Representation of Biological Neurons Using Artificial Neural Networks

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Abstract

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This research aims to replicate human neuronal mechanisms using artificial neural networks, focusing particularly on the Hodgkin-Huxley model. The Hodgkin-Huxley model is crucial for understanding the dynamics of biological neurons, precisely describing the mechanisms of excitation and propagation of action potentials.

Our goal is to represent the neuronal mechanisms of specific visual areas (V1, V2, V3, V4, V5, ...) using Spiking Neural Networks (SNN), which not only consume less energy but also simulate neuronal complexity more realistically. SNNs also enable a more dynamic and temporal approach to modeling, reflecting the real processes of the visual cortex.

However, accurately modeling the complex neuronal circuits of the visual cortex poses significant challenges, particularly in terms of model parameter calibration and interpretation of obtained results.

The method involves training these models on diverse visual datasets, focusing on recognizing and interpreting complex visual patterns. The desired outcomes will provide a better understanding of human neuronal processes, particularly in the context of visual processing, and offer new design insights for robotics and artificial vision systems.

Contents

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Chapter 1

Introduction

1.1 Context and Motivation

Artificial Intelligence (AI) has been striving to replicate and simulate human intelligence since its inception. However, despite significant advancements in this field, artificial neural networks still lag behind in efficiency and complexity compared to human biological neurons. One of the primary motivations of current AI research is to bridge this gap by developing artificial neuron models that closely resemble the functioning of biological neurons.

Biological neurons communicate through electrical signals known as action potentials, and these interactions form the basis of all cognitive functions, from bodily movements to abstract thinking. The Hodgkin-Huxley model, introduced in 1952, provides a detailed description of the electrochemical mechanisms responsible for the generation and propagation of these action potentials. Understanding and simulating these mechanisms are essential for creating AI systems that faithfully mimic the human brain.

Simultaneously, concepts such as Spike-Timing-Dependent Plasticity (STDP) and Rate Encoding are being explored to model learning and memory. STDP, for example, captures how synapses strengthen or weaken based on the timing of electrical impulses, reproducing a crucial aspect of biological learning.

The aim of this research is to integrate these biological concepts into artificial neural networks to enhance their ability to mimic the human brain. This approach has the potential to revolutionize several areas of AI, from image recognition to autonomous decision-making, and modeling complex cognitive behaviors. By more faithfully representing human neuronal mechanisms, we hope to create more robust, adaptive, and efficient AI systems.

The motivation behind this work is twofold: deepening our understanding of neuronal processes using AI tools and improving the performance of

intelligent systems by making them more biologically plausible. By merging knowledge from neuroscience and artificial intelligence, we can move towards machines that not only perform complex tasks but do so in a manner similar to human intelligence, opening new vistas for the future of AI.

1.2 Research Objectives

- **Study and understand biological neuron models**, especially the Hodgkin-Huxley model, to grasp the fundamental mechanisms of action potentials.
- **Explore synaptic plasticity mechanisms**, including STDP, and their role in learning and memory in biological neural networks.
- **Implement artificial neural networks** capable of simulating dynamics of biological neurons, using tools like Brian2 and Python.
- **Test and analyze model performances** on classification tasks, including MNIST dataset classification into 10 classes.
- **Visually represent emitted spikes** by neurons, creating visualizations of neuronal signals to better understand action potential dynamics and propagation in the network.
- **Evaluate experimental conditions** required to optimize model performances, such as input signal periodicity and random weight initialization with complementarity.

1.3 Organization of the Report

This report is structured into several chapters to comprehensively cover various aspects of the research:

Introduction: Presentation of the context, motivations, and objectives of the research.

- Description of the research context.
- Identification of the main motivations.
- Presentation of specific study objectives.

Theoretical Foundations: Description of biological neuron models, including the Hodgkin-Huxley model, as well as synaptic plasticity and neuronal coding concepts.

- Hodgkin-Huxley model and its fundamental principles.
- Synaptic plasticity: concepts and mechanisms.
- Neuronal coding: methods and theories.

Implementation and Methodology: Details of the tools used, specific implementations, and methodologies adopted to conduct experiments.

- Simulation tools used (Brian2, Python, etc.).
- Specific approaches to implementing neuronal models.
- Experimental methodologies and chosen parameters.

Testing and Results: Presentation of experimental conditions, observations during testing, and obtained results.

- Description of experimental conditions.
- Analysis of observed results.
- Discussion on conclusions drawn from tests.

Discussion: Analysis and interpretation of results, identification of study limitations, and proposals for future work.

- Critical analysis of obtained results.
- Identification of study limitations.
- Proposals for future research directions.

Conclusion: Summary of research contributions and perspectives for improvement and future application.

- Recapitulation of main study conclusions.
- Suggestions for improving methodologies and results.
- Perspectives on applying obtained results.

Appendices: Inclusion of used source code, experimental data, and relevant mathematical formulations.

- Source code used for simulations.
- Collected experimental data.
- Detailed mathematical formulations used in the study.

This report aims to provide a comprehensive overview of representing biological neurons using artificial neural networks, highlighting challenges, solutions, and perspectives offered by this approach.

Chapter 2

Theoretical Foundations

2.1 Models of Biological Neurons

Models of biological neurons form the fundamental basis for simulating neurobiological processes using artificial neural networks. These models aim to mathematically and computationally replicate the behavior of neurons observed in biology. Among the most influential and detailed models is the Hodgkin-Huxley model, which accurately describes the electrical dynamics of neuronal cell membranes.

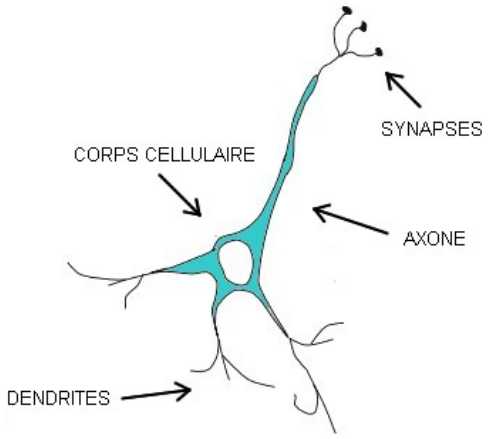

Figure 2.1: Anatomical diagram of a neuron.

2.2 Anatomy of a Neuron

A typical neuron consists of several main components:

1. **Soma (Cell Body)**: This is the central part of the neuron where the cell nucleus and essential cellular organelles for cell function are located.

2. **Dendrites**: Branching extensions of the soma that receive nerve signals from other neurons or sensory cells.

3. **Axon**: A long nerve fiber that transmits electrical signals from the soma to other neurons, muscles, or glands. It is often surrounded by a myelin sheath to accelerate the transmission of nerve impulses.

4. **Synapse**: Synapses are specialized junctions between neurons or between a neuron and another cell (such as a muscle or gland cell). They enable the transmission of electrical or chemical signals from one neuron to another.

5. **Synaptic Vesicles**: Located at the end of the axon, these vesicles contain neurotransmitters that are released into the synaptic cleft when an action potential reaches the synapse.

6. **Axon Terminals**: Axon terminals, or synaptic boutons, are the endings of the axon where synapses are formed. Each axon terminal can make connections with several dendrites of other neurons, allowing for selective and complex communication.

Synapses play a crucial role in transmitting information between neurons. Here's how they work:

- When an action potential reaches the end of the axon (the axon terminal), it triggers the release of neurotransmitters from synaptic vesicles into the synaptic cleft.

- Neurotransmitters diffuse across the synaptic cleft and bind to specific receptors located on the membrane of the postsynaptic neuron (usually on dendrites).

- This neurotransmitter-receptor binding causes changes in the ionic permeability of the postsynaptic membrane, thereby generating a postsynaptic potential (excitatory or inhibitory) that alters the likelihood of generating an action potential in the postsynaptic neuron.

- Synaptic transmission can be modulated by various mechanisms, including synaptic plasticity such as Spike-Timing-Dependent Plasticity (STDP), which plays a crucial role in neuronal learning and memory.

2.3 Hodgkin-Huxley Model

The Hodgkin-Huxley model is a detailed mathematical representation of neuronal action potential, describing the underlying ionic mechanisms responsible for the transmission of electrical signals in neurons. Proposed in 1952 by Alan Hodgkin and Andrew Huxley, this model is essential for understanding neuronal cellular physiology and laid the groundwork for modern computational neuroscience.

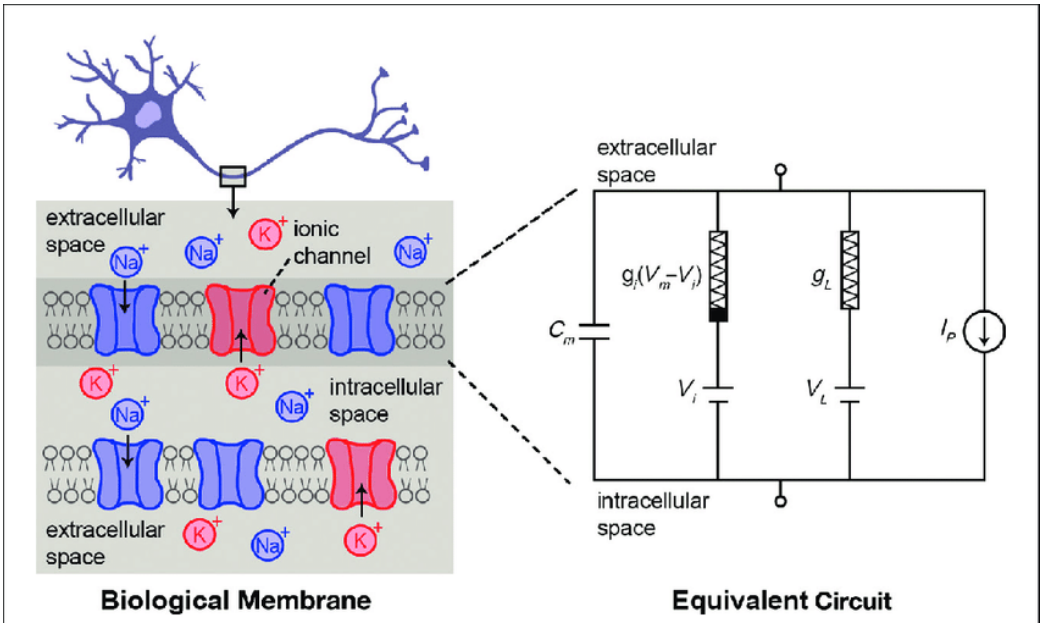

Figure 2.2: Diagram of a biological membrane

The Hodgkin-Huxley equations primarily consist of the following differential equations:

$$
\begin{aligned}
C\frac{dV}{dt} &= -\bar{g}_{Na}m^3h(V-E_{Na}) - \bar{g}_K n^4(V-E_K) - \bar{g}_L(V-E_L) + I_{\text{ext}} \\
\frac{dm}{dt} &= \alpha_m(1-m) - \beta_m m \\
\frac{dh}{dt} &= \alpha_h(1-h) - \beta_h h \\
\frac{dn}{dt} &= \alpha_n(1-n) - \beta_n n
\end{aligned}
$$

Where:

- V is the membrane potential,
- C is the membrane capacitance,
- $\bar{g}_{Na}, \bar{g}_K, \bar{g}_L$ are the specific conductances of sodium, potassium, and leak channels respectively,
- m, h, n are the activation rate variables of ion channels,
- E_{Na}, E_K, E_L are the equilibrium potentials for sodium, potassium, and leak channels respectively,
- I_{ext} is the applied external current.

These equations describe the complex dynamics of ionic currents across the neuronal membrane, thus modulating action potential propagation and overall neuron function.

2.4 Spike-Timing-Dependent Plasticity (STDP)

Spike-Timing-Dependent Plasticity (STDP) is a model of synaptic plasticity inspired by biological observations, demonstrating that the strength of a synapse between two neurons can be modified based on the timing of pre-synaptic and post-synaptic spikes.

2.4.1 STDP Rule

The STDP rule is based on the following empirical observation: the synapse becomes potentially strengthened when the post-synaptic spike closely follows the pre-synaptic spike, and it weakens when the order is reversed. Mathematically, the change in synaptic weight Δw as a function of time difference Δt between pre-synaptic (t_{pre}) and post-synaptic (t_{post}) action potentials can be described by the following formula:

$$\Delta w(\Delta t) = \begin{cases} A_+ e^{-\frac{\Delta t}{\tau_+}} & \text{if } \Delta t > 0 \\ -A_- e^{\frac{\Delta t}{\tau_-}} & \text{if } \Delta t < 0 \end{cases}$$

Where:

- A_+ and A_- are the amplitudes of positive and negative modifications respectively.

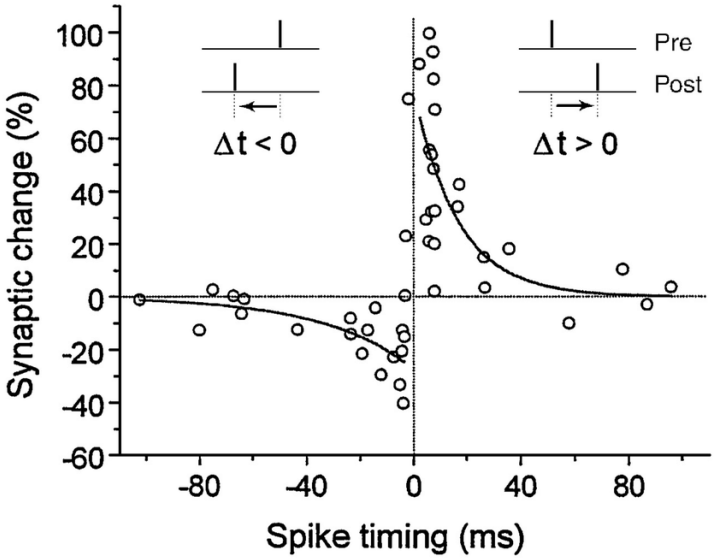

Figure 2.3: Evolution of STDP

- τ_+ and τ_- are the positive and negative time constants, which regulate the temporal window over which STDP is effective.

Typically, τ_+ is smaller than τ_-, reflecting the synapse's greater sensitivity to pre-synaptic events close in time.

The STDP rule is commonly used in artificial neural networks to optimize unsupervised learning and temporal pattern recognition.

2.5 Rate Encoding

Rate encoding is a method of neural information representation where stimulus features are encoded by the frequency of neuron firing. Unlike amplitude encoding (where information is encoded by the amplitude of action potentials), rate encoding uses the frequency of action potentials to represent continuous information such as brightness, position, etc.

In the context of artificial neural networks, rate encoding is often used to capture temporal and dynamic features of data. For example, in pattern recognition or classification, important features can be represented by the frequency at which certain neurons fire.

The primary advantage of rate encoding is its ability to efficiently handle continuous and complex information using neuron models that integrate and sum incoming signals to produce an output corresponding to firing frequency.

2.5.1 Application in Neural Networks

In artificial neural networks, rate encoding is used to represent analog inputs or continuous data features. This allows neural networks to process information such as audio signals, grayscale images, or other data where variations in the frequency of neuronal firing are relevant to the task at hand.

Chapter 3

Implementation and Methodology

3.1 Tools Used

In this study, we utilized two main tools for implementing and experimenting with our neuron models: Brian2 and Python.

3.1.1 Brian2

Figure 3.1: Brian2 logo

Brian2 is a simulator for biologically realistic neural networks, written in Python. It allows for easy definition of biophysically detailed neuron models and efficient simulation of their activity. We used Brian2 to model neuron networks incorporating mechanisms such as Spike-Timing-Dependent Plasticity (STDP) and other biologically inspired rules.

3.1.2 Python

Python served as the primary programming language for developing our implementation and analyzing results. Its flexibility, numerous libraries, and ease of use make it an ideal choice for data manipulation, implementing machine learning algorithms, and visualizing results.

3.2 Description of Implementation

We conducted several experiments to evaluate the capabilities of our neuron models. Two main implementations are presented in this section: modeling a 2-pixel image representation and classifying the MNIST dataset into 2 classes.

3.2.1 2-Pixel Image Representation

To model the recognition of a 2-pixel image, we used a simple neural network architecture with inputs corresponding to the pixels of the image. Each pixel was represented by an input neuron, and the network output was interpreted as the predicted class of the image (e.g., 0 or 1).

We used Brian2 to create this model by defining input neurons, synaptic weights, and weight update rules based on STDP. We then trained the network on a synthetic dataset to assess its ability to recognize simple patterns in images.

3.2.2 MNIST 2-Class Classification

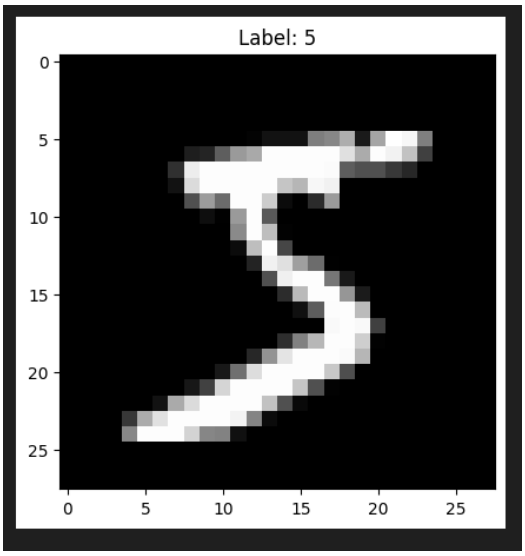

Figure 3.2: Image of class 5

For the MNIST dataset 2-class classification, we adapted a similar approach using Brian2 to model a neuron network capable of distinguishing between two specific digits from the MNIST dataset. Each MNIST image was represented by a series of input neurons, with synaptic weights adjusted to optimize classification accuracy.

We trained and tested the model on a subset of the MNIST dataset, measuring its performance in terms of classification accuracy and its ability to generalize to unseen data.

Chapter 4

Tests and Results

4.1 Experimental Conditions

4.1.1 Periodicity of Input Signals

In initial experiments, input signals were generated with random frequencies. These random signals resulted in inconsistent or nonsensical outcomes. To achieve more meaningful results, we opted for sinusoidal input with frequencies ranging from 0 to 64 Hz, where a frequency of 64 Hz corresponds to white pixels.

Mathematically, the input signal $x(t)$ can be represented as:

$$x(t) = A\sin(2\pi ft)$$

where A is the amplitude of the signal, f is the frequency in Hertz, and t is time. By modulating the frequency f between 0 and 64 Hz, we generated structured inputs corresponding to pixel intensity variations in an image. This modulation enabled the creation of well-defined periodic signals, facilitating the analysis of artificial neuron responses to stimuli.

Results obtained with this method showed significant improvement in the coherence of neural responses, allowing for better interpretation of behaviors observed within the artificial neural network.

4.1.2 Random Initialization of Weights with Complementarity

During initial random weight initialization, neurons tended to assign equal average importance to each pre-neuron X. This situation was suboptimal

for learning as it hindered the specialization of synaptic connections and the formation of distinct neural representations.

To overcome this issue, we introduced complementarity-based weight initialization. Each weight w was initialized to favor specific importance for each synaptic connection. This initialization followed a normal distribution defined by mean and variance dependent on the input size.

Specifically, each weight w was randomly drawn from the following normal distribution:

$$w \sim \mathcal{N}\left(\mu, \sigma^2\right)$$

where:

$$\mu = \frac{8}{n}$$
$$\sigma^2 = \frac{1}{n}$$

and n represents the size of the input. Thus, each weight w is distributed as:

$$w \sim \mathcal{N}\left(\frac{8}{n}, \frac{1}{n}\right)$$

This distribution ensures that the mean weight is proportional to the input size while introducing sufficient variance to ensure complementarity between synaptic connections.

This initialization method allowed for more pronounced differentiation of synaptic connections, promoting neuron specialization and improving overall network performance. As a result, each neuron could develop more specific and distinct connections, enhancing learning and the generalization ability of the artificial neural network. Experimental results demonstrated significant improvements in network convergence and stability, highlighting the effectiveness of this approach.

4.1.3 The NON Rule

As part of our research, we implemented a specific rule called the NON rule to optimize network performance. This rule is based on the principle of synaptic depression within Spike-Timing-Dependent Plasticity (STDP).

The objective of the NON rule is to decrease the probability of undesired spikes in output neurons. In practice, this means that whenever an output

neuron generates a spike when it should not, the synaptic connections responsible for that spike are weakened. This process occurs recurrently to adjust connection weights, reducing classification or detection errors.

To implement this rule, we utilize a feedback mechanism where spikes are continuously monitored. When an incorrect spike is detected, synaptic depression is applied, thereby reducing the strength of connections that contributed to the error. This process helps refine network behavior and increase overall precision by reducing false positives.

Applying this rule has improved network robustness against errors, leading to more precise responses and reduced undesired spikes. Results from subsequent sections illustrate the effectiveness of this approach in various application contexts.

4.2 Results Analysis

4.2.1 Movement of Image by 2 Pixels

When implementing representation of movement in an image by 2 pixels, the primary goal was to test the network's ability to detect and accurately represent movement in a minimalist environment. To achieve this, we used periodic input signals and randomly initialized weights with complementarity.

After a training period of 1000 ms, the results were remarkable. The network successfully identified and accurately represented the movement of the 2-pixel image with 100% precision. This performance can be attributed to the simplicity of the problem and the effectiveness of the learning algorithms used, particularly Spike-Timing-Dependent Plasticity (STDP) and rate encoding.

The application of the NON rule also played a crucial role. By applying synaptic depression to reduce the strength of connections responsible for undesired spikes, we further refined the network and eliminated potential errors. Additionally, complementary weight initialization diversified synaptic connections, enhancing overall network robustness.

These results demonstrate that even with a minimalist configuration, artificial neural networks can effectively reproduce complex neural behaviors such as motion detection. This opens avenues for advanced applications where similar networks could be used for more complex image and video processing tasks.

4.2.2 MNIST 2-Class Classification

To evaluate the network's ability to perform more complex classification tasks, we applied our model to a subset of the MNIST dataset, initially focusing on 2-class classification and subsequently expanding to 3 classes.

When tested on 2-class classification, the network achieved 95% accuracy. This result demonstrates that, with the configurations and learning algorithms used, the network can effectively distinguish between two distinct categories of handwritten digits. The high accuracy achieved indicates that artificial neurons, with adequate training, can learn to recognize specific visual patterns reliably.

Expanding the number of classes to 3 resulted in a decrease in accuracy to 85%. This performance reduction is expected as the classification task becomes more complex with additional classes. However, an 85% accuracy rate remains significant, especially given the relatively simple nature of the model used and experimental constraints.

The application of different rules, such as the NON rule and complementary weight initialization, was essential in achieving these results. The NON rule helped minimize undesired spikes, while weight complementarity improved the diversity and robustness of synaptic connections, enabling the network to generalize better and handle more diverse data.

These results suggest that while the model is capable of handling basic classification tasks with high accuracy, further improvements and optimizations would be necessary to maintain high performance as problem complexity increases. Future adjustments could include hyperparameter optimization, increasing the size and diversity of training datasets, and exploring more sophisticated artificial neuron models.

Discussion

Interpretation of Results

The results obtained in the previous sections clearly demonstrate the ability of artificial neural networks to replicate complex neuronal behaviors and perform classification tasks with notable accuracy. The Spike-Timing-Dependent Plasticity (STDP) rule combined with Rate Encoding has significantly improved network performance by reducing unwanted spikes and diversifying synaptic connections.

For the motion representation from a 2-pixel image, the network achieved 100% accuracy after 1000 ms of training, showcasing its effectiveness in a minimalist framework. In the MNIST data classification task, the network

achieved 95% accuracy for 2 classes and 85% for 3 classes, indicating good generalization despite increased problem complexity.

These results demonstrate that the applied techniques and rules (such as the NON rule and complementary weight initialization) are effective in optimizing network behavior. However, it is also clear that improvements are necessary to address more complex problems and increase classification accuracy.

Study Limitations

Despite the promising results obtained, several limitations emerged during this study:

- **NON Rule Limited to Output Neurons**: The NON rule was applied only to output neurons. Hidden layers did not benefit from this rule, which could limit the overall effectiveness of the network in terms of reducing unwanted spikes.
- **Absence of Potentiation in the NON Rule**: The current NON rule allows only synaptic depression (weakening of connections) and does not account for potentiation (strengthening of connections). This limitation could restrict the network's ability to learn and adapt effectively to variations in input data.
- **Hodgkin-Huxley Model Speed**: The Hodgkin-Huxley neuron model used in this study is relatively slow, which may pose challenges for applications requiring rapid responses.
- **Lack of Supervised Rules for STDP**: Learning in this work mainly relies on unsupervised rules. The absence of supervised rules for Spike-Timing-Dependent Plasticity (STDP) may limit the network's ability to effectively learn complex tasks requiring supervised cues.

Future Work

To overcome identified limitations and improve network performance, several research and development avenues are proposed:

- **Extension of NON Rule to Hidden Layers**: Currently, the NON rule is applied only to output neurons. Extending this rule to hidden layers could help further reduce unwanted spikes and improve the overall efficiency of the network. This will require designing mechanisms to effectively apply synaptic depression in intermediate layers.

- **Integration of Potentiation into NON Rule**: The NON rule could be enhanced by integrating both synaptic depression and potentiation. Allowing synaptic connections to strengthen or weaken based on spike errors could enable the network to adapt more quickly and accurately to input data variations.

- **Optimization of Hodgkin-Huxley Model Speed**: While effective for simulating biological neuronal behaviors, the Hodgkin-Huxley neuron model is relatively slow. Research should explore optimizing this model or investigating faster alternatives while maintaining fidelity to biological neuronal dynamics.

- **Development of Supervised Rules for STDP**: To enhance the network's ability to learn complex tasks, supervised rules for Spike-Timing-Dependent Plasticity (STDP) should be developed. These rules would allow the network to benefit from external cues during learning, thereby improving classification accuracy and robustness.

By exploring these research directions, we aim to significantly enhance the performance and efficiency of artificial neural networks for various applications, bringing them closer to biological neuronal behavior.

Conclusion

This study has demonstrated the ability of artificial neural networks to model complex neuronal behaviors and perform classification tasks with significant accuracy. By employing techniques such as Spike-Timing-Dependent Plasticity (STDP), Rate Encoding, and the NON rule, we optimized the network to effectively represent motion from a 2-pixel image and classify handwritten digits from the MNIST dataset.

The obtained results, with 100% accuracy for motion detection and 95% and 85% for 2 and 3-class classification rates respectively, illustrate the effectiveness of the approaches used. However, several limitations were identified, including the restricted application of the NON rule to output neurons only, the absence of potentiation in this rule, the slowness of the Hodgkin-Huxley neuron model, and the lack of supervised rules for STDP.

To address these limitations, several future research directions have been proposed, including extending the NON rule to hidden layers, integrating synaptic potentiation, optimizing the speed of the Hodgkin-Huxley model, and developing supervised rules for STDP. These improvements should strengthen

the learning capabilities and robustness of artificial neural networks, making them more suitable for complex and diverse applications.

In conclusion, this study makes significant contributions to understanding and optimizing artificial neural networks inspired by biological neurons. Future work based on these findings could open new perspectives in the fields of artificial intelligence and computational neuroscience.

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