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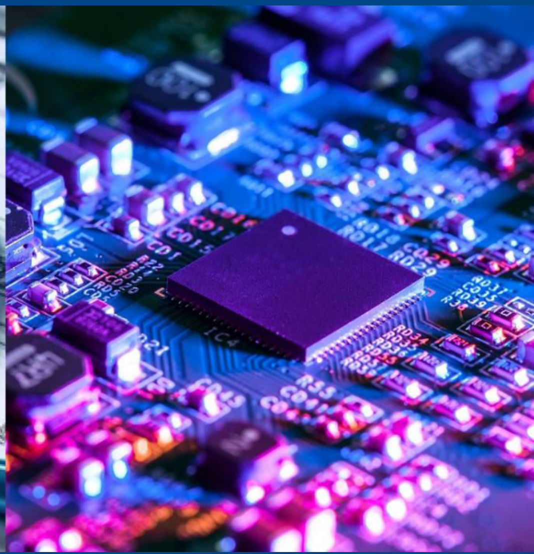

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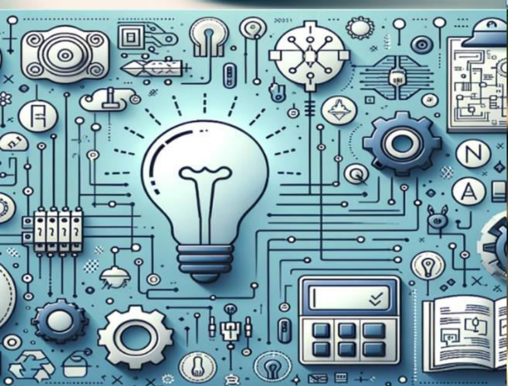

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Neuromorphic Computing & Spiking Neural Networks

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ABSTRACT: Neuromorphic computing is an approach to computing that draws inspiration from the human brain in order to address the limitations of traditional digital systems. It seeks to mimic the way biological neurons process and transmit information. Spiking Neural Networks (SNNs) serve as the core computational model in neuromorphic systems by encoding information using discrete electrical spikes rather than continuous numerical signals. This paper explores neuromorphic computing and SNNs in detail, covering their biological origins, neuron models, learning mechanisms at the synapse level, and supporting hardware platforms. A comparison with conventional artificial neural networks is also presented to demonstrate the advantages of spike-based processing in terms of handling time-dependent data and reducing energy consumption. In addition, this work reviews major application areas, existing technical challenges, and emerging research trends, highlighting the role of neuromorphic intelligence in shaping future computing technologies. Index Terms: Neuromorphic computing, Spiking neural networks, Synaptic learning, Event-based processing, Energy-efficient artificial intelligence

KEYWORDS: Neuromorphic computing, spiking neural networks, Synaptic learning, Event-based processing, Energy-efficient artificial intelligenceIntroduction

I. INTRODUCTION

Most of today's computing systems are built on the von Neumann model, in which the processor and memory are separate units. While this design has been successful for decades, it causes frequent data transfers between memory and the processor, resulting in high energy usage and performance limitations known as the von Neumann bottleneck. In contrast, the human brain can carry out highly complex tasks using only a small amount of power, mainly because it operates through massively parallel and distributed neural networks.

Neuromorphic computing aims to reduce this gap by developing computing systems that follow principles observed in biological neural systems. In these architectures, storage and computation are tightly coupled, and operations occur in response to events rather than under the control of a global clock. Spiking Neural Networks (SNNs) are a specialized type of neural model that imitate the way biological neurons communicate using brief electrical pulses. By incorporating time into their operation, SNNs provide an efficient way to process temporal information. This paper examines the fundamental ideas behind neuromorphic computing and explains how SNNs contribute to the development of low-power intelligent systems.

II. BIOLOGICAL BASIS OF NEURAL COMPUTATION

A typical biological neuron is composed of dendrites that receive incoming signals, a central cell body that processes these signals, and an axon that carries electrical impulses to other neurons. Neurons communicate with one another through short voltage signals called spikes or action potentials. The strength of these connections is controlled by synapses, which can change over time depending on neural activity, enabling learning and adaptation.
The brain represents information in several ways, including how frequently neurons fire, the exact timing of their spikes, and the collective behavior of groups of neurons. These biological coding strategies motivate computational approaches that focus on parallel processing, local storage of information, and adaptive behavior, all of which are essential features of neuromorphic systems.

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III. NEUROMORPHIC COMPUTING FRAMEWORK

A. Concept and Scope

Neuromorphic computing involves the design of both hardware and software systems that imitate the organization and operation of biological neural circuits using electronic devices. Such systems are built from neuron-inspired processing units and synapse-like memory components, allowing them to perform learning and decision-making tasks in a manner similar to natural neural networks.

B. Distinctive Properties

Neuromorphic systems are generally characterized by the following attributes:

- They operate without a centralized clock, relying instead on asynchronous processing.
- Computation is driven by events, meaning that activity occurs only when meaningful signals are present.
- Power consumption is significantly lower compared to conventional digital systems.
- They can continue functioning reliably even in the presence of noise or hardware faults.
- Memory and computation are combined within the same physical structures.

C. Representative Hardware Platforms

A number of neuromorphic processors have been developed to implement these ideas in practice:

- **IBM TrueNorth:** A digital neuromorphic chip designed for ultra-low-power inference tasks.
- **Intel Loihi:** A flexible processor that supports on-chip learning using programmable synaptic plasticity.
- **SpiNNaker:** A massively parallel computing system created for simulating large-scale spiking neural networks.
- **BrainScaleS:** An analog neuromorphic platform intended for fast and efficient modeling of neural dynamics.

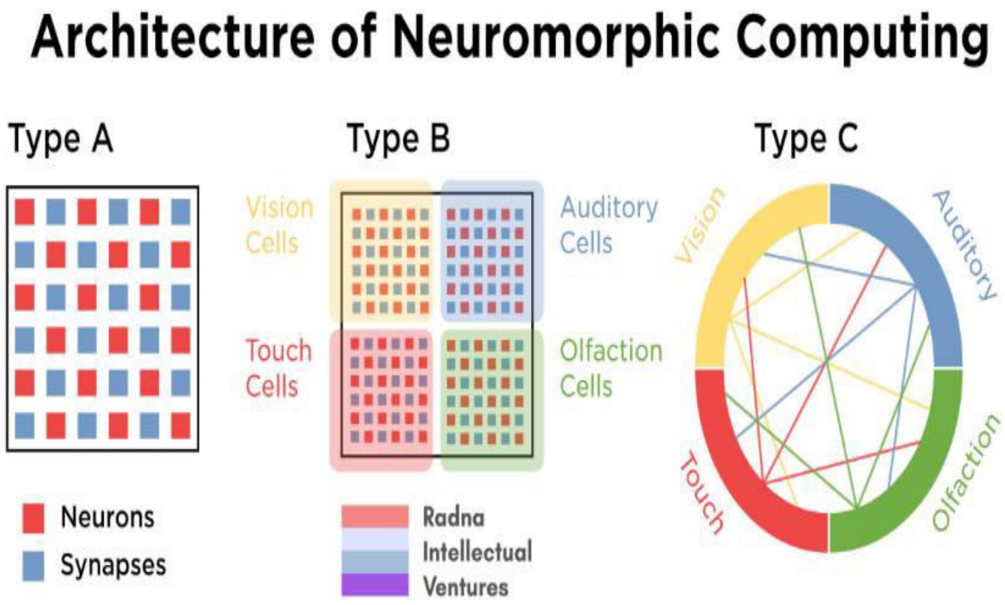

Figure1. Neuromorphic computing architecture (source: medium.com/@radnaventures)

IV. SPIKING NEURAL NETWORK MODELS

A. Neuron Modeling

Leaky Integrate-and-Fire (LIF) Model:

The LIF model explains how a neuron's membrane voltage changes over time in response to incoming current. The voltage gradually increases as inputs arrive and slowly decays due to leakage. When this voltage crosses a predefined threshold, the neuron generates a spike and the voltage is reset to its resting level.

τdV(t)dt=−V(t)+RI(t)\tau \frac{dV(t)}{dt} = -V(t) + RI(t)τdtdV(t)=−V(t)+RI(t)

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Hodgkin–Huxley Model:
This model provides a detailed and biologically accurate description of neuron behavior by modeling the dynamics of ion channels in the cell membrane. Although it closely matches real neural activity, it is computationally expensive and therefore less suitable for large-scale simulations.

Izhikevich Model:
The Izhikevich model offers a balance between realism and efficiency. It is able to reproduce many biological firing patterns while requiring significantly fewer computational resources than the Hodgkin–Huxley model.

B. Spike Encoding Techniques
To enable SNNs to work with real-world data, analog or continuous signals must be converted into sequences of spikes. Several encoding methods are commonly used:

- Rate-based encoding, where information is represented by spike frequency
- Temporal or latency encoding, where information is carried by spike timing
- Population encoding, where groups of neurons jointly represent values
- Event-driven encoding using neuromorphic sensors such as dynamic vision cameras

V. LEARNING MECHANISMS IN SPIKING NETWORKS

A. Spike-Timing Dependent Plasticity (STDP)
STDP is a learning rule inspired by biological synapses in which the strength of a connection changes according to the time difference between spikes of connected neurons. If the presynaptic neuron fires shortly before the postsynaptic neuron, the synaptic weight increases. If the firing order is reversed, the connection weakens.
Δw={A+e−Δt/τ+,when the presynaptic spike precedes the postsynaptic spike−A−eΔt/τ−,when the postsynaptic spike occurs first\Delta w = \begin{cases} A_+ e^{-\Delta t/\tau_+}, & \text{when the presynaptic spike precedes the postsynaptic spike} \\ -A_- e^{\Delta t/\tau_-}, & \text{when the postsynaptic spike occurs first} \end{cases}Δw={A+e−Δt/τ+,−A−eΔt/τ−,when the presynaptic spike precedes the postsynaptic spikewhen the postsynaptic spike occurs first

B. Supervised Training Methods
Supervised learning in spiking networks is achieved by modifying conventional backpropagation techniques so that they work with spike-based signals. This is typically done using surrogate gradient approaches or by unfolding the network over time to allow gradient-based optimization.

C. Reinforcement-Based Learning
In reinforcement learning, spiking networks improve their behavior by combining feedback from the environment with local synaptic updates. Reward signals guide the learning process, enabling the network to acquire control and decision-making capabilities through interaction.

VI. COMPARISON WITH CONVENTIONAL NEURAL NETWORKS

Feature	Artificial Neural Networks	Spiking Neural Networks
Signal type	Continuous numerical values	Discrete spike events
Treatment of time	Implicit or not modeled	Explicitly represented
Energy usage	Comparatively higher	Much lower
Hardware support	CPUs and GPUs	Neuromorphic chips

While SNNs are more energy-efficient and naturally suited for time-dependent data, their training process is generally more complex than that of traditional deep neural networks.

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VII. APPLICATION DOMAINS

Neuromorphic and spiking-based systems have found applications in several fields, including:

- Robotic sensing and motor control
- Event-driven visual perception
- Brain–computer interface technologies
- Medical and physiological signal processing
- Edge computing and Internet of Things devices
- Autonomous vehicle navigation
- Speech recognition and pattern analysis

VIII. CHALLENGES AND LIMITATIONS

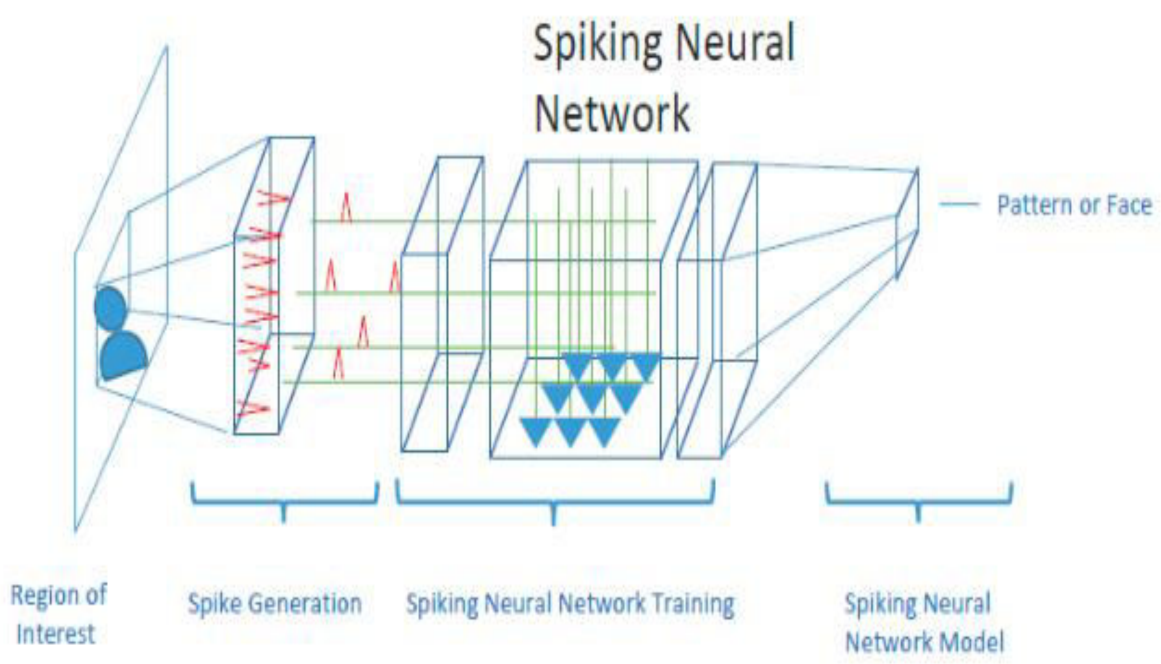
Despite their potential, neuromorphic systems still face important obstacles:

- Efficient and scalable training methods are limited
- Standard evaluation benchmarks are lacking
- Debugging spike-based models is difficult
- Hardware programmability remains constrained
- Performance often trails behind deep learning systems in accuracy

IX. EMERGING RESEARCH TRENDS

Current research efforts are directed toward:

- Hybrid architectures that combine conventional neural networks with spiking models
- Hardware learning based on memristive devices
- Continuous and lifelong learning frameworks
- Event-based visual and auditory sensing technologies
- Attention and memory mechanisms implemented with spiking neurons



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X. CONCLUSION

Neuromorphic computing and spiking neural networks represent an important shift toward brain-inspired artificial intelligence. By modeling computation using spikes and temporal dynamics, these systems offer a promising alternative to conventional neural networks, particularly in scenarios where energy efficiency and real-time processing are critical. Through the use of biologically motivated neuron models, adaptive learning rules, and specialized hardware platforms, neuromorphic systems demonstrate the ability to process information in a more natural and efficient manner.

Although significant progress has been made, several challenges still limit the widespread adoption of this technology. Training spiking networks remains complex, standard evaluation frameworks are still under development, and current implementations often fall short of deep learning models in terms of accuracy. Nevertheless, continuous advances in neuromorphic hardware, learning algorithms, and hybrid network designs indicate strong potential for future growth. As research in this area continues, neuromorphic computing is expected to play a key role in enabling low-power intelligent systems for applications ranging from robotics and healthcare to edge and embedded devices.

REFERENCES

[1] C. Mead, "Neuromorphic electronic systems," Proceedings of the IEEE, vol. 78, no. 10, pp. 1629–1636, 1990.
[2] W. Maass, "Spiking neural networks as a new generation of neural models, " *Neural Networks*, vol.10, no. 9, pp. 1659–1671, 1997.
[3] G. Indiveriand S.-C. Liu,"Memory and information processing in neuromorphic systems," *Proceedings of the IEEE*, vol. 103, no. 8, pp. 1379–1397, 2015.
[4] M. Davies et al., "Loihi: A neuromorphic processor with on-chip learning capabilities," *IEEE Micro*, vol. 38, no. 1, pp. 82–99, 2018.
[5] S. Furber et al.,"The SpiNNaker architecture for large-scale neural simulation," *Proceedings of the IEEE*, vol. 102, no. 5, pp. 652–665, 2014.
[6] E. Chicca, F. Stefanini, C. Bartolozzi, and G. Indiveri, "Neuromorphic circuits for spike-based learning," *Neural Networks*, vol. 23, no. 8–9, pp. 1082–1093, 2010.
[7] Y. LeCun, Y. Bengio, and G. Hinton,"Deep learning methods and architectures," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
[8] Q. Liu, M. van der Zande, and R. A. van Schaik, "Event-driven sensing and processing for neuromorphic vision," IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 11, pp. 4299–4312, 2020.

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