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Evolution of spiking neural networks

TALANOV Max^{1,2}, FEDOROVA Alina³, KIPELKIN Ivan⁴, VALLVERDU Jordi⁵, EROKHIN Victor⁶

(1.Engineering Department, University of Messina, Messina, Italy;

2.Institute for Artificial Intelligence R&D of Serbia, Belgrade, Serbia;

3.Kazan Federal University, ITIS, Kazan 420008, Russia;

4.Lobachevsky State University, StoLab, Nizhny Novgorod 603022, Russia;

5.ICREA, Philosophy Department, UAB, Catalonia, Spain;

6.Institute of Materials for Electronics and Magnetism, Italian National Research Council (IMEM-CNR), Parma 43124, Italy)

Abstract: Spiking neural networks (SNNs) represent a biologically-inspired computational framework that bridges neuroscience and artificial intelligence, offering unique advantages in temporal data processing, energy efficiency, and real-time decision-making. This paper explores the evolution of SNN technologies, emphasizing their integration with advanced learning mechanisms such as spike-timing-dependent plasticity (STDP) and hybridization with deep learning architectures. Leveraging memristors as nanoscale synaptic devices, we demonstrate significant enhancements in energy efficiency, adaptability, and scalability, addressing key challenges in neuromorphic computing. Through phase portraits and nonlinear dynamics analysis, we validate the system's stability and robustness under diverse workloads. These advancements position SNNs as a transformative technology for applications in robotics, IoT, and adaptive low-power AI systems, paving the way for future innovations in neuromorphic hardware and hybrid learning paradigms.

Key words: spiking neural networks; memristor; phase portraits; energy-efficient AI; neuromorphic computing

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1 Introduction

The development of spiking neural networks (SNNs) has been a journey through decades of interdisciplinary research, marked by significant milestones in computational neuroscience and neuromorphic engineering. From their foundational roots in bio-plausible neuron modeling to their modern applications in hybrid AI systems, SNNs have continuously evolved to bridge the gap between biological inspiration and computational efficiency.

1.1 A historical introduction

The journey began in 1952—1965, with the introduction of foundational neuron models such as the Hodgkin-Huxley model, the FitzHugh-Nagumo model, and the Leaky Integrate-and-Fire (LIF) model. The Hodgkin-Huxley model was pivotal as the first mathematical description of a neuron's ionic action potentials, providing a bio-realistic framework that later informed simplified models like FitzHugh-Nagumo for computational feasibility^[1-2]. These models became the cornerstone of computational neuroscience, enabling

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Biography: TALANOV Max, doctor, specializing in: neuroscience and artificial intelligence. Email: max.talanov@gmail.com

initial explorations into neuronal dynamics. By the **1980s—1990s**, advancements in neuromorphic hardware and the discovery of spike-timing-dependent plasticity (STDP) added new dimensions to SNNs. Carver Mead's early analog neuromorphic circuits were transformative, introducing hardware architectures inspired by biological neurons^[3]. Concurrently, STDP emerged as a synaptic learning rule, demonstrating that synaptic strength could be modified based on the precise timing of spikes, thereby aligning spiking models more closely with observed biological learning mechanisms^[4]. Concurrently, the development of memristors — a class of nanoscale, non-volatile memory devices — introduced hardware capable of emulating synaptic plasticity, such as long-term potentiation and depression, with high energy efficiency.

The **2000s** saw a shift toward computational efficiency, highlighted by Eugene Izhikevich's neuron model, which combined low computational cost with the ability to replicate a wide range of spiking behaviours^[5]. This era also witnessed the formalization of spike-based learning algorithms, such as STDP-based reinforcement models and supervised learning paradigms, which further expanded the potential applications of SNNs in robotics and sensory processing. Memristors gained traction during this period as essential components for implementing synaptic behavior in neuromorphic systems. Their ability to store and adapt weights dynamically made them ideal for real-time learning, as seen in STDP-based applications.

From the **2010s to the present**, SNNs have matured with efforts toward standardization and integration into practical applications. Frameworks like NEST and Brian, and NEURON^[6] have provided accessible tools for simulating spiking dynamics, while neuromorphic hardware like IBM's TrueNorth and SpiNNaker made large-scale implementations possible^[7-8]. More recently, hybrid AI models incorporating SNNs into deep learning architectures have enabled novel solutions in edge computing, adaptive systems, and low-power AI applications. Memristors have further

enhanced these systems by enabling energy-efficient, high-density synaptic matrices, particularly in edge computing devices. Despite their promise, memristor-based systems face challenges such as variability and training complexity. However, ongoing advancements in in-memory computation and probabilistic programming are addressing these limitations, making memristors a cornerstone technology in the evolution of SNNs. This progression underscores the dynamic interplay between theoretical advancements and technological innovations, marking SNNs as a field with deep historical roots and promising future directions.

The above technological steps of development can be summarized as the following.

1952—1965: Foundational neuron models (Hodgkin-Huxley, FitzHugh-Nagumo, LIF).

1980s—1990s: Emergence of neuromorphic hardware and STDP.

2000s: Computationally efficient models (Izhikevich) and spike-based learning algorithms.

2010s—Present: Standardization, hybrid AI-SNN models, and practical applications.

A historical detailed evolution of these technologies can be seen from Table 1.

Therefore, we can see that the technological evolution of spiking neural networks (SNNs) highlights a balance between biological inspiration and computational efficiency. Early models prioritized bio-plausibility, as exemplified by the Hodgkin-Huxley model, while later advancements like the FitzHugh-Nagumo^[2,9] and Izhikevich models^[10] focused on scalability and computational simplicity. These foundational developments enabled the exploration of neuronal dynamics and laid the groundwork for real-world applications. The emergence of neuromorphic hardware^[11], such as IBM's TrueNorth and SpiNNaker, underscores the drive for energy-efficient computing, while standardized frameworks like NEST and Brian have accelerated research and collaboration. Memristors, as a breakthrough hardware innovation, have further enhanced this progress by

Table 1 History and applications of spiking neural networks (SNNs)

Year	Milestone/Model/ Technology	Description	Real models/Applications
1952	Hodgkin-Huxley Model	First bio-plausible neuron model describing ionic mechanisms of action potentials	Basis for biological neuron models; used in neuroscientific research and computational biology
1961— 1962	FitzHugh-Nagumo Model	Simplified Hodgkin-Huxley model with reduced computational complexity	Used in neural simulations requiring basic excitability models
1965	Leaky Integrate-and-Fire (LIF) Model	Abstraction of neurons as threshold-based mechanisms.	Widely applied in theoretical SNN studies, such as in sensory processing and population coding
1986	Spike Response Model (SRM)	Extension of LIF with precise spike timing	Models for event-driven spike simulations, such as in olfactory and visual neural processing systems
1980s	Analog Neuromorphic Circuits	Early neuromorphic hardware by Carver Mead	Hardware prototypes for analog neural network simulations
1997— 1998	Spike-Timing-Dependent Plasticity (STDP)	Discovered plasticity mechanism based on spike timing	Used in learning systems for robotics, such as adaptive motor control
2003	Izhikevich Model	Computationally efficient model with rich spiking dynamics	Applied in models of large-scale brain networks simulating cognitive processes and epilepsy studies
2011	IBM's TrueNorth	Neuromorphic hardware mimicking spiking neural networks	Deployed for real-time image recognition, anomaly detection, and low-power AI applications
2014	SpiNNaker	Large-scale SNN simulation hardware	Used for simulating entire cortical models and brain-inspired computing systems
2000s— 2020s	Spike-Based Learning Algorithms (e.g., STDP, ReSuMe)	Learning algorithms for spiking networks	Applied in robotics (e.g., reinforcement learning), pattern recognition, and sensory integration
2010s	SNN Simulation Frameworks (NEST, Brian, BindsNET)	Open-source tools for simulating SNNs	Used for research in brain modelling, neural dynamics, and hybrid deep-spiking networks
2020s	Spike-Based Edge Computing	Application of SNNs for energy-efficient real-time systems	Real-time applications in IoT devices, neuromorphic sensors, and low-power edge AI (e.g., drones)

enabling nanoscale, non-volatile memory devices capable of mimicking synaptic plasticity with high energy efficiency^[12]. Their role in neuromorphic systems allows real-time learning mechanisms like spike-timing-dependent plasticity (STDP) to be implemented effectively, making them crucial for large-scale, energy-efficient SNN architectures, particularly in edge computing and IoT applications.

SNNs have increasingly integrated advanced

learning mechanisms, such as STDP, and hybridized with deep learning, expanding their applicability to temporal data processing, robotics, and real-time decision-making^[13]. Furthermore, memristors play a pivotal role in hybrid neuromorphic architectures, enabling dense synaptic matrices and advancing cognitive applications in fields like robotics and sensory systems. These developments contribute not only to practical applications but also to neuroscience, enabling

insights into brain functions and disorders. Despite challenges in scaling, training, and hardware integration, SNNs and their associated technologies, such as memristors, show great promise for addressing modern computational demands. By bridging biological principles with cutting-edge AI applications, SNNs are poised to advance both artificial intelligence and cognitive science, marking a transformative evolution in computing technologies.

1.2 Advanced theoretical perspectives on SNN dynamics in memristive and hybrid systems

The dynamics of spiking neural networks (SNNs) depend heavily on the interplay between neuron models, synaptic mechanisms, and external stimuli. Memristive systems, as nanoscale devices mimicking synaptic plasticity, introduce unique dynamical properties into SNNs. These include nonlinear voltage-current relationships, history-dependent behavior, and energy-efficient state retention, which collectively enhance the emulation of biological synaptic functions^[14]. One of the critical theoretical aspects of SNNs in memristive systems is the role of spike-timing-dependent plasticity (STDP). Memristors enable STDP-like behavior by adjusting their conductance based on the temporal alignment of input spikes, thereby capturing the essence of biological learning^[15]. This dynamic coupling between neurons through memristive synapses facilitates the emergence of self-organizing patterns, oscillatory behaviors, and stable attractors, essential for temporal and spatial data processing^[16]. Hybrid learning systems, combining SNNs with traditional deep learning architectures, further expand the theoretical landscape. By leveraging the event-driven nature of SNNs alongside the hierarchical feature extraction capabilities of deep networks, these hybrid systems can address temporal tasks with unprecedented efficiency^[17]. The introduction of memristors into such architectures provides an additional layer of adaptability, allowing on-chip learning and reduced energy consumption^[18]. Theoretical models exploring these hybrid systems focus on the co-evolution of spiking and non-spiking

components, emphasizing phase synchronization, information encoding efficiency, and resilience to noise. Nonlinear dynamics play a pivotal role in understanding the stability and transition phenomena within these systems, such as the formation of stable limit cycles in recurrent architectures and phase-locking in coupled oscillatory networks^[16].

Future research should focus on refining these theoretical models, particularly in scaling memristive hybrid systems for real-world applications. This involves addressing challenges such as variability in memristor behavior, optimizing spike-coding schemes, and integrating neuromorphic and conventional hardware into cohesive frameworks.

2 Experimental methodology

2.1 Basic workflow

The workflow involves optimizing Spiking Neural Networks (SNNs) by transitioning from a bio-plausible model to real-time simulation and eventually to memristive device implementation. The key steps include: (1) **Development of Phase Portraits**: Starting with transient results from the bio-plausible SNN, phase portraits are created. These serve as validation criteria for the model's dynamics. (2) **Focus on Locomotion Neural Circuits**: Flexor and extensor neurons in the model exhibit alternating, antiphase activity, which mirrors natural locomotion. This pattern ensures efficient and coordinated movement, with the flexor neurons driving forward motion and the extensor neurons contributing to stability and propulsion.

2.2 The methodology

The methodology described in Fig. 1 of the document can be summarized as follows: (1) **Use of Nonlinear Dynamics**: Techniques from nonlinear oscillations and dynamical systems theory validate and analyze patterns, transitions, and attractors in the neuronal interactions between flexor and extensor circuits. (2) **Formation of Stable Limit Cycles**: The analysis identifies repetitive amplitude alternations that

form a stable limit cycle. This self-oscillating mode corresponds to synchronized interactions between the neurons. (3) **Influence of Synaptic Delays:** Synaptic transmission delays, axonal conduction times, and neuronal processing contribute to the dynamics observed, including the formation of limit cycles.

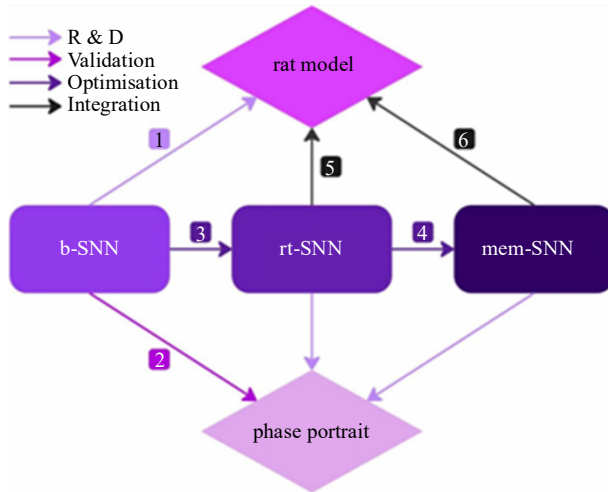


Fig. 1 The workflow of the SNN optimization from the bio-plausible SNN through the real-time to memristive device implementation

This methodological approach combines bio-inspired modelling with computational techniques to achieve validation and insights that guide practical implementations in memristive systems.

We used the transient results of the bio-plausible SNN to develop the phase portrait, which can later serve as validation criteria later. Fig. 2 illustrates the

organization of extensor and flexor modules, including extensor muscles (muscle), flexor muscles (must), extensor motor neurons (M-E), flexor motor neurons (M-F), extensor rhythm generators (RG-E), flexor rhythm generators (Rg-F), skin sensory neurons (cut), a left-right balancing mechanism, and the involvement of the brainstem in modulating and coordinating rhythmic activity. In our model (Fig. 2), flexor and extensor neurons display alternating-phase activity, which is crucial for coordinated locomotion.

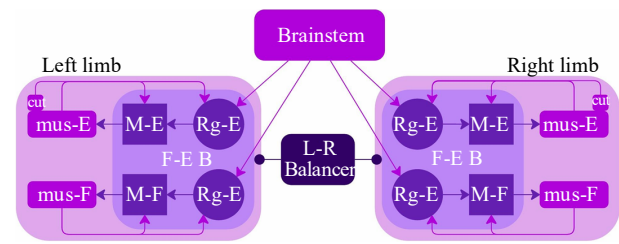


Fig. 2 A schematic diagram of the Central Pattern Generator (CPG) network

Fig. 3 shows the membrane potentials of selected neurons. Fig. 3(a) and 3(b) show the reciprocal firing patterns of flexor and extensor neurons respectively. The simulation spanned a duration of 2 500 ms, with each simulation step lasting 1 200 ms. Within each step, the first 600 ms represented the extensor phase, followed by 600 ms corresponding to the flexor phase. The extensor neurons activate during the extension phase, enhancing joint stability and propulsion, while flexor neurons

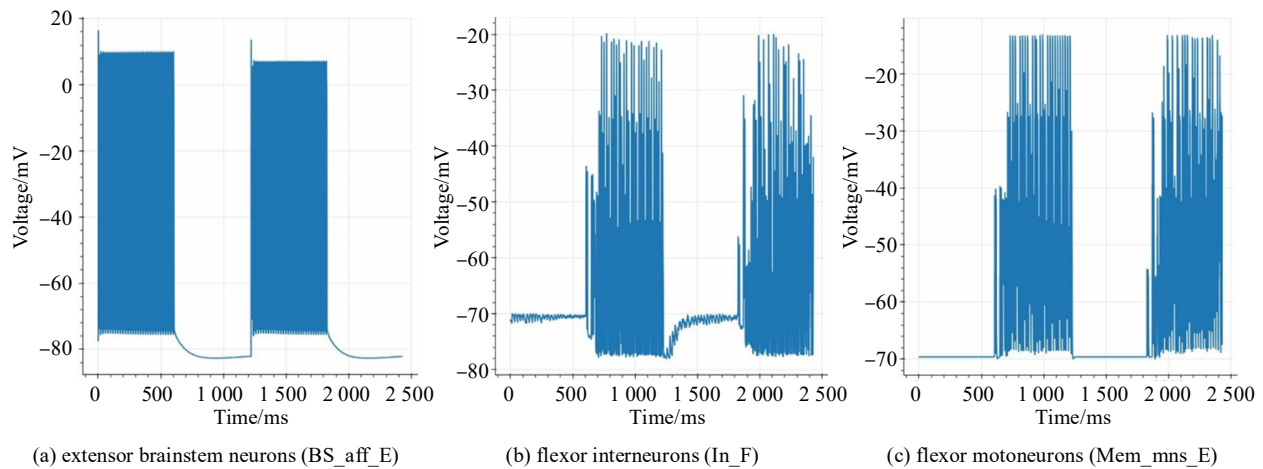


Fig. 3 The average membrane potential measured in millivolts (mV) for three key neuronal types in a simulated spiking neural network (SNN) model of a rat

dominate during the flexion phase, driving limb lifting and forward motion. This alternating activation pattern replicates the natural locomotor rhythm, preventing co-contraction and ensuring smooth, efficient movement, effectively mirroring the physiological behaviour of these neural circuits.

We used methods from the theory of nonlinear oscillations and dynamical systems to validate and identify different patterns, transitional processes, and attractors in our model spinal cord between flexor and extensor muscles. In particular, we constructed phase portraits, which represent the geometric representation of trajectories in two- and three-dimensional parameter spaces (see Fig. 4).

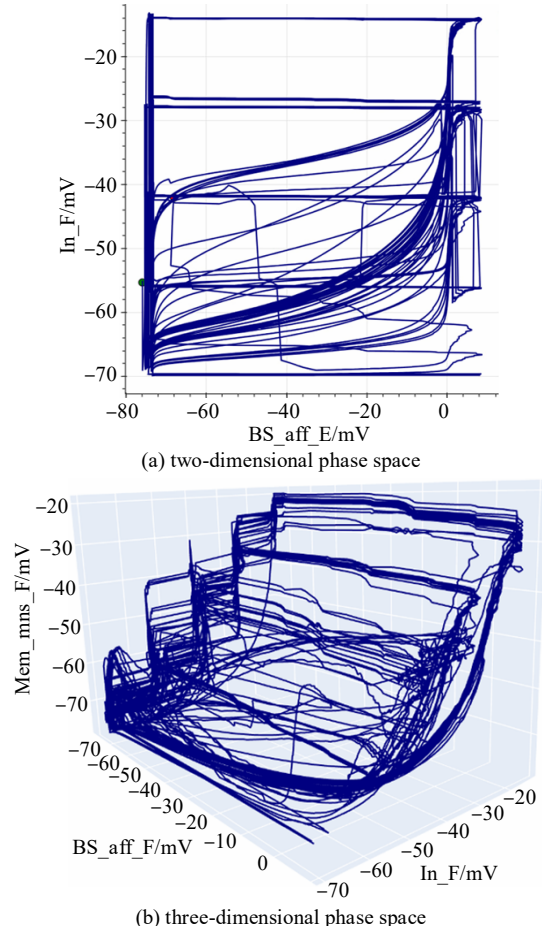


Fig. 4 Phase portraits of the studied system, illustrating changes in the amplitude of neural activity in flexor (F) and extensor (E) muscles

In our study of two- and three-dimensional phase portraits, we identified patterns of activity characterized

by repetitive and continuous amplitude jumps. These jumps smoothly transitioned into a closed, isolated phase trajectory — a stable limit cycle with a negative characteristic exponent. This indicates that any small perturbations or deviations from the cycle will eventually decay, allowing the system to return to its periodic state. Physically, this limit cycle is coarse and corresponds to a self-oscillating mode.

Amplitude jumps arise due to differences in oscillation frequencies, while the limit cycle forms due to synchronous interactions between flexor and extensor muscles. Additionally, the formation is influenced by time delays associated with synaptic transmission, axonal conduction, and neuronal processing.

2.3 Hardware systems with memristive devices

The term “memristor” has been theoretically introduced by Leon Chua in 1971^[19]. According to him, this device is a resistor with memory – the resistance must be a function of the charge, that passed through it. Currently, a term “memristive device” is more often used, because the most of realized elements do not have properties required for ideal memristors.

Over the past 15 years, there has been increasing activity in constructing neuromorphic systems based on memristive devices^[20], mimicking important features of nervous system.

Most of the realized memristive devices have inorganic nature^[21], which is due to the presence of well-established fabrication technologies in the field of microelectronics and easy interfacing with CMOS elements^[22]. However, over the last years organic materials begun to be widely used for the realization of memristor-based neuromorphic systems^[23], which is due to several important properties of these elements, such as low weight, flexibility, processability, low energy consumption, etc.

The first reported organic memristive device was done from polyaniline^[24]. The working area of this device is a contact of the conducting polymer with solid electrolyte, fabricated from lithium salt doped polyethylene oxide. Working principle of the device is

based on the very high ratio of the polyaniline conductivity in oxidized and reduced states. Thus, ON/OFF ratio of the fabricated devices can reach the value of 10^5 [25]. It was shown that the conductivity of these elements is directly proportional to the ionic charge, passed through the device [26].

We do not describe here the fabrication procedure and all characteristics of these device. They can be found in [27]. We will consider here only important properties, related to spiking and neuromorphic systems.

(1) *Oscillators*

The possibility of working in the oscillator mode is very important for the realization of neuromorphic systems [28-29]. In the case of polyaniline based memristive devices the oscillator behavior has also been observed [30]. It was only enough to insert external capacitor or to make one electrode from a material, capable of accumulating ions. In our particular case this material was highly oriented pyrolytic graphite: lithium ions were able to penetrate into the lattice of the material.

(2) *STDP*

Spiking neuromorphic systems must provide the possibility of learning according to STDP. In fact, in nature this learning rule establishes automatically causal relationship between two events: pre- and post-synaptic spikes, which allows unsupervised learning of the system. For this reason, memristive-based circuits were also widely used for the realization of systems allowing STDP learning [31-32]. This possibility has been also demonstrated using polyaniline based memristive devices [33].

In order to demonstrate the possibility of unsupervised learning, based on STDP, a classic example of conditioning (Pavlov dog learning) has been demonstrated [34]. In this case, learning results in the association of initially neutral signal (bell ring) with the presence of food. It is to note that many memristor based circuits have emulated such behavior [35-36]. However, only in [34] the STDP has been applied for the realization of classic conditioning. It was done by

the feedback between output spiking neuron and one of the input neuron, responsible to the sound application. Thus, only in the case of the simultaneous presence of both stimuli (sound and food) the synaptic connection between the sound-related input neuron and salivation related output neuron was increased.

(3) *Synaptic behaviour*

Memristive devices have attracted the attentions of numerous research groups mainly due to the fact that, they can mimic essential properties of synapses [37-38]. Similar features were observed also in polyaniline based memristive devices [39].

However, the direct evidence that the memristive devices (in particular, polyaniline based memristive devices) can be considered as synapse analogs has been demonstrated in [40]. In this work two live neurons from rat cortex, not coupled via biological synapses, were contacted through patch-clamp electrodes. Polyaniline-based memristive device was inserted in a circuit, connecting the output of the patch-clamp electrode of the first nervous cell with the input of the patch-clamp electrode of the second nervous cell. Experimental results have demonstrated the effectiveness of such coupling: when the synaptic strength related to the memristive device conductivity reached an adequate value, the delay between pre- and post-synaptic spikes was found to be 2–3 ms, in the absolute agreement with the situation in nervous systems and brain.

(4) *Neuron Networks*

Synapse mimicking characteristics of memristive devices was the reason for the realization of neuron networks based on them [41-43], including systems based on polyaniline memristive devices [44-45].

During last years the importance of the shifting to spiking algorithms become obvious, resulting in numerous publications related to SNNs, which were based on memristive devices [46-48].

Particular interest in the field of SNNs attracts reservoir computing systems [49-51], as they allow to vary the output parameters not only according to vectors of

input data, but also by taking into account their temporal variations.

Temporally varied signals are applied to arrays of inputs and training of the system can be done by reinforcement or inhibition of weights of the last layer (perceptron) by external action (supervised learning) or by providing adequate feedbacks, guaranteeing the performance of the weights adjustment automatically (unsupervised learning). In both cases the system must contain both volatile (in the reservoir body) and nonvolatile (in the output layer) elements.

Such system has been realized on polyaniline memristive devices^[52-53] for the digit recognition functions. Input signals were analyzed by 3×5 pixels matrix in binary code (with white pixel corresponds to “1” and black one to “0”). The inputs of the system contained 5 terminals, where temporal sequences were applied, according to appearance of white and black pixels in the row. Thus, it was possible to reduce the number of inputs from 15 to 5. It is already a big advantage: we decreased three times the required number of inputs. What seems even more important is that, the volatile nature of polyaniline based devices allows to distinguish rather precisely the temporal sequences, allowing the digit recognition with high fidelity (more than 95%), even considering the possibility of having significant device to device and cycle to cycle variation of parameters..

Despite the fact that this approach has demonstrated a significant capability of image recognition, the used system cannot be strictly considered as a reservoir, because there is no connection between elements in different rows (what is typical for practically all reservoir systems, realized using memristive devices). The only exception, probably, is that made from stochastically organized fibrillar systems, containing polyaniline^[54]. Even if the classification capability in this case was lower than that in previous ones, the approach seems to be very promising, and we will discuss its advantages in the section dedicated to further perspectives.

(5) *Neuro-prostheses*

Previously presented data have demonstrated that memristive devices (in particular, polyaniline-based memristive devices) can mimic essential properties of nervous system. Thus, it was natural to try to use them for the realization of the model systems that are already existing, repairing damaged zones, resulting in limited possibilities of patients.

The damage of the spinal cord, responsible for the walking pathology, was taken into consideration, because the model of the walking pattern generation has already been proposed^[55-56].

The proposed models required the use of very large number of neurons and synapses for the hardware implementation of them. Thus, the idea was to simplify the model for making its possible physical realization.

As a result, the model was super-simplified, requiring the use of only three memristive devices for the reproduction of bio-plausible walking pattern^[57]. It is to note that the use of memristive devices, varying their weights, was absolutely necessary, because a bio-realistic walking pattern appeared only when these weights were adjusted according to the required feedbacks.

(6) *Energy efficiency*

Energy efficiency is one of the key parameters in practically all aspects of the current life of the humankind. A special attention is dedicated to the use of AI search and classification engines, based on software implementations. If the development will go in the same direction, after some years we will need to have a nuclear station near server complexes, responsible for replying all requests of users^[58]. Thus, the breakthrough in this field can be done only through an innovative hardware system. However, as it is demonstrated in [58], traditional CMOS-based systems can provide only partial gain in energy consumption with respect to the software solutions, due to the reason that it is significantly higher, comparing to energy efficiency of the brain.

Instead, the best energy efficiency has been demonstrated for organic systems^[59]. However, the used

geometry does not allow to consider it as a key element, mimicking synaptic behaviour.

Even if polyaniline-based devices are not so energy efficient, scaling on their dimensions to sub-micron dimensions is expected to result in similar energy efficiency.

3 Conclusion and future work

Future advancements in spiking systems will require interdisciplinary collaboration across technology, material science, and computational neuroscience. Among the most promising directions is the development of self-structured 3D stochastic systems, which dynamically form and eliminate signal pathways based on internal activity and training algorithms. These systems can be conceptualized as an “ideal reservoir,” where each element exhibits short-term memory and structural features akin to a newborn brain.

Earlier studies demonstrated the ability of such networks to exhibit both short-term and long-term memory (imprinting) under supervised learning conditions^[60], with theoretical support for unsupervised learning^[61]. However, these efforts, conducted in 2012–2013, relied exclusively on DC mode characterization, leaving the potential of spiking technologies unexplored. By integrating spiking inputs into such systems, future research could unlock their full potential, enabling more adaptive and energy-efficient neuromorphic architectures.

This work establishes a foundation for combining spiking neural networks (SNNs) with memristive devices, addressing critical challenges in neuromorphic computing, including dynamic stability, real-time adaptability, and low power consumption. By leveraging the unique properties of memristors — such as nanoscale density, energy efficiency, and history-dependent learning — this study demonstrates how SNNs can achieve robust performance for tasks involving temporal data processing and real-time decision-making. Phase portrait analyses validated the system’s dynamic

stability, while the theoretical groundwork points toward exciting opportunities for unsupervised and hybrid learning paradigms.

Moving forward, several avenues for exploration emerge. Benchmarking with larger datasets and standardized tasks is crucial for comparative evaluation against state-of-the-art systems. Addressing variability in memristor performance and optimizing hybrid learning frameworks that combine SNNs with deep learning architectures are essential steps toward realizing the full potential of these technologies.

The insights presented here lay the groundwork for advancing fields such as robotics, IoT, and adaptive AI systems, where energy-efficient, brain-inspired computation is in high demand. By bridging the gap between biological principles and cutting-edge neuromorphic technologies, this work contributes to the realization of next-generation spiking systems poised to revolutionize interdisciplinary domains and pave the way for a new era in AI and computational neuroscience.

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脉冲神经网络的发展

TALANOV Max^{1,2}, FEDOROVA Alina³, KIPELKIN Ivan⁴, VALLVERDU Jordi⁵, EROKHIN Victor⁶

(1.梅西纳大学 工程系, 意大利 梅西纳;

2.塞尔维亚人工智能研发研究所, 塞尔维亚 贝尔格莱德;

3.喀山联邦大学 信息技术与智能系统学院, 俄罗斯 喀山 420008;

4.罗巴切夫斯基大学, StoLab, 俄罗斯 下诺夫哥罗德 603022;

5.加泰罗尼亚高等研究院 哲学系, 西班牙 加泰罗尼亚;

6.意大利国家研究委员会(IMEM-CNR)电子与磁性材料研究所, 意大利 帕尔马 43124)

摘要: 脉冲神经网络(SNNs)代表了一种生物启发计算框架, 它将神经科学和人工智能联系在一起, 在时序数据处理、能效和实时决策方面具有独特优势。探讨了 SNN 技术的演化过程, 强调了其与高级学习机制的集成, 如尖峰时间依赖可塑性(STDP)和与深度学习架构的融合。利用忆阻器作为纳米级突触设备, 显著提高了能效、适应性和可扩展性, 解决了神经形态计算中的关键问题。通过相图和非线性动力学分析, 验证了系统在不同工作负载下的稳定性和鲁棒性。这些进步使 SNNs 成为机器人、物联网和自适应低功耗人工智能系统等应用领域的一项变革性技术, 为神经形态硬件和混合学习范式的未来创新铺平了道路。

关键词: 脉冲神经网络; 忆阻器; 相图; 高能效人工智能; 神经形态计算

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