

Use of Animatlab in Neuromechanical modeling

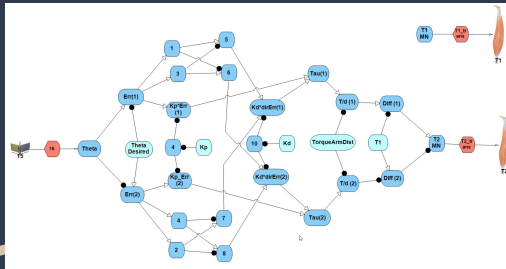
Jake Chung and Jonathon Tran

A dark blue diagonal gradient bar that starts from the bottom left and extends towards the top right, covering the lower half of the slide.

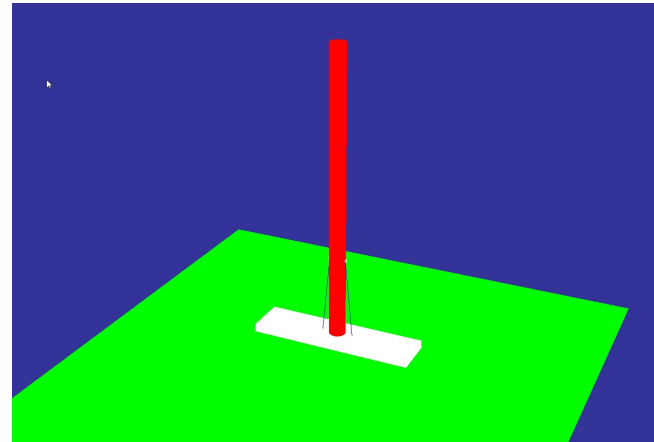
What is AnimatLab?

AnimatLab is a software tool that combines biomechanical simulation and biologically realistic neural networks.

It allows us to build the body of an animal, robot, or other machine and place it in a virtual world where the physics of its interaction with the environment are accurate and realistic.



Control
Signal



Project Idea



- Had Zero Experience with AnimatLab
- Wanted to gain a basic understanding of AnimatLab modeling.
- Wanted to gain a basic understanding of neuro-sensory physiology.
- Wanted to be able to create our own individual models.
- We looked at prior works in human postural control using an inverted pendulum that included the use of AnimatLab.

Prior Works – Peterka

Robert Peterka, Study:

“Simplifying the complexities of maintaining balance”.

Wade Hilts, Master’s Thesis:

“Emulating Balance Control Observed in Human Test Subjects with a Neural Network”

Tiffany Hamstreet, Master’s Thesis:

“Input Dependence in Bio-Constrained Neural Control with an Eye Toward Human-Like Adaptability”.

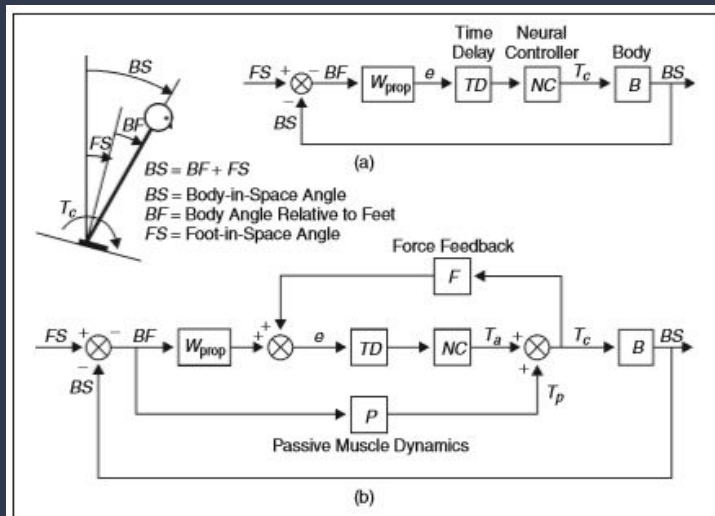


Fig. 1. (a) A simple postural control model formulated as a negative feedback position control system with sensory orientation information from proprioceptors sensing body orientation relative to the support surface. A weighting factor W_{prop} is applied to proprioceptive sensory information, and this information is processed by a neural controller to generate corrective torque T_c . The stick figure defines the positive directions of orientation angles and corrective torque. (b) Modified model that includes passive muscle dynamics P and a positive feedback loop conveying force-related sensory information F . Passive muscle properties generate passive corrective torque T_p that sums with active torque T_a derived from sensory information to give the overall corrective torque T_c applied to the body.

Prior Works – Peterka

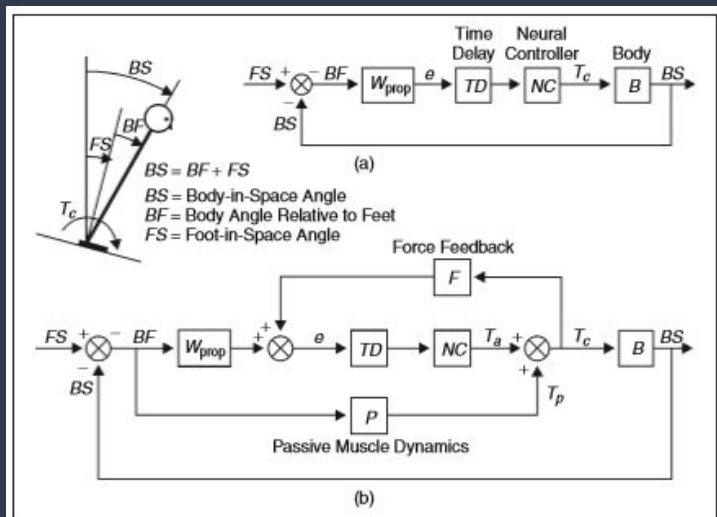


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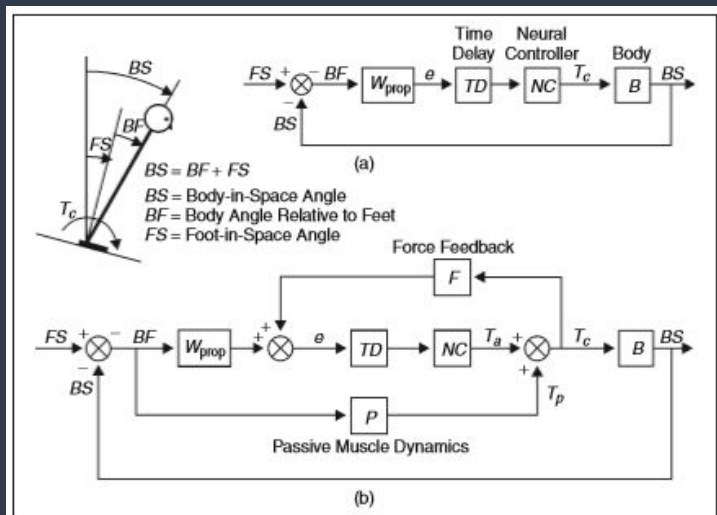


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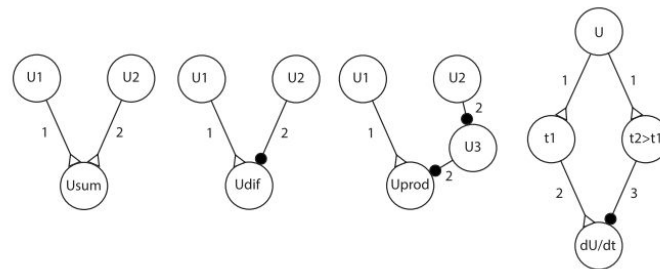


Fig. 4. Graphical representations of the neurons and synapses. From left to right: addition, subtraction, multiplication and derivative subnetworks. Synapses terminating in a triangle are excitatory, whereas the shaded circular terminals are inhibitory synapses. For details, see [13].

Prior Works – Peterka

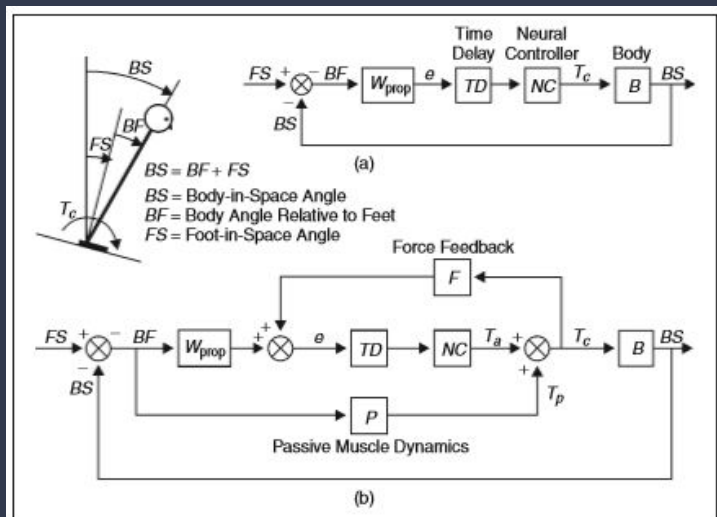


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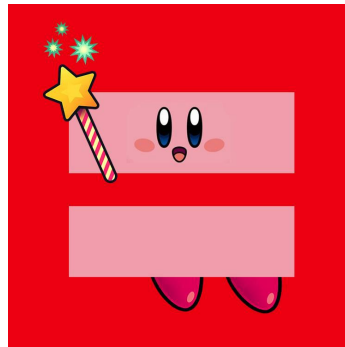
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Prior Works – Hilts

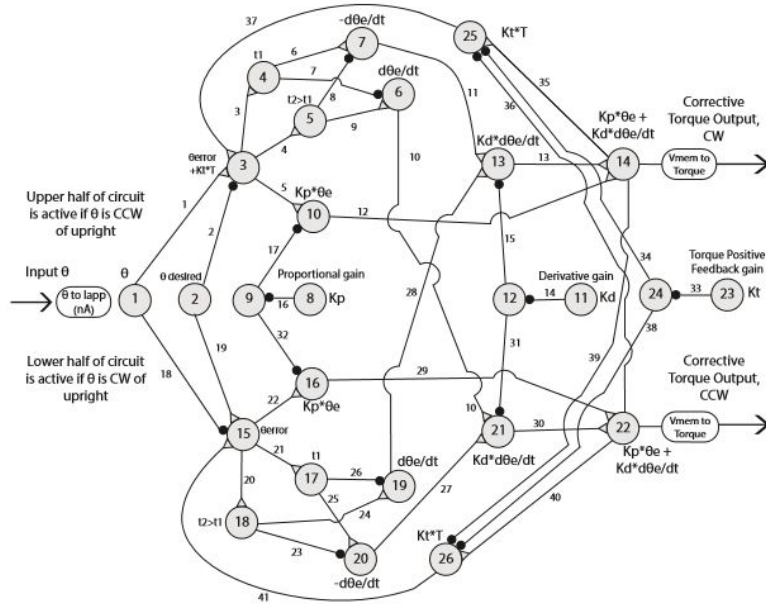


Figure 3.1: A network of neurons and synapses that outputs a torque command based on a joint angle input signal. The circuit is a collection of interconnected addition, subtraction, multiplication and derivative subnetworks and is broken into two sections, each governing the clockwise and counterclockwise regions (about the marginally stable midpoint) of the pendulum system. CW and CCW torque response signals are manifest in the membrane potentials of neurons 14 and 22.

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Prior Works – Hilts



Fig. 1. Controlled system used in experimentation. This system models human balance control and is comprised of a several pieces of steel rigidly fastened together, with a torque controlled servomotor acting as the base joint.

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Prior Works – Hamstreet

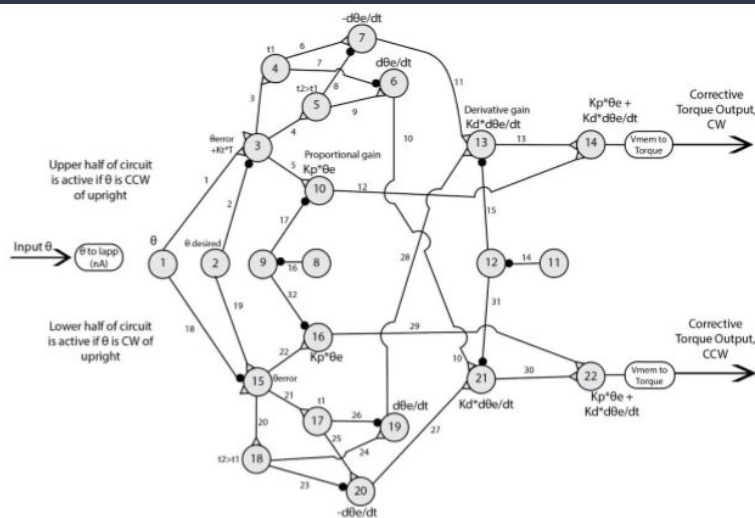


Figure 3: The neural network PD controller is developed from subnetworks tuned to perform mathematical operations using biological constraints [2, 4]. The controller is top-bottom symmetric to handle both positive and negative input angles, and the proportional gain K_p occurs at Neurons 10 and 16 and derivative gain K_d occurs at Neurons 13 and 21. Triangle connections indicate excitatory synapses and filled circles indicate inhibitory synapses.

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Neural Network of Wade and Tiffany

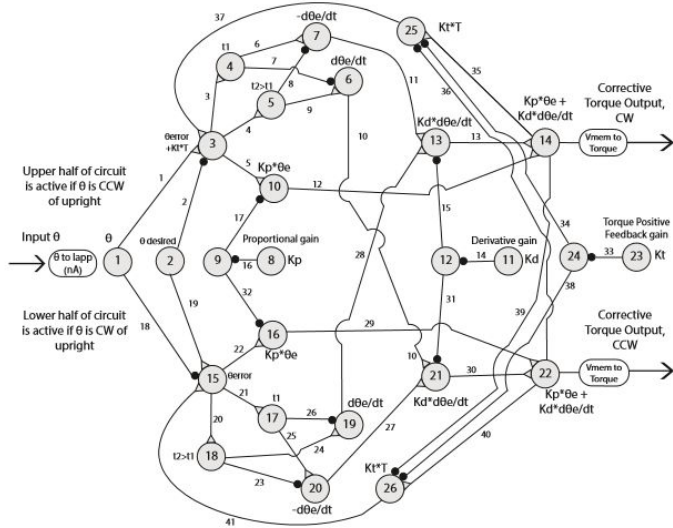


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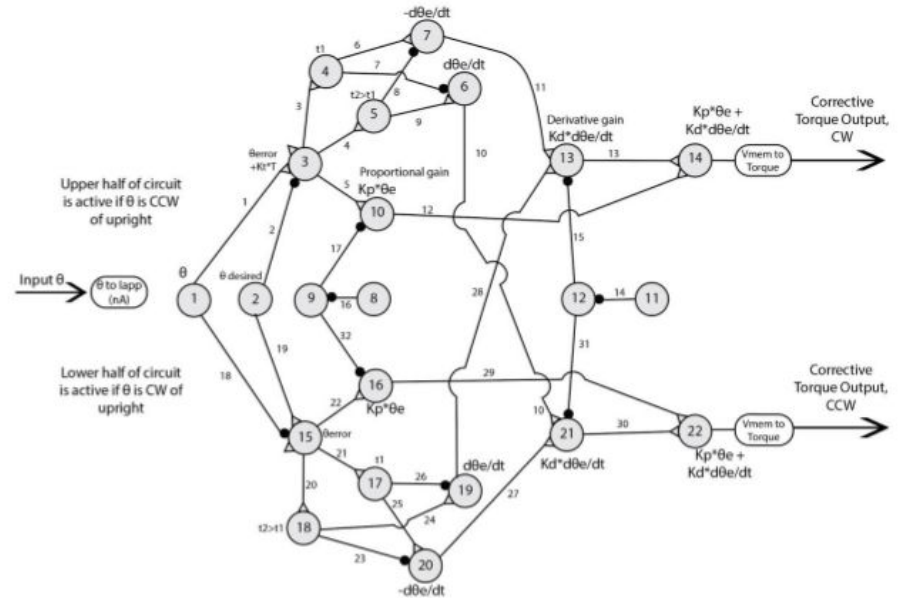


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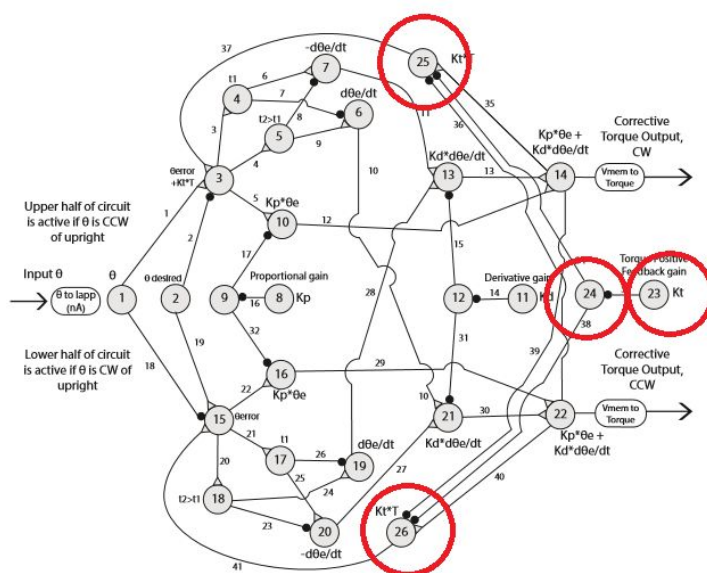


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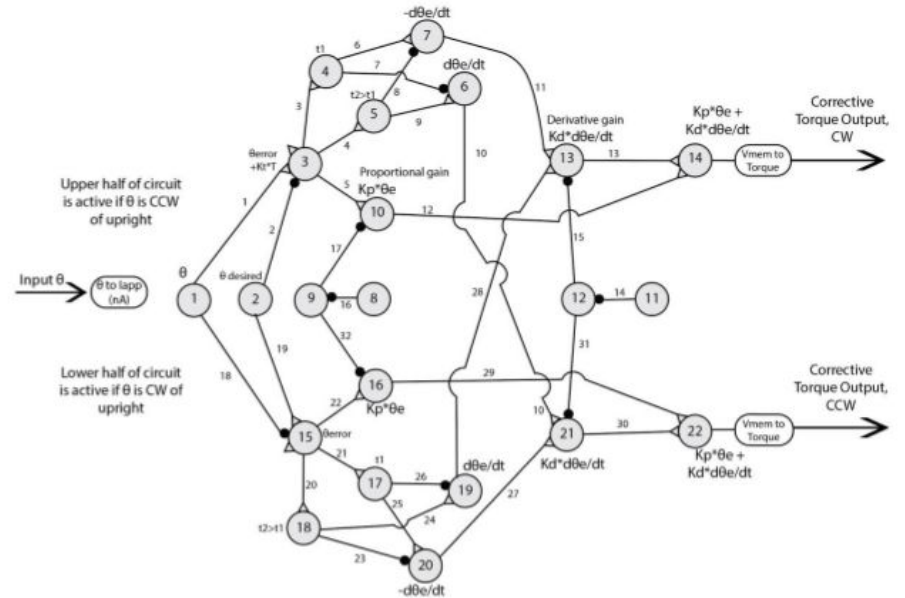
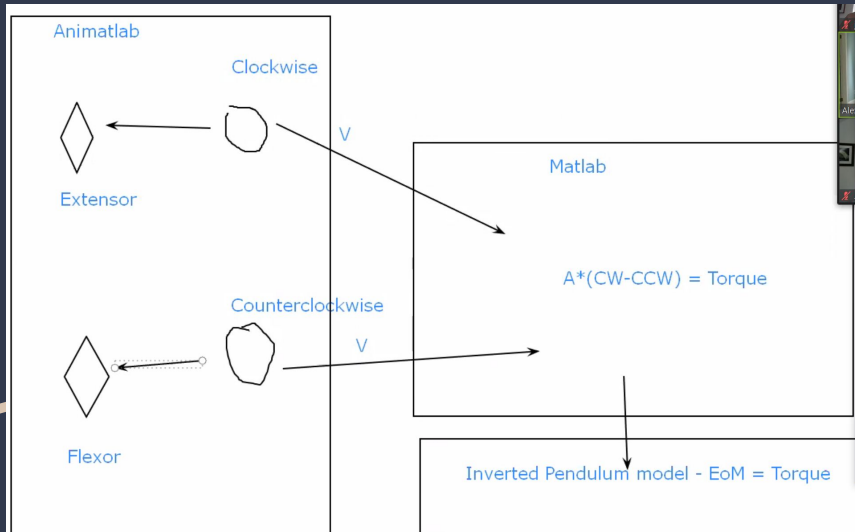


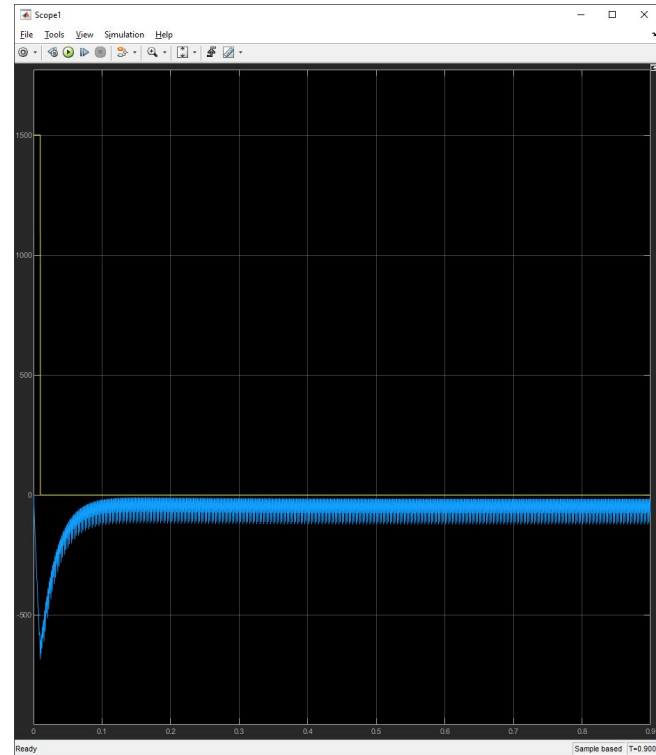
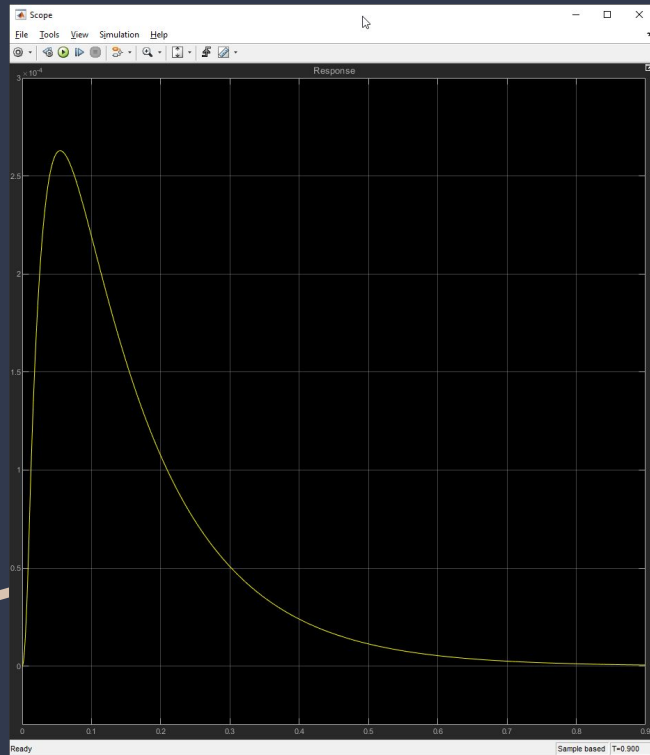
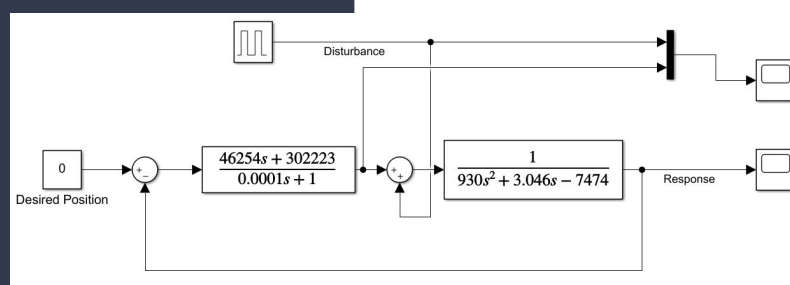
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Steps to take:

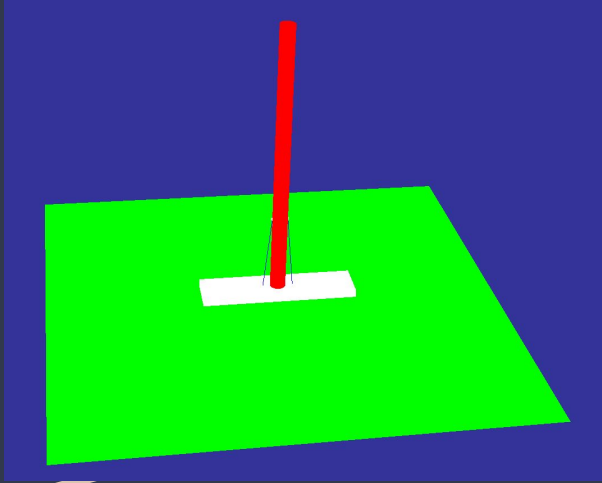
- Derive the Linear Inverted Pendulum governing equation with muscles as the actuators.
- Design the classical PD controller using Matlab.
- Test the PD controller using Simulink.
- Build the neural control network based on Wade's and Tiffany's network.
- Tune the network to produce a similar response to the response in Simulink.



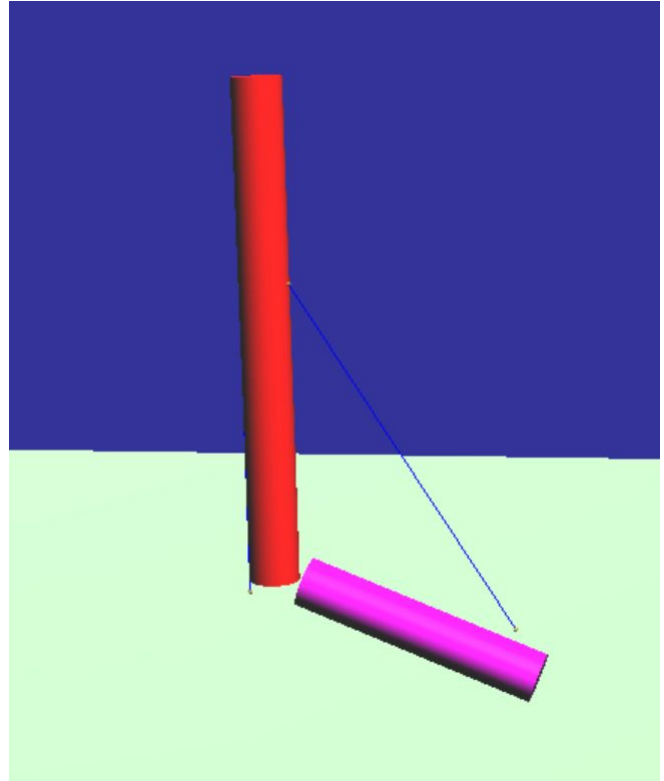
Simulink



AnimatLab Models

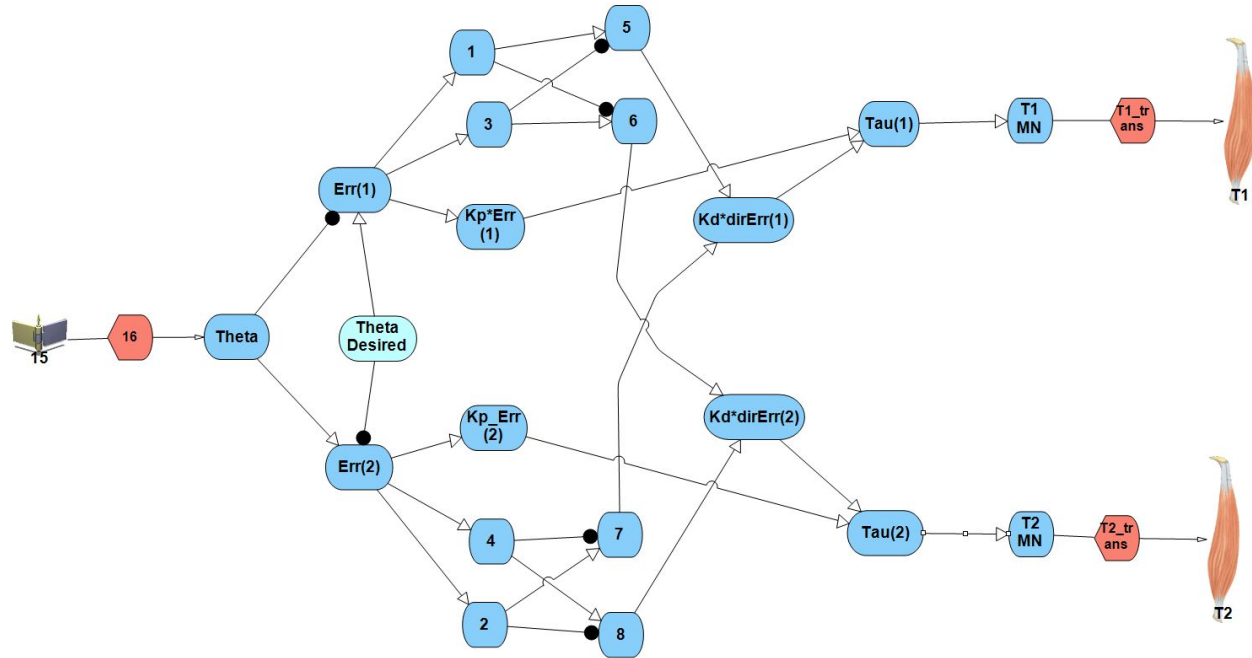


This is what our AnimatLab Models looked like in the end:

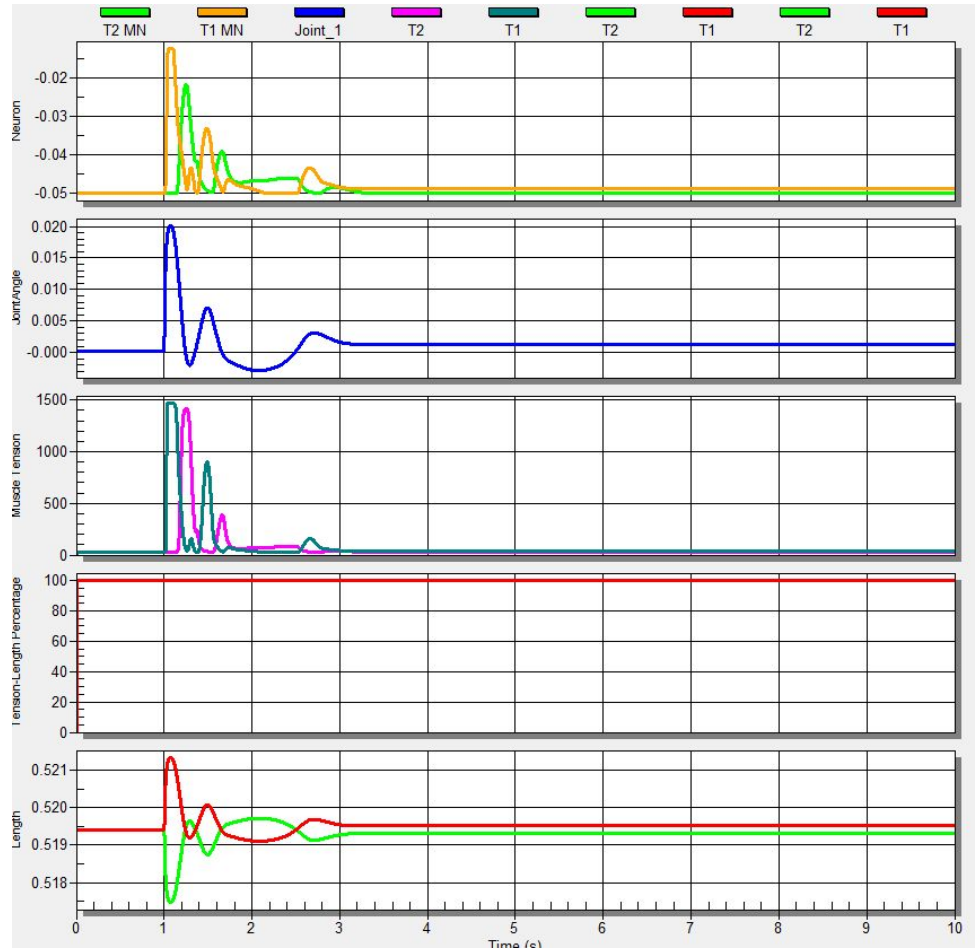


AnimatLab Neural Networks

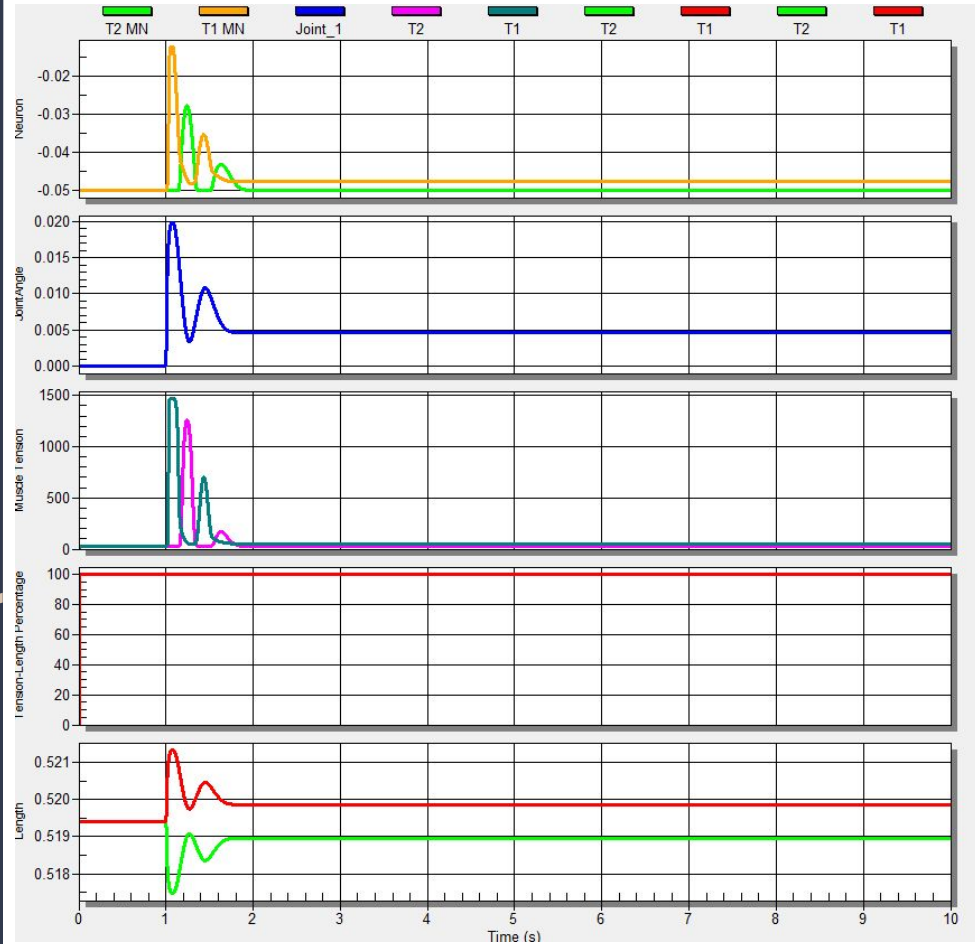
This is what our Neural Networks looked like:



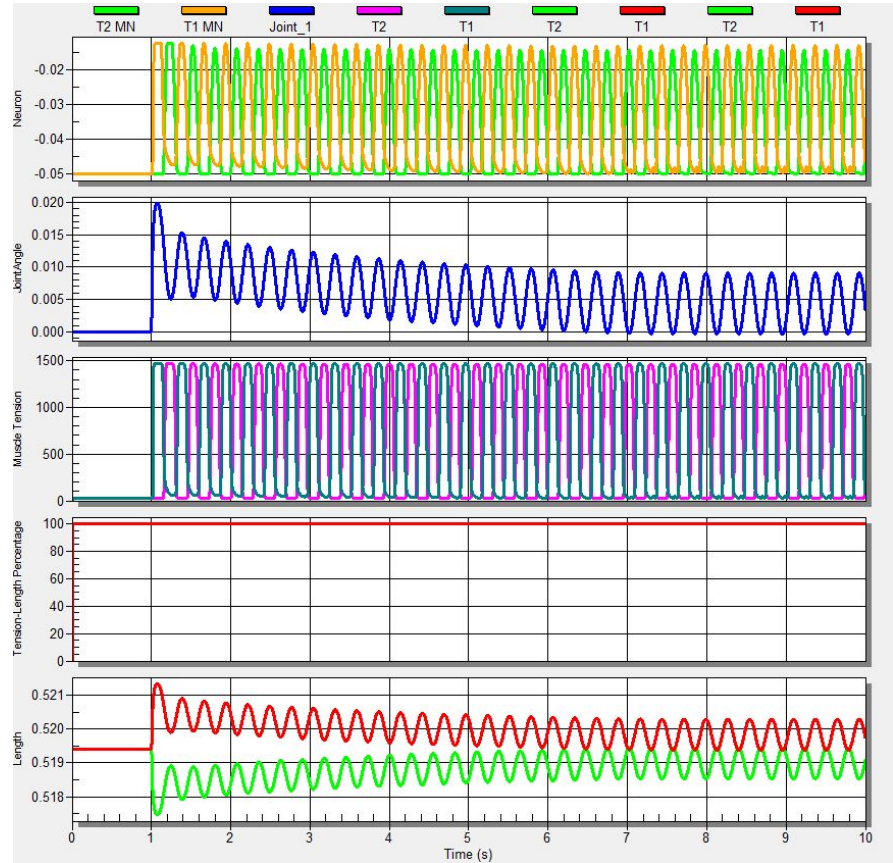
Kp syn 2
Kd syn 5



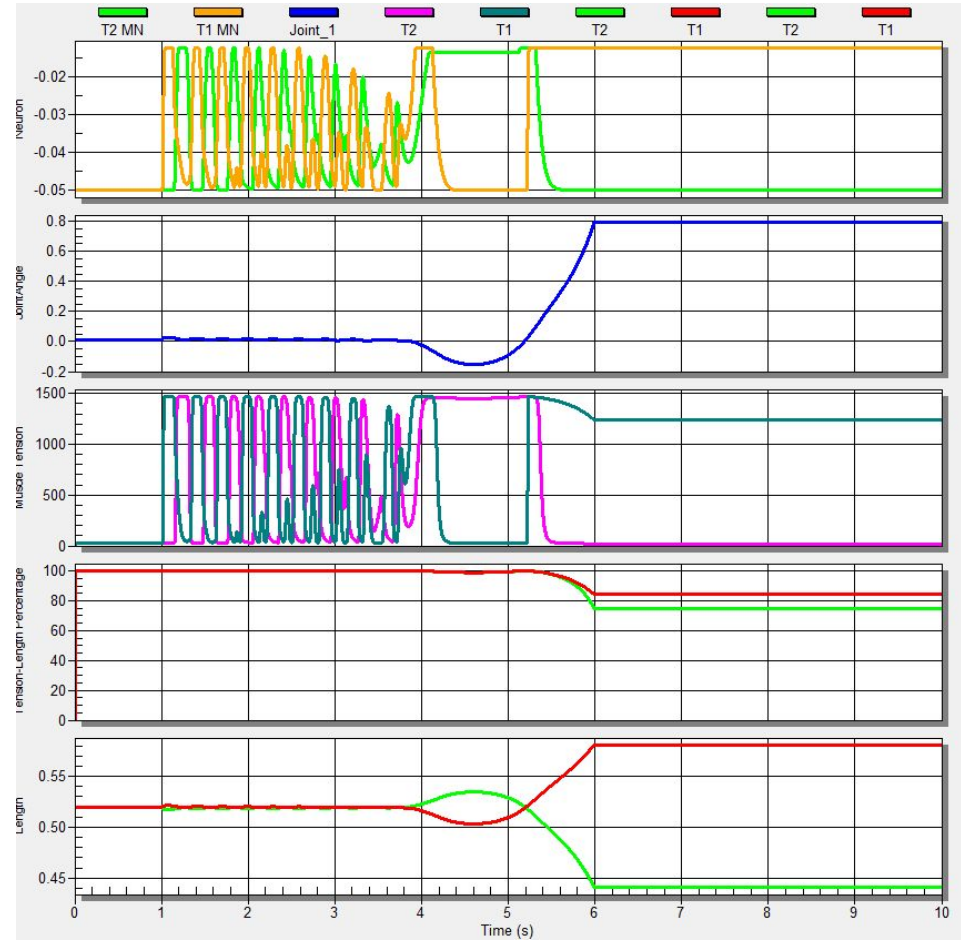
Kp syn 1
Kd syn 5



Kp syn 1
Kd syn 7



Kp syn 2
Kd syn 7

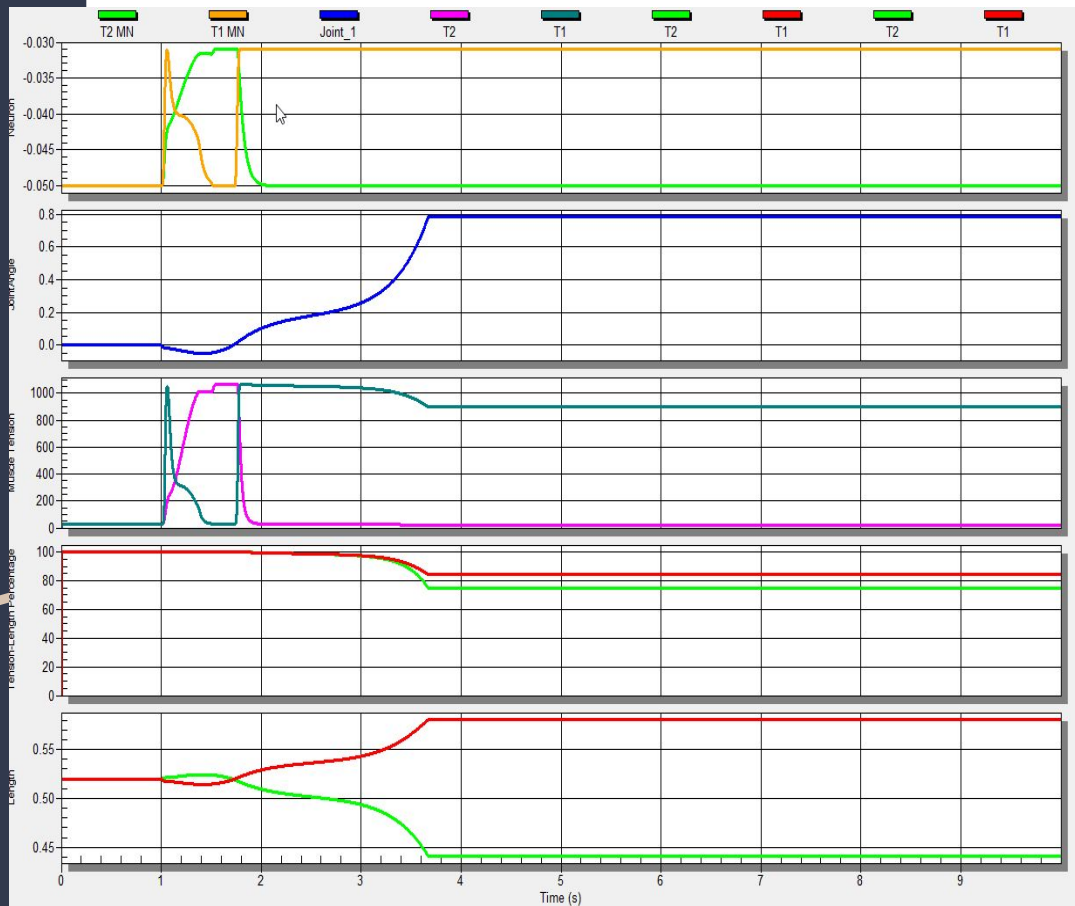


Asymmetrical
behavior despite of
symmetrical neural
network

Kp syn 2

Kd syn 5

The pendulum falls
- 0.02 rad
disturbance



What we learned:



- AnimatLab is not user friendly.
- Gained a larger understanding of neurophysiology and how neurons function as a whole within the entire nervous system.
- Learned more about neurotransmitters, the exchange of information within synapses and resting/action potentials.
- A deeper understanding of prior works leading up to increased studies using AnimatLab.

Complications:



Setting Parameters

Limited knowledge on neuromechanical modeling - made it difficult to digest Wade & Tiffany's work.

Limited understanding of control systems, MatLab.

Time was of the essence.

Thanks



We would like to thank

Dr. Robert Peterka for his work on the human balance control as a PD Controller.

Wade Hilts for his work on his physical Inverted Pendulum.

Tiffany Hamstreet for her work on the simulated inverted pendulum.

Dr. Alex Hunt for torturing us with AnimatLab.



Path Forward:

- Tune the network to produce a similar response to the response in Simulink.
- Gain a deeper understanding of AnimatLab and Neuromechanical Modeling.