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Using Bio-Realistic Gaussian-Shaped Population and Dopamine-Modulated STDP for Training a Self-Balancing System

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Abstract: Human body balance is a gradual formation through repetition of actions, trial and error, and improving the mechanism of muscular-skeletal architecture for adapting to the demands of the environment. In the learning process, sensory receptors continuously send signals to the brain, then the brain to muscles and make a new signals pathway. Each time the body performs an action, millions of new synaptic connections are formed, and repetitive actions strengthen connections. So, a balanced body reuses the learned mechanism without performing any complex calculations. In contrast, the balance problem of a self-balancing robot has been solved by many different control algorithms. In this work, we propose a novel way to balance a two-wheeled self-balancing robot using bio-realistic Spiking Neural Networks (SNNs) to learn self-balancing, which is closely related to the way babies learn. To accomplish this, the gaussian shaped sensory neuronal population is connected with motor neurons through Spike-Timing-Dependent Plasticity (STDP) based synapses, further controlled with dopamine neurons. The key aspects of this approach are its bio-realistic nature and zero dependencies on data for adopting a new behavior compared to Deep Reinforcement Learning. Furthermore, this biologically-inspired mechanism can be used to improve the methodology for programming the robots to mimic Biological Intelligence.

Keywords: brain-inspired AI; spiking neural network; neurorobotics; spike-timing-dependent plasticity; dopamine-modulated; self-balancing robot.

1. Introduction

For analyzing the environment and adapting to earth's gravity, the vestibular system plays an important role for living beings, as they can localize and reorient themselves with respect to their surroundings through the sensory inputs thus received [1–3]. The process follows the pathways to the cortex that provides a sense of gravity and movement. Vertebrate sensory systems provide information about the head position, spatial orientation, motion, and involvement with motor functions allowing the organisms to remain balanced, stabilize the body during movement, and maintain a particular posture [4,5]. The vestibular system incorporates a set of reflex pathways to allow compensatory movement and body position changes. The information comprising of magnitude and direction of the linear and angular movements for the head (while moving or rotating across the space), stabilizing the body while moving or performing any task and maintaining a posture, etc., is sent by this system to the central nervous system, which receives this information as a frequency code of impulses by the eighth cranial nerve. This information, combined with other sensory inputs converging on the vestibular nuclear sites, is used to determine a vertical representation of the body in space called a gravito-inertial vector [6,7].

Researchers have offered traditional controls such as Soft PD (Proportional-Derivative), PID (Proportional-Integral-Derivative), PD+I, and LQR (Linear Quadratic Regulator) as solutions to solve the self-balancing problems [8–11]. Such techniques require manual calibration and, thus, are based on several trials and errors to reach optimum controller values, resulting in their failure to achieve most of the time-optimal qualities. MPC (Model Predictive Control) has also been applied to solve robot balancing problems [12,13] by allowing optimization on the current time slot while taking care of the future ones across a finite time horizon. An active timeslot and the optimizer are repeatedly implemented in MPC, making it different from LQR. Although MPC has the predictive ability, it is not a bio-realistic solution. Reinforcement learning (RL) methods are also used to train the robots for self-balancing [14–16], where a robot obtains a reward only if it minimizes the error angle and continues to engage with the environment. In such a learning scheme, the optimum approach is decided through trial and error, making the robot optimize its actions based on previous experience and generate the maximum rewards. Although RL is one of the most powerful ideas linking neuroscience and AI and has been used to overcome sophisticated programming techniques, it is not considered a bio-realistic solution. In fact, Artificial Neural Networks (ANNs) have adapted to even more effective and biologically realistic models since the course of their creation.

In this research, we propose a new way with intrinsic dimensional representation to stabilize a two-wheeled robot utilizing bio-realist SNNs (Spiking Neural Networks)[17,18] and have a strong ability to solve complicated time-dependent problems in time series. SNNs are the third generation of ANNs, which consist of spiking neurons, where the information is transferred in the form of spikes sequence through biological neurons. The temporal and spatial information used to encode the knowledge in SNNs gives a fresh insight into brain dynamics and can be helpful if we apply it to "real" dynamic environments. Because mobile robots frequently operate in unstructured and complex settings, SNNs are better suited than conventional ANNs for robotic controller design. The proposed solution is to implement a Gaussian function that controls the firing rate of the sensory neurons population according to the current error in the angle. Dopamine[19] neurons are implemented for the reward system, the strength of connections between presynaptic and postsynaptic controlled with dopamine neurons connected through STDP (Spike-Timing-Dependent Plasticity)[20] based synapses. So, using bio-realistic SNNs, robots can learn to balance according to their past experience. Robotics applications using bio-realistic SNNs can contribute to the development of realistic, more intelligent systems, which can further help to improve the current robotics and can help to validate neuroscience models. Model-free movement control influenced by the human brain mechanisms will also enhance the programming and versatility of robots.

2. Materials and Methods

2.1. Synaptic plasticity.

Hypotheses and beliefs about brain functionality have evolved significantly over the years. It was assumed for a long time that neural connections or synapse density inside the brain were fixed and then eventually disappeared or faded. While modern research has shown that the brain is more versatile, it never stops changing through learning. Plasticity [21] or neuroplasticity is the ability of the brain to adapt or change from the experience outcomes. The synaptic density starts increasing from the early stages of fetal development. Research in this field says that at the time of birth, the cerebral cortex single neuron has an estimated 2,500 synapses; by three years, this number rises to 15,000 synapses. Then, this count reaches a stable state for short periods of time. After the age of 5, the removal cycle begins, and often-used neurons develop stronger connections. The shift that occurs in synapse strength is called Synaptic plasticity [22–24]. While rarely used, it gradually dies, decreasingynaptic density; the mechanism is known as synaptic pruning [25,26]. The synaptic strength is not fixed but can vary in the short and long term. Sub-second level synaptic strength change refers to Short-term synaptic plasticity, while in Long-term synaptic plasticity, the synaptic strength stays for a long time, anywhere from minutes to hours, days, or years, and contributes to the construction of new memories.

2.2. Dopamine-modulated STDP.

Mammalian learning is usually thought to be incorporated by synaptic strength adjustments in simpler species. Historically, efforts to offer a scientific interpretation of learning were largely inspired by Hebb's postulate called Hebbian Learning [27–29]. In the fields of neurology and psychology, Hebbian Learning is broadly accepted. This is one of Neuroscience's basic principles. Hebbian Learning can solve certain fascinating problems, but it's not evident that this learning can solve processes that cause animals to learn challenging tasks, such as limited rewards in complex settings. Hebbian Learning suggests a method where a synapse weight of two neurons is strengthened when both neurons have highly correlated outputs, and it relies on the pre- and postsynaptic operation as well as on the weight itself.

Current plasticity laws have recently become a significant representative for blurring the lines between microscopic and macroscopic learning, as learning also depends on a third non-local neuromodulating signal caused by the presence of neuromodulators such as dopamine, serotonin acetylcholine, and norepinephrine in traditional laws it was only based on pre- and postsynaptic behavior. Neurons mainly present in the basal forebrain and brainstem produce these neuromodulators that excite other brain parts using long-range connections [30–32]. Based on current plasticity laws, we used dopamine-modulated spike-timing dependent plasticity synapse [33,34] to make robot learning.

2.3. Gaussian-shaped population.

The excitation mechanism for presynaptic sensory neurons can be regulated with Gaussian function, with an equation of the form:

$$f(x) = \alpha.\exp((-(x-b)2)/2c2) \tag{1}$$

Here α, b and c are arbitrary real constants, where α defines the height of the curve's peak, b represents the center of the peak, c is the standard deviation, and x is the id of the current neuron. In Figure 1, a Gaussian graph is demonstrated with a typical symmetrical "bell curve" form. In this approach, the gaussian equation is a function of sensory neuron id (from 0 to 17), that excites a subset of neurons from a set of sensory populations. A Gaussian function is applied to all sensory neurons to calculate the fire rate according to an error in the pitch angle.

The following equation is used to calculate the gaussian curve's peak center (b) as a function of error in the pitch angle.

$$b=(pitch - (-\pi/2)) / ((\pi/2) - (-\pi/2)) \quad (2)$$

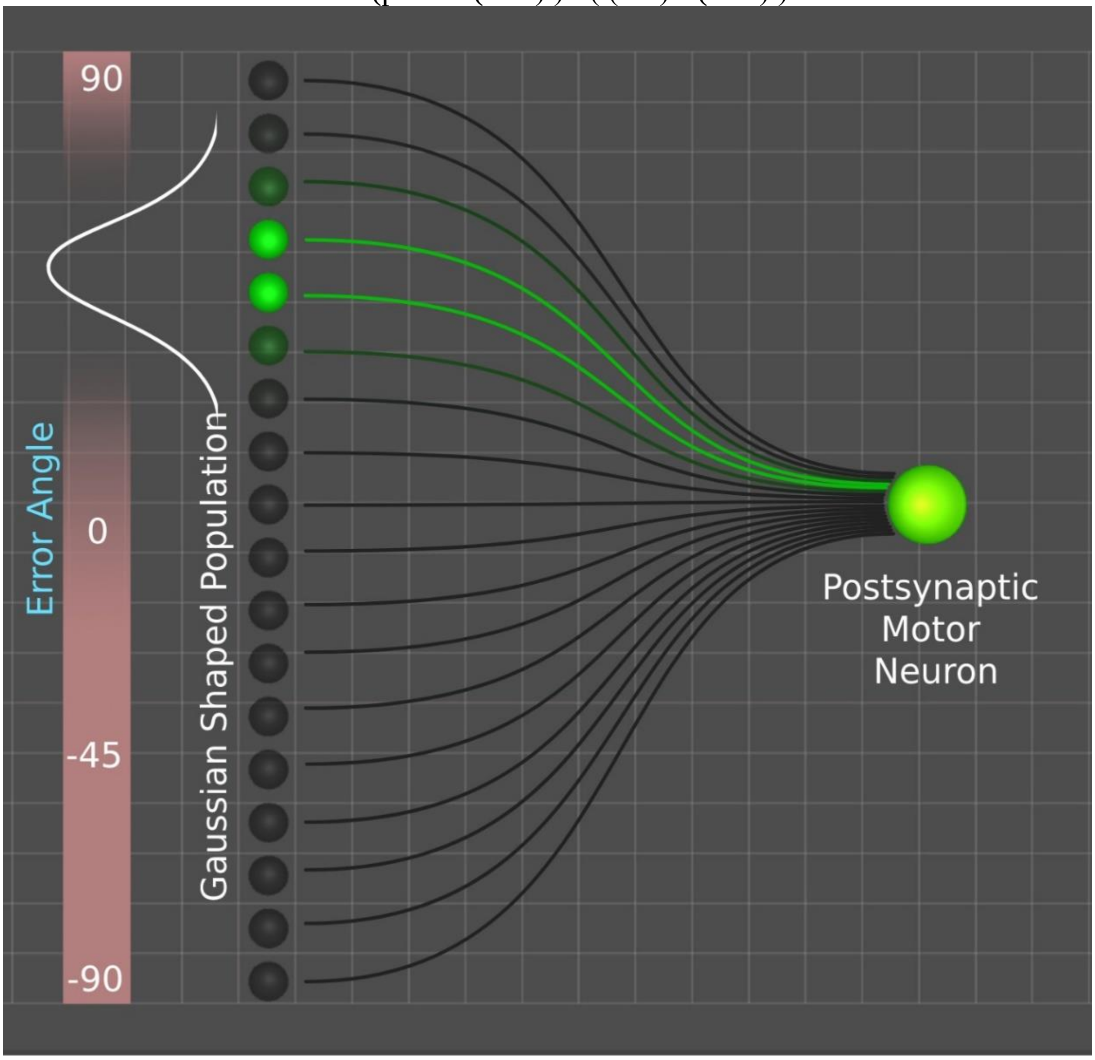

Figure 1. Gaussian graph with a typical symmetrical form of the "bell curve".

Error in the pitch angle varies between a lower range value (-90 degrees or - π/2 radian) and a high range value (90 degrees or +π/2 radian).

2.4. System implementation for a self-balancing robot.

2.4.1. Platform.

In experimentation, a two-wheeled balancing robot has been implemented using bio-realistic SNNs. Similar to vestibular systems in organisms, IMU (Inertial Measurement Unit) sensors have been used to provide an orientation of the robotic body. Tilted angle encodes into temporal spike sequences, where higher tilt causes a higher firing rate of presynaptic sensory neurons controlled with gaussian function. In this bio-realistic system, presynaptic neurons electrically excite the postsynaptic cells through spike transmission using synapses. Further, motor neuron stimuli cause the robots to move using the action potential in order to mimic the somatic motor systems in organisms. Thus, the information from the simulated IMU sensor is converted into electrical signals; these sequences of signals form spiking trains and are processed in a simulated brain. Further processed signals produce movement with the help of robot motor commands directly mapped with postsynaptic neurons.

To solve this multidisciplinary problem, the experiment implementation has been done in the Neurorobotics Platform (NRP) [35–37], which is a sub-project of EBRAINS, the research infrastructure created by the Human Brain Project (HBP) [38]. NRP enables researchers or neuroscientists to connect the SNNs to simulated and real robots. The users can also utilize High-Performance Computing (HPC) clusters, another HBP sub-project, to conduct the embodiment experiments. NRP uses the Closed Loop Engine (CLE) to simulate experiments in closed perception-action loops. NRP maps the brain and robot simulation using Transfer functions (TFs). Robot Operating System (ROS) [39] facilitates communication in NRP, where ROS nodes send and receive data using topics and messages through two-way communication while publishing and subscribing to topics. Being a middleware framework, it can easily interface with robot simulators, physics libraries, and other most common libraries. As shown in Figure 2, ROS nodes illustrate the robot's interaction with a closed-loop engine in NRP. There are two types of transfer functions (TFs) used for data communication between the robot and brain stimulation; one is 'Neuron2Robot' used for transferring data from brain to robot, and the other is 'Robot2Neuron' used for facilitating two-way communication between robot and brain.

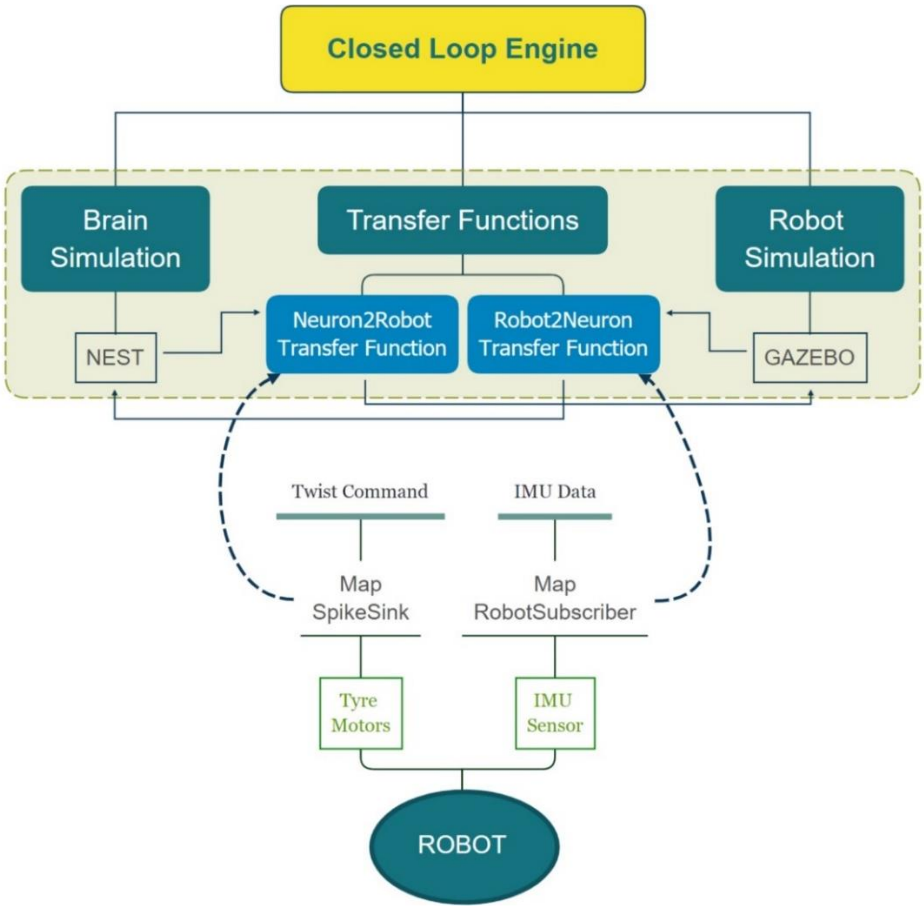

Figure 2. Robot interaction with a closed-loop engine in NRP.

In NRP, NEST [40,41] is used as a brain simulator which is currently provided by the abstraction layer of PyNN [42] (it is a Simulator-independent language for building neuronal network models) and runs in a centralized and parallel environment. On the other hand, Gazebo [43,44] is used for realistic robot simulation. Robot tilt angle is measured by an embedded IMU sensor, published over ROS Topic, further subscribed, and mapped with the brain with TF for processing. Once a decision is processed from the brain network, it is sent back to the robot as a twist command to provide robot movement.

2.4.2. Sensory perception.

The cerebellar sensorimotor system [45,46] is responsible for providing fine movement and balance skills in humans or animals, where operational conditioning is the most fundamental and effective learning mechanism in the sensorimotor system. This learning occurs through rewards and punishments for behavior. The ability to balance movements counts for this mechanism's progressive development and improvement.

In this approach, mounted IMU sensors on robots sense the body orientation and behave as sensory organs. IMU rotation information further encodes into neural signals and provides translational and rotational information (For the present study, only rotational information is considered). The simulated brain has 18 sensory neurons implemented and excited with a gaussian function according to the delta error angle ranging from -90 to 90 degrees. These presynaptic neurons form a gaussian shaped population.

2.4.3. Brain network.

The current approach utilizes synaptic weights of the simulated brain, where the network trains the system to learn balance. Imitation of the brain learning process is implemented with a reward system using dopamine-moduled spike time-dependent plasticity. A simulated brain network consists of 28 neurons. The network has been divided into two sub-networks working in parallel. One is the main network consisting of 18 sensory neurons, 1 motor neuron, and 1 dopamine neuron, and it is responsible for providing smooth motion. The other one is a multiplier network consisting of 6 sensory neurons, 1 motor neuron, and 1 dopamine neuron, and it handles the robot's responsiveness. Each sensory neuron is connected with the motor neuron through STDP, producing a quick response to minimize the error. With an initial synaptic weight equal for all connections, the network automatically adjusts this weight once the robot starts learning.

The balance problem of two-wheeled robots in a nonlinear system is based on an inverted pendulum [47–50]. Recently, this topic has been an area of interest for the research community due to its unstable status. This experiment involves a simulated two-wheeled robot with extra weight added to the body to maximize the center of mass. Suppose the center of mass in this system is higher than the wheel axis. In that case, the robot will be more stable in balance, as a high value of the center of mass implies a greater moment of inertia, leading to a lower angular acceleration or slower fall.

2.4.4. Two-wheeled robot.

The robot is designed and simulated in a Gazebo Simulator using an SDF file (Simulation Description Format), which contains robot information like links, joints, visuals, collision information, and gazebo plugins. Part inertia is also calculated and added to the SDF file for each robot. For simulating an Inertial Motion Unit (IMU) sensor, the GazeboRosImu Gazebo plugin has been used and attached with a robot body link. The controller for differential drive wheel systems was also implemented using the ROS pack. This controller controls the robot with velocity commands by extracting the x component of the linear velocity component and the z component of the angular velocity components.

The IMU data provides information related to the angle of tilt in the system and directs the velocity command in response. For example, in Figure 3, if the robot is tilted in the right direction at an angle θ, the velocity command moves the robot in a clockwise direction to keep the robot body horizontal. Achieving balance for every movement through mathematical computing is computationally intensive. To overcome this, we propose a novel way using SNNs where the robot is able to balance itself through behavior iteration and learning in a model-free external environment, as a human being or an animal does.

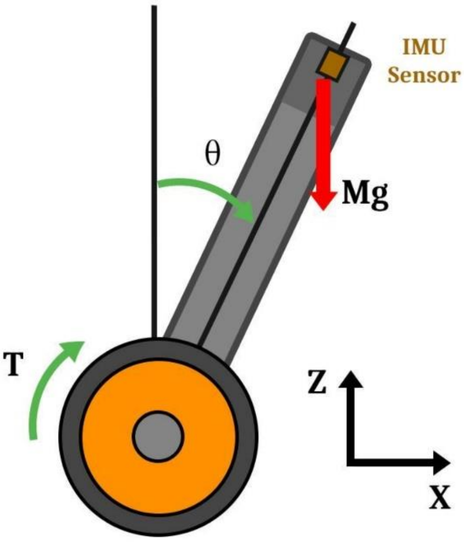

Figure 3. Velocity command working in response to the angle of tilt for the self-balancing robot.

2.4.5. Environment.

NRP uses a two-wheeled self-balancing robot with Gazebo designing tools for robot simulation. The Gazebo can simulate populations of robots and can train AI agents accurately and efficiently in complex environments. The NRP environment is configured in the Experiment Configuration file available in the XML Schema document. In this file, high-level information is added, like the name and description of the experiment, the total time of the experiment, and rendering settings as required. Figure 4 demonstrates the experiment with the robot, environment, and corresponding graphs. In the experiment, quality is set to high for realistic rendering with real-time lights and shadow, and the robot is simulated on terrain enclosed by four walls.

For proper visualization, NRP provides camera control with a keyboard. The NRP state machine is used to reset the robot in its default orientation and position. Sp spikes, train plots, and brain visualization tools can monitor Experiment neural activity. Robot orientation is monitored with rqt_plot, a ROS package that visualizes numeric values in a 2D plot. The experiment world model is implemented in an SDF file having light settings, like position, orientation, type of light, and ambient light settings. The world SDF file also contains 3d model information about the world, like visual properties of 3d models, textures, and collision properties.

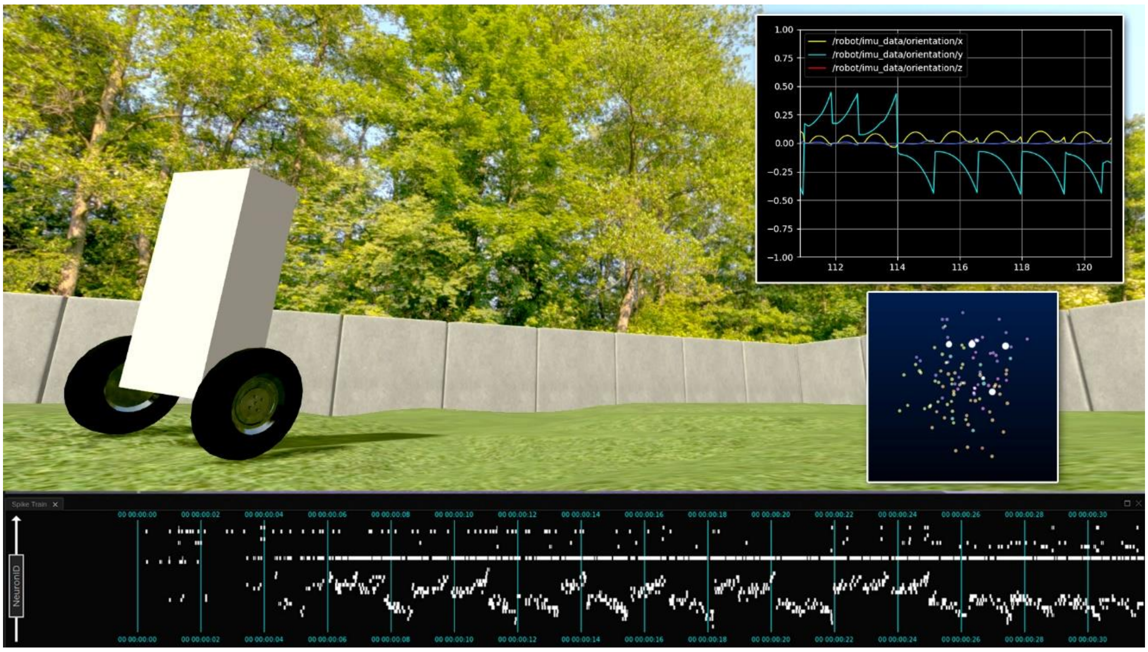

Figure 4. Experiment demonstration through graphs.

2.4.6. Functional implementation.

The connection between self-balancing robots and artificial brains is established with the BIBI file (Brain Interface and Body Integrator). BIBI file contains all the information to couple the simulations. For this experiment, brain information in the form of neurons has been declared with different functionality, and robot model information has been provided through transfer functions (TFs).

The IMU Sensor attached to the simulated robot publishes data declarations on /robot/imu_data ROS topic with roll, pitch, and yaw values. Two Robot2Neuron transfer functions (TF1 and TF2) have been implemented as Python programs. TF1 takes care of encoding sensor data into neural signals. In the TF1 python program, the MapRobotSubscriber mapper function has been used for mapping the sensor topic to a TFs variable. Similarly, MapSpikeSource is a mapper function used for mapping sensor data back to neural activity. The mapping provided in TF1 excites a set of sensory neurons using the Gaussian function according to the tilt angle received from the IMU sensor.

Here Gaussian function defines the rate of sensory neurons (main and multipliers), Where main neurons excite a motor neuron that is used for providing motion with direct feeding voltage of neuron in command velocity of robot. The second motor neuron excited from multiplier sensory neurons works as voltage multipliers for the main motor neuron, causing the system to be more responsive at higher error angles. Because a higher error angle causes a higher sensory rate, it results in a quicker response to minimize error.

Before training, the strength of all synapses connecting sensory and motor neurons was randomly defined. But after passing through training, these strengths changed with the implementation Robot2Neuron transfer function (TF2) that updates dopamine neuron rate according to reward and punishment. This program checks if a motor neuron has been spiked or not, and accordingly, the activation level of dopamine neurons is changed using a Poisson generator. In this learning phase, the system tries to produce continuous spike trains from motor neurons for smooth balancing movement. It sets the dopamine level for the voltage multiplier according to an error in angle to make the system quickly responsive to a higher error in angle. As shown in Figure 5, the STDP synapse functions with Volume Transmitter, as the plasticity depends on both pre and postsynaptic activations and non-local third neuromodulatory signals. Dopamine neuron spikes are collected to the volume transmitter and delivered to the connected STDP synapse. Thus, these dopamine neurons strengthen or weaken the synapse between sensory or motor neurons. On every iteration, the system checks the robot's state and activates sensory neurons, further exciting motor neurons that produce a response in the form of movement. According to this movement and neural activity, dopamine level is calculated as a reward or punishment and can be added to or removed from the weight STDP synapse. Dopamine neurons help robots achieve a smooth spike train for smooth movement and a desirable voltage multiplier for motor neurons connected with the command velocity ROS topic for providing motion to robots.

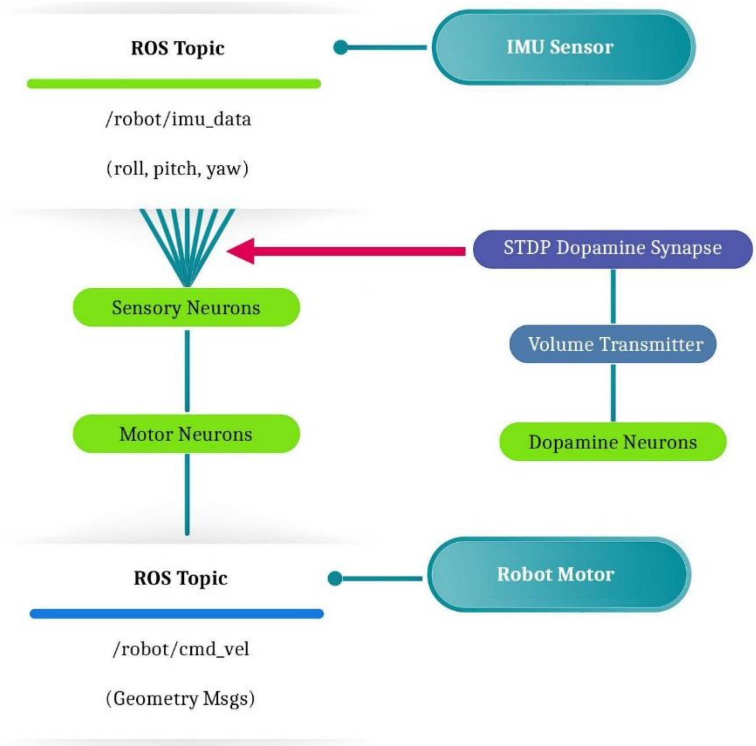

Figure 5. STDP synapse function with volume transmitter.

3. Results and Discussion

To demonstrate the results, a graphical representation has been used. Figure 6 shows the robot orientation plot in the form of Euler angles extracted from simulated IMU sensory attached to the robot.

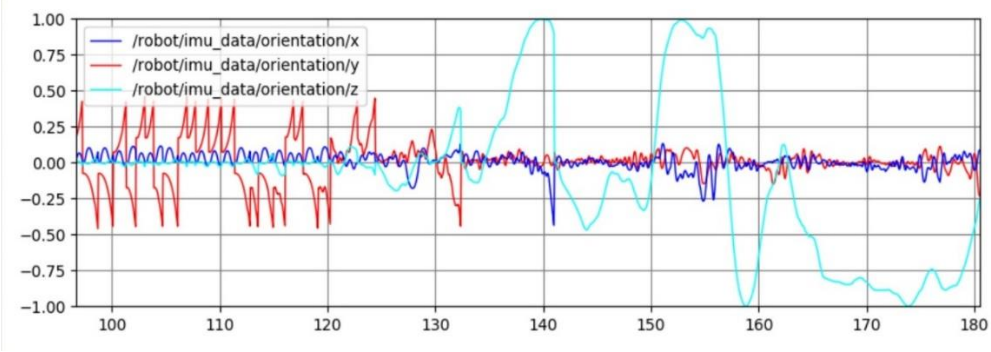

Figure 6. Robot orientation plot throughout the training.

A graph was plotted while the system was being trained. It is noticed that initially, the curve for Y orientation continually reached a peak and was suddenly reset, demonstrating the quick falling of the robot. After running the simulations for some time, the system became stabilized. This can be noticed in the Y orientation curve, where the peak counts caused due to error angle are eventually minimized to zero. The IMU data for Y orientation does not fluctuate and is almost a straight line after the training.

Figure 7 demonstrates the spike trains from both sensory and motor neurons, both from main and multiplier neurons, at the start of training. It can be noticed that there were less number of neurons activated because of random synapse strengths. Disconnected spike train peaks in the figure convey the initial non-stability of the system. It also demonstrates the influence of errors in the Y angle on the spike trains.

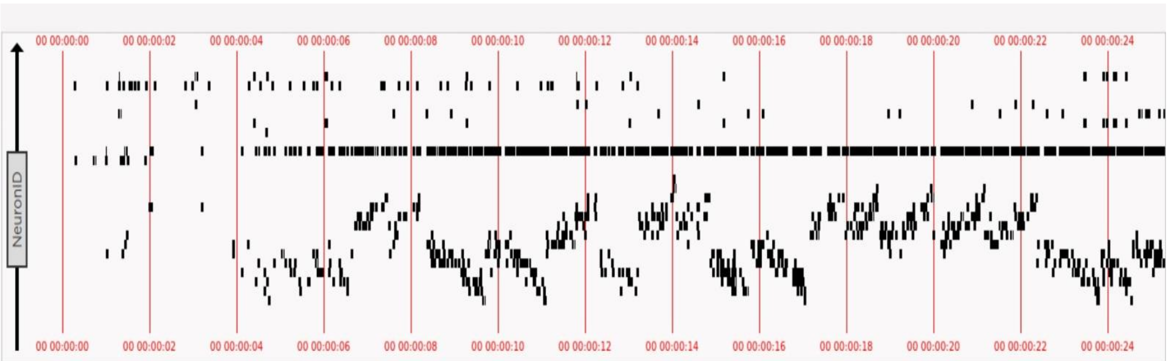

Figure 7. Spike trains at the start of training.

As conveyed by Figure 8, the spike train is more stable after some training has been provided to the system, as more neurons get activated as per the requirements. At this point, approximately the same neurons are excited in a continuous fashion, strengthening all the synapses. In this phase, the system reaches a balanced stage with lower error in the angle.

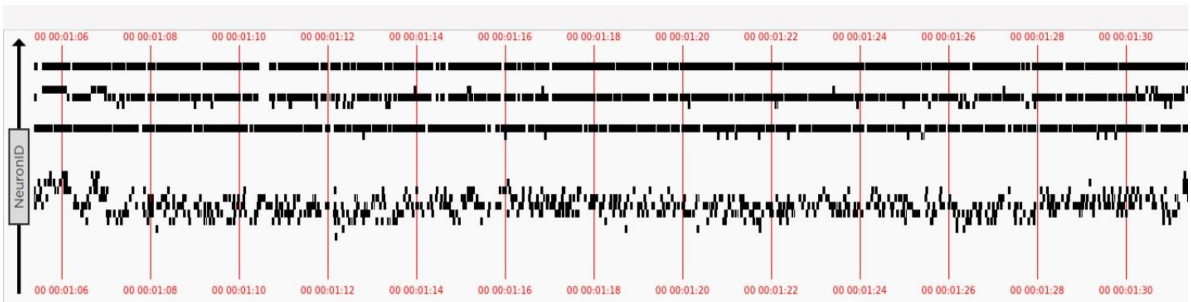

Figure 8. Spike trains at the start of training.

4. Conclusions

This work presents a novel way to self-balance a two-wheeled robot using bio-inspired SNNs (Spiking Neural Networks), where the robot learns to balance itself using dopamine STDP (Spike-Timing-Dependent Plasticity) and gaussian shaped sensory neurons. In this approach, neurons communicate with each other in the temporal domain while transmitting the spikes. The experimentation part has been established with the Neurorobotics Platform, which is a sub-project of HBP (Human Brain Project). In the experiment, the two-wheeled robot simulates an embodied IMU sensor which has been used as an input sensory device. Offset (error value) from desired orientation causes the SNNs to produce electrical impulses, stimulating the motor commands and providing further motion to the robot for balancing itself.

The reduced value of input stimuli minimizes the error value in orientation, enabling the dopamine neurons to strengthen the synapse between presynaptic sensory neurons (based on gaussian function) and postsynaptic motor neurons. Thus, the biologically-inspired system presented in this work does not require external data, such as from Machine Learning, for its training. Systems of such kind can contribute to the development of bio-realistic robotics, helping researchers conduct neuroscience experiments.

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Conflicts of Interest

The authors declare no conflict of interest.

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