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Spiking neural networks in intelligent control systems: a perspective

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Artificial intelligence (AI) has undergone substantial advancements in recent years, prompting an era of innovation in various domains. Among the groundbreaking contributions, neural networks stand at the forefront, powering applications ranging from computer vision and natural language processing to intelligent control systems [1, 2]. Within the realm of neural networks, a growing subset has drawn considerable attention, namely, spiking neural networks (SNNs). Unlike other types of neural networks that process information continuously, SNNs incorporate the concept of time directly into their functioning, using discrete events called spikes to communicate and process information [3]. These spikes are binary events that occur at specific points, analogous to the electrical impulses used by neurons in the brain. SNNs are designed to simulate the dynamic processes of learning and information processing as observed in biological systems, making them particularly suitable for tasks that involve temporal patterns and sensory data derived from the real world. As computing power has increased, so has interest in SNNs, owing to their potential for greater computational efficiency and their capacity to model complex, time-dependent problems. These computationally potent models are known to closely mimic the functioning of the human brain; elements such as the neuron's membrane potential, resistance, and reset potential, and factors such as neuron communication through spikes, are all simulated within SNNs (see Figures 1(a) and (b)), attracting the curiosity of researchers and engineers alike [4]. Intelligent control systems have begun employing this technology for its potential to provide real-time decisions, reduced energy consumption, and enhanced adaptability compared to conventional artificial neural networks (ANNs) [5].

Advantages of SNNs compared to conventional artificial neural networks. (1) Biologically-inspired architecture: SNNs closely emulate the operation of biological neurons through their use of spikes as a means of communication and signal processing, whereas traditional neural network models rely on continuous value-based activations [6]. This remarkable similarity allows for the seamless translation of neuroscience insights to the computational domain, fostering rapid advancements in replicating complex cognitive tasks. (2) Energy efficiency: SNNs reduce energy consumption significantly through their event-driven and spike-based information processing, making them particularly well-suited for those applications requiring low-power consumption [7]. (3) Temporal dynamics: SNNs natural propensity for handling spatiotemporal data allows them to process time-based signals efficiently [8]. This inherent support for temporal information processing gives SNNs the edge over conventional networks and deep learning methods in dynamic applications, such as that in unmanned aerial vehicle control [9]. (4) Robustness and fault tolerance: The distributed and localized nature of information processing in SNNs makes them more resistant to failure and noise than traditional neural network models [10].

Role of SNNs in intelligent control systems. SNN incorporation into control systems has led to significant advancements in areas such as real-time control, natural sensor data processing, fault tolerance, and learning from the environment. The application process can be seen in Figure 1(c). Each of these areas confirms the superiority of SNNs over traditional methods, which we will explore indepth.

(1) Real-time control: The biological plausibility of SNNs can be traced back to their time-critical, event-triggered communication style, mirroring that of neurons in the brain. Events are processed as individual spikes, enabling swift responses. Real-time applications, such as controlling autonomous vehicles and industrial automation systems, benefit greatly from these quick response times [11]. An exploration into the usage of SNNs in real-time control systems, for example, confirmed the suitability of SNNs for providing decisions in real-time [12].

(2) Natural sensor data processing: Unlike other types of neural networks, SNNs can naturally process sensor data as "spikes". These spikes can encode different sensor modalities such as visual, infrared, ultrasonic, tactile, and even auditory data. Neuromorphic sensors, when coupled with SNNs, can boost power efficiency and processing speed [13].

(3) Fault tolerance: SNNs have high fault tolerance due to their fundamentally distributed computative approach. If part of the system suffers damage, this does not affect the functioning of the entire system. This feature is of immense value in industries where system failure can have disastrous consequences, such as nuclear control systems [14].

(4) Learning from the environment: One of the crucial aspects highlighting the importance of SNNs in control sys-

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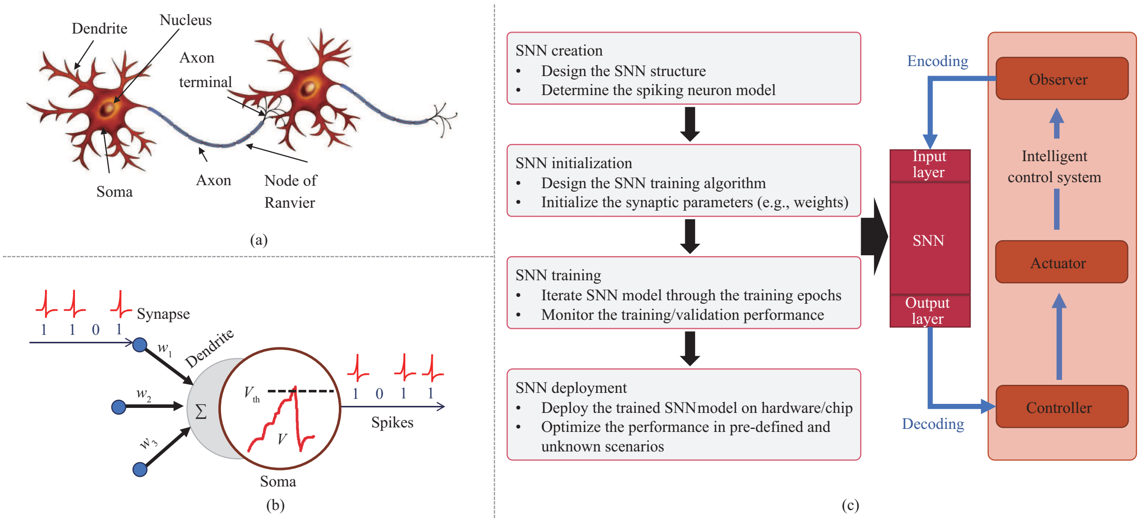

Figure 1 (Color online) Spiking neurons are modeled mathematically, drawing inspiration from the structure and operating principles of biological neurons, and are consequently constructed into SNNs for use in intelligent control systems. (a) Structural composition and connections of biological neurons; (b) spiking neuron model; (c) the application process of SNN in intelligent control systems.

tems is their ability to adapt by learning from the environment. Synaptic plasticity mechanisms, such as spike-timing-dependent plasticity (STDP) [15], intrinsic plasticity [16], and threshold plasticity [17], that alter the connection strength between neurons based on the timing of spikes or alter the neuronal intrinsic state have showcased the adaptation capabilities of SNNs.

Applications. As studies continue, more extensive applications of SNNs in control systems are bound to emerge, bringing us closer to creating real-time and self-adaptive intelligent control systems. Here, we list some typical applications to show SNNs' potential in this field.

(1) Robotics: In robotics, SNNs can mimic neurobiological processes to improve the interaction between robotic systems and their environments. For example, robotic arms in manufacturing can use SNNs to process sensory information (such as touch, pressure, and vision) to perform tasks with greater precision and adaptability. In humanoid robots, SNNs could be used to manage bipedal locomotion, allowing smoother and more natural movements by mimicking the way animals control their muscles.

(2) Autonomous vehicles: Autonomous vehicles rely heavily on sensor fusion and decision-making algorithms. SNNs can provide a framework where information from LIDAR, radar, cameras, and ultrasonic sensors is processed in an energy-efficient manner, thereby enabling the vehicle to react to driving conditions in real time. The event-driven nature of SNNs would be particularly valuable in emergency scenarios requiring quick reflexes and decisions, such as in avoiding sudden obstacles.

(3) Prosthetics control: Advanced prosthetic limbs aim to restore the functionality of the missing limb. SNNs could improve the interface between amputees' neural signals and their prosthetic devices, enhancing real-time interpretation of neural activity for seamless prosthetic control. The temporal resolution of SNNs makes them ideal for decoding the spike trains that represent neural commands from the user to the prosthesis.

(4) Drones and aerial vehicles: SNNs have the potential to process data from inertial measurement units, GPS, and onboard cameras to control the flight of drones precisely. Their efficiency in processing temporal data could help in managing the real-time dynamics of flight patterns, enabling drones to navigate complex environments autonomously and react promptly to changes.

(5) Biomedical engineering: SNNs hold promise for enhancing brain-machine interfaces. This could empower individuals with motor impairments to control external devices directly with their neural activity. Precise decoding of spiking activity from the brain could allow for the smooth operation of wheelchairs, computers, and other assistive technologies.

Benefits of SNNs in control systems. Intelligent control systems stand to reap numerous benefits from incorporating SNNs, including the following.

(1) Real-time decision-making: SNNs' low-latency and rapid information processing capabilities can help generate real-time control decisions in dynamic environments, found to be essential in applications such as autonomous vehicles and robotics [18].

(2) Adaptability and learning: SNNs can learn from and adapt to evolving scenarios, enabling the salient control systems to be resilient and self-tuning [8]. This adaptability also aids in addressing unforeseen circumstances and changes in the control environment.

(3) Efficient use of resources: The energy-efficient nature of SNNs reduces power consumption, making them viable for power-critical control systems like remote monitoring stations or energy-harvesting driven systems [7].

(4) Enhanced handling of sensory data: Due to their advantageous temporal dynamics, SNNs can process multimodal sensory data effectively in real-time, providing improved decision-making capabilities in control systems with sensor fusion requirements [8].

SNNs offer several compelling advantages over conventional neural networks and other deep learning methods, particularly in the context of intelligent control systems. These advanced computational models have the potential to revolutionize the way we approach the design and implementation of intelligent control systems, shaping the future of AI-driven applications.

Challenges and perspective. For each of the control applications, the specific architecture and learning rules of the SNN are tailored to the temporal and spatial aspects of the control task at hand. While SNNs offer compelling advantages, such as high temporal resolution and potential energy efficiency, there are significant challenges to be overcome, particularly in terms of training complexity and hardware compatibility. The integration and optimization of SNNs into intelligent control systems present an interesting blend of challenges and future opportunities.

(1) Training and adaptation: SNNs face a steep curve in training complexity due to their temporal spike-based nature. However, there is an opportunity for the development of novel learning algorithms and training methods tailored specifically to their unique dynamics. Progress in this area could enable SNNs to learn and adapt with higher efficiency compared to conventional neural networks, particularly in time-sensitive control tasks.

(2) Standardization and benchmarks: The current landscape lacks standard models and practices for SNNs, which presents a challenge for establishing reproducibility and comparison. Nevertheless, this also presents an opportunity for the research community to set benchmarks and best practices, which could ultimately facilitate wider adoption and better performance evaluation in control systems.

(3) Computational demands and hardware synergy: Simulating SNNs is computation-intensive due to the need to track discrete events over time. Pioneering work in neuromorphic engineering, which aims to develop hardware that imitates neural architectures, holds great promise to mitigate this challenge by providing a more natural and efficient substrate for running SNNs.

(4) Real-time processing: The necessity for real-time decision-making in control systems calls for fast, reliable SNN operation. This represents an opportunity to explore the design of spiking neural architectures that can excel in real-time environments, exploiting the intrinsic temporal processing capabilities of SNNs.

(5) Energy-efficient control: One of the most notable aspects of SNNs is their potential for low-power operation. This aligns perfectly with the growing demand for energy efficiency in control systems, especially when it comes to autonomous systems that must routinely operate on limited power budgets.

(6) Interfacing and integration: The assimilation of SNNs into existing control frameworks is not straightforward and brings integration challenges. However, this integration is also a stepping stone toward more sophisticated control systems that leverage the benefits of bio-inspired computation for enhanced adaptability and resilience.

(7) Edge and distributed computing: Spiking neural networks are well-suited for edge computing given their efficiency, which can greatly benefit those distributed control systems that require decentralized decision-making. Advancements here could translate into more responsive and adaptive control networks in sectors such as transportation, energy management, and manufacturing.

Overall, SNNs in the context of control systems represent a frontier where the attendant challenges pave the way for technological innovations. Tackling issues related to learning complexity, standardization, and real-time operation requires a concerted effort from multiple disciplines. However, as neuromorphic technology evolves, it becomes the foundation on which SNNs fulfill their potential, leading to intelligent control systems that are not only power-efficient but also immensely capable of dealing with the dynamism and unpredictability of real-world environments.

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