BULETINUL INSTITUTULUI POLITEHNIC DIN IAŞI
Publicat de
Universitatea Tehnică „Gheorghe Asachi” din Iaşi
Volumul 68 (72), Numărul 2, 2022
Secţia
ELECTROTEHNICĂ. ENERGETICĂ. ELECTRONICĂ
DOI:10.2478/bipie-2022-0012

A SHORT SURVEY OF THE DEVELOPMENT AND APPLICATIONS OF SPIKING NEURAL NETWORKS OF HIGH BIOLOGICAL PLAUSIBILITY

BY

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Received: November 9, 2022
Accepted for publication: March 17, 2023

Abstract. Spiking neural networks (SNNs) are inspired from natural computing, modelling with high accuracy the interactions and processes between the synapses of the neurons focusing on low response time and energy efficiency. This novel paradigm of event-based processing opens new opportunities for discovering applications and developing efficient learning methods that should highlight the advantages of SNNs such as the large memory capacity and the fast adaptation, while preserving the easy-to-use and portability of the conventional computing architectures. In this paper, we do a brief review of the developments of the past decades in the field of SNNs. We start with a brief history of the SNN and summarize the most common models of spiking neurons and methods to implement synaptic plasticity. We also classify the SNNs according to the implemented learning rules and network topology. We present the computational advantages, liabilities, and applications suitable for using SNNs in terms of energy efficiency and response time. In addition, we briefly sweep through the existing platforms and simulation frameworks for

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SNNs exploration. The paper ends with conclusions that show predictions of future challenges and the emerging research topics associated with SNNs.

Keywords: spiking neural network, neurorobotics, neuromorphic hardware, Hebbian learning, survey.

1. Introduction

In biological world the brain uses spikes or impulses to process information and adapt. They are the pillars of perception and control providing the living creatures exceptional adaptation in the real environment, making them able to outperform the conventional robots in most aspects of life. For the last decades, natural intelligence served as a source of inspiration for the development and improvement of the emerging computing technologies and paradigms. These enhancements rely on computing techniques inspired by the brain's mechanisms of information processing (Bing *et al.*, 2018).

The following capabilities are required to obtain autonomy for robots and make them operate in the real world:

- Perceive and understand the environment using sensors;
- Process high amount of information with a low power consumption;
- Adapt using self-learning capabilities.

By analyzing the state-of-the-art methods used in automatic control it is obvious that either the methods based on kinematics or even the ones based on conventional artificial neural networks (ANNs) are not able to reach up to those requirements. Conventional methods for automatic control based on kinematic approaches often fail to function correctly in unexpected scenarios (Bing *et al.*, 2018), while conventional ANNs are far from being efficient from computational speed perspective. The outstanding liabilities of ANNs are: *i*) training time. Training ANNs take a lot of time even for modern computing architectures while training on massive-distributed systems is costly to process *e.g.*, AlphaGo 1,202 CPU and 176 GPU (Silver *et al.*, 2016); *ii*) power consumption. Using general purpose hardware architectures to do calculations with large ANNs also requires huge amounts of energy. For example, some autonomous vehicles software that uses ANNs runs on hardware systems that consume over a hundred times more power than a human brain, which requires, with only about 20 watts of power. Particularly for embedded applications and mobile devices, where real-time response is rather mandatory and power supply is limited, these are significant drawbacks (Drubach, 2000).

Natural neural networks process information using spikes which are delivered between neurons with a relatively precision regarding time synchronization. Those mechanisms are considered to be enough to implement the capabilities to learn and adapt, and therefore a possible solution to the challenges prior-mentioned for controlling robots in an efficient manner using neural networks that model the basic processes of the nervous system. Because of its similar characteristics to those of observed at nervous system from power consumption to data storage capacity perspectives, SNNs can process information and learn, and they are suitable for building large-scale brain models, neural hardware or neuromorphic sensors. Furthermore, SNNs have shown to be suitable for several different problems like voice recognition (Hulea, 2008), signal processing or robot control and orientation (Uleru *et al*., 2022a).

SNNs are also regarded as the third generation of neural networks (Maass, 1997). They communicate directly through individual spike sequences like its biological counterpart. They employ the spike coding mechanism, which suggests chronological codification of data, as opposed to employing abstract information signals. This aspect is missing in most ANNs as pulse frequency average is used. In theory, these models have been proven to be more robust and fault tolerant than perceptrons and sigmoidal gates. Taking those aspects into consideration, SNNs may provide perspectives for decreased-latency and low-energy alternatives to conventional automatic control or previous generation neural networks. They may be proven suitable for robotics applications, as well as efficient tool to study the nervous system and to help explain how the human brain works and process information such effectively.

This article is organized in 6 sections. In section 2, a short history of the spiking neuron and synaptic plasticity will have a quick introduction based on their physiological justification. Section 3 presents the SNN classification considering topology and learning rules. Then we will discuss the main advantages, liabilities, and applications of the SNN (section 4). Finally, in section 5 we will try to emphasize over the future development directions and potential of SNNs, as well as mentioning some of the frameworks used for exploring neurorobotics topics. Section 6 will try to conclude this survey. As follow up to all the work that has been done in the field of SNNs by the authors, this paper will reference previous papers according to the discussed topics.

2. Spiking neurons and synaptic plasticity

Even today, the comprehension of the natural nervous system if far from being at least slightly complete, while the human brain is still one of the most complicated puzzles. More information about our neural structure has been released in the past two decades. Since Santiago Ramón y Cajal's preliminary uncover of the basic structure and functions of the nervous system in the early 20th century (Ramón y Cajal, 1909), a rough theory of how neurons work has been developed. Neurons are essentially fundamental units that receive and process information in the form of electrical signals and transmit new signals at their output. When multiple neurons are connected together, they form complex networks that can perform computations and help us make sense of the world around us. This principle is observed throughout nature, from simple creatures like jellyfish which have a small number of neurons to anthropogenic brain that contains an average of 90 billion neurons (Herculano-Houzel, 2012).

The human brain's representative neuron structure, illustrated in Fig. 1, is situated within a saline extracellular fluid. The neuronal membrane potential is modified by signals originating from several dendrites. Upon reaching a particular threshold, the soma (cell body) generates a potential pulse, commonly known as a spike. This mechanism produces a rapid and brief (lasting 1ms) rise in voltage and is frequently referred to as a spike or neuronal activation. Following a firing event there is a brief interval of inactivity referred to as the refractory timeframe, when the neuron cannot transmit additional spikes regardless of the stimulus it receives. After the neuron reaches its membrane potential threshold and becomes activated, the resulting output pulse is transmitted along the neuron's lengthy axon, which can divide into numerous branches that connect to other neurons.

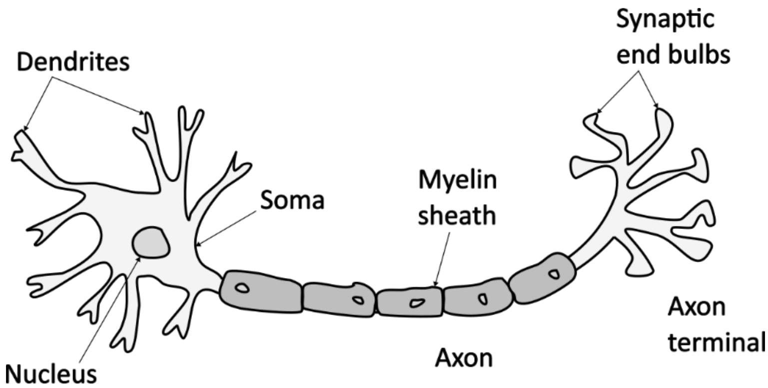

Fig. 1 – Typical structure of a neuron.

The signals are conveyed to other neurons or muscular cells at the axon terminal. Studies have demonstrated that the synapse is among the most intricate components of a neuron, as it not only transmits information but also functions as a signal preprocessor, playing a crucial role in learning and adaptation. As depicted in Fig. 2, the incoming pulse may prompt a synaptic vesicle to move toward the presynaptic membrane of the axon terminal. The activated vesicle fuses with the membrane and releases the deposited neurotransmitter over the extracellular fluid-filled synaptic cleft at the presynaptic membrane. The neurotransmitter molecules, after diffusing into this space, must reach a corresponding receptor and bind to them towards the border of the synapse space. The toggling state of post synaptic ion channels is induced either directly or indirectly, subsequently triggering an ionic flow that propagates through the dendrites to the somatic activation region, there by modulating the accumulated charge on the membrane of the postsynaptic cell. The information transmission is mediated by various neurotransmitters that may have divergent effects on the excitability of postsynaptic neurons. Excitatory postsynaptic potentials or postsynaptic inhibitory potentials are the effects that enable postsynaptic cells to trigger action potentials. The efficiency of synaptic transmission is determined by the amount and type of neurotransmitters released, as well as the number of activated ion channels. This dependence on various factors is commonly known as synaptic efficiency. After some time, the receptors release the neurotransmitter molecules again toward the synaptic cleft where they either undergo reabsorption into the axon of the presynaptic neuron or extracellular fluid enzyme degradation.

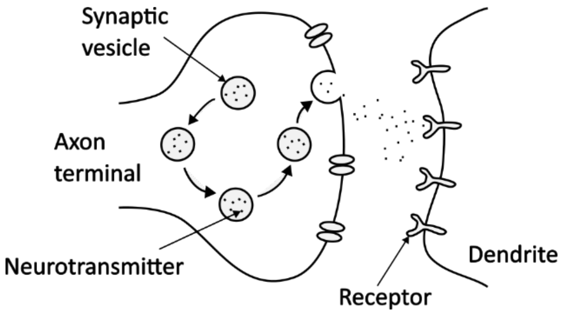

Fig. 2 – The basic mechanics of a synapse.

The capabilities and characteristics of the synapse as a signal preprocessor (*e.g.*, the chance to deploy or regenerate the vesicle and the number of receptors) are dynamic and constantly alter according to both internal and external factors. Neurons in the extracellular fluid can temporarily affect pre- and post-synaptic terminations, by amplifying vesicle remodeling or by obstructing neurotransmitters from triggering receptors. The primary idea behind the majority of learning principles and models is synaptic plasticity, which refers to all of these modifications to the impact of incident spikes on postsynaptic membrane potentials.

In a theoretical study published in 1943, mathematician Walter Pitts and neurophysiologist Warren McCulloch described how neurons may function by utilizing electrical circuits to create a straightforward neural network model (McCulloch, 1943). These first-generation neural networks can produce digital impulses when a neuron's threshold for integrating input signals is reached, thus executing binary mathematical operations. Powerful ANNs like multi-layer perceptrons and Hopfield networks have effectively included them (Hopfield, 1982). This idea was expanded as more powerful computation became available by adding continuous activation functions, such as sigmoid, that also handle analog inputs and outputs (Han, 1995) or hyperbolic tangent functions. By adjusting the network information flow of massive neural networks with continuous activation functions via their synaptic weights, analog functions may be arbitrarily well approximated. The strongest and most popular supervised learning algorithm, called back propagation (Hecht-Nielsen, 1992), leverages continuous activation functions using gradient-descent over an error function. Second-generation neurons, on the other hand, do not replicate the electrical impulses that are used by their organic peers, and their continuous signals can be processed as codes. Encoding the pulse frequencies into an analog signal by averaging their firing speed over a time window is giving these patterns a more plausible biological meaning.

In most cases, ordinary differential equations may be used to define mathematical models of neurons. Spiking neural models, which process excitatory and inhibitory inputs employing variables and parameters depicting an internal state, have been described mathematically in a variety of ways (Hulea, 2011). Integrate-and-Fire design and its variations are the most often employed models for SNNs (Burkitt, 2006) and the Hodgkin-Huxley model (Hodgkin and Huxley, 1952). The biological plausibility and complexity must be balanced in order to select the optimal model from the many available neuron models (Izhikevich, 2004).

Encoding is the process of converting real acquired data, like the displacement of an item, into a neural behavior, like the triggering frequency of a neuron. Conversely, decoding involves interpreting and translating the activity of neurons to understand how they relate to brain function and behavior. The aim of neural activity interpretation is to describe how the electrical activity of neurons influences brain activity and responses. A prevalent method for interpreting is rate-based, whereby greater activity of neurons typically corresponds to increased physical values. When describing how the brain encodes information, two distinct domains can be distinguished: the physical domain and the neural domain. The physical domain pertains to the observable characteristics of things, like their color, shape, position, motion, or temperature, whereas the neural domain refers to the features of individual neurons, like their triggering frequency. Various methods for encoding neural information have been proposed, which are summarized in Table 1.

Table 1

Neural information encoding methods (Bing et al., 2018)

Encoding	Description
Binary coding (Gütig, 2006)	The modeling of neurons is limited to binary values (on/off) and fails to account for the temporal aspect and multiple occurrences of spikes.
Population coding (Probst *et al.*, 2012)	A population of neurons functions as a single unit for encoding information.
Temporal coding	The timing of spikes conveys the representation of

	information.
Rate coding (Wade *et al.*, 2010)	Poisson technique to model spike trains with features similar to those of biological neurons.

After the neuron model, the synapse design must be wisely selected to bind the neurons of the SNNs layers and slices. Based on theoretical analysis (Hebb, 1949), due to its influence on the membrane charge of all linked neurons, synaptic plasticity was initially considered as a method for adjusting the weights and memorization. Even today, most implementations employ relatively basic synaptic plasticity models. They may be divided into two groups based on the relationship between input-output, neural triggering, and synaptic plasticity: rate-based and spike-based. These categories distinguish on the type of variables used as input. The original and widely used meaning of the term firing rate relates to an average number of spikes across a time frame (Andrew, 2003). Fig. 3 presents the generic input/output spike train encoding of a SNN.

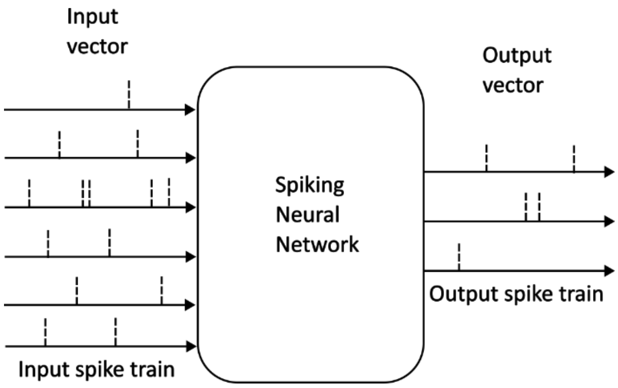

Fig.3 – Spiking network generic input/output train encoding.

The results of the experiments indicate that the synaptic plasticity is affected by the precise scheduling and order of pulses. When a presynaptic pulse is succeeded by a postsynaptic pulse, it leads to an enhancement of the synaptic strength. Conversely, if the order is reversed, a depression in synaptic strength is observed. This phenomenon is referred to as Spike-Timing-Dependent-Plasticity (STDP). Anti-STDP is the process for the reversed order. Inputs to neurons that contribute to their activation are reinforced, while inputs that do not contribute are weakened (Hulea, 2014).

3. SNN classification and learning rules

The SNN network model simulates synaptic interactions among neurons. The initial and most basic type of network architecture is a feed-forward network, in which data always travels from the input nodes, through mid-layer nodes (if any), to the output nodes, but never in reverse, as presented in Fig. 4. Feed-forward networks have the main purpose to gather and send collected data in biological nervous system. Likewise, these networks are typically deployed in robotic systems for low-level perception, such as tactile sensing, sight, and olfaction (Hulea *et al.*, 2022).

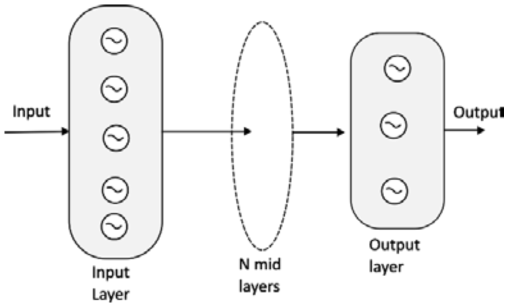

Fig. 4 – Feed-forward network topology.

The second type of networks is recurrent neural networks (RNNs). Apart from the feed-forward networks, they transmit the information with a guided loop and implement evolving temporal patterns, as shown in Fig. 5. It should be emphasized that RNNs are recursive with a specific structure like a directed graph. Biological networks seem to use this process to interpret arbitrary sequences of data having the memory stored in RNNs. Robotics applications use RNNs for dynamic control, sight, and scheduling (Hulea *et al.*, 2019).

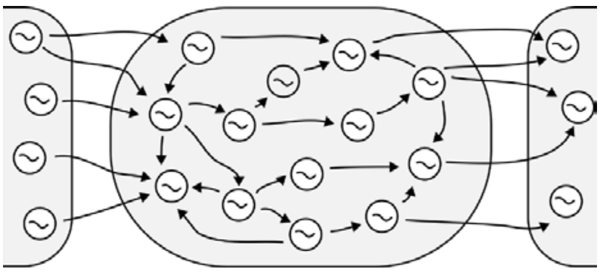

Fig. 5 – Recurrent network topology.

The physiological mechanism underlying learning is believed to be the variation in synaptic strength between neurons (Vasilaki *et al.*, 2009). These synaptic weights can be gated by neuromodulators that convey the existence of incentives or internal systematic activation between neurons and their links. The network is often expected to learn a function that converts given information into a certain result. Once properly trained, the network is able to carry out basic activities like following a lane, avoiding obstacles, hitting a target, taxiing, or feeding. Most of the time, the network information comes straight from the robot's sensing terminals, ranging from simple unidimensional olfactory translators to analogue highly complex sensors, like sight detectors. For different instances, the data source may be already processed information, as in the case of an electroencephalogram (EEG). Outputs can also vary from simple binary control instructions to multi-dimensional continuous values. Simulated control problems solving was accomplished initially by manually varying the network parameters. This technique could only be used to solve straightforward behavioral problems in relatively small network designs with few weights. As follow up to this problem, a wide range of training techniques for adapting SNNs weights has been studied and reported.

In 1949, one of the earliest hypotheses in neuroscience outlining the adaption of synaptic weights in the brain throughout the process of learning was presented in The Organization of Behavior by Donald Hebb (Hebb, 1949). As stated in the sentence “Cells that fire together, wire together”, the concept is mathematically identified as:

$$\Delta w_{ij} \propto v_i v_j \tag{1}$$

where Δw_{ij} pertains the fluctuation of synaptic weight between the presynaptic neuron *i* and the postsynaptic cell *j*, and *v* represents the activities of those cells, respectively. Hebbian learning rule is based on the precise synchronization of pre- and post-synaptic spikes. Hebb’s learning method has been found effective in solving tasks like formation of associative memories, pattern recognition, dimensionality reduction, or construction of self-organizing correlations (Hinton, 1999).

According to STDP, the synaptic strengthening, called Long Term Potentiation (LTP), can be observed when a presynaptic pulse followed a postsynaptic pulse, while the depression, or Long-Term Depression (LTD), is caused by the reversed order. This weight adjustment method is usually named unsupervised learning (Hinton, 1999) due to the lack of well-defined targets, correction mechanisms or a knowledgeable supervisor. Learning based on STDP technique has been employed effectively in multiple situations like pattern recognition, input clustering, and spatial navigation.

Lately, there has been a great success in non-spiking neural networks defined by the various effective techniques of learning from tagged information. The supervised learning is the method of weight adjustment where a neural network imitates behavior identified from a provided data collection (Hastie *et al.*, 2001). Some neuroscientific investigations have proved that this learning technique is also found in the human brain, *e.g.*, in movement and adaptation (Thach, 1996). Despite the intensive research of this topic, the precise mechanics of supervised learning in organic neurons is yet to be fully explained. Supervised learning is the way of training SNNs by providing an external training stimulus that adjusts the synapses. This will make the network to efficiently imitate the training stimulus after an initial training phase. Though this technique presents a basic, easy-to-use method for training networks, the downside is that it is reliant on an external mechanism.

Classical conditioning pertains to the learning process where a biologically significant stimulus, such as food, is repeatedly complemented by unbiased excitation, such as a bell, resulting in the neutral stimulus acquiring the ability to elicit a response similar to that of the biologically significant stimulus. This results in a reaction (*e.g*., salivation), that is frequently activated by the strong stimulus. In the well-known study on classical conditioning, Pavlov's dog learns to link an unconditioned stimulus (NpreUS), represented by food, and a conditioned stimulus (NpreCS), a bell (Pavlov and Anrep, 2003). Subsequent studies proved classical conditioning also for SNNs (Hulea, 2017). Fig. 6 displays how the STDP learning rule can train a synapse to associate NpreUS and NpreCS provoking a response even in the absence of NpreUS.

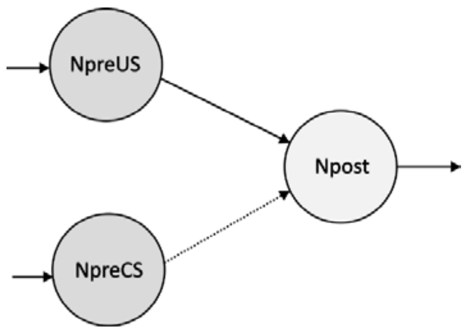

Fig. 6 – Classical conditioning between NpreCS and Npost. The conditioned stimulus (NpreCS) activated before its associated unconditioned stimulus (NpreUS) will strengthen its weight so Npost will fire even if NpreUS will not.

Reward-based learning rule implies certain chemicals released by a neuron, which affect other groups of neurons through a process called neuromodulation. Within the mid brain, dopamine neurons are important neuromodulators that play a critical role in various functions like control, decision-making, inspiration, reassurance, and incentives. Generally, many kinds of rewards in neuroscience are linked to higher levels of dopamine in the brain, which can activate specific neural pathways that have been trained or learned. The impacts of STDP events are gathered, similar to dopamine neurons in the brain, and a global reward signal results in changes in synaptic weight, as illustrated in Fig. 7. In contrast to supervised training, rewards can be linked to input stimuli even if they arrive later.

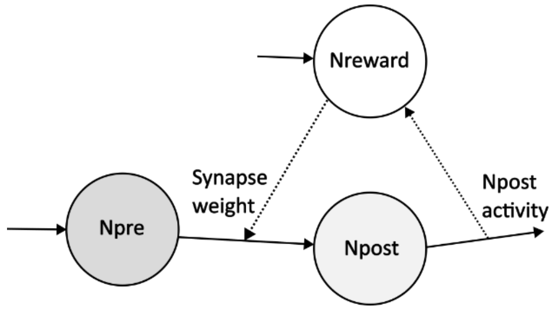

Fig. 7 – Reward-modulated STDP synapse.

The classical reinforcement learning is a much more complex approach in which the learning methods preemptively takes into consideration several stages using a Markov Decision Process (MDP) for constructing the reward. As a result, a few approaches integrating SNNs with traditional reinforcement learning algorithms, such as temporal difference or model-based approach, have been proposed.

4. Advantages, liabilities, and applications of SNN

Looking at it from a neuroscience perspective, SNNs achieve a higher degree of biological plausibility by employing spike patterns for both computation and communication, much like real neurons do. Experimental findings gathered in recent years have provided evidence that organic nervous systems can represent data using synchronization of pulses (Maass, 2001). Accurate modeling of timing in spike neural networks provides a critical foundation for carrying out robust computations that adhere to neurobiological principles. As presented in Table 2, which contains the main advantages and limitations of SNNs, there are multiple features, other than biological plausibility, that differentiate SNNs from its counterparts.

Table 2
Major advantages and limitations of SNNs in comparison with conventional ANNs.

Advantage	Limitation
Suitable for processing spatio-temporal event-based information (Mostafa, 2018)	Low accuracy on typical benchmarks (Russakovsky *et al*., 2015)
Efficient for computation of biological inspired features (Osswald *et al*., 2017)	Difficult to design and assess training algorithms due to the uneven and interrupted processing method
Hardware implementation has a very good signal to noise ratio and benefits from fast response due to parallel operation of neurons	Low compatibility with conventional computing. May require conversion from conventional data encoding into spike trains (Pfeiffer and Pfeil, 2018)

Fast computing (Thorpe *et al.*, 2001), low memory complexity and energy efficient (Drubach, 2000)	

Although there have been hardware advancements that allow for the use of large neural networks in solving real-world problems, such progress typically does not extend to robotics platforms with limited computing power and resources. However, because the transmission and reception of time-encoded data involves only a small number of spikes, there exists the potential for creating SNN-based platforms that are both fast and efficient. For instance, research has shown that humans are capable of analyzing and categorizing visual patterns in as little as 100 milliseconds, a process that involves only ten synapses starting with the retina until the parietal lobe (Thorpe *et al.*, 2001). Conversely, when considering energy efficiency, sustaining the proper function of the neural system for executing different activities necessitates a constant supply of power. From this angle, the human brain requires a mere 20 watts of electricity (Drubach, 2000).

SNNs have been demonstrated through experiments to be capable of effectively processing information by utilizing a comparatively limited number of pulses to facilitate weight adjustment and control flows (Uleru *et al.*, 2023). In addition, the SNN surpasses other ANNs that do not utilize temporal data, as the precise timing of events generated by spike synchronization offers accurate and precise temporal information. As an illustration, consider the auditory system of a barn owl that is able to precisely pinpoint noise sources on a flat surface with a remarkable accuracy of one to two degrees. This means that there is only a tiny time interval of 5 microseconds between the instances when audio vibrations reach its both ears (Gerstner *et al.*, 1999).

SNNs uses a pulse coding mechanism to incorporate temporal data that may have been wasted when abstracting pulse frequencies their average. This quality is essential for both organic and synthetic entities seeking to operate in a changing time-based scenarios and environments. Neurobiologists have studied the processing of stimulus encoding using the weakly electric fish as a model (Gabbiani *et al.*, 1996). It was discovered that pyramidal cells don't precisely communicate the timing of a stimulus, but they consistently capture the oscillations of sporadic variations in spike bursts. Furthermore, effectively integrating diverse sensor information in an assembly, a challenge referred to as dynamic association, remains a complex task in neural networks. SNN has the ability to efficiently identify relationships between basic units across a large input grid in a manner that is both efficient and independent of position (tasks related to data classification and image recognition).

The focus of SNN research centers around three main areas: modeling, training, and implementation. Fig. 8 illustrates the typical design pattern for managing bio-inspired robots. Generally, achieving autonomy in robot control involves a three-stage cycle of perception, decision-making and execution. In general, robots rely on translators and motors to detect and interfere with their surroundings. Nevertheless, the SNN can serve as a decision-making center, connecting input interpretation and action, by receiving data from the sensors and translating it into motor commands for the robot. To be precise, the SNN's architecture model needs to be established, encompassing neurons and synapses. The neuron functions as a signaling unit in the nervous system, while the synapse acts as a conduit for communication signals between neurons. To initialize and train a SNN, specific parameters and learning rules must be established, similar to traditional ANNs. The selection of an appropriate learning rule significantly influences network performance, with the Hebbian rule being the most commonly used for SNNs (Uleru *et al.*, 2022b). Following training, SNNs undergo validation in different scenarios and are optimized if necessary.

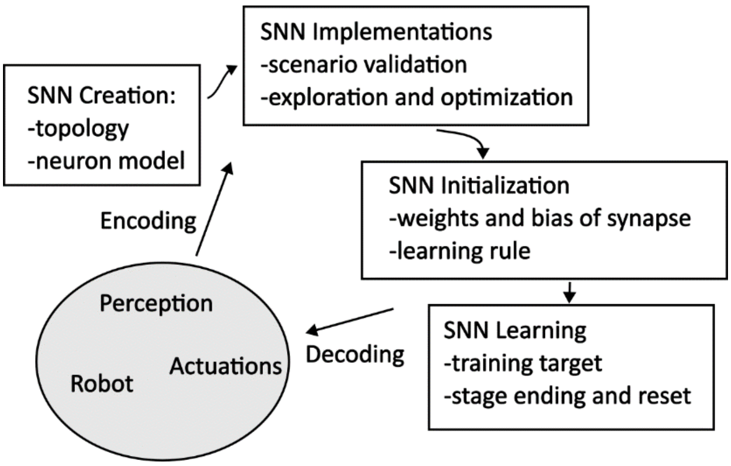

Fig. 8 – A framework for designing robot control systems inspired by learning.

In summary, the unique characteristics of SNNs make them well-suited for the advancement of autonomous robots. However, their potential has yet to be fully realized due to limited practical application, as research on SNNs has mostly been focused on theory. Nonetheless, the increasing knowledge and popularity of SNNs continue to attract researchers and drive the development of new applications based on this technology.

5. SNN simulation, and exploration

Advancements in neuroscience and the chip industry have led to the rapid development of large-scale, polymorphic neural hardware that utilizes spike neural networks. The goal of these studies is to replicate the speed and energy efficiency of animal brains, achieving the same level of capability through innovative hardware designs. For example, SpiNNaker (Furber *et al.*, 2013) is a platform with a million cores for real-time simulating of increased-size SNNs. TruthNorth (Merolla *et al.*, 2014) consumes less than 100 mW and contains 1 million programmable pulse-basedneurons. Other polymorphic neural computing platforms are Neural Grid (Benjamin *et al.*, 2014) and NeuroFlow (Cheung *et al.*, 2016). At the same time, a growing number of interactive models have been researched to support robotics development, like Gazebo (Koenig and Howard, 2004) and VRep (Rohmer *et al.*, 2013). The use of simulators significantly simplifies research tasks pertaining simulation and modeling ofsensors, mechanical systems, and architectural control flow.

iSpike is an early attempt to integrate SNNs with robots, accomplished through a C library that interfaces between an SNN simulator and the iCub robotic humanoid. This library utilizes a bioinspired strategy that transforms sensory data from the robot into spikes, which are then provided as input to a neural network simulator. The network's resultant pulses are translated into motor commands that the robot is controlled by (Gamez *et al.*, 2012). Brian is also another neural simulator (Goodman and Brette, 2009). AnimatLab is a generalized system designed to manage simulated robotics platforms. It offers a range of capabilities, including control modeling for robots and plugins that enable the importation of input-output models (Cofer *et al.*, 2010).

The HBP Neural Platform (NRP) was recently released in its initial iteration (Falotico *et al*., 2017). It was created as part of the EU Human Brain Flagship Program. Scientists now have an all-in-one toolchain at their disposal, allowing them to connect bespoke and pre-existing brain models with finely detailed simulations of the robot's surroundings and physical attributes during small-scale experiments. This integrated system provides a new level of capability for researchers in the field.

Current machine learning algorithms are not equipped to perform general learning for any task in the same manner as Backpropagation and its variants can achieve for ANNs. As a result, there is no universal design framework that can provide both modeling and training capabilities. Forming these types of networks is particularly challenging, particularly when dealing with deep network architectures. One obstacle faced by scientists working with SNN is the discrepancy between the simple brain models used for robot control and the highly complex models developed by neuroscientists. The detailed models are difficult to integrate into real-world applications due to their complexity, and there is a need to learn how to map these networks to robots operating in dynamic and sensory-rich environments. To get beyond this obstacle, a full collection of tools that allow neuroscientists and roboticists to design large computational models of neural networks, high-fidelity setups, and virtual robot models must be made available.

6. Conclusions

In this paper, we provide the readers with an analysis of the previous work on SNN-based robotic control and regulating systems, related training and modeling approaches and provide inspiration for researchers. By imitating the basic mechanics of the brain in a much more realistic way, spiking neural networks have shown significant potential for developing sophisticated robotic intelligence in terms of speed and computing power. We present the biological evidence of SNNs and their main driving force in their application to the field of early robotics. Next, we present common modeling approaches to SNN design in terms of neurons, synapses, and networks. SNN learning solutions are often divided into two categories centered on Hebbian rules and reinforcement learning. Finally, some popular SNN simulation platforms or interfaces for robotics are briefly presented. The greatest barrier for SNN-based control tasks is the absence of an approach for storage in analogue hardware of the synaptic weights that can be modified in real time following biological plausible learning rules. Therefore, more knowledge and interaction in the fields of robot control, nanomaterials science, and neuroscience are required to continue investigating this area of study.

Acknowledgements. The Doctoral School of TUIASI provided support for this study.

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SCURT STUDIU AL DEZVOLTĂRII ȘI AL APLICAȚIILOR BAZATE PE REȚELE NEURONALE CU IMPULSURI, DE INSPIRAȚIE BIOLOGICĂ

(Rezumat)

Rețelele neuronale cu impulsuri (Spiking neural network – SNN) sunt inspirate din modelul computațional natural, modelând cu mare acuratețe interacțiunile și procesele dintre sinapsele neuronilor, axându-se pe timp scurt de răspuns și eficiență energetică. Această nouă paradigmă bazată pe procesarea evenimentelor deschide noi oportunități pentru descoperirea de aplicații și dezvoltarea de metode de învățare care să pună în evidență avantajele SNN cum ar fi capacitatea de memorare și adaptarea rapidă, păstrând în același timp ușurința folosirii și portabilitatea arhitecturilor de calcul convenționale. În această lucrare, facem o scurtă trecere în revistă a progresului cercetării în domeniul SNN din ultimele decenii. Lucrarea începe cu o scurtă istorie a SNN și prezintă principalele modele de neuroni bazați pe impulsuri și metodele de implementare a conexiunilor dintre sinapse, urmate de avantajele și dezavantajele computaționale ale SNN. De asemenea, se prezintă o clasificare a SNN în funcție de metodele de învățare implementate. Sunt prezentate domenii de aplicații potrivite din punct de vedere energetic și ca timp de răspuns pentru utilizarea SNN și se enumeră câteva dintre platformele de simulare și bibliotecile utile pentru explorarea SNN în medii virtuale. Lucrarea se încheie cu concluzii ce prezintă predicții despre viitoarele provocări și arii de cercetare asociate cu SNN.