined and depicted five possible roles and learning mechanisms of cerebellum in a control loop.



# 3

## IMPLEMENTATION OF CEREBELLUM SIMULATION MODEL

"What I cannot create, I do not understand."

---

— Richard Feynman

**T**o understand the actual working principles of cerebellum it is required to probe and measure the signals and responses of neurons individually and as a population of neurons. Existing technologies does not allow to perform system identification techniques with ease and repeatability. Building a simulation model will therefore allow researchers to perform experiments that are not possible to be performed on a living subject. This is in accordance with the views of Neuroscience regarding the steps to be taken in future for its progress discussed in 1. Though there have been many attempts at implementing such simulations in the past not until recently has the computational power truly allowed to implement simulations that are close to brain structures. But even the current simulations face challenges and require enormous amounts of power for simulations. Real-time simulations are highly difficult to implement in the order of number of neurons and synapses that occur in brain structures. This chapter discusses the implementation of a real time Cerebellum model under certain assumptions. Section 3.1 discusses a brief over-view of existing techniques for brain structure simulations that are available and also explains the principles of firing rate models used for simulating the cerebellum. Section 3.2 gives details on the implementation of cerebellum simulation. Section 3.3 describes the learning rules used in the simulation for training cerebellum model in real time.

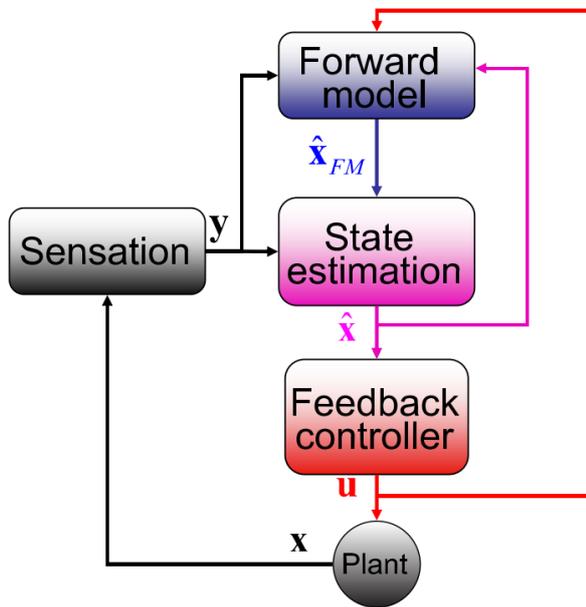
### 3.1. DIFFERENT METHODS OF IMPLEMENTATION

As understood from Chapter 2, the processing of Cerebellum can be formulated in simple terms as "mapping a set of time dependent input signals into another set of time dependent output signals". In the past attempts to implement the action of Cerebellum has in computer simulations been many. Simulation techniques can be broadly classified into two types :

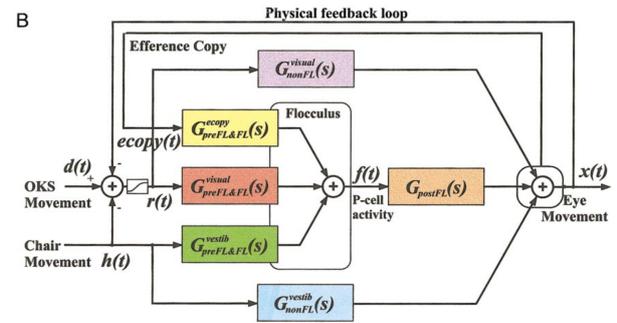
#### 3.1.1. MACRO FUNCTIONAL SIMULATION

These are simulations techniques where the functionality of cerebellum is concerned at a macro level. One way to implement these models is to start with an assumption about the role of cerebellum from previous studies and then try to implement the transformation functions without having the structure and micro details as a constraint for modeling. These models help testing theories and hypothesis in motor

control scenarios that the cerebellum is known to be influential. Simulations can be using mathematical equations or more abstract approaches like artificial neural network. In (Frens and Donchin, 2009) cerebellum is tested as a forward model that predicts future sensory information based on current motor commands and previous sensory feedback. There is no focus on the learning mechanisms or micro level computations of the cerebellum. The forward model action is implemented using a Kalman filter for sensory prediction. Another approach for functional models is using system identification techniques from control theory. (Hirata and Highstein, 2001) treated every important brain structure involved in vestibular ocular reflex as a black box and then estimated their transfer functions based on the input and output cell recordings at each structure. This approach sheds light on to the possible actions involved in each stage of a task with real data and minimal assumptions. The shortcoming of this approach is that the system under study is linearized which may over simplify important actions of each block, no information can be extracted on how these actions are performed as the parameters estimated are not in the same dimensions as the original system. fig. 3.1a and fig. 3.1b show the block diagrams of the techniques discussed above for functional model simulations.



(a) State Predicting Feedback Control (Frens and Donchin, 2009)



(b) System Identification technique for Vestibulo-ocular Reflex (Hirata and Highstein, 2001)

### 3.1.2. MICRO FUNCTIONAL MODELS

In this approach not only the function of the cerebellum is considered but also the micro cellular structure responsible for the function is also given equal importance. The most famous one is the theory proposed by Marr (Marr, 1969) and Albus (Albus, 1971), Marr view was that Cerebellum acted as an associative memory which learns to associate a random input pattern (proprioception) to a motor/action state and the learning happens at the PF-PC synapses based on Long-Term Potentiation with error signals supplied from the climbing fibers originating at the Inferior olive nucleus. Albus extended the binary pattern recognition to a continuous model called CMAC (Cerebellar Model Articulation Controller) which could approximate different time based functions. The latter model's learning was based on Long-Term Depression unlike the former theory. Later these two theories were extended as an adaptive filter by (Fujita, 1982) to explain the workings at both micro and macro level of its function and has been widely used in cerebellar studies using simulations. Figure 3.2 shows how the adaptive filter structure is similar to the simplified network in the Cerebellum. One of the short comings of this model is that it has been applicable to only systems where the plants mass and inertias are negligible (Wilson *et al.*,

2015). Another limitation of this model is that there are no recurrent connections which were discussed in chapter 2.

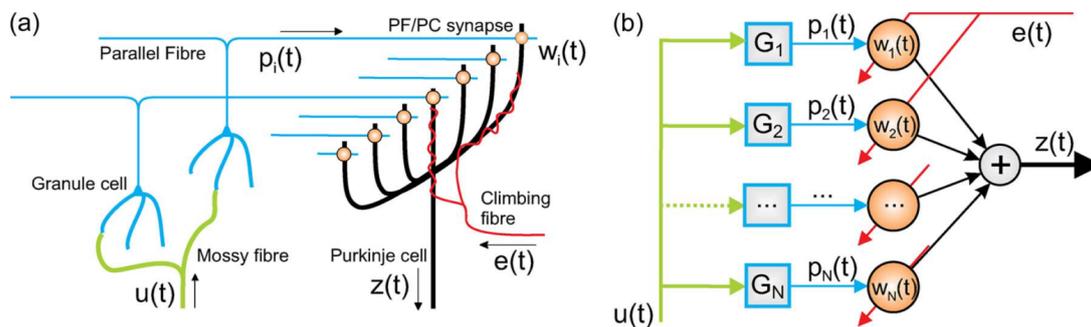


Figure 3.2: Adaptive filter model comparison with cerebellum cellular structure (Alexander *et al.*, 2009) ©IEEE

Where,  $u(t)$  : Input to the cerebellum/Adaptive filter  
 $p_i(t)$  Delayed input signals through parallel fibers  
 $w_i(t)$  Adaptive weight vectors/ Plasticity site at Parallel Fiber-Purkinje Cell synapses  
 $e(t)$  Error/teaching signal (Adaptive filter) from climbing fiber  
 $z(t)$  Output from the cerebellum/Adaptive filter

A more detailed approach than the one mentioned above is to consider not only the way the cells in cerebellum are connected but also the dynamics of each type of cell present. The third generation of artificial neural networks known as spiking neural networks consists of neurons that mimic the spiking activity of biological neurons. The most influential study conducted in Neuroscience that lead to the Hodgkin-Huxely model of neurons still stand as the foundation for building spike based neural networks. (Boucheny *et al.*, 2005) used a real time spiking neural network for the control of a robot arm. The implementation is one of the most detailed real time cerebellum model in a computer simulation. But the work did not apply the same technique for other brain regions and this lead to a hybrid implementation of realistic cerebellum model in a classical engineering control environment.

### 3.1.3. FIRING RATE MODELS

Above mentioned modeling approach can be implemented either as mathematical models, Artificial Neural Networks or spiking neural networks. Mathematical modeling is way too complex for realizing any realistic brain region functionality. After much exploration of existing cerebellum implementations it was decided to go for a spiking neural network (SNN) based approach for this work. Carrying out an evaluation for real time medium scale spiking neural networks, none of the existing frameworks seem to be computational efficient enough to be used on conventional current generation desktops (Quad Core, 8GB RAM, 3.8 GHz). They either require parallel processors or GPU's for close to real time capabilities. EDLUT (Ros *et al.*, 2006) an Event Driven Look-Up table showed real time performance capabilities under limited computational resources. The authors have also shown implementations of the framework in control of real time robots (Carrillo *et al.*, 2008; Casellato *et al.*, 2014). Unfortunately the complete source code is not fully supported and the framework lacks compatibility with robot frameworks like ROS. Hence it was not possible to use the spiking neural network for simulation of the cerebellum model. Next best alternative was to simulate the cerebellum model using a firing rate model.

Firing rate models fall under the second generation artificial neural network where the input and output signals of the neuron represent an average firing rate of a population of particular family of neurons.

The drawback of this approach is that no information can be encoded between two distinct spikes and the concept of spike timing cannot be captured. But most of the Neuroscience studies on cerebellum make use of spike rates to understand the information exchange (Belton and McCrea, 2000; Bengtsson and Hesslow, 2006; Clopath *et al.*, 2014). Though the exact dynamics of the individual neurons will not be modeled and studied here, an overall average response of a population of real neurons will be represented by the activity of individual neuron's in the simulated model. This also means that a smaller model would represent the activity of a large number of neurons in the actual brain.

Basic artificial neural networks (ANN) are made up of fundamental processing units called neurons. A neuron receives one or more inputs that are weighted at any given instant of time, the inputs are weighted, summed and thresholded to produce a single output signal. Various thresholding techniques exist and the most basic one is a simple binary threshold. That is the neuron produces a binary high or low if the sum of its weighted inputs is larger or lesser than a given threshold respectively. Building on, several of these simple processing units are inter-connected to produce complex networks. Another important concept of NN's are how these interconnections are made. Biologically neurons get connected to other neurons dynamically over time to produce required outputs. Once connected, a neuron can either excite or inhibit the neurons it is connected to. This process of excitation or inhibition in an ANN is controlled by a parameter called weights. Figure 3.3a shows the model of a simple neuron with multiple inputs ( $x_n$ ) and a single output. The weights are denoted by ( $w_n$ ). Figure 3.3b<sup>1</sup> shows an intern connection of such neurons to form what is called as a simple neural network. The number of neurons may range from tens to thousands depending on the complexity of the problem.

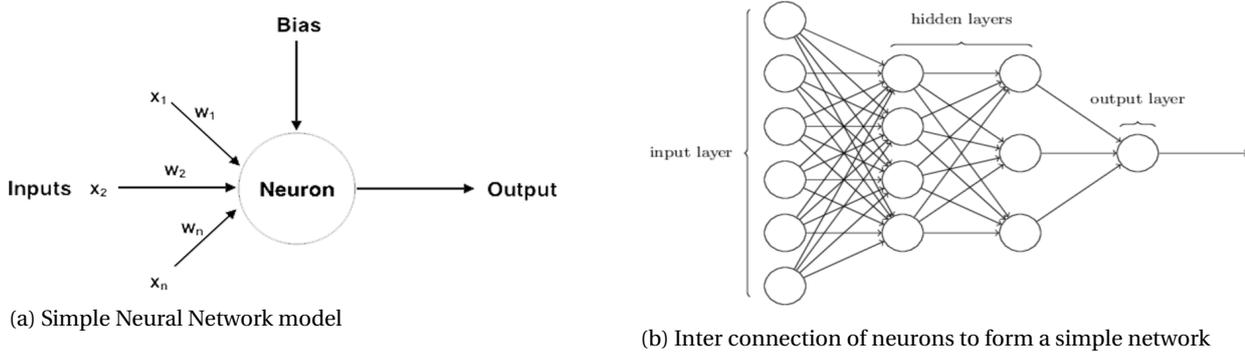


Figure 3.3

The above discussed network is an example of a multi layer perceptron network. The firing rate model discussed in this work differs from the conventional Artificial Neural Networks at various aspects. One of the most significant differences is the network architecture. Unlike the connect one to all approach of ANN, the model here has connections that mimic its biological counter part, the cerebellum. More details on the connections are discussed in the next section. Another important difference is the learning rule employed. Conventional supervised learning rules include a gradient based approach where an error function is reduced by varying the weights based on the gradient computed between the ground truth and error. This type of learning requires multiple epochs before convergence. In chapter 2 the learning rules of cerebellum was discussed and the same concepts are applied for real time on-line learning for the model.

### 3.2. IMPLEMENTATION DETAILS

Based on the work of (Hirata and Ruben-Dario Pinzon-Morales, 2014; Tanaka *et al.*, 2010; Pinzon-Morales and Hirata, 2013) the cerebellum model was implemented in Matlab for a real time implementation to

<sup>1</sup>Fig 3.3b - <http://neuralnetworksanddeeplearning.com/chap1.html>

work with ROS. Upon reviewing existing frameworks that are available for implementation of real time cerebellum models (Gewaltig and Diesmann, 2007), (Goodman and Brette, 2009), (Ros *et al.*, 2006) it was found that model proposed by (Tanaka *et al.*, 2010) was the most optimal in terms network architecture that was similar to the real cerebellum's connectivity and at the same time offering good performance for real time studies.

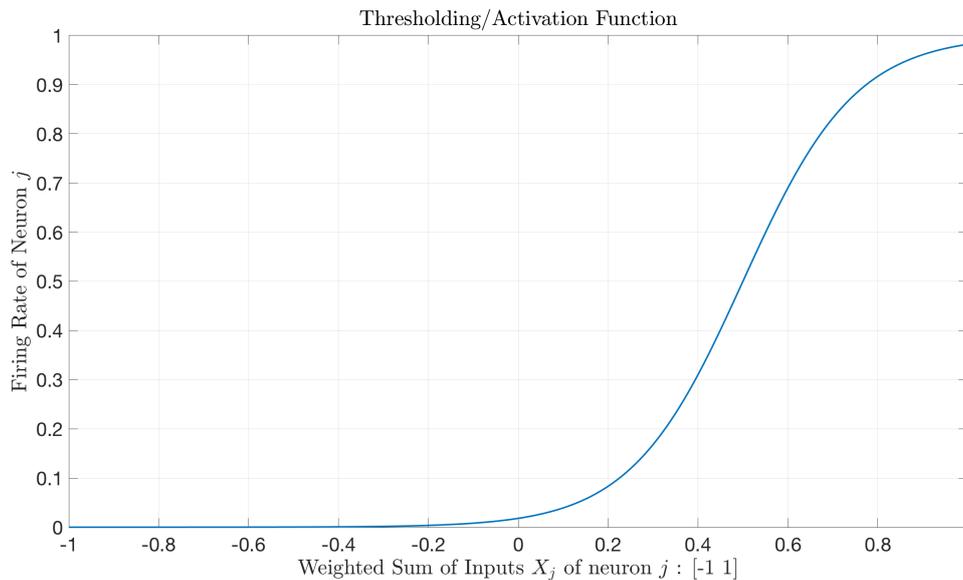
### 3.2.1. NEURON

The building block of the simulation model is the neuron. The neuron represents a population of biological neuronal activity. Each neuron accepts  $n$  number of inputs  $x_n$  which represents average firing rates of previous neurons. Each input is weighted by a factor  $w_n$ . The weighted sum of the inputs for a given neuron  $j$  is computed as shown in eq. (3.1). To simulate the dynamics of the population of neurons a thresholding function  $f(x)$  is used. Equation (3.2) shows the thresholding/activation function for a neuron  $j$  used in this work. After passing the inputs through the activation function, the neuron produces a firing rate between  $[0\ 1]$ . 0 represents no firing and a 1 represents a maximum relative firing rate. The output firing rate of a neuron  $j$  is represented by  $Y_j$ .

$$X_j = \sum_{k=1}^n x_k * w_k \quad (3.1)$$

$$f(X_j) = \frac{1}{1 + e^{4*(-2*X_j+1)}} \quad (3.2)$$

Figure 3.4: Activation Function response for an weighted sum input  $[-1\ 1]$



### 3.2.2. ARCHITECTURE

The building blocks discussed in the previous section can now be used to build a network that is similar in architecture to a cerebellum. Another assumption to be mentioned at this point is that a homogeneous network is assumed. Meaning that all neurons behave the same irrespective of their mapping to its biological counterpart. This assumption can be supported by the fact that neurons in the simulation represent a population and not any individual biological neuron types. Even in the Neuroscience literature all neural measurements are assumed to be rate based meaning that their activities are measured with the same encoding strategy.

The major cells which constitute the cerebellum were discussed in chapter 2. In the simulation model all the 6 major cell types are modeled :

- Mossy Fibers
- Granule Cells
- Golgi Cells
- Basket Cells
- Purkinje Cells

#### MOSSY FIBERS :

Mossy fibers are one of the two sources of input to biological and simulated cerebellum. As we have seen in the real cerebellum mossy fibers carry information from a wide range of nuclei. These include proprioception, auditory, visual, somatosensory and goal related information. In the simulation model they represent the firing activity of robot states such position, velocity, and visual inputs like optical flow information. These inputs are in different ranges and domains and need to be converted to firing rates. After scaling the inputs (more details are on scaling is given in chapter 5) using the activation function equation 3.2 the inputs are converted to firing rates. Equation 3.3 shows the conversion of normalized robot states to firing rates.

$$Y_{mf} = \frac{1}{1 + e^{4*(-2*X_{mf}+1)}} \quad (3.3)$$

#### GRANULE CELLS :

Granule cells receive inputs from mossy fibers and golgi cells. The firing rate of granule cell is computed based on the equation 3.4.  $W_{Gr-Mf}$  represents the weights between granule cells and mossy fiber synapses and  $W_{Gr-Go}$  represents weights between granule cells and golgi cell synapses.

$$X_{Gr} = \sum_{Mf=1}^n W_{Gr-Mf} * Y_{Mf} + W_{Gr-Go} * Y_{Go} \quad (3.4)$$

$$Y_{Gr} = f(X_{Gr}) \quad (3.5)$$

#### GOLGI CELLS :

Golgi cells receive inputs from mossy fibers and granule cells. The firing rate of golgi cell is computed based on the equation 3.6.  $W_{Go-Mf}$  represents the weights between golgi cells and mossy fiber synapses and  $W_{Go-Gr}$  represents weights between golgi cells and granule cell synapses. The golgi cell provides feedback to granule cells.

$$X_{Go} = \sum_{Mf=1}^n W_{Go-Mf} * Y_{Mf} + \sum_{Gr=1}^p W_{Go-Gr} * Y_{Gr} \quad (3.6)$$

$$Y_{Go} = f(X_{Go}) \quad (3.7)$$

#### BASKET CELLS :

Basket cells receive input from the parallel fibers and  $W_{Ba-Gr}$  represents the weights between them. Equation 3.8 represents the firing rate of Basket cells.

$$X_{Ba} = \sum_{Gr=1}^q W_{Ba-Gr} * Y_{Gr} \quad (3.8)$$

$$Y_{Ba} = f(X_{Ba}) \quad (3.9)$$

### PURKINJE CELLS :

The final cell modeled in the network are the Purkinje cells. These are the only output from the cerebellum simulation model. Equation 3.10 shows the firing rate response of the purkinje cells with  $W_{Pk-Gr}$  being the weights between parallel fibers and purkinje cells and  $W_{Pk-Ba}$  are the weights between purkinje cells and basket cells.

$$Y_{Ba} = \sum_{Gr=1}^r W_{Gr-Pk} * Y_{Gr} + \sum_{Gr=1}^s W_{Pk-Ba} * Y_{Ba} \quad (3.10)$$

### 3.2.3. MODEL CONSTRUCTION

Now that network architecture is discussed, the next step is to construct simulation model based on the elements in previous sub section. The following steps are based on the work of (Hirata and Ruben-Dario Pinzon-Morales, 2014). Model construction involves three steps :

- Neuron Allocation
- Synaptic Connection
- AER Representation

#### NEURON ALLOCATION

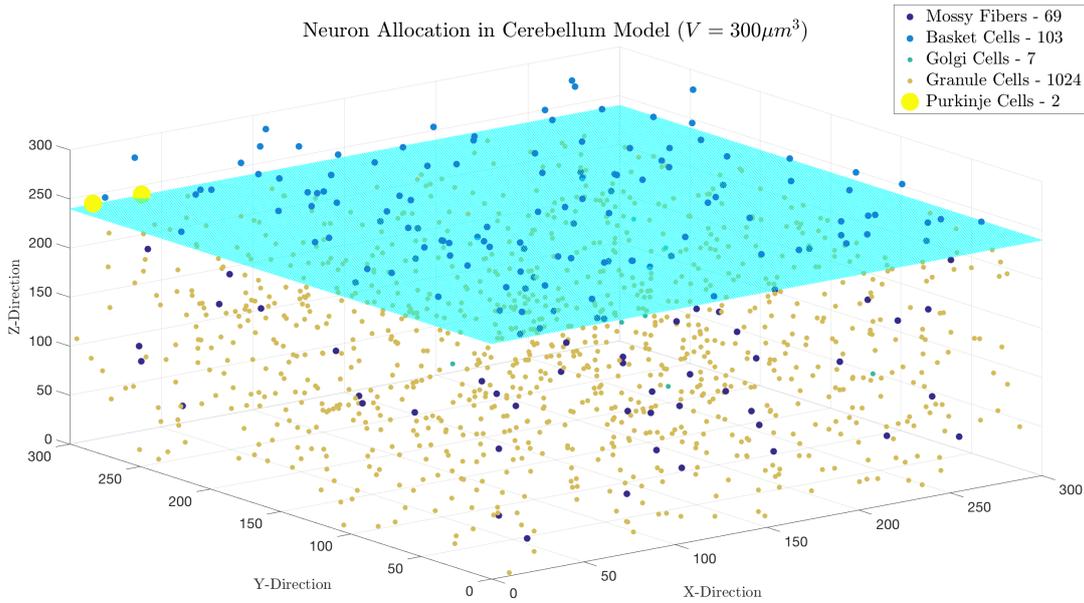
In order to have spacial accordance with the real cerebellum, the neurons are dispersed in the same way in given space. The simulation model is first defined by a region in spatial  $x$ - $y$ - $z$  direction and the total volume  $V$  is defined by  $V = x * y * z$ . The limits in each direction restrict the possible location of any given neuron in the model. The maximum limits restrict the total number of neurons that be can allocated. From chapter 2, the cerebellum was divided into three layers based on its cell locations. In the simulation model purkinje and molecular layers are combined to be one. Hence the model is divided into two layers, the bottom layer in terms of height ( $z$ -direction) is the granular layer which contains mossy fibers, golgi cells ans granule cells. This layer comprises 80% of the total volume allocated for the cerebellum. Remaining 20% of volume is dedicated to purkinje cells and basket cells making it the purkinje layer..

To differentiate between neurons and to keep the cell ratio similar to biological system, every type of neuron is modeled as a sphere and attributed to a fixed radius size. Ratio of number of cells in the system with respect to granule cells is computed. These ratios are in accordance with the neuroscience data. Table 3.1 shows the details about the ratio and radius of each neuron with respect to granule cell. Hence defining the number of granule cells would define the other cells in the network based on the pre computed cell ratios.

To initialize the model, volume ( $V \mu m^3$ ) of the total cerebellum and the number of granule cells are defined by the user. After calculating the number of other cells based on the ratios, each neuron is allocated randomly to its particular layer along with a Identification number (ID). If the location is not feasible due to an already existing neuron or if the size of the neuron cannot fit between two already existing neurons an alternative random location is looked for. If no position is feasible then the neuron is discarded. Following this procedure the complete volume is randomly filled with the total number of neurons. As an example 1024 granule cells are chosen for a volume density of  $300 \mu m^3$ . Figure 3.5 shows the distribution of different neurons in the volume for the example considered. The blue layer differentiates between granular layer and the purkinje layer.

Neuron	Ratio	Radius
Mossy Fiber	1/15	1
Basket Cell	1/10	2
Golgi Cell	1/150	4
Granule Cell	1	1
Purkinje Cell	1/1000	6

Table 3.1: Neuron density ratios and radii with respect to Granule Cells

Figure 3.5: Allocation of Neurons in a Volume of  $300\mu\text{m}^3$  cerebellum

### SYNAPTIC CONNECTIONS

After allocating the neurons in the specific volume, the next step is to connect the neuron for exchange of information. To do this most important thing is to know the number of connections each neuron makes with other neurons. It is impractical to know the number on a per neuron basis but an approximate estimate can be found in the literature for connections between neurons. Number of synapses a neuron  $j$  makes with other subsequent neuron of a particular type is known as its divergence number. The number of synapses a particular neuron  $j$  receives from other neurons is known as its convergence number.

As seen in chapter 2 there are recurrent connections between some neurons in the structure. In total the network has 9 unique synaptic types and are tabulated in table 3.2. Each synaptic connection has been given a divergence and convergence ration based on literature (Hirata and Ruben-Dario Pinzon-Morales, 2014). To make this more clear let us pick an example of  $mf \rightarrow gr$ , the divergence number is given as 1:59 which means that every mossy fiber in the network will innervate 59 granule cells and the convergence number 4:1 means that every granule cell receives 4 mossy fiber inputs. Along with these constraints, synapses are formed based on the nearest neighborhood principle. This makes sure there is a uniqueness to every network created and brings in the relevance of spatial positioning of neurons in the volume of cerebellum. Each synapse in the network is associated with a weight that determines the strength of the firing rate that is passed on to the subsequent connecting neuron. Initialization of these weights is also an important step that will determine the performance of the network. The weights are randomly picked from a normal distribution with mean  $\mu = 0.9$  and standard deviation  $\sigma = 0.1$  in a

range of  $[0.8, 1]$ . The value is then weighted by a factor  $d$  which is the inverse of the number of inputs a particular neuron receives and weight gain  $G$  which decides if a particular synapse is of type excitatory or inhibitory. The weights can be any real value between  $[-1, 1]$ , a negative value indicates that the synapse is of type inhibitory and positive values indicate a excitatory synapse. Inhibitory will decrease the probability of the subsequent neuron and vice-versa with the excitatory. This ensures that the inputs are normalized and kept without bounds and avoids saturation of information since firing rates are limited to  $[0, 1]$ . (Hirata and Ruben-Dario Pinzon-Morales, 2014) showed that this random initialization still performs with good repeatability in performance by testing 25 randomly initialized networks to perform the same control action.

Synapse	Divergence	Convergence	Weight Gain
$mf \rightarrow gr$	1:59	4:1	1
$mf \rightarrow go$	1:7	66:1	-0.3
$gr(pf) \rightarrow go$	1:12	1639:1	1
$go \rightarrow gr$	1:586	4:1	1
$gr(pf) \rightarrow ba$	1:3	41:1	2
$gr(pf) \rightarrow pk$	1:4	1024:1	2
$ba \rightarrow pk$	1:7	110:1	-0.1
$pk \rightarrow ba$	1:55	3:1	-0.1
$gr(pf) \rightarrow ba$	1:3	41:1	-0.5

Table 3.2: Synaptic Divergence and Convergence ratios between neurons from (Hirata and Ruben-Dario Pinzon-Morales, 2014)

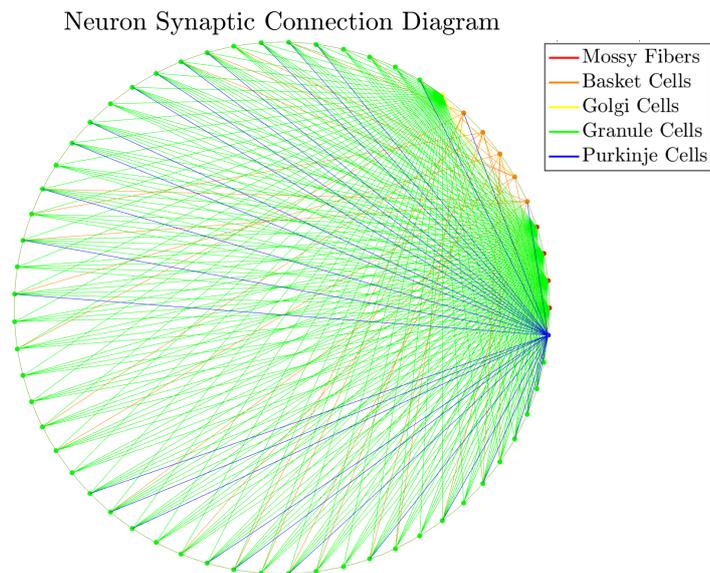


Figure 3.6: Synaptic Connectivity between neurons with 50 Granule Cells

In order to have a better visualization of how the synapses are connected in the network, fig. 3.6 can be a method to do it. The figure is an example of 50 granule cells in dispersed in a volume of  $50 \mu m^3$ . Each dot on the cell represents a neuron in the network. Every line in the diagram represents a connection between two neurons. The colors indicate the type of neuron from which the synapse is coming from. The intensity of the line is proportional to the weight of the synapse. This way the weights can visualized over time to see how the synapses evolve, become stronger or even disappear.

### AER REPRESENTATION

The final step in the computational model is to represent the above neurons and synaptic connections in a computationally efficient manner. Address Event Representation (AER) is a four vector structure of the cerebellum model. The first vector  $\mathbf{I}$  encodes a identification number (ID) for every neuron in the model. The ID is assigned to each neuron while placing it in the 3D grid of the cerebellum. If there are  $N$  number of total neurons in the model  $\mathbf{I}$  is  $1 \times N$ . The second vector  $\mathbf{K}$  stores the number of pre-neurons of each neuron. This means it represents the number of inputs a particular neuron  $j$  receives. The size of vector  $\mathbf{K}$  is  $1 \times N$ . Third vector  $\mathbf{Q}$  stores ID's of pre synaptic neurons, this vector helps in retrieving the neurons that connect to a neuron  $j$  and the number of neurons is given by  $\mathbf{K}$ . The size of  $\mathbf{Q}$  is  $1 \times S$ , where  $S$  represents the total number of synapses in the network for  $N$  neurons. The fourth vector  $\mathbf{W}$  stores the corresponding weights of synaptic connections and its size is  $1 \times S$ .

### 3.3. LEARNING IN SIMULATION

Learning in the real cerebellum was discussed in chapter 2, it is accepted that learning is mainly driven by two processes at the PF-PC synapses.

1. Write about plasticity
2. Learning by Long Term Depression (LTD) : Reduction in the PF-PC synaptic weights during correlated firing between granule cells and climbing fibers is LTD. In simulation this is modeled as shown in eq. (3.11). The product between  $cf(t)$  and  $pf_i(t)$  makes sure that LTD happens only when the parallel fiber and climbing fiber fire simultaneously.

$$\delta W_{pf_i} = \gamma_{ltd} * cf(t) * pf_i(t) \quad (3.11)$$

Where

- $\delta W_{pf_i}$  : Change in the weight of  $i^{th}$   $pf$  synapse.
  - $\gamma_{ltd}$  : Learning rate for LTD
  - $cf(t)$  : Climbing fiber firing rate at time  $t$
  - $pf_i(t)$  : Firing rate of  $i^{th}$  parallel fiber
3. Learning by Long Term Potentiation (LTP) : Increase in the weight between PF-PC when climbing fiber firing rate is below a threshold is known as LTP. In simulation this is modeled as shown in eq. (3.12).

$$\delta W_{pf_i} = \gamma_{ltp} * pf_i(t) \quad (3.12)$$

Where

- $\delta W_{pf_i}$  : Change in the weight of  $i^{th}$   $pf$  synapse.
- $\gamma_{ltp}$  : Learning rate for LTP
- $pf_i(t)$  : Firing rate of  $i^{th}$  parallel fiber

### Summary

1. Discussed two ways of looking at and defining cerebellum's functionality
2. Discussion on limitation of spiking neural networks and use of firing rate models as alternative
3. Biologically realistic model construction
4. Spatially relevant neuron allocation
5. Modeling of Long Term Potentiation and Long Term Depression learning methods in simulation
6. Efficient AER representation for real time model response computation



# 4

## VESTIBULO-OCULAR REFLEX IN BRAIN AND SIMULATION

"Tell me and I forget, teach me and I may remember, involve me and I learn."

---

- Benjamin Franklin

In the previous chapter cerebellum simulation model was shown in simple control scenario. In this chapter a more biologically realistic scenario to test the cerebellum is discussed. As said in chapter 1 to test the cerebellum model VOR is used as the test case. Though we have seen that cerebellum is involved almost all voluntary and many involuntary movements, control of eye reflexes and voluntary eye movements makes it a good candidate for the study of cerebellum due to its simplicity in neuronal connection and eye bio-mechanics. We have seen in chapter 2 on how it is important to isolate a brain structure to fully study its involvement. There are plenty of examples in the literature that have used VOR for testing and understanding hypothesis on the cerebellum (Alexander *et al.*, 2009; Menzies *et al.*, 2010; Porrill and Dean, 2007). Apart from VOR commonly used other test scenarios are classical eye blink conditioning (Casellato *et al.*, 2014) and multi joint arm control (Casellato *et al.*, 2012). Since classical eye blink conditioning does not have much use in a robot control scenario it is decided not to use it as test case and a multi-joint arm control involves too many higher and lower brain regions that are difficult to simulate (Working of some regions involved is still not known) and makes it difficult to isolate the responsibility of cerebellum during simulation studies.

Section 4.1 first discusses what VOR is and the neuronal circuits involved in it. In parallel to this section 4.1 details about how these circuits are modeled as transfer functions based on the literature. Section 4.2 describes the robot head set up used in this work to be used as analogous to a biological head. The section also details other components implemented that are required for the simulation of VOR. Section 4.3 sums up the compensatory eye movements. Section 4.4 talks about Robot Operating System framework used in the thesis for interfacing the software and hardware.

### 4.1. VESTIBULO-OCULAR-REFLEX

In order to make sense of the world visually it is of at most importance to form a clear image on the retina. A blurred image on the retina can be due to two reasons, one when the head or body moves in space and second when the object or the background in the world itself moves. In either cases eye has to compensate for the changes to produce a stable image on the retina. Since there are two distinct possibilities of producing a blur in the image, there are two distinct mechanisms to compensate the disturbances. VOR

provides compensatory eye movements for stabilizing images on the retina for movements produced by head and body. In the early 90's VOR received attention due to its distinct three neuron arc. In the later years VOR became a subject of interest due to the involvement of cerebellum in its modulation (Ito, 1998).

At this point it is important to understand the bio-mechanics of the eye. Figure 4.1 shows the 6 extra-ocular muscles involved in control of eye movements. The six muscles work in pairs as agonist and antagonist muscles to produce 3 degrees of freedom for the eyes. Medial and Lateral rectus muscles are responsible for abduction and adduction motion. Superior and Inferior rectus muscles control the elevation and depression movements. Superior and Inferior oblique muscles work to produce intorsion and extorsion movements.

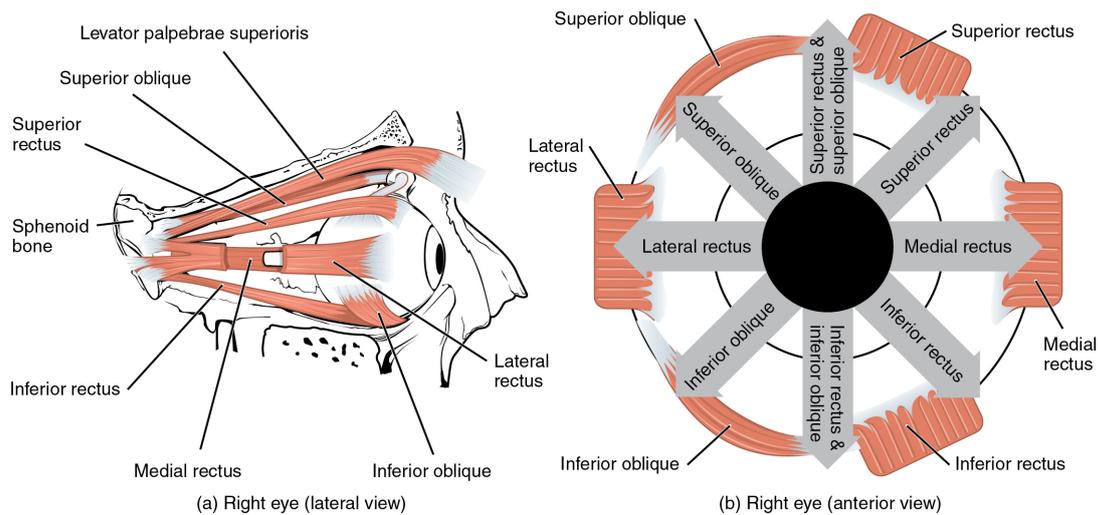


Figure 4.1: Bio-Mechanics of the eye

VOR is responsible for producing compensatory eye movements for linear (lvor) and angular (AVOR) disturbances due to head and body movements. To simplify the problem and focus more on the influence of cerebellum, in this work only horizontal angular VOR is considered meaning the eye is now capable of only compensating in the x-y plane and involves only lateral and medial rectus muscles to produce these movements. From here on any mention of the term AVOR/VOR only refers to horizontal angular VOR movements. AVOR is achieved by the distinctly famous three neuron arc circuitry. For perfect compensation of horizontal disturbances eyes have to move in the opposite direction as that of the head with same magnitude. This means eye velocity is 180 degree out of phase with respect to the head velocity. For the control of two eyes three neuron arc exists on both the left and right hemispheres of the brain. These pathways cross paths at different levels and are discussed later in the section. The three neurons involved in the VOR are :

- Semi-Circular Canals (Vestibular Ganglion) (SCC)
- Vestibular Nuclei (VN)
- Oculomotor Nuclei (OM)

Since head movement is responsive to angular accelerations, for perfect compensation these accelerations have to be integrated twice to produce the required position signal that can drive the eyes in opposite direction. More details on where these integrations occur in the system are discussed in the coming sub sections. The control of both the eyes is via two sets of the above mentioned three neuron arc. The circuitry of both left and right side three neuron arc is shown in fig. 4.2. It should be kept in

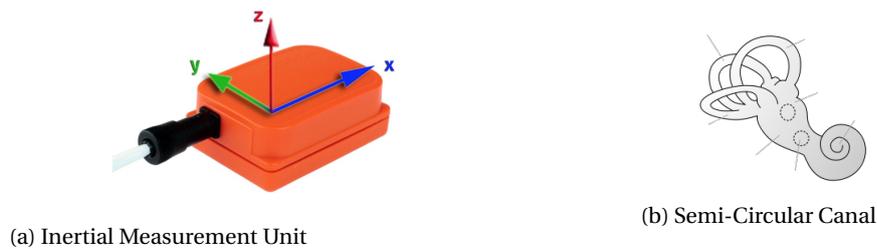


Figure 4.3: Inertial Measurement Unit analogous to Semi-Circular Canal

mind that this is a simplified version of the connectivity involved in the VOR pathway. As it can be seen in fig. 4.2 there are pathways that cross sides before reaching the final eye muscles. This strategy is useful in producing conjugate eye movements. Same connectivity is followed for the robot as well.

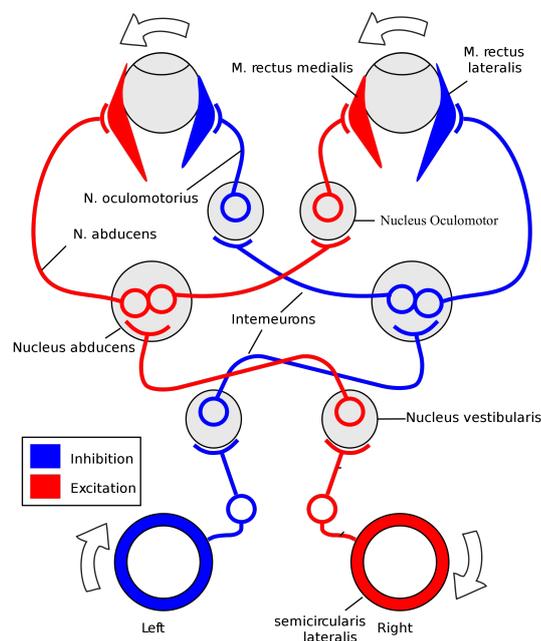


Figure 4.2: Three Neuron Arc VOR Pathway

#### 4.1.1.1. SEMI-CIRCULAR CANALS (VESTIBULAR GANGLION)

The first neuron of the three involved in VOR is vestibular ganglion. These are nerve afferents connected to the hair cells present in semi-circular canal (SCC) for detecting angular accelerations of the head along three different axes. The vestibular system is capable of detecting both angular and linear accelerations of the head and body in space. Since the thesis focuses only AVOR for horizontal movements, only the action of semi circular canal responsible for detection of horizontal movements is considered. The first integration of the two talked about earlier is performed by the mechanical action of SCC itself. The sensed head accelerations are converted to head velocity signals by the SCC and are transported by the vestibular ganglion to other regions.

In the robot, angular velocities are measured using an Inertial Measurement Unit (IMU). An IMU consists of three different components, an accelerometer, a gyroscope and a magnetometer. While an accelerometer measures linear accelerations and a magnetometer points to the magnetic north of earth, a gyroscope is the one that measures angular velocities about the world axes. Since IMU's directly measure velocity, in order to make their response similar to the measurements made by the semi-circular

canals the velocity signals are first differentiated to produce acceleration signals and then integrated with an integrator whose response is similar to SCC. The responses of systems are modeled using Laplace transforms. The dynamics of SCC is modeled based on the work of (Zhang *et al.*, 2004). Equation (4.1) shows the transfer function for the SCC. It is a simple first order integrator with a time constant  $\tau_s$  multiplied by a differentiator block.  $s$  in the numerator differentiates the signal to compute head accelerations from the IMU and then integrated to produce the velocity response of scc. Typically the time constant is around 15-20 seconds (Zhang *et al.*, 2004) and in this work a time constant of 15 seconds is chosen. Figure 4.4 shows the frequency response of the semi-circular canal. Canal's performance is best at the higher frequencies with unity gain and zero phase shift, which is the typical requirement of VOR

Another distinctive feature of the semi-circular canal is that it is direction sensitive. Horizontal left canal provides excitatory signals for clockwise rotations and vice-versa. To have the same in simulation, the left side of the simulated scc is made to respond to only velocities in clock-wise direction by suppressing all the counter-clockwise velocity measurements by the gyroscope to zero. The opposite is done for the right side scc. This establishes the two simulated semi-circular canals to have similar characteristics as that of its biological counterpart.

$$H_{scc} = \frac{\tau_s * s}{\tau_s * s + 1} \quad (4.1)$$

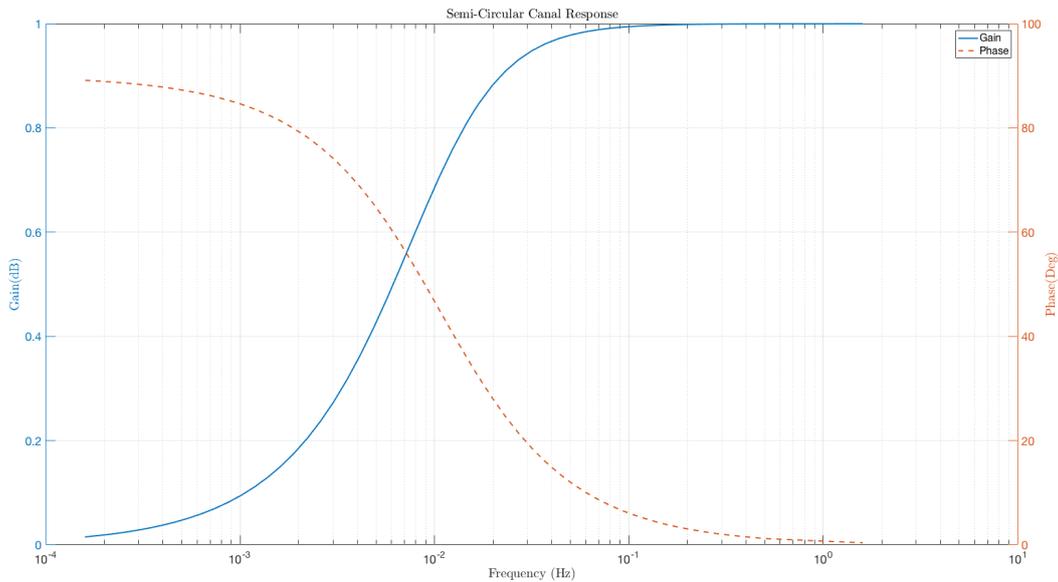


Figure 4.4: Bode plot of Semi-circular canal response

#### 4.1.2. VESTIBULAR NUCLEI

The main nuclei in the three neuron arc is the vestibular nuclei. It is located in the brain stem and consists of four sub nuclei. But since this work only deals with horizontal eye movements, medial vestibular nucleus the sub nuclei responsible for control and compensation of horizontal head and body movements is considered.

Medial vestibular nuclei (MVN) innervates oculo-motor neurons which are motor neurons that control the eye muscles. Since the MVN receives inputs about the head and movements from semi-circular canals via vestibular ganglion and projects to motor neurons, its role has to be to map the input signals to relevant motor commands for head movement compensation. (Robinson, 1976) proposed that there

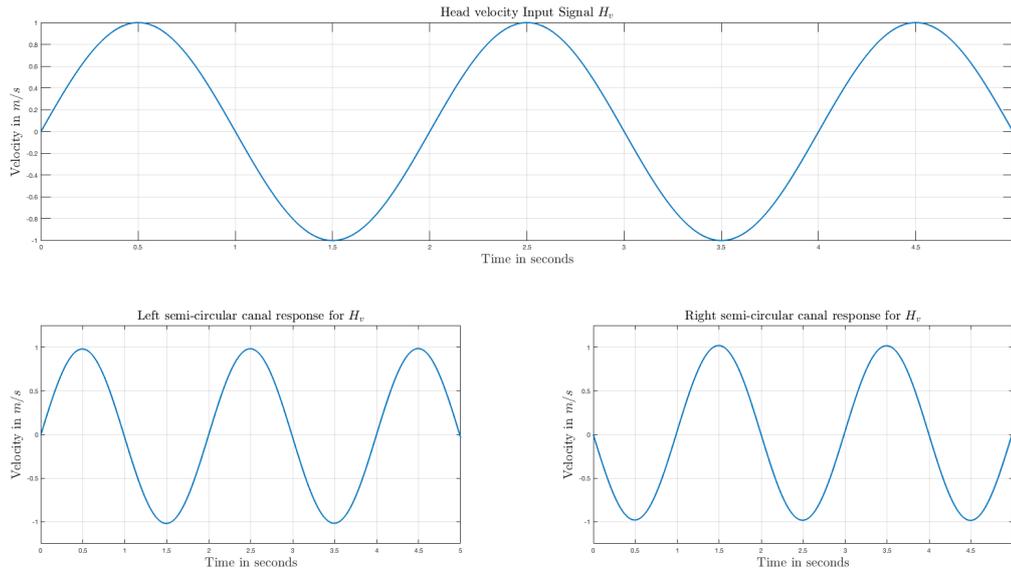


Figure 4.5: Semi-circular canal responses for sinusoidal head rotation velocity of 0.5 Hz with 1 m/s amplitude

has to be a secondary integrator between the scc and motor neurons. And this second integrator was detected to be performed in the brain stem. The concept of vestibular nuclei acting as leaky integrator for velocity to position conversion was proposed by (Skavenski and Robinson, 1973). (Kramer *et al.*, 1995) discuss that the neural integrator (NI) should be most prominent in the range of 0.1 - 1 Hz. Apart from integrating the velocity signals from the semi-circular canals, the NI also integrates signals necessary for other conjugate eye movements such as saccades, smooth pursuit and opto-kinetic reflex. These movements are discussed again in later sub sections with vestibular nuclei.

Since the neural integrator is not a perfect one, it is modeled as a first order integrator with a time constant  $\tau_{vn}$  as show in eq. (4.2) and time constant is chosen to be 16 seconds (Zhang *et al.*, 2004). Along with the leaky integrator, the vestibular pathway also contains a direct pathway (Cannon and Robinson, 1987) (Zhang *et al.*, 2004) (Kramer *et al.*, 1995). Thus the complete processing between the vestibular ganglion to the oculomotor neurons can be modeled as given by eq. (4.3).

MVN only provide a phasic burst commands and in order to maintain the eyes in same position even after SCC firing has gone down, there is a feedback integrator that feeds back the VN output to itself to produce tonic firing. The nucleus responsible for this actions is Vestibular pause nuclei (VPN). Transfer function of vpn nucleus is modeled as shown in eq. (4.5). With the feedback, the final transfer function is shown in eq. (4.6)

$$H_{NI} = \frac{\tau_{vn}}{\tau_{vn} * s + 1} \quad (4.2)$$

$$H_{vn} = G_{vn} * (H_{NI} + G_d) \quad (4.3)$$

$$H_{vn} = \frac{G_{vn} * (\tau_{vn} + G_d * (\tau_{vn} * s + 1))}{\tau_{vn} * s + 1} \quad (4.4)$$

$$H_{vpn} = \frac{0.7}{\tau_{vpn} * s + 1} \quad (4.5)$$

$$H_{VN} = \frac{H_{vn}}{1 - H_{vn} * H_{vpn}} \quad (4.6)$$

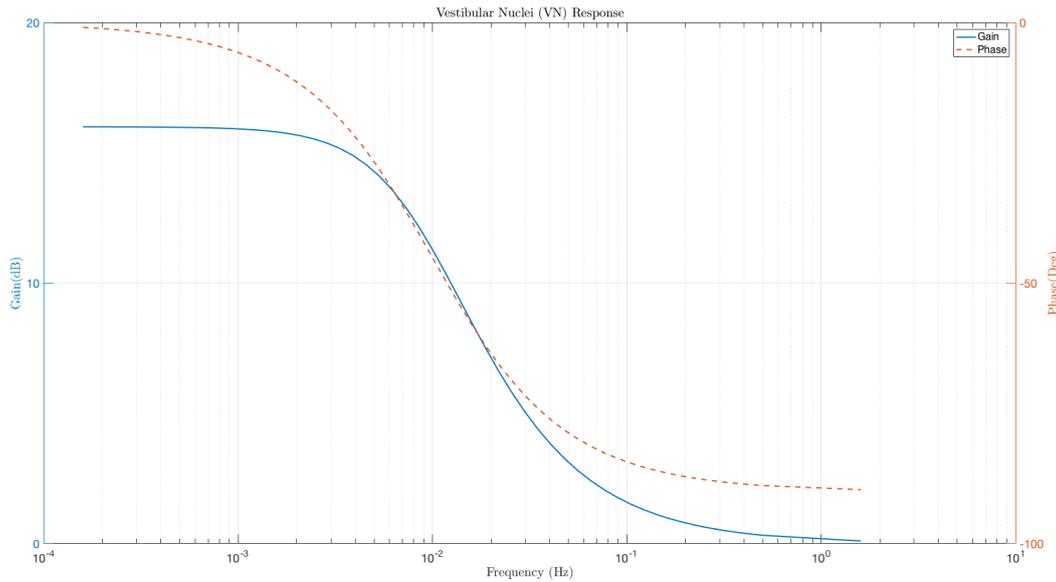


Figure 4.6: Frequency response of vestibular nuclei

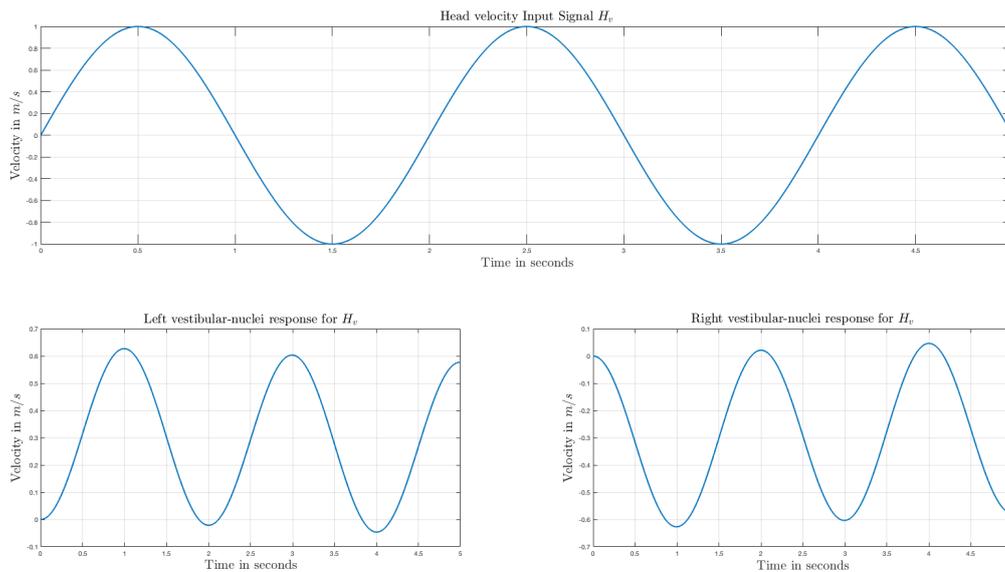


Figure 4.7: Vestibular nuclei responses for sinusoidal head rotation velocity of 0.5 Hz with 1 m/s amplitude

#### 4.1.3. OCULO-MOTOR NEURONS

The final set of neurons involved in VOR are the oculo-motor neurons. These are responsible in driving the eyes to the desired position by generating relevant muscle commands. Two sets of nuclei are responsible for the control of medial rectus and lateral rectus muscles. Abducens nuclei directly project on to lateral rectus muscles. Abducens nuclei are innervated by vestibular nuclei originating from the contra lateral side. Medial rectus muscles are controlled via the oculo-motor neurons which innervated by the abducens nuclei from the contra lateral side of the brain stem. This crossing of pathways is what introduces the complementary conjugate eye movements. In this work the motor neurons are modeled

as simple gains that modify the processed signal from vestibular nuclei to appropriate ranges for the robot control. Both lateral and medial rectus muscles can only the eye, to have this effect the gain of medial rectus is made negative. This way lateral rectus applies a positive torque producing adduction of eyes and medial rectus applies a negative torque producing abduction of eyes. Since there is no agonist-antagonist type of actuator the net driving force is derived by adding the contribution of medial and lateral rectus muscles. This produces the same effect of having parallel muscle architecture.

#### 4.1.4. SUPPLEMENTARY EYE MOVEMENTS

Apart from VOR there are other conjugate eye movements that make use of the same circuitry. They add to the performance of VOR system and try to reduce the over all blur on the retina. It is therefore important to include these systems as well for the study. Two other eye movements are involved, one is the opto-kinetic reflex and other is the saccade.

##### OPTO-KINETIC REFLEX

As discussed at the beginning of this section, a blurred image can be formed on the retina for two reasons. OKR is responsible for reducing image blur when objects in the world move. Since this involves an external feedback, there are delays before the system can recognize that there was an image slip on the retina. Typically these delays are around 100 ms (Porrill and Dean, 2007). Thus the OKR is limited to work at low frequencies. Together with VOR, OKR can increase the bandwidth of compensatory eye movement.

What is important for the work is not how the retinal slips are computed in the brain but that slip velocities reach the vestibular nuclei and then integrated again by the integrator in brain stem to produce conjugate eye movements to compensate for the slip (Kawato and Gomi, 1992). Retinal slip information is also very important for VOR adaptation via cerebellum. Cerebellum receives retinal slip information mainly along two sources of its inputs, one excitatory retinal slip signals are carried by mossy fibers and second source are inhibitory signals arising from the inferior olive and innervating the purkinje cells as climbing fibers. Thus retinal slip signals serve as the supervisory signal for cerebellar learning. In section 4.3 optical flow used in the robot to detect retinal slips is discussed a bit more in detail.

##### SACCADES

Saccades are ballistic eye movements for quick fixation on a target. In case of VOR system when the eyes reach their mechanical limits of rotation the eyes it is required to reset the eyes to their neutral position quickly. In this work saccades are realized by setting the position of the eye to zero relative to the head when ever they move beyond the given limits of the robot eye. A classical example of this is when a person is rotated on a continuously rotating chair while tracking a stationary object on screen. The eyes counter act the chair movement and when they reach their extreme they are reset to zero quickly by saccades so that head chair rotation can be compensated again.

## 4.2. ROBOT HEAD

In order to test the VOR and study cerebellum, a test bed that can simulate the scenario had to be created. In this work a robot head created at the BioRobotics Lab, TuDelft has been used (Wang and Jonker, 2013). The operation should be able to mimic the head and eye movements required to replicate the VOR studies. For horizontal VOR, head needs to have one rotational degree of motion in the transverse plane. The second requirement is that each eye has one rotational degree of motion, in anatomical terms two eyes are capable of abduction and adduction motion. In total the robot setup is required to have 3 degrees of freedom. Figure 4.8 shows the setup used, both real hardware setup and a simplified diagram depicting all the elements and rotational degrees of freedom. It consists a total of 4 degrees of freedom,

apart from head rotation it is also possible to rotate the neck in the sagittal plane but this motion is not utilized for this work.

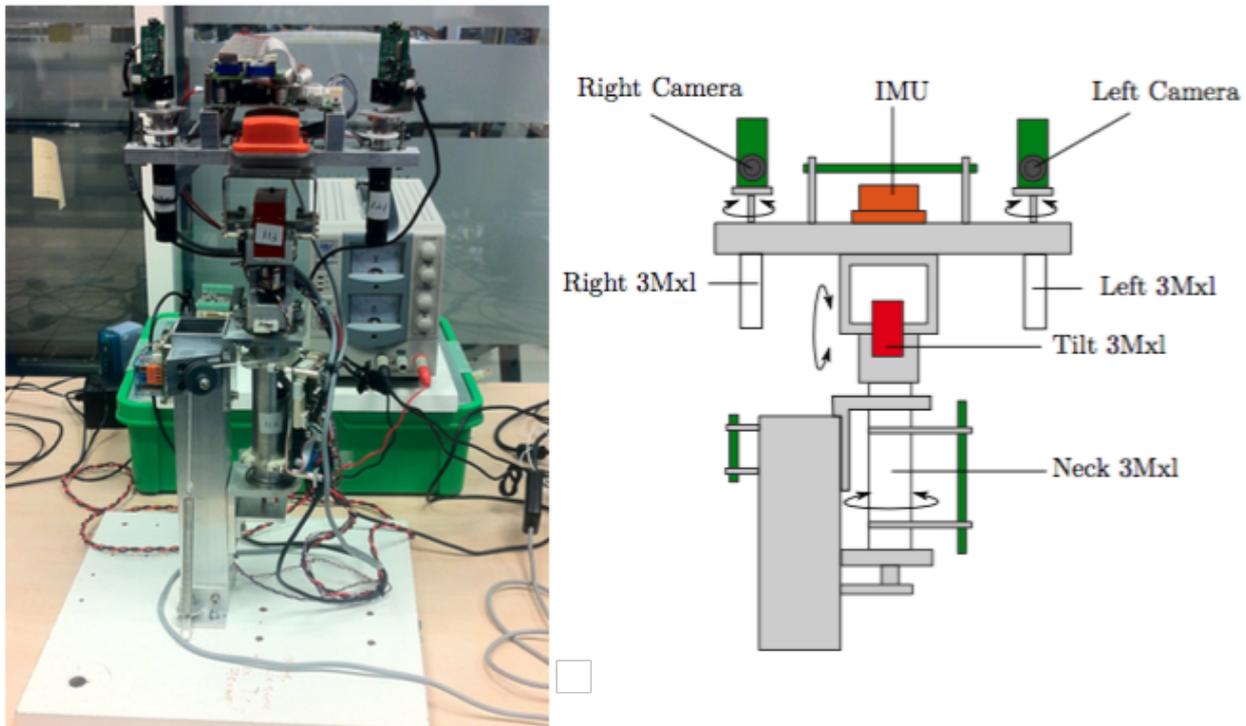


Figure 4.8: Robot Head setup used during the experiments for VOR

#### 4.2.1. ACTUATORS

There is distinct difference between how biological systems are actuated and how robotic systems are actuated. Biological systems are driven by muscles whereas robots are driven by motors. Though both these types produce rotations about a point by producing a torque, the dynamics of them are extremely different. Unfortunately in the literature studies that involve understanding the central nervous system often ignore the importance of bio-mechanical aspect of the control. (Crespi *et al.*, 2013) show that just by the bio-mechanics of a system introduces stability with no need for a control system at all. Thus it is important to stay relevant to the biomechanics while studying control actions of brain. In this work though muscle like actuators are not used, through some software tricks a push pull mechanism similar to the bio-mechanical eye is reproduced on the rotary motors. The robot uses 3Mxl motors whose modules and firmware is developed by BioRobotics Lab, TU Delft. Each motor operates in two modes of operation, one position control and second velocity control. Each are controlled by a low level PID control whose gains can be tuned to achieve desired dynamics.

#### 4.2.2. VISION

The robot comprises of two cameras that on top of the robot head. They are the source of visual information to software. The camera can operate at a maximum of 640x480 pixels but in order to keep the computational load light it the cameras are down sampled to produce frames of size 320x240 pixels. The cameras operate at a speed of 30 frames per second. Though the cameras can work at higher rates, in order to replicate the delays like in human vision system which is usually introduces a delay of around 100 ms.

The main task of the compensatory eye movements is to reduce the image blur on the retinal slips,

in case of the real hardware this would translate to reduction of blurred images on the camera while in motion. Image blur can be quantified using an image processing technique, Optical Flow.

#### OPTICAL FLOW

Optical flow is an image processing technique to detect motion in images. Motion of an object, an edge or a contour is measured using the difference between current and the previous frame. Hence this methodology utilizes two frame method for computation of flow information. Optical flow can be used to detect horizontal, vertical and in plane rotational motion in a given image. Figure 4.9 shows the motion detected by optical flow along the three different eye movements possible. Arrows in the flow indicate the vector motion of the corresponding pixel and whose magnitude is equal to the change in pixels between the current and previous pixel. Direction of the vector indicates direction of motion detected for the corresponding pixel between the current and previous frame. Because the system is restricted to only horizontal motions, optical flow along this direction is considered and the other are discarded for this work. A dense optical flow is adopted to compute the flow velocity at every pixel in the frame. To simulate the effect of fovea a narrow field of vision is cropped at the center of the image and dense optical flow is computed only for this region of interest. The flow values are then averaged over the produce the average velocity and direction of the fovea for that particular frame. In order to compute the dense optical flow at the foveated region, (Farneback, 2003) one of the most commonly used methods to detect dense flow is used. OpenCV, image processing package which readily provided the algorithm for detecting optical flow made it easy to set-up the system and obtain data from the cameras. Optical flow is computed at the same rate as that of the camera, i.e. at 30Hz.

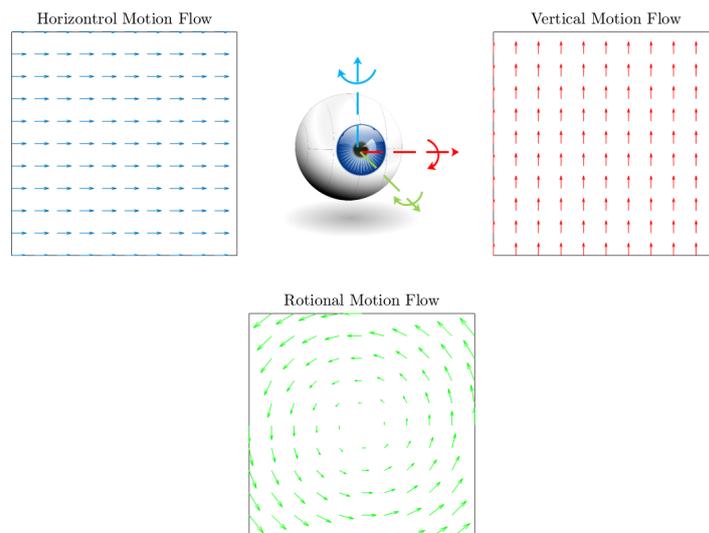


Figure 4.9: Visual Motion Detected by optical flow in horizontal, vertical and rotational directions

### 4.3. COMPENSATORY EYE MOVEMENTS WITH CEREBELLUM

Now that all components of the vor has been discussed, all the blocks can be put together to form the circuitry for compensatory eye movements which reflects the biological connectivity of the network involved in the brain. Figure 4.11 shows all blocks and their connectivity between each blocks. The red paths indicate the regions arising from the left hemisphere of the brain and right paths indicate regions from the right hemisphere. The input to the system is horizontal head movements and this results in conjugate compensatory eye movement at the end. Cerebellum model again has a bi-hemispheric model

and it has been supported in the literature that cerebellum projects on the ipsilateral side (Hirata and Ruben-Dario Pinzon-Morales, 2014; Ito, 1998). This also helps in controlling the timing of movements since two compensatory circuits needs to work in synchrony, cerebellum model has to adapt to this and produce coordinated movements to reduce image blur in the system.

#### 4.4. ROBOT OPERATING SYSTEM (ROS)

In order to connect and communicate between the different actuators, sensors and the software for the robot, Robot Operating System (ROS) framework has been used in this work. ROS is a widely used framework in robotics that has excellent community support for debugging and a stable platform with constant improvement. ROS is the layer that helps programs and hardware communicate with each other. Every task in the system is treated as a node in ROS. Each node can subscribe and publish to messages/information via what are called as topics. Nodes, data-sets, libraries and configuration files are organized under ROS packages. Each sub-system of the robot compiled as a package to help distinguish between different modules present in the system and make the organization of the code much cleaner.

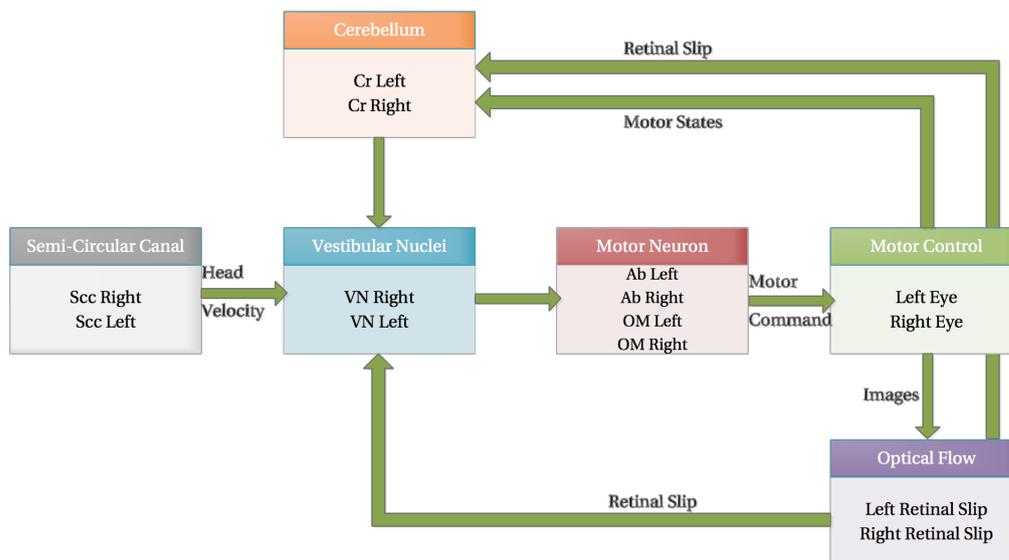


Figure 4.10: Overview of ROS network connection for the VOR setup with Cerebellum

Each of the subsystems discussed earlier in this chapter are depicted as nodes in boxes and the exchange of information is indicated by the arrows connecting the nodes. Figure 4.10 shows the simplified ros connectivity diagram used during the thesis. ROS allows running scripts from different computers connected over the network and also from different programming language. This allowed for developing the cerebellum simulation model on MATLAB@and running other modules on C++. In order to simulate realistic time delays in the network each module was run at different speeds. Table 4.1 shows the average speed of each module used.

<b>Module</b>	<b>Speed</b>
Semi-Circular Canal	100Hz
Vestibular Nuclei	100Hz
Motor Neurons	100Hz
Motor Control	50Hz
Cerebellum	50Hz
Optical Flow	30Hz

Table 4.1: Ros nodes communication speeds

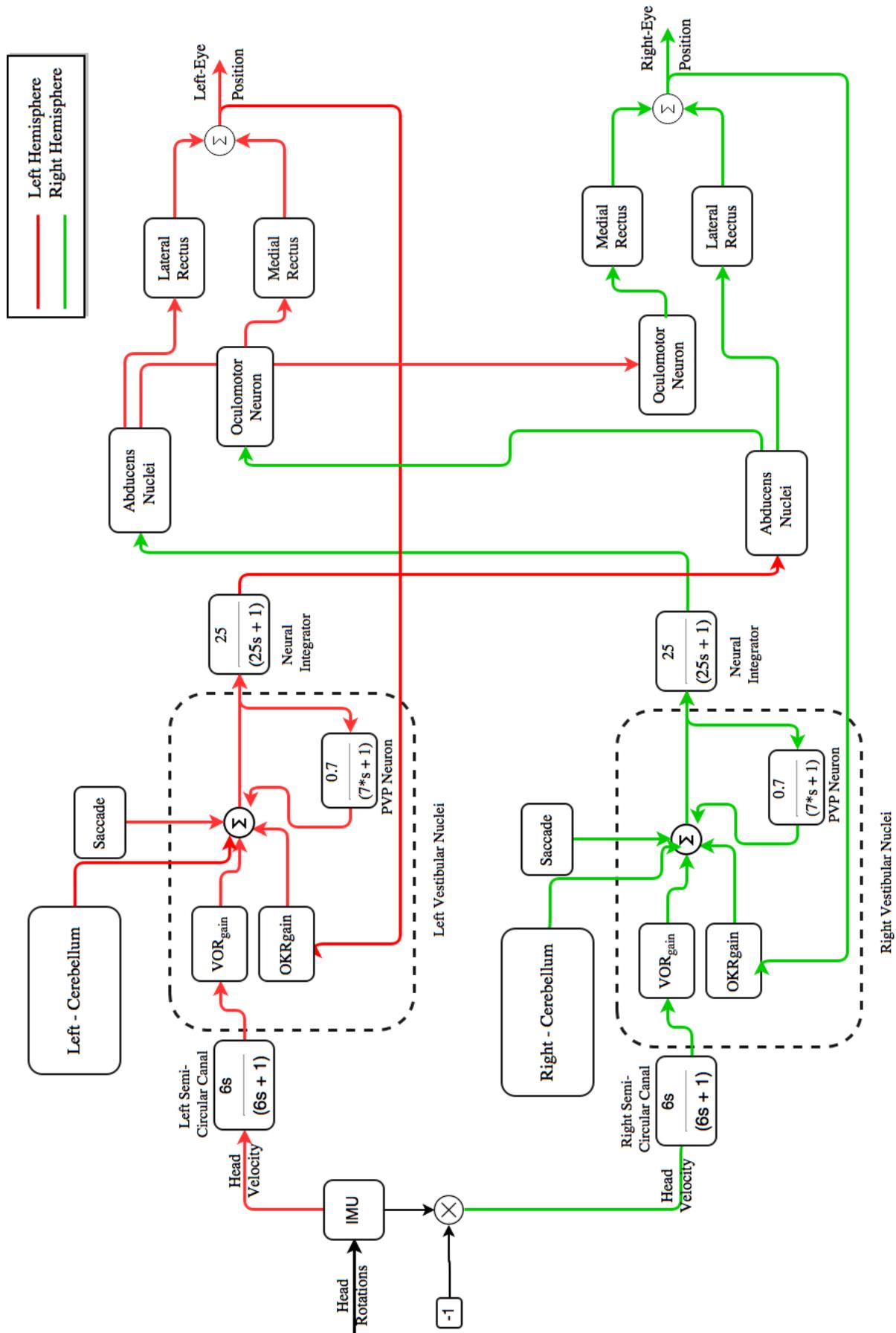


Figure 4.11: Vestibulo-Ocular-Reflex computational model

### Summary

1. To test the involvement of cerebellum in a biological system, VOR was chosen as the test case.
2. A biologically realistic three neuron arc working of the VOR was implemented.
3. Since other compensatory eye movements work together with VOR, OKR and saccades were also implemented.
4. Dense optical flow technique is used detect retinal slips on the fovea.
5. ROS framework is used to interface software, hardware and sensors.
6. ROS allowed simulation of realistic time delays in the system.



# 5

## EXPERIMENTS AND RESULTS

"All the powers in the universe are already yours. It is we who have put our hands before our eyes and cry that it is dark"

— Swami Vivekananda

In section 5.1 of this chapter experiments are performed on the simple control scenarios discussed in chapter 3. System description and parameters settings are first described and then the results of each model is shown. In section 5.2 a more biologically realistic scenario of cerebellum's involvement which was discussed in chapter 4 is evaluated.

### 5.1. CONTROL SCHEME EVALUATIONS

Cerebellum has known to be key in movement control but the number of roles trying to explain its functionality has given rise to confusion and no unification in explaining the working. In literature involving simulated cerebellum models authors always begin with an assumption of cerebellum's role for a particular task and then test its validity. When a different research group tries to validate another model it is often under a totally different control paradigm. This has lead to a problem of not being able to deny a theory because it works in one case and has not been tested in all other cases. Therefore in this work it was decided to come up with a simple control scenario to test various theories on cerebellum's role with the simulation model built in chapter 3. The description of the control scenario was already given in chapter 3. There are five different variations considered for evaluation. For all of the evaluations below, the model used is the scenario of position control of a DC motor. Before proceeding the parameters for designing the motor model and the control law used is discussed under each case as we proceed along.

#### 5.1.1. DC MOTOR MODEL

The governing equations of the motor model used is given in section 5.1.1 and the parameter values used are tabulated in table 5.1. Motor model is controlled by single input, voltage signal  $V$  in volts and states of the motor are angular position( $\theta$ ) ranging between  $[-\pi \pi]$  rad , angular velocity( $\omega$ ) ranging between  $[-8\pi 8\pi]$  rad/s and current( $i$ ) ranging between  $[-4.5 4.5]$ .

$$i = \frac{V_{app}}{L} - \frac{R}{L}i - \frac{K_{\phi}}{L}\omega \quad (5.1)$$

$$\dot{\omega} = \frac{K_{\phi}}{J}i - \frac{b}{J}\omega \quad (5.2)$$

Parameter	Type	Value
$L$	Inductance	0.1 H
$K_\phi$	emf constant	0.3
$J$	Load Inertia	0.1 $Kg.m^2$
$b$	Viscous friction	0.01
$R$	Internal resistance	2 $\Omega$

Table 5.1: DC Motor Simulation Parameters

### 5.1.2. EVALUATION OF CEREBELLUM UNDER SIMPLE CONTROL SCENARIO

Figure 2.4 in chapter 2 shows the DC motor model with one input Voltage( $V$ ) with a pid feedback control loop. To control the position of the motor, PID control law based on position and velocity feedback is used. Tuning the proportional ( $K_p$ ), differential ( $K_d$ ) and integral ( $K_i$ ) gain to following values :

$$K_p = 15$$

$$K_d = 5$$

$$K_i = 0$$

With the above values, the system exhibits a stable response shown in 5.1 for a square wave input of magnitude 1 and -1.

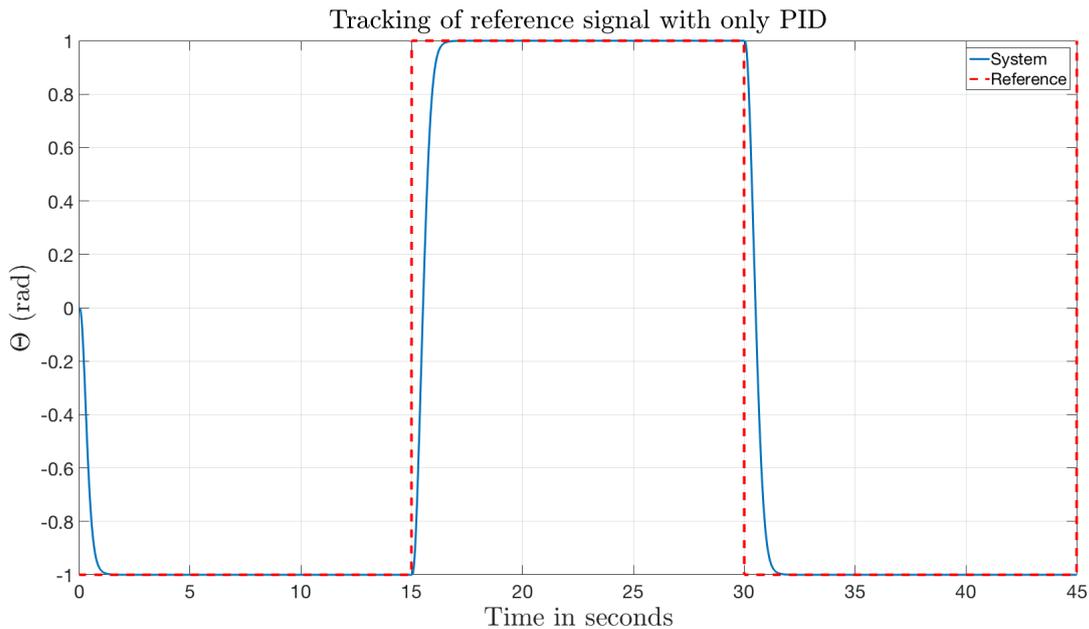


Figure 5.1: PID control response for a square wave input

Cerebellum model with 64 granule cells is constructed and converted to AER format. Using pre-defined cell ratios tabulated in table 3.1, number of other cells used in the simulation model are shown in table 5.2a. The model consists of 507 synaptic connections. For all the different models to be tested, mossy fibers receive the same inputs. Inputs are normalized by gains before inputting it to the model so as to have equal importance to each of the inputs. Gains are chosen by the maximum values of the inputs. The list of inputs and their gains are tabulated in table 5.2b. Two sets cerebellum models are used simultaneously to replicate the two-hemisphere anatomy. Both hemispheres receive the same inputs but the error signals are complimentary to each other. (Hirata and Ruben-Dario Pinzon-Morales,

2014) showed that a bi-hemispheric structure is critical for motor learning. The average firing rate of the left cerebellum is denoted by  $Cleft_{fr}$  and for the right by  $Cright_{fr}$ . The combined output of both the hemispheres is given by eq. (5.3) and the negative sign indicates the inhibitory output of the cerebellum. For different models cerebellum's output is scaled accordingly to have comparative ranges with the system variables. Finally Climbing Fiber's carry error signals, basically difference between the reference position and motor position.

In order to validate the performance of the system, two disturbances are introduced.

1. Load Variation : A uniformly distributed random noise ranging between [0,10] is added to the motor external load ( $J = 10$ ). This variation depicts the external disturbances that can arise in a control scenario.
2. Sensory Variation : Uniformly distributed random noise ranging between [0,0.05] is added to the feedback from the motor. This variation depicts the internal noises and sensory measurement errors in the system.

$$C_{fr} = -(Cleft_{fr} - Cright_{fr}) \quad (5.3)$$

Cell Type	Number
Mossy Fibers	5
Basket Cells	7
Golgi Cells	1
Granule Cells	64
Purkinje Cells	1

(a) Cell distribution in the simulation model

Input	Gains
Motor Position	1
Motor Velocity	1/25
Voltage(V)	1/10
Error	1
Reference Position	1

(b) Mossy fiber inputs

#### FORWARD MODEL SENSORY ERROR

The first model tested here is the case where cerebellum influences and modulates the sensory information. This is one of the most popular theories about the cerebellum but has not been tested widely using realistic cerebellum models. Sensory error that is the difference between the desired and actual motor position drives the learning in cerebellum. Control used for the motor control is as shown in eq. (5.4) and the sensory correction is given in section 5.1.2. Model operates under normal conditions and learns the right motor operation for 500 seconds at a step size of 0.01 seconds. Which means the models learns for 50,000 iterations. After this point the system is introduced to operate under the two different disturbances discussed previously. Performance under these disturbances with and without the cerebellum is shown in fig. 5.2. The weights at PF-PC synapses evolve during the training and evolution of weights at the end of 500 seconds is shown in fig. 5.3

$$u = K_p * (\sin(\theta_{ref} - \theta)) + K_d * (-\omega) \quad (5.4)$$

$$\theta = \theta + C_{fr} \quad (5.5)$$

$$\omega = \omega + C_{fr} \quad (5.6)$$

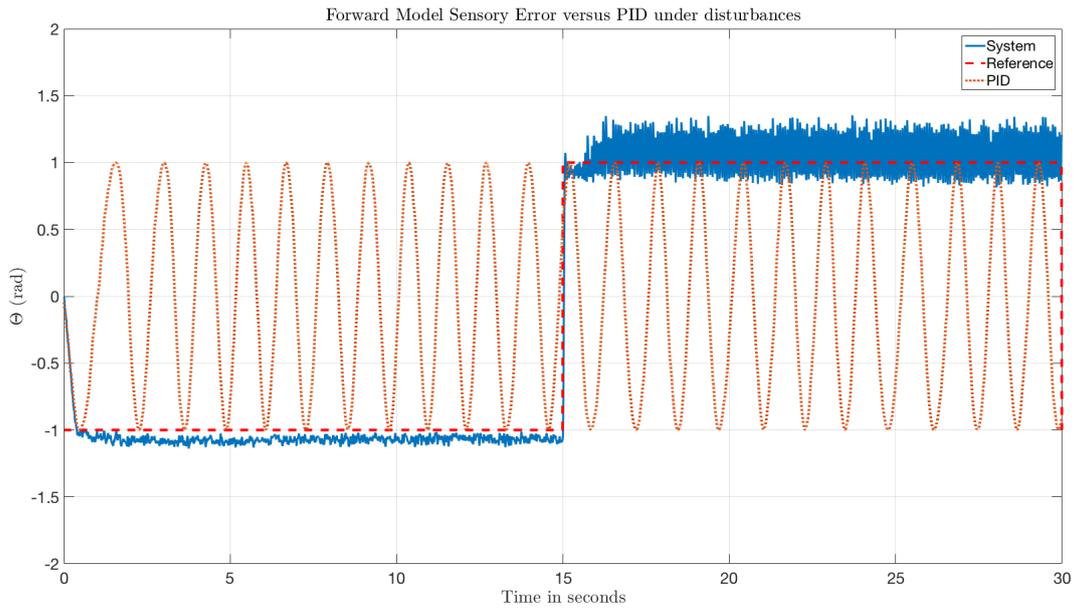


Figure 5.2: Response of controller with and without cerebellum under disturbances in FMSE

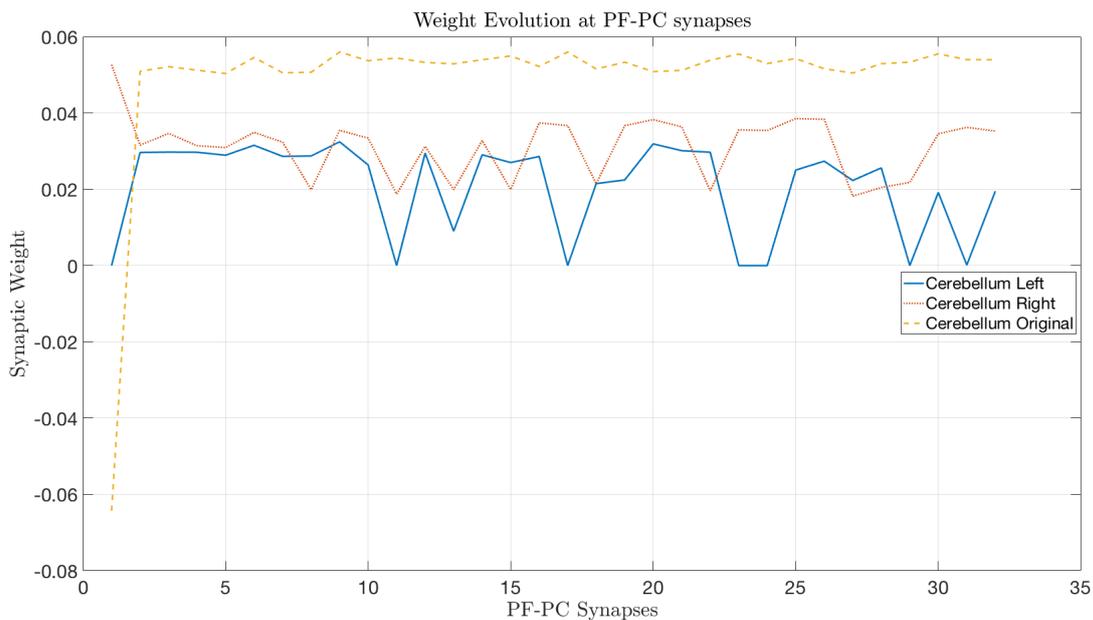


Figure 5.3: PF-PC weight evolution

### FORWARD MODEL MOTOR ERROR

The second cerebellum model tried is similar to the previous one with only difference being the error/learning signal. Climbing fibers now carry the motor command as the error signal. Meaning that cerebellum's role is to learn to minimize the control input will reaching the desired position. The control law (eq. (5.4)) and cerebellum's corrective signal (section 5.1.2) remain same as in the case of FMSE. Figure 5.4 shows the response of whole system versus the PID after learning for 500 seconds and then applying disturbances (both in  $J$  and state).

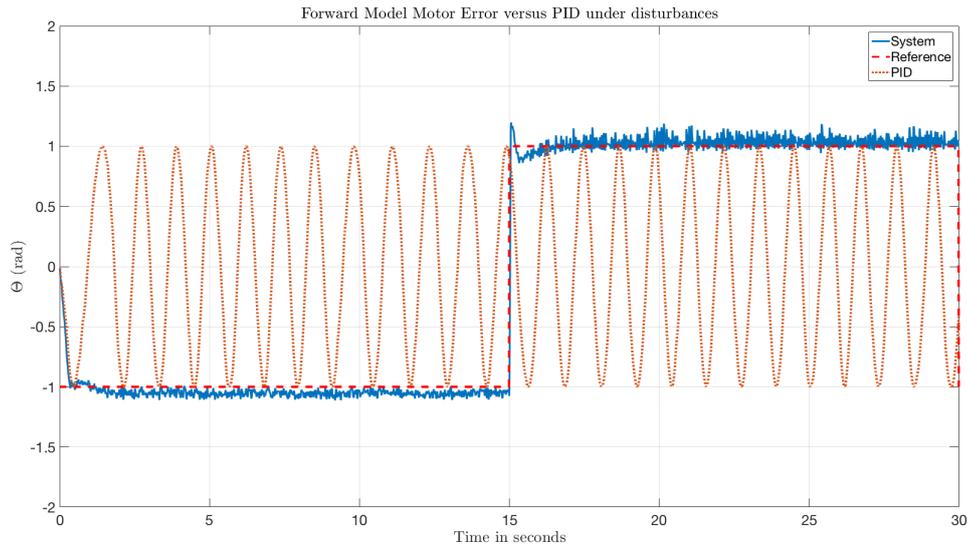


Figure 5.4: Response of controller with and without cerebellum under disturbances in FMME

### INVERSE MODEL SENSORY ERROR

The third consideration of cerebellum model is an inverse model with sensory error for learning. In this case cerebellum influences the output pid control block to achieve optimal results with minimum sensory error. The control law for this case is given in eq. (5.7). The influence of cerebellum's two hemispheres is directly in the control law. Where  $G$  is the gain to match the input range. In this case since the limit of input voltage is  $\pm 10$  the gain is chosen to be 10. Response of the system after training for 500 seconds with and without cerebellum is shown in fig. 5.5. The response shown is only for disturbances on the motor load ( $J$ ) and not on the sensory feedback since disturbance on the states made with system unstable even with cerebellum model.

$$u = K_p * (\sin(\theta_{ref} - \theta)) + K_d * (-\omega) - G * (C_{fr}) \quad (5.7)$$

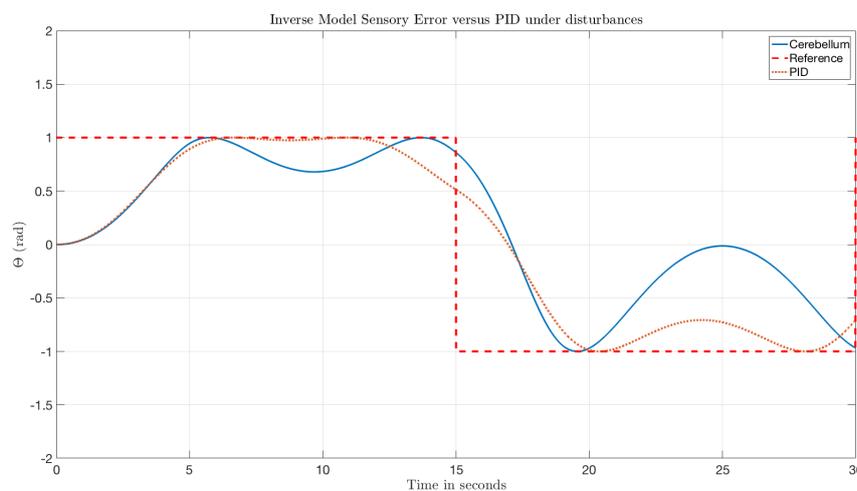


Figure 5.5: Response of controller with and without cerebellum under disturbances in IMSE

### INVERSE MODEL MOTOR ERROR

Fourth consideration is similar to the third. The only difference here is the error signal now is a motor error instead of sensory. The same control law applies as in the case of IMSE. Again in this module the system was unstable when subjected both errors and hence the response shown in fig. 5.6 is only for load disturbances.

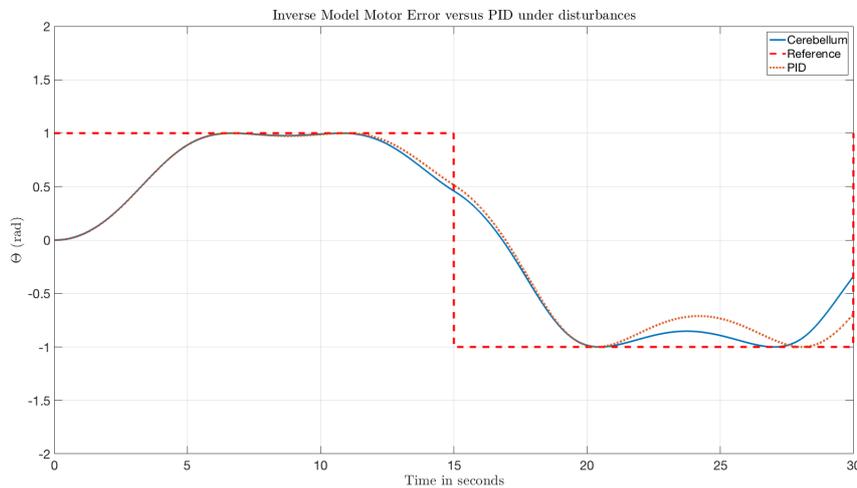


Figure 5.6: Response of controller with and without cerebellum under disturbances in IMME

### MODEL PARAMETER TUNING

In the final cerebellum role it is used to vary the control parameters of the system to there by achieve stability and improvement in performance. In this work only the P-control ( $K_p$ ) is manipulated by the cerebellum's output. As in previous cases the model was trained for 500 seconds initially and then subjected to disturbances. Like in IMSE and IMME, the model was unstable/divergent for disturbances in states. Hence the results shown in fig. 5.7 is the performance graph for inertial load disturbances only.

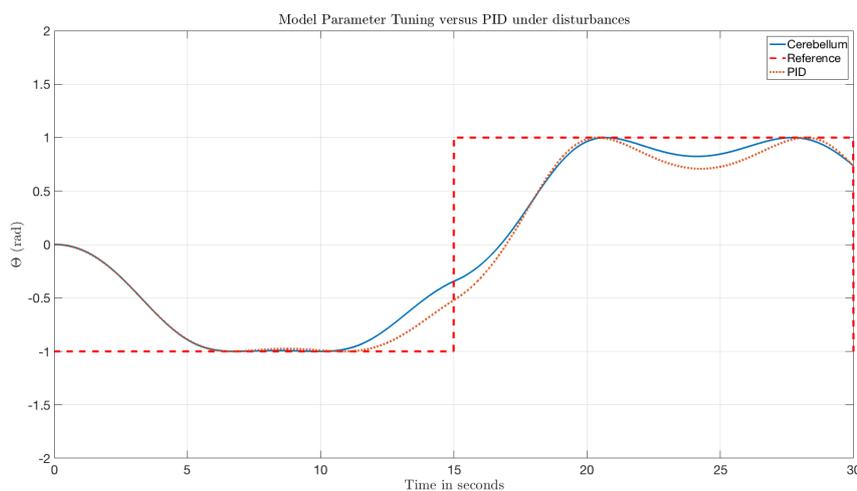


Figure 5.7: Response of controller with and without cerebellum under disturbances in MPT

### 5.1.3. COMPARATIVE MODEL EVALUATION

In the previous subsection all cerebellum models were tested in a control scenario and their responses were plotted. In order to have a better comparative evaluation, control related performance measures are compared across all types. The metrics used for evaluation are :

1. Settling Time ( $T_s$ ) : It is time take from the onset of the control action for the controlled state variable to be within  $\pm 5\%$  of the desired value.
2. Steady State Error (SS) : It is the difference between the actual state of the system and the desired state at time  $t \rightarrow \infty$
3. Over Shoot ( $Y_{peak}$ ) : percentage overshoot relative to  $Y_{FINAL}$
4. Root Mean Square error (RMSE) : The square root of the mean/average of the square of difference between desired and actual state of the system for give time window.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5.8)$$

Where,

- $n$  : Number of time steps
- $y_i$  : Desired response of the system at time  $i$
- $\hat{y}_i$  : Actual response of the system at time  $i$

Model	Settling Time( $T_s$ )	Steady State Error (SS)	Over Shoot ( $Y_{peak}$ )	RMSE
PIDideal	0.8033	0	0	0.1382
$PID_J$	3.4090	0.0521	26.2823	0.1899
$PID_x$	$\infty$	$\infty$	$\infty$	6.4600
$PID_{J-x}$	$\infty$	$\infty$	$\infty$	41.0122
FMSE	14.7129	0.0356	10.3914	0.0539
FMME	$\infty$	$\infty$	19.5277	0.0815
IMSE	3.4904	0.0516	31.8627	0.1882
IMME	3.3625	0	27.6773	0.1934
MPT	3.7541	0.0521	33.4833	0.1863

Table 5.3: Performance evaluation for different roles of cerebellum

## 5.2. VESIBULO-OCULAR REFLEX EXPERIMENTS AND RESULTS

In section 5.1.2 various models of cerebellum in a simple DC motor position control was seen. In order to test, validate and understand the cerebellum it is necessary to have a simulation that reflects real biological system . In chapter 4 one such model was developed. Role of cerebellum in tuning and aiding the performance of VOR has been well established through a number of experiments. Cerebellum is also key in VOR adaptability. The VOR experiments were first carried out in a simulation environment that replicated the real robot head in Gazebo.

### 5.2.1. CEREBELLUM

As it has been discussed throughout this report there is no consensus on the role of cerebellum yet. In the previous scenario a choice had to be made about the cerebellum's role before the beginning of the experiment which limits the chances of exploring the true workings of cerebellum. But in a realistic case like this with a neural model, there is no need for any assumption. Only necessary things is to make sure the model receives right inputs and terminates its outputs at the right nodes. Since the VOR circuit has two pathways and runs across two hemispheres, it is necessary to have two cerebellum hemispheres controlling each side. Since cerebellum is ipsilateral control, left side of VOR is innervated by the left hemisphere of cerebellum and vice-versa.

For real time performance consideration each module has 512 granule cells in a volume of  $200 \mu m^3$ . With this the cerebellum model has 34 mossy fiber inputs and one purkinje cell. The number of other cells can be calculated from the table 5.2a. Inputs and their normalizing gains to the cerebellum are tabulated in table 5.4, same inputs apply for both left and right hemispheres with the information arising from respective sides of the vor circuit. Since there are 18 mossy fiber inputs and only 8 distinct inputs, the rest repeated randomly across them. From literature study it well established that for VOR the climbing fibers carry retinal slip signals and hence in this work the same is followed with retinal slips from optical flow being the learning signal. Each of the two modules in one of the hemisphere has preference for either positive or negative errors.

Input	Gains
SCC response	0.2
VN response	0.2
Retinal slip	1
Eye position	1.66
Eye velocity	0.1
Abducens Nuclei	0.1
Oculomotor Nuclei	0.1
Head position	0.6
Head velocity	0.2

Table 5.4: Mossy fiber inputs for vor simulation

### 5.2.2. SIMULATION

With the flexibility of using a simulation model, an environment similar to a testing scenario for neuroscience experiments was created, an example of such real experiment can be seen in the work by (Beraneck and Cullen, 2007). This lays a ground work for future experiments to conduct simulations that are acceptable by neuroscience community to validate the results from real experiments. The simulated environment scene consists of an optical drum around robot with an optical checkers pattern on it. Figure 5.8 shows the robot head in an optical drum. Left and Right cameras of the eye can only see the pattern printed on the drum. Using the optical flow technique described in chapter 4, both cameras measure the pattern moving when either the drum moves or the robot itself moves. Optical flow is computed over a small region around the center of the image to act as fovea in a real eye (fig. 5.9). Anything which moves in this field of vision will excite OKR and a compensatory movement will be produced.

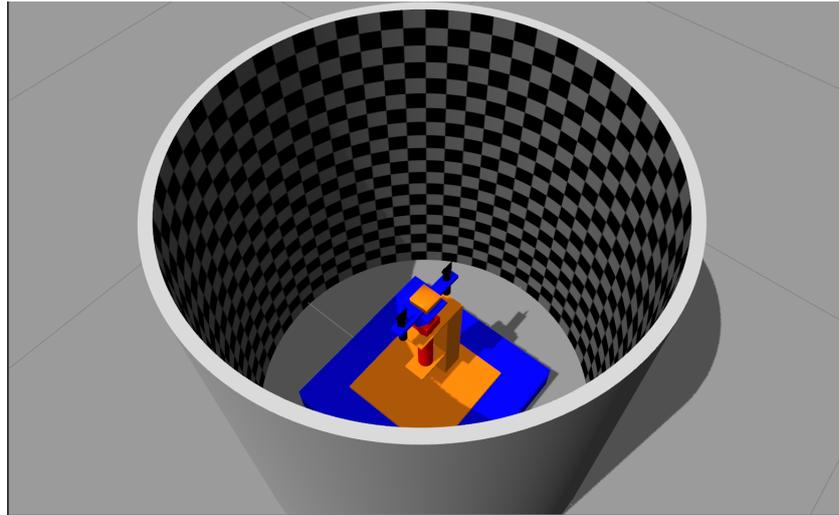
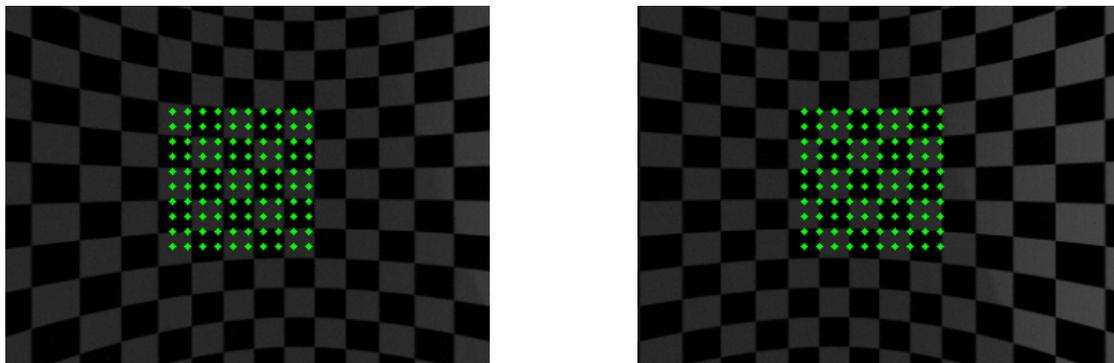


Figure 5.8: Simulation of the robot inside an optical drum



(a) Left camera

(b) Right camera

Figure 5.9: Camera view of the pattern with optical flow on the fovea

### EXPERIMENTS & RESULTS

In order to excite VOR the head needs to produce disturbances. Two types of head rotations are considered. One a square wave and second sinusoidal rotations. Square wave magnitude ranges between  $[0.5 -0.5]$  *rad* with a frequency of  $0.2$  *Hz* and sinusoidal rotations have an amplitude of  $0.4$  *rad* with frequency ranging between  $0.1$  *Hz* and  $0.4$  *Hz*. Both these inputs are position control of the neck for horizontal movements. In the square wave input, once the eyes compensate for the movement and neck stops rotating. The excitation of semi circular canal now drops and lead to a drift in the eye to align itself with the head. This drift is avoided by VPN nuclei for a certain time by providing tonic bursts of the VN.

All the experiments are performed for a duration of 30 seconds. For each frequency sweep three different experiments are performed. First the vor model is used in the feed-forward mode with input from the cerebellum (VOR). The retinal gain in circuit is doubled, which means the eye detects more slip than actual movement. In this case first the cerebellum is removed and then the optical flow is measured. In the third case the cerebellum acts along with the vor circuit in order to compensate for extra retinal gain. These type of experiments are also conducted in neuroscience to check for adaptability vor circuitry. The final set of experiments involve the training of cerebellum for 50 seconds under normal conditions and then the retinal slip is doubled to induce disturbances. The cerebellum will now have to learn to compensate for these changes.

Since a frequency sweep was not performed for the square wave testing, in this section results from

only the sinusoidal inputs are discussed. Before discussing the results are evaluated by comparing the average optical flow form both left and right eyes. Data evaluation is performed for 30 seconds for each of the experiment. Figure 5.10 shows head versus eye position for a sinusoidal input of 0.1 Hz. In this case even without the cerebellum, feed-forward network produces the required compensatory eye movements. From fig. 5.11 we can see that the optical flow of the image is reduced by the cerebellum when there are disturbances (Increase in retinal gain) but the improvement is not as good as the original network when there are no disturbances.

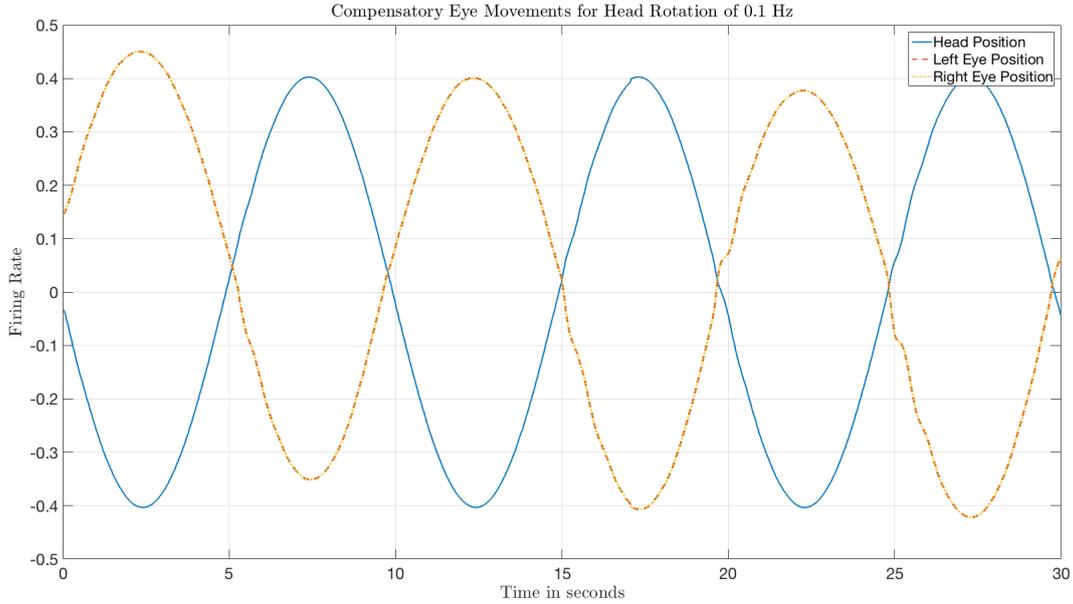


Figure 5.10: Compensatory head-eye movement VOR

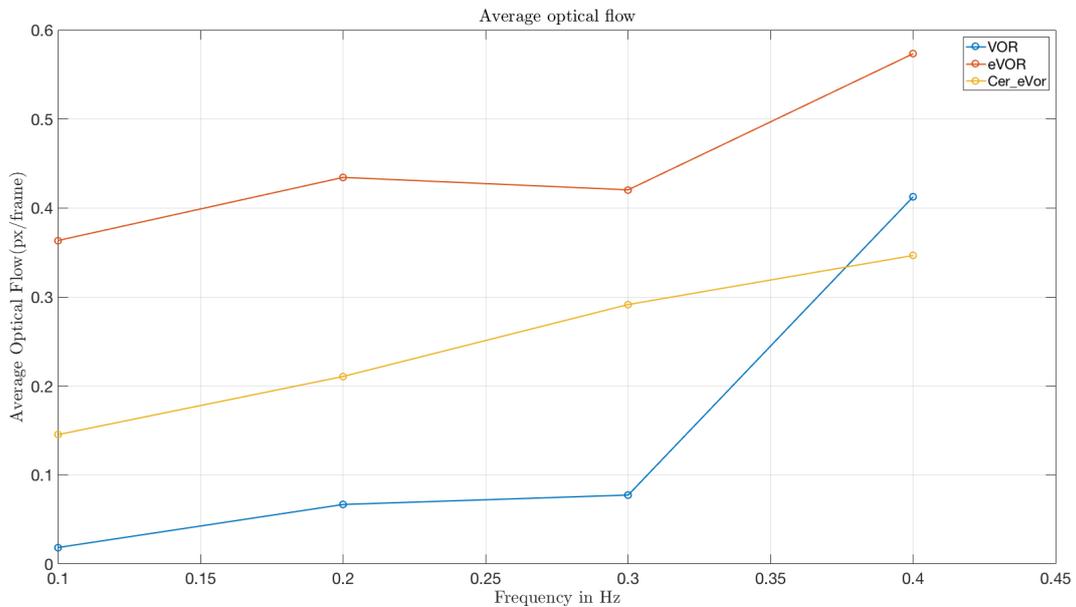


Figure 5.11: Compensatory head-eye movement VOR

### Summary

1. To test the cerebellum model in simulation and real hardware to compensate for disturbance and learn in real time, two control scenarios were employed.
2. First, a classical engineering problem of DC motor position control with a PID control is used.
3. Five different hypothesis on the cerebellum were tested for same load disturbances.
4. Only forward models were able to compensate for errors in sensory feedback.
5. Inverse models only compensated external inertial loads.
6. Model parameter tuning did not introduce any more benefits than inverse model.
7. Learning was possible with sensory errors and motor actions as well. Showed that with neural networks error signals are much easier to change.
8. Second, model was tested with a feed-forward model of VOR.
9. Proved to be more challenging to improve the performance than in the case of PID control.
10. Experiments were similar to the ones performed by neuroscience.
11. Provides a platform to readily hypothesis by neuroscientists.



# 6

## DISCUSSIONS, CONCLUSION AND FUTURE WORK

"Life is just a certain amount of time and energy. Outting this time and energy to maximum use for everyone's wellbeing is all that matters"

---

— Jaggi Vasudev

**I**n this chapter, section 6.1.1 reviews and discusses all the steps taken during this thesis. Section 6.2 concludes the thesis by going through all the goals set initially and reflects if the goals were met or not. The final section 6.3 of this master thesis discusses the future steps to be taken.

### 6.1. DISCUSSIONS

Before starting the discussions an overview of the thesis is given. To begin with, a computational model of the cerebellum was constructed which was biologically realistic in dynamics, spatial arrangement and synaptic connectivity. Since the modeling involved no assumption on the role of cerebellum it was possible to test the model as 5 different functionalities to control a dc motor. Next the vor model was implemented to test the cerebellum in a more biologically realistic situation.

#### 6.1.1. THEORIES ON FUNCTIONALITY OF CEREBELLUM

As seen through out this thesis there have been references to evidence showing that cerebellum has multiple roles and functionalities. The biggest mystery is that all the different functionalities have been possible with the same homogeneous cell connectivity. Cerebellum initially evolved to control movement and balance has now extended itself to higher cognitive roles. High density of cells in a compact region is another evidence for the significance of cerebellum beyond just movement control and co-ordination. In chapter 2, regional classification showed the regions to which the cerebellum extends to. From it can be seen that there is no direct influence of it on the higher regions expect via the thalamus. Due to the lack of direct involvement it is harder to devise experiments to identify the role of cerebellum. Until now lesion studies were the only possible way to understand the role. But now with more realistic cerebellum simulation models it is possible to test the existing hypothesis in more practical ways.

Unfortunately such attempts have been less in the literature. For example (Casellato *et al.*, 2014) use cerebellum as an inverse model to drive the robots, though they built a highly realistic model with spiking

neural networks the simplifications of using it as a direct controller limited them to extend their findings to the real cerebellum model. (Frens and Donchin, 2009) proposed cerebellum as a state predictor and constructed a control scheme to show with biological evidence that the proposed control loop might explain the workings. This difference in proposals and still being able to provide supporting evidence for the hypothesis is the biggest reason for not having a consensus on cerebellum. It may be time to accept that cerebellum is capable of performing multiple of these proposed functions at the same time. (D'Angelo and Casali, 2012) proposed a more unified theory that cerebellum might be general purpose processor that is capable of adapting itself to the task at hand. But the problem now is that there is no common protocol under which these theories need to be tested with. There needs to be a common platform and protocol to be established to test any proposed theory for its validity. If that is established first then research would speed up since models and hypothesis can accepted or denied more quickly than at present.

Another major drawback in the current research frame work describing the functionality of cerebellum is the lack of importance given to bio-mechanics of the body. (Crespi *et al.*, 2013) work shows that higher brain centers were able to drive complex motions in a robot salamander just by changing the strength in amplitude of input signal to the spinal cord model. This sort of distributed control architecture exists in all species and reduces the load on higher brain centers. By considering this bottom up approach the role of cerebellum can be simpler than current proposals or even entirely different from existing theories. Again this draws to a need for creating an biological simulation environment that would allow to just plug in any cerebellum model that comply with the set of inputs and outputs to be tested and validated.

Taking all of these into consideration it was therefore decided to test the cerebellum simulation model under most number of possible hypotheses as described in chapter 2. Though the number of models tested are limited, it is a pointer for future to be taken up more seriously by research works focused on developing simulation models.

### 6.1.2. LEARNING IN CEREBELLUM

In the previous sub section it was seen that there are problems in confidently evaluating the functionality of the cerebellum. But learning mechanism of the cerebellum is more confidently accepted. Originally started with the work (Marr, 1969) and (Albus, 1971) who proposed the PF-PC plasticity and a supervised learning via the Climbing Fiber signals has been adapted in almost all the current theories. With strong support to this learning mechanism, it was decided to go ahead with the same for this work as well. The two mechanisms used were learning LTP and LTD. There were some difficulties which were encountered with learning mechanism during this thesis.

The first was model initialization. Usually in previous research cerebellum is always used in collaboration with another control loop that is stable (Hirata and Ruben-Dario Pinzon-Morales, 2014; Frens and Donchin, 2009). In this case when the cerebellum is added to the control loop, it produces random actions that would lead to some errors and this results in LTD of the pf-pc synapses. Now the effectiveness of inhibitory purkinje cell reduces. If this reduction does not aid the the control action then it would lead to more errors further reducing the weights and eventually leading to complete suppression of purkinje cell activity. Since most works use a feedback controller as the primary control loop, it compensates for the wrong actions produced by cerebellum and which would allow it to undergo LTP and learn the mistake. This calls for two significant questions.

- Is it necessary for cerebellum to be always aided by another control loop that is adaptable to the changes produced by the cerebellum?. (Menzies *et al.*, 2010) discuss the adaptability required in the vestibular nuclei for the cerebellum to be able to learn under error supervision from climbing fibers. (Porrill and Dean, 2007) also discusses the importance of having additional adaptability in the cortical structures for the cerebellum to compensate for high frequency disturbances.

- Second question that arises is, "*Are there more plasticity sites inside the cerebellum?*". This has been addressed in the literature but being more accepted in recent times. (D'Angelo *et al.*, 2016) have shown in their work that having multiple sites of plasticity within the cerebellum will help learning mechanisms and offers more flexibility. Along with neuroscience evidence they also showed that it is indeed necessary for simulations studies too.

These questions are critical and need to be taken more seriously. Therefore the learning mechanism employed in this work is just one of the many plasticity sites in the cerebellum and other assisting nuclei. This work shows that it is indeed necessary to model other nuclei in the control loop of cerebellum with more adaptable networks than just a simple pid control loop.

It is also interesting to think on how this might be happening in biological system. When does the cerebellum start to learn and what are the mechanisms that allow this transfer of learning and action between different brain regions.

### 6.1.3. CHOICE OF NEURAL NETWORK MODEL

At the end of literature phase in this master thesis, it was decided to go ahead with an implementation of a spiking neural network to have the most realistic cerebellum model currently possible. After exploring most of the state-of-art spiking neural network frameworks, none were found that met the real time requirements and the computational resources available. The next best option was to use artificial neural networks for developing the simulation model. Based on the work of (Hirata and Ruben-Dario Pinzon-Morales, 2014; Tanaka *et al.*, 2010; Pinzon-Morales and Hirata, 2013) the model was developed in MATLAB. Not only did this offer the necessary computational processing advantage but it was also the only artificial neural network to the best of authors knowledge that included all the recurrent connections of the cerebellum with realistic spatial and synaptic modeling.

One advantage of the model is that no prior assumption was required to model the network. All cells and its connections were purely based on the anatomical studies of the cerebellum. This allowed to perform multiple model tests using the same architecture by just manipulating the inputs, outputs and learning signals of the network. This is also in accordance with the fact that cerebellum's uniform architecture can be used for different computational tasks based on its inputs and outputs. The models flexibility also allows for easily incorporating multiple sites of plasticity that was discussed in the previous sub section for future work.

### 6.1.4. DIVISION OF CLASSICAL CONTROL VERSUS BIOLOGICAL CONTROL SYSTEM

In this work an attempt is made to have a clear distinction between the use cerebellum model studies is classical control scenarios and more biologically realistic control situations. Since one of the objective of this thesis was to understand cerebellum's working that could benefit the robotics community. By directly applying the cerebellum model in an engineering application might not lead to explaining the actual working of cerebellum but it showed that just with the architecture and simple learning rules can be beneficial aiding classical control algorithms for adaptability in robots. Also the use of classical control allowed us to explore various possibilities in which the cerebellum can learn and act upon in a control loop.

One of the other objective of this work was to test the cerebellum model in a more realistic biological system. Just from the VOR implementation it was clear that by considering bio-mechanics and all the nuclei involved in control action simplifies the load and responsibility of cerebellum tremendously. The feed-forward network is self sufficient to produce compensatory eye movements which allows the cerebellum to perform the role of adaptation only when disturbances are present and fine tune the control loop. This type division has not been taken up in the past research. Doing this allows to clearly draw conclusions on the cerebellum model's principles separately and allows for studying the cerebellum and simultaneously applying it to a practical application.

### 6.1.5. EXPERIMENTS AND RESULTS

The experiments were again divided based on two testing scenarios discussed previously. In the first scenario, the aim was to see if the cerebellum model can compensate for disturbances during position control of motor. Since different models were being evaluated it was necessary to their influences on all types of disturbances. The disturbances were designed to be arising both internally and external. In (Pinzon-Morales and Hirata, 2015) an inverse model proposal of the cerebellum was tested in different control applications like a balancing robot and quad-rotor but limited to only external noise disturbances. It is shown in this work that including internal sensory noise led to instabilities that were not compensated by the inverse model but only by a forward model. The inverse model approach of the cerebellum did not improve the performance not did it perform any better than pid control loop. The same was in the case with model parameter tuning case. It in fact performed slightly worse than just the pid. In order to have a better qualitative comparison between models, standard control parameters described in section 5.1.3. Using these parameters the performance of all the models are tabulated in table 5.3. From the table the best performance is observed for forward model with sensory error. Not only can it compensate for load variations but also internal sensory noise. These results show that it is possible to stabilize a unstable control system with the help of cerebellum model and there exists different variations which can be chosen based on requirements of the application. The table again supports the claim that cerebellum works as a forward model to compensate and modulate sensory information. By doing so not only can it act on internal noise but also for external load variations. Another important observation that can be made here is that with the help of neural network models it is possible to show that in conventional control loops stability can be introduced not by one solution but by many. Thus starting with a model assumption might lead to wrong conclusions about the actual working of the cerebellum in a biological system.

In the VOR model, experiments were done to replicate studies from neuroscience. The robot head was placed in an optical drum and then perturbations were provided by applying sinusoidal motion to the robot head. From fig. 5.10 an example of conjugate counter eye movements for head rotations can be observed. The head and eye positions are complementary to each other there by producing clear images on the camera. In order to test the model, sinusoidal frequencies ranging between 0.1-0.4 Hz was applied and then the average optical flow between the two eye were measured. From fig. 5.11, VOR circuit with the cerebellum does reduce image blur when the retinal slip increases. But it does not match the performance with original VOR with the right retinal gains. One of the reasons for this could be that the cerebellum can inhibit the VN response only to a certain threshold. When the errors get larger the cerebellum reduces its inhibitory effect and there by not regulating the VOR anymore. This is an important observation since, there have been no studies on the convergence of cerebellum's learning mechanism it will be interesting to see how the learning actually converges for different types of errors. Also due to the time constrain of the thesis the number of tests that could be performed on the real robot were limited and hence the results are not shown in this report. The dynamics of the robot also plays an important roles in the ability of the network. The robot used in this experiment did not have the quick dynamics as of a human eye. This constrained the range of experiments that could be performed on the robot.

Experiments on the robot was performed with different communication speeds and latencies in the information. Even with these latencies the network was able to cope with the disturbances to a reasonable extent. These experiments show that when conventional control loops are not used, it becomes much more difficult to control the robot with the cerebellum and demands for more pressing questions that do not arise other wise. Hence it is necessary to stick to the actual neural circuitry as much as possible to avoid any simplifications that can misleading.

## 6.2. CONCLUSIONS

During the course of the project the complexity of things we take for granted, even a simple eye movement will truly humble anyone. With an ambitious goal of trying to understand the long standing debate in neuroscience about the cerebellum was highly challenging. The plethora of literature that is available is more often confusing than helpful. But let us see if the goal set initially were possible or not.

The primary goal of the thesis was to understand the existing theories about cerebellum and review why there is so no consensus yet. What was evident from the literature review is that all the proposed models do find evidence in some physiological experiments and they are hard to be tested to accept or deny. The theory that come up the most is the internal model theory which describes the functionality of cerebellum. Multiple model proposal problem lead us to come up with most of the possible solutions that could be tested during this thesis and then evaluating them individually allowed us to understand how each model works and then comment on its feasibility. Thus the primary goal was tackled and gave insights on how to proceed further in an attempt to understand deeper about the cerebellum. Yes, there could be a possibility of cerebellum having an internal model of the body and environment but it what is more important is to understand how this information is made useful to other brain regions to achieve fine movement and co-ordination.

The second goal was to construct a cerebellum model least number of assumptions on its functionality. Quite a lot of time was spent on trying look for a framework that met our requirements. After exploring many spiking neural network models and then deciding to use firing rate models led to the work of [Pinzon-Morales and Hirata \(2013\)](#) which was very helpful in realizing the cerebellum model to meet the real time requirements of the system. Thus the goal of having a realistic model for simulation was successful.

The third goal was to use the cerebellum model constructed in previous step to test the theories that were discussed at the end of first goal. After testing these models one conclusion is that it is possible to have different set-ups and still achieve stability using neural networks. Researchers have to be careful while using neural networks due to their ability to learn what is taught. We saw that irrespective of the type of error the model was still able to achieve similar performances in the control scenario test. Though the test scenario was dynamically very simple and needs further complex testing, it does show the flexibility of neural models. At the end the forward model with sensory error performed the best among all other proposals. This does not mean that the cerebellum is a forward model but it means it could be one of its various other functionalities.

The final goal was to create an environment to mimic a biological scenario where the cerebellum is known to be a playing a prominent role. Vestibulo-Ocular Reflex proved to be the best choice due to its comparatively simple architecture. After realizing the model, it was possible to generate conjugate compensatory eye movements for a limited range of disturbances. The use of cerebellum in the network showed that the cerebellum model was capable of monitoring the gain of VOR to reduce retinal slips. But achieving this proved more challenging than implementing the cerebellum in an engineering control application. The implementation lead to several interesting questions that were previously discussed. Even in the current VOR implementation a number of simplifications have been made. This has to be improved upon in the future work. Another drawback of this implementation is the combination of firing rates with real valued sensory signals. This proved to be very challenging and it is therefore preferable to convert and model all nuclei using artificial neural networks to a common way of information exchange.

### 6.3. FUTURE WORK

Understanding the cerebellum still remains an open question and hence the possibilities of future work are plenty. From my experience the first step in the future for testing control related brain structures would be to have a bottom up approach than a top to bottom one. A system that has similar dynamics as that of a real biological system is crucial. More specific steps for the future on the current work are:

- The current cerebellum model has only one site plasticity. From the evidence of literature it needs to be extended to multiple sites of learning.
- Neurons in the current model are modeled with simple sigmoid thresholding function. This can be replaced with more computationally efficient spiking neurons like the izhikevich neuron models.
- Due to focus on implementation of the framework not much effort was spent on looking at the inner computations of the model. Now that there is a simulation model that can be torn apart, information processing at each stage can be looked and it will be interesting to see if there are new techniques to process information.
- The control scenario should be extended to a more complex and dynamical system in purely control engineering way to fully exploit the potential of the simulation.
- Unfortunately I was unable to collaborate fully with the Neuroscience team at ERASMUS University. It is highly advisable to work with neuroscientists to save a lot of time digging through the literature.
- EDLUT, an event driven spiking network seemed very promising for real time implementation. Due to their lack of support for the model currently it was not possible to use but in the future it could be the one for simulation studies.
- Current VOR model was limited to horizontal angular eye movements only. This can be extended to linear and angular movements both in horizontal and vertical movements.

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