TABLE OF CONTENTS

Introduction

Artificial intelligence is currently experiencing rapid growth, with the objective of extending its applications beyond domestic environments, as exemplified by drones, augmented reality (AR), and navigation. Among the crucial considerations, power consumption stands out, necessitating the development of novel algorithms and, more significantly, advanced hardware. Taking inspiration from the human brain, scientists are endeavoring to create a spiking neural network[1], which represent one of the most efficient approaches. This entails transmitting minute pulses between neurons and transistors exhibit inefficiency due to the need for charging parasitic capacities while maintaining a tiny continuous current flow when they are in the cut-off area, resulting in a significant energy inefficiency when considering the scale of a neural network. Simultaneously, neurons establish connections with millions, if not billions, of other neurons, thereby intensifying the fanout problem. This paper presents the utilization of lasers as neuron substitutes under specific conditions, effectively mitigating the fanout problem, preventing current leakage, and facilitating faster inter-neuron communication.

1.1 THE HUMAN BRAIN

The human brain stands as a remarkable example of intricate networks, recognized as one of the most complex entities known to humanity. It encompasses an estimated 100 billion neurons, along with approximately 100 trillion synapses[i], which account for merely 10% of the total cellular composition within the brain [5]. It is noteworthy that the brain's power consumption remains impressively efficient, with a maximum energy utilization of 25W or a typical daily usage of 10W [4]. To provide a tangible perspective, this energy consumption equates to that of an LED light bulb and on the other hand, there is a growing concern regarding the environmental impact associated with the power consumption of current AI models; hence, the imperative to develop novel technologies for machine learning and artificial intelligence arises.

1.2 NEUROMORPHIC MACHINE LEARNING

Neuromorphic machine learning refers to the integration of neuromorphic computing principles and techniques with machine learning algorithms. Neuromorphic computing aims to design and develop computer systems inspired by the architecture and functioning of the human brain's neural networks.

Traditional computing systems, based on the von Neumann architecture[2], have a clear separation between memory and processing units. In contrast, neuromorphic computing systems aim to bring memory and processing closer together, mimicking the parallel and distributed nature of the brain's neural networks. These systems typically employ specialized hardware, such as neuromorphic chips or neuromorphic processors, designed to efficiently perform neural network computations. When applied to machine learning, neuromorphic approaches seek to leverage the unique properties of neuromorphic hardware[3] to enhance the efficiency and performance of learning algorithms. By emulating the brain's neural networks, neuromorphic machine learning models can potentially offer benefits such as improved energy efficiency, faster processing, and the ability to process sensory data in real-time.

Neuromorphic machine learning models often incorporate spiking neural networks (SNNs), which operate based on the concept of spiking neurons that communicate through discrete electrical pulses. SNNs have been shown to be particularly suitable for processing spatiotemporal data and have the potential to achieve high energy efficiency and low latency.

1.3 NEURONS

In order to advance in the engineering of neuromorphic machine learning chips, it is crucial to gain a comprehensive understanding of the functionality and mechanisms of neurons. They are the building blocks responsible for transmitting electrical and chemical signals, allowing communication within the nervous system and between the nervous system and other parts of the body. Neurons communicate with each other through synapses. When an electrical impulse (action potential) reaches the axon terminals of a neuron, it triggers the release of neurotransmitters into the synapse. These neurotransmitters then bind to receptor sites on the dendrites or cell body of the next neuron in the pathway, generating a new electrical impulse in that neuron. This process allows for the transmission of information and the coordination of various activities in the body. The classification of neurons encompasses several distinct types, notably sensory and motor neurons[6] . Nevertheless, for the present objective of creating a neuron-like model, we prioritize simplicity, thus not focusing in detail on how each neuron behaves.

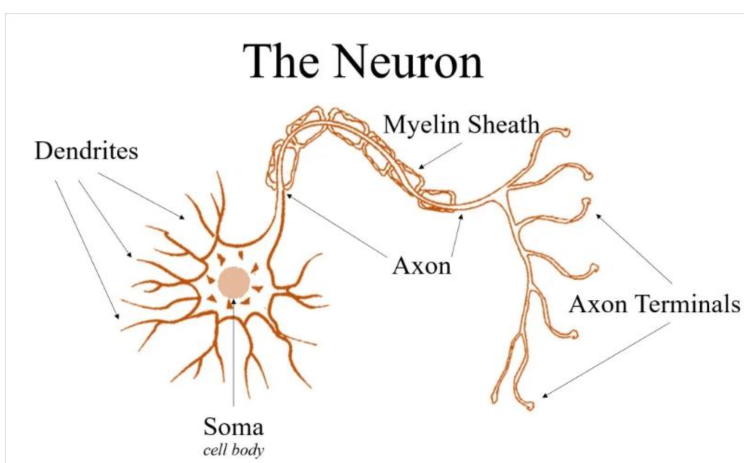

Figure 1: representation of a neuron. Teen Brain Talk "Neuron"

1.3 SPIKES

The soma, or cell body, of a neuron is responsible for integrating incoming signals from the dendrites and initiating the generation of electrical pulses, also known as action potentials or spikes. The process by which the soma generates pulses is a result of changes in the membrane potential[ii]. Each cell has a resting Membrane potential, which is the electrical charge difference across their cell membrane when they are not actively transmitting signals. At rest, the inside of the neuron is more negatively charged compared to the outside, typically around -70 millivolts (mV).

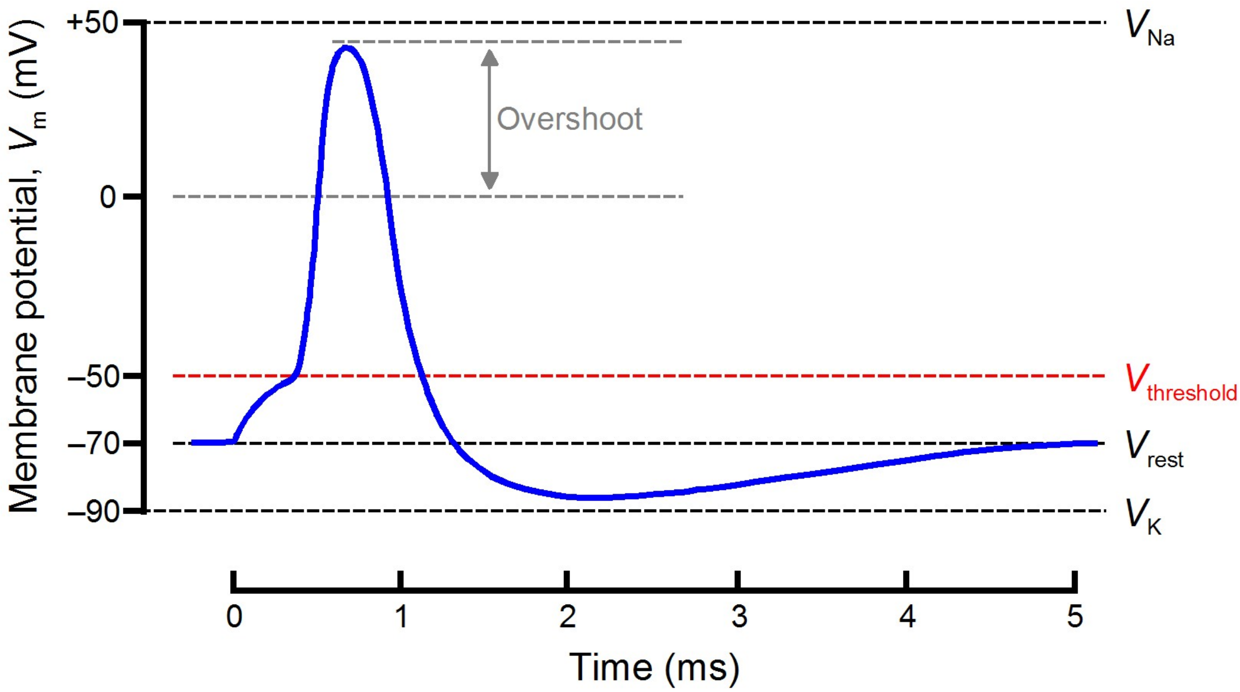

Figure 2: illustrates the concept of membrane potential generating an action potential once it surpasses the threshold level. Image from www.physiologyweb.com

Upon receiving excitatory input from other neurons or sensory receptors, the neuron becomes stimulated. If this stimulation reaches a specific threshold level, a crucial point typically around -55 to -50 millivolts (mV), voltage-gated sodium channels in the cell membrane open. Subsequently, there is a rapid influx of sodium ions into the neuron, leading to a significant depolarization event[7].

As the depolarization progresses, the membrane potential rises towards a positive value. Upon surpassing the threshold, an all-or-nothing response known as an action potential is triggered. During the action potential, the membrane potential experiences a rapid and substantial depolarization, reaching approximately +40 mV. At this stage, voltage-gated potassium channels open, enabling potassium ions to leave the neuron, initiating the repolarization or reset phase.

It is important to note that once the action potential is triggered, it propagates along the neuron's axon, allowing the rapid transmission of signals to communicate with other neurons or effector cells within the nervous system. The mechanism depicted in Figure 2 underlies the fundamental process by which neurons process and transmit information in the nervous system.

1.3.2 neuron modeling

Given the intricate nature of neurons, attempting to employ static equations to address their complexities would be an exceedingly challenging task. Nevertheless, by formulating the neuron as a dynamical system, the intricacy of the problem becomes notably more manageable. Dynamical systems, with their capacity to integrate time-dependent variables and consider the evolving states over time, offer a more suitable and efficient approach to describe the behavior of a neuron. By capturing the dynamic interactions and temporal evolution of various neuron parameters, a dynamical systems framework facilitates a deeper understanding and analysis of neural activities without becoming entangled in the overwhelming complexity posed by static equations.

Over the course of years, numerous models have been developed to describe neurons within the context of spiking neural networks (SNNs). This arises from the profound trade-off between attaining biological plausibility and enabling swift computational processing. While the Hodgkin-Huxley(HH)[7] model meticulously captures the intricacies of neuron biology, implementing it in large-scale SNNs necessitates immense computational resources.

Extensive studies exploring neuron morphology and physiology have yielded insights that the Leaky-Integrate-and-Fire (LIF) model emulates a diverse array of observed biological phenomena while remaining amenable to realistic computational demands for large-scale SNNs. The LIF model provides a more simplified and computationally efficient representation of neuron behavior, making it particularly appealing for simulating vast neural networks.

1.4. DYNAMICAL SYSTEM

The 1.0 equations derive from the analysis of the neuron as a dynamical system, they constitute a fundamental mathematical framework for describing the behavior and evolution of various systems over time. A dynamical system is characterized by three key components: state variables, time and dynamics. Each state represents a system’s condition. Time serves as the independent variable, capturing the system's evolution over a continuous or discrete temporal domain. Dynamics, or the evolution rule, specifies the mathematical relationships governing the interplay of state variables and their changes over time. Dynamical systems theory is a powerful tool used in various fields such as physics, engineering, biology, economics, and chaos theory. It helps in understanding and predicting the behavior of complex systems and plays a significant role in modeling and simulating real-world phenomena. Before analyzing neurons and lasers, a simple example of a dynamical analysis is presented.

1.4.1 Pendulum as a dynamical system

The pendulum's oscillatory motion is among the most iconic and instructive demonstrations of employing differential equations and phase portraits to characterize its dynamics over time. Its ubiquity in daily life and the simplicity of its underlying mechanics makes it an ideal exemplary for illustrating the principles of dynamical systems analysis. The oscillation can be described using a second-order linear differential equation[iii], which relates the angular displacement and velocity of the pendulum with respect to time. This equation derives from the fundamental principles of classical mechanics and assumes small-amplitude oscillations.

At any given time, the system possesses a variable θ denoting the angular displacement of the pendulum from its equilibrium position. Thus, θ serves as one of the state variables characterizing the system's configuration.

In addition to θ, the system exhibits another state variable, V, representing the velocity of the weight (or pendulum bob). The velocity of the weight, denoted as V, can be expressed as the angular velocity of θ, denoted as θ', which arises from the correlation between the angular displacement and the sine of θ as well as the length of the string.
Mathematically, the relationship can be represented as follows:

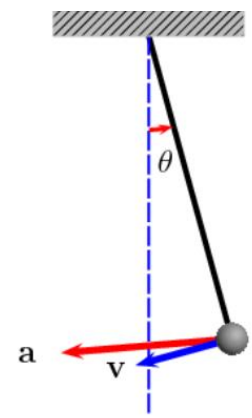

Figure 2: pendulum in motion with arrows denoting position and velocity. Image taken from Wikipedia

$$V = L\frac{d\theta}{dt}\, sin\theta \quad (1.1)$$

To predict the forthcoming state of the system, it necessitates the angular acceleration, denoted as $\ddot{\theta}$,[iv] in addition to the angular displacement θ. Hence, the state of the system at any specific time is contingent on two variables, θ and $\ddot{\theta}$, which will be the state variables. To come up with the equations that govern the system, finally an equation that describes the angular acceleration based on the displacement is needed. Which can simply be found by using the first derivative of the equation 1.1:

$$\ddot{\theta} = -\frac{g}{L}\sin\theta(t) \quad (1.2)$$

At this point, we have the system variables and the system's equations, thus we can procced at creating a phase portrait

1.4.2 LIF MODEL

The Leaky Integrate-and-Fire (LIF) model operates through a periodic integration of the inputs received at the dendrites, whereby the resulting value is added to the current membrane potential. If this cumulative potential surpasses the threshold value, the neuron generates an action potential or spike. The term "Leaky" signifies that the membrane potential gradually returns to the resting membrane potential in the absence of input spikes over time.

An essential feature of the LIF model involves the reset mechanism, wherein, upon firing an action potential, the membrane potential is instantaneously reset to a predefined value, often set to the resting membrane potential or another designated value (Vreset). This reset process enforces a refractory period during which the neuron remains unresponsive to new inputs immediately after spiking, preventing rapid successive firing.

The equations the describe the LIF model are as follows:

$$\dot{V_m}(t) = \frac{V_L}{\tau_m} - \frac{V_m(t)}{\tau_m} + \frac{1}{C_m} I_{app}(t) \qquad \begin{cases} if\ V_m(t) > V_{threshold} \\ then\ fire\ and\ V_m(t) = V_{reset} \end{cases} \quad (2)$$

Where $\dot{V_m}(t)$ is the rate of change of the membrane potential $\frac{V_L}{\tau_m}$ is the active pumping, $\frac{V_m(t)}{\tau_m}$ describes the leakage and $\frac{1}{C_m} I_{app}(t)$ adds the external spikes.

The spike will simply be a dirac function $\delta(t - \tau_j)$ where τ_j is the delay of the spike.

1.5 REFERENCES

1. H. Amin and R. Fujii, "Spike train decoding scheme for a spiking neural network," 2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541), Budapest, Hungary, 2004, pp. 477-482, doi: 10.1109/IJCNN.2004.1379956.
2. von Neumann, J. (1982). First Draft of a Report on the EDVAC. In: Randell, B. (eds) The Origins of Digital Computers. Texts and Monographs in Computer Science. Springer, Berlin, Heidelberg
3. Heemskerk, Jan NH. "Overview of neural hardware." Neurocomputers for brain-style processing. Design, implementation and application (1995).
4. R.C. Merkle, "Energy limits to the computational power of the human brain" Foresight Update No. 6 August 1989
5. Herculano-Houzel S. The human brain in numbers: a linearly scaled-up primate brain. Front Hum Neurosci. 2009 Nov
6. J.B Furness Types of neurons in the enteric nervous system Journal of the Autonomic Nervous System Volume 81, Issues 1–3 2000 Pages 87-96 ISSN 0165-1838
7. Rodolfo R. Llinás, "I of the Vortex: From Neurons to Self", The MIT Press ISBN electronic: 9780262278454
8. HODGKIN AL, HUXLEY AF, KATZ B. Measurement of current-voltage relations in the membrane of the giant axon of Loligo. J Physiol. 1952 Apr;116(4):424-48. doi: 10.1113/jphysiol.1952.sp004716. PMID: 14946712; PMCID: PMC1392219.

[i] Synapses: the connections between neurons. The point where the dendrites meet the axon terminals.

[ii] Membrane potential: refers to the difference in electrical charge that exists across the cell membrane of a neuron.

[iii] Second-order DE: an equation that involves the second derivative of a dependent variable

[iv] In the context of dynamical systems and differential equations, the dot notation on top of variables indicates the derivative of the variable with respect to time.