Balance and Gait

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Outline

Balance in Humans

- In biomechanics, balance is the ability maintain the line of gravity (vertical line from centre of mass) of a body within the base of support with minimal postural sway[1]
- Sway is the horizontal movement of the centre of gravity even when a person is standing still
- Balance in humans is achieved by inputs from 3 types of system namely:
  - **Proprioceptive** input – Input from Muscles and Joints
  - **Vestibular** input - Determined by the level of a fluid called endolymph in the labyrinth, a complex set of tubing in the inner ear.
  - **Visual** input - Input from the eyes

Sway in Humans

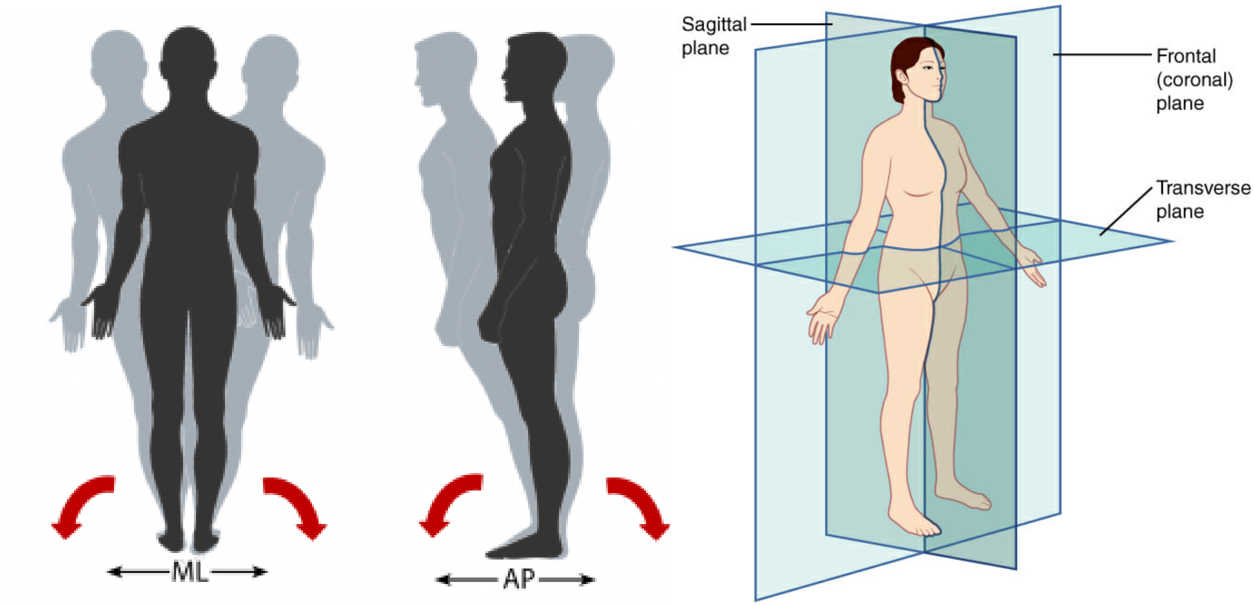


Figure 1: ML : Mediolateral - Frontal Plane , AP : Anterioposterior - Sagittal Plane

Measurement of Sway

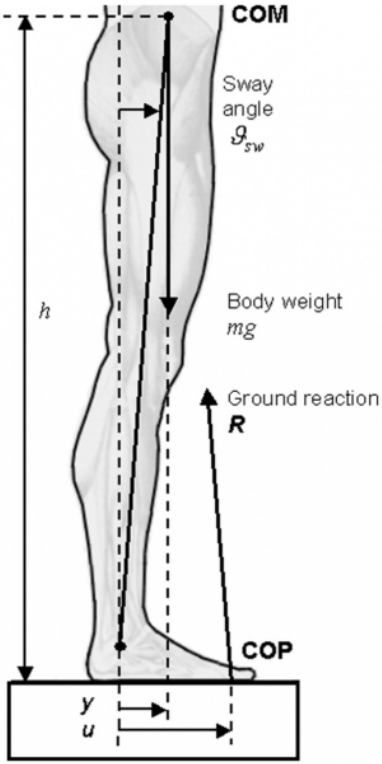


Figure 2: Sway = y vs time

Reinforcement Learning

- Reinforcement learning (RL) is learning what to do, given a situation and a set of possible actions to choose from, in order to maximize a reward.[2]
- The learner, which we will call agent, is not told what to do, he must discover this by himself through interacting with the environment.
- The goal is to choose its actions in such a way that the cumulative reward is maximized.

Figure 3: Mario as RL example

- The basic aim of our RL agent is to maximize the reward.

Block Diagram for the RL model

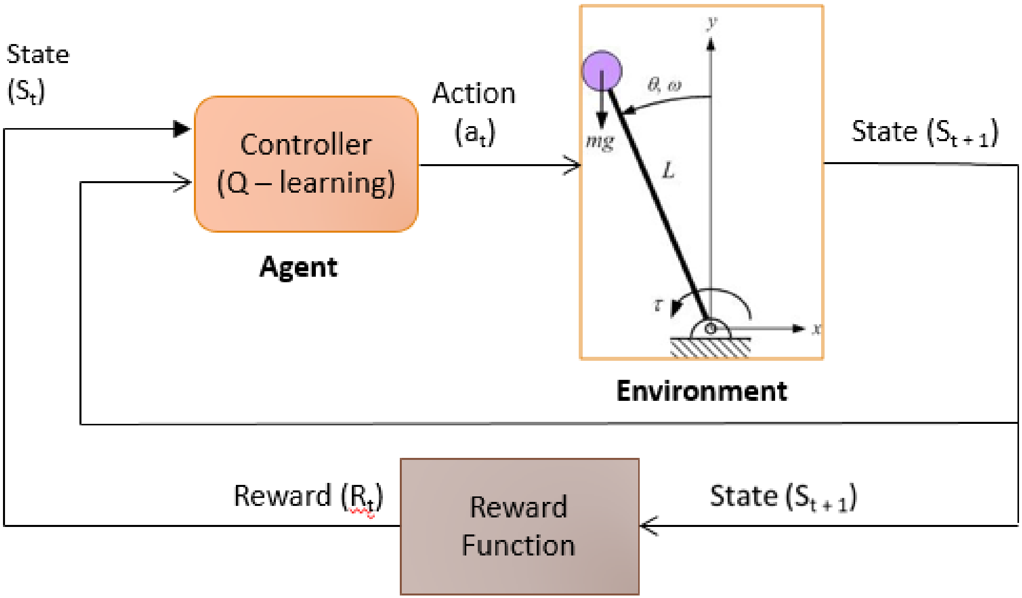


Figure 4: Block Diagram of the Model

Environment - Inverted Pendulum

Dynamical Equation :

$$I\frac{d^2\theta}{dt^2} = \tau(t) + mglsin(\theta) - b\dot{\theta} - k\dot{\theta} \tag{1}$$

where,

- I - Moment of Inertia
- l - Length of Center of Mass (i.e. Position of 2nd Lumbar Vertebrae) = 110 cm
- m - mass of healthy adult human = 65 kgs
- k & b - pivot joint properties of the inverted pendulum characterizing ankle joint, k - stiffness constant and b - damping constant

Reward :

$$reward = -(\theta^2 + 0.1\dot{\theta}^2) \tag{2}$$

Agent - Neuronal Controller

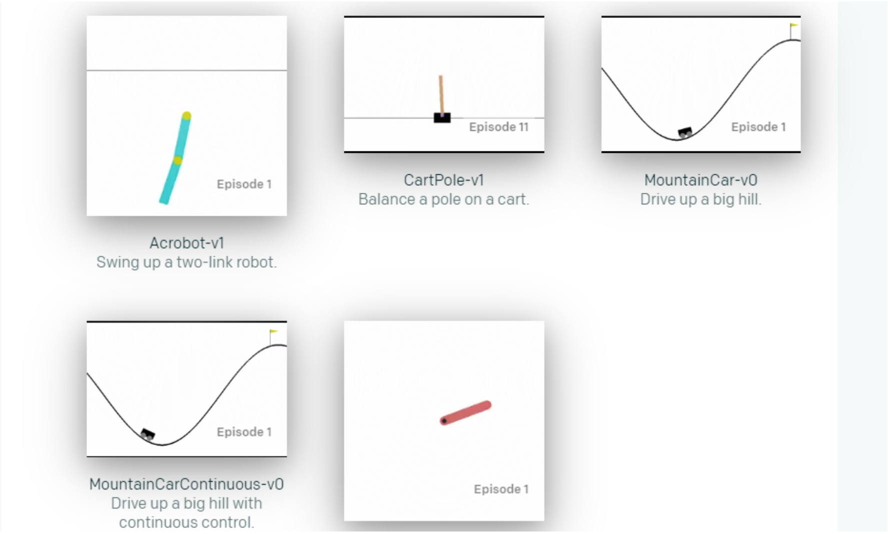
$$\tau = \tau_{nc} + c\mathcal{N}(0,1) \tag{3}$$

$$\tau(t) = \lambda\tau(t) + (1-\lambda)\tau(t-1) \tag{4}$$

where,

- τ_{nc} - torque applied by the neuronal controller
- $\mathcal{N}(0,1)$ - white gaussian noise of mean 0 and variance 1
- c - noise amplitude
- λ - filtering factor

OpenAI gym : RL framework



- Gym is a toolkit for developing and comparing reinforcement learning algorithms
- Customize your environments and implement your agent to achieve goals in the complex uncertain environment

Experimental Data

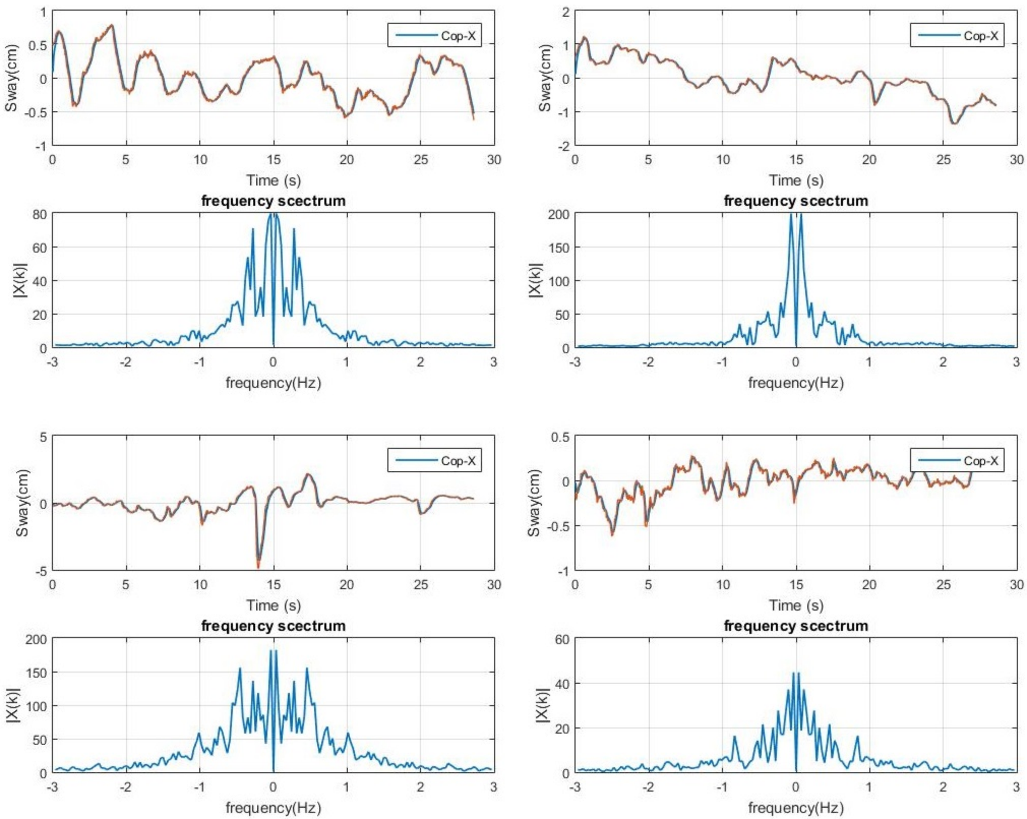


Figure 5: Sway of 4 Healthy Adults and their respective Frequency Spectrum

Implementation

- A deep reinforcement learning algorithm called **Deep Deterministic Policy Gradient (DDPG)** algorithm was used for continuous action space for our environment [3]
- DDPG was implemented using **Stable Baselines**, a python module for Deep Reinforcement Learning
- Over 50 models were trained by tuning parameters such as filtering factor, noise amplitude, learning rate, training time etc. to find optimal set of parameters for the model[4]
- Each model took over 150 minutes and was then tested over the environment

Results consistent with experimental data : Model 1

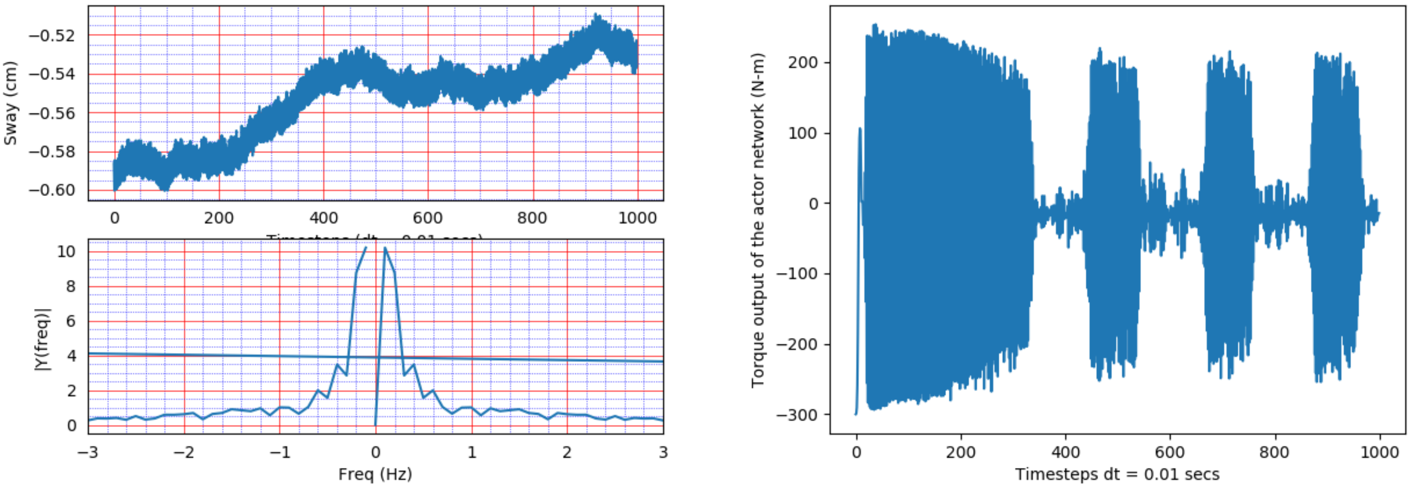


Figure 6: DDPG model where Learning Rate of actor network is increased 10 times

Model 2 : Sway

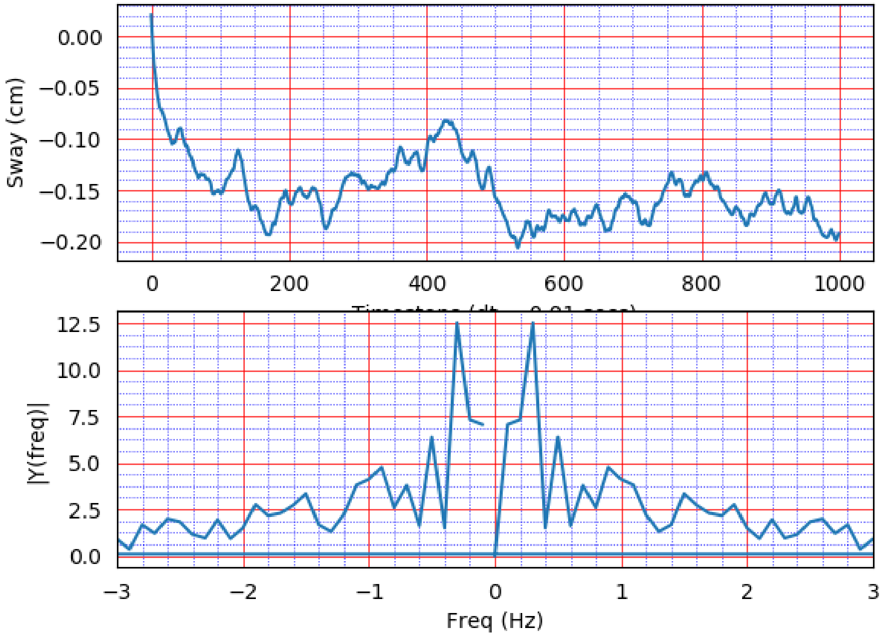


Figure 7: Sway vs Time ; Frequency Spectrum

Model 2 : Torque Outputed by Actor Network

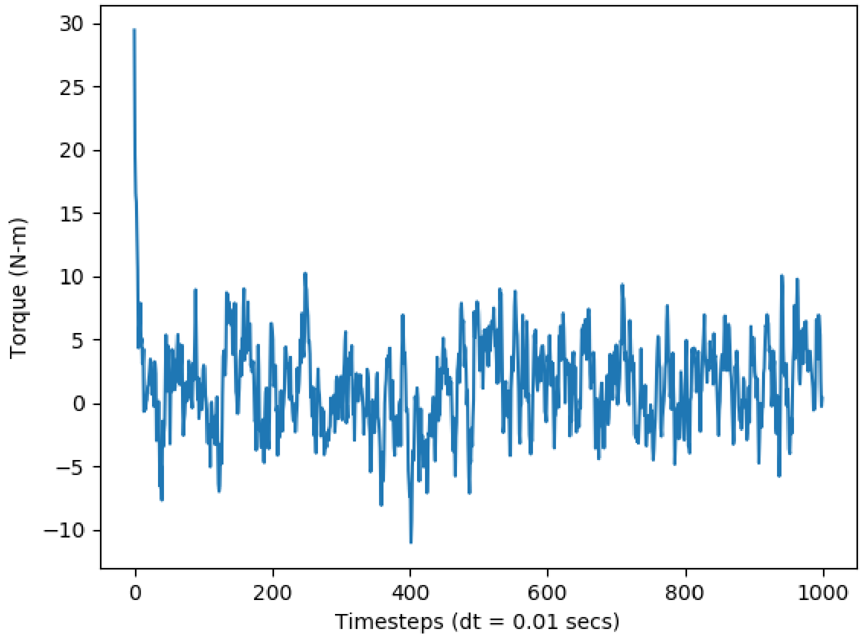


Figure 8: Torque Outputed by Actor Network

Model 2 : Angular Velocity vs Time

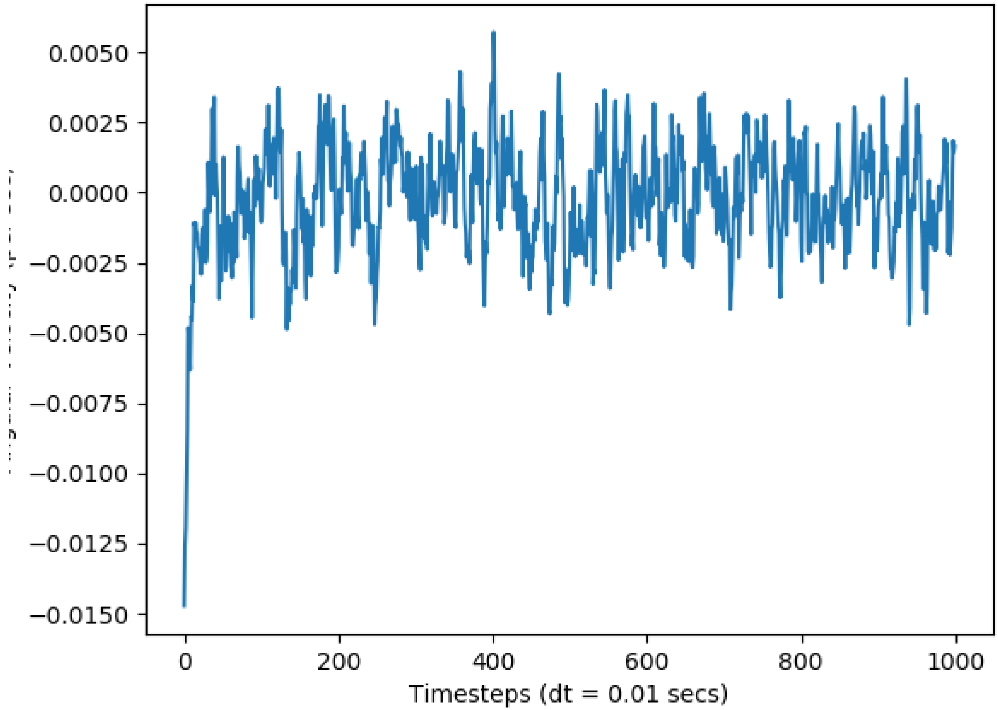
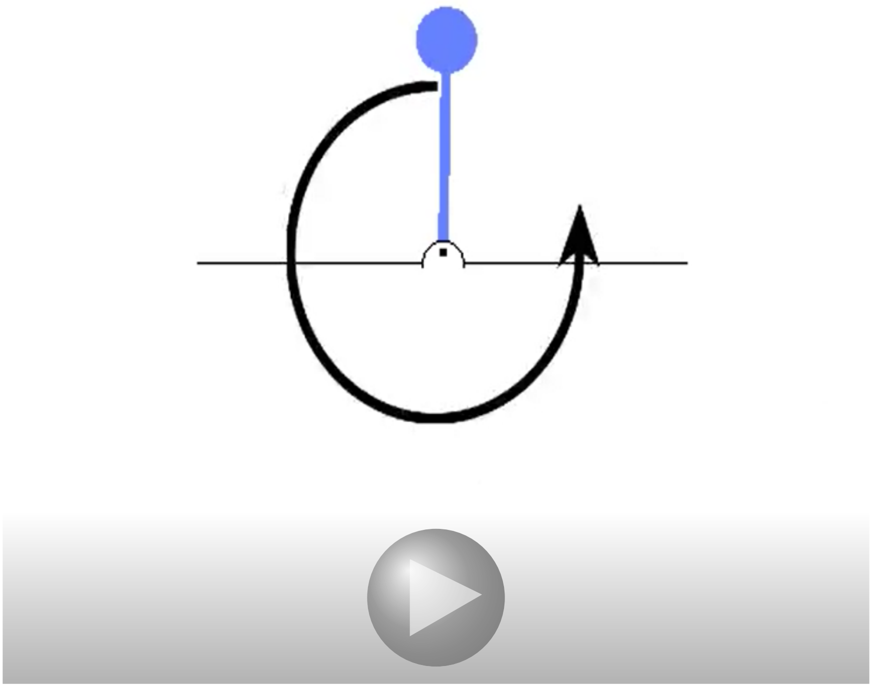
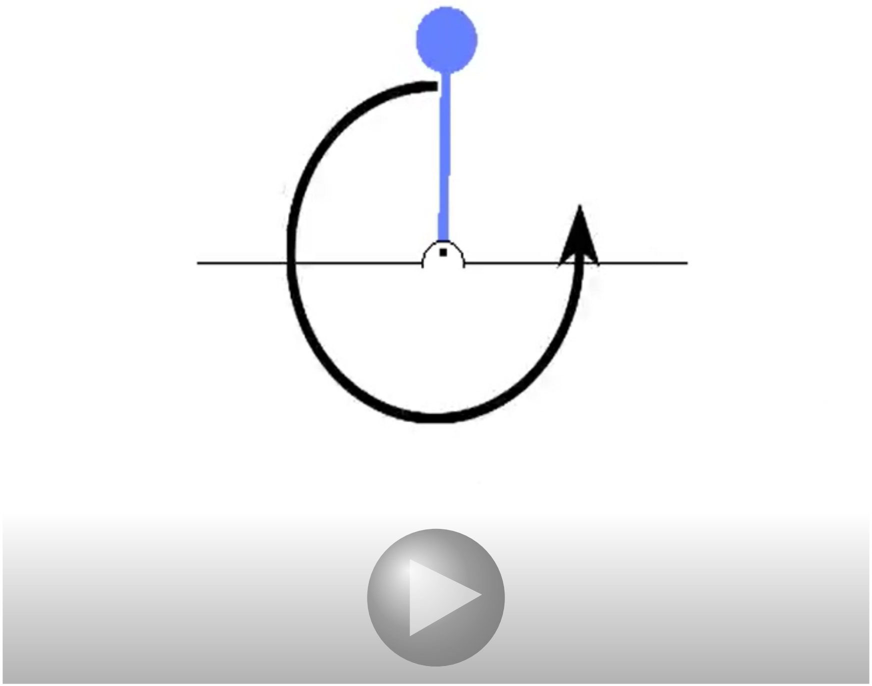


Figure 9: Thetadot vs Time

Demo - Real Time Testing



Model 2



Future Work

- Model can be developed to fit the experimental data more accurately by proper tuning of parameters
- Also introduction of scaling factor or the use of Genetic Algorithms to reduce the search space for the actor network could be tried
- Model can be further fitted for pathological conditions, specifically Parkinson's
- Model can be extended to 2-dimension
- Visual feedback could be incorporated

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