A Systematic Review of Spiking Neural Networks for Human-Robot Interaction in Rehabilitative Wearable Robotics

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***Abstract*—Recent advancements in spiking neural networks (SNNs) have highlighted their advantages, including energy efficiency, real-time processing, and compatibility with neuromorphic hardware. These features make SNNs particularly well-suited for human-robot interaction (HRI) in rehabilitative wearable robotics, where real-time adaptability and low power consumption are essential. However, there is still a lack of comprehensive reviews on SNNs' application to HRI. This paper addresses this gap by providing a detailed overview of the latest advancements in SNNs from the perspective of embodied intelligence in rehabilitative wearable robots. We systematically examine recent progress in SNNs, including spiking neuron models, encoding methods, and learning mechanisms. These advancements are then analyzed with a focus on HRI, addressing specific challenges in rehabilitative wearable robots from three key perspectives: human motion decoding, robotic control, and neuromorphic implementation for embedded systems. By reviewing current research, this paper highlights the potential benefits and limitations of SNNs in achieving embodied intelligence and identifies crucial areas for further investigation, offering new insights and directions for their future applications in rehabilitative wearable robotics.**

***Index Terms*—Spiking neural network, embodied intelligence, rehabilitative wearable robots, human-robot interaction.**

I. Introduction

RECENT years have witnessed rehabilitative wearable robots, such as exoskeletons [1]–[3], prosthesis [4], [5], supernumerary robotic limbs [6] and etc., being widely recognized for their ability to assist patients with hemiplegia and amputees in performing daily activities and rehabilitation exercises. These robots can adjust training programs [7], facilitate gait reconstruction [8], enhance muscle strength [9], and maintain balance [10]. These personalized approaches significantly improve rehabilitation efficiency, and save the efforts of healthcare professionals [11]. Achieving these benefits requires effective HRI, which involves decoding physiological signals, interpreting movement intentions and developing appropriate control strategies to address the specific needs of rehabilitation tasks [12]. However, current robotics technology struggles to accurately model, predict, and adapt to real-time human movement due to the complexities of the human neuromusculoskeletal system.

With the recent advancement of artificial intelligence, embodied intelligence has emerged as an essential focus, emphasizing the ability of robots to perceive, act, and understand the environment like humans. This sophisticated approach requires robots to autonomously sense, respond and adapt to varying contexts [13], [14]. In rehabilitative wearable robots, embodied intelligence combined with effective HRI enables real-time adjustment of assistance by translating sensory feedback into tailored support for individual users [15], [16]. This significantly enhances rehabilitation outcomes by providing personalized and responsive treatment. Consequently, integrating advanced learning algorithms and adaptive technologies highlights embodied intelligence as a key to advancing wearable robots and improving patient recovery.

In the process of achieving embodied intelligence, artificial neural networks (ANNs) play a crucial role and have achieved significant success in processing physiological data for rehabilitative wearable robots [17]. After decades of development, ANNs still encountered challenges in capturing long-term dependencies and dynamic changes within time-series data, primarily due to fixed network structures and limited ability to manage temporal dependencies. To address these issues, recent research has introduced variants of recurrent neural networks (RNNs) and time-series processing models, including long short-term memory (LSTM) [18], gated recurrent unit (GRU) [19], bidirectional LSTM [20], etc., which are better suited for handling time-series data. Nevertheless, these models still face challenges due to the large volume of floating-point operations required for high temporal resolution which demands significant time and computational resources [21].

SNNs, as computational models closer to biological neural systems, are gradually gaining attention. Unlike ANNs, SNNs process dynamic inputs and time-series data by simulating the pulse-based signal transmission of biological neurons [22]. This pulse-based mechanism allows SNNs to capture the subtle, time-dependent aspects of human movement more accurately, resulting in more precise and responsive control of rehabilitative wearable robots [23]. Meanwhile, the biolog-

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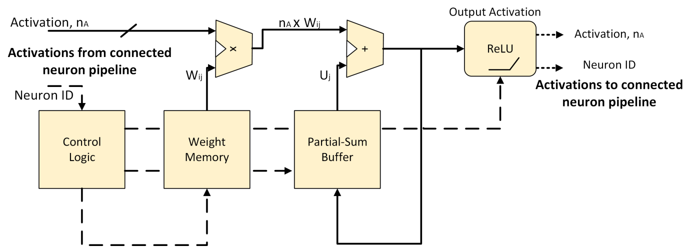
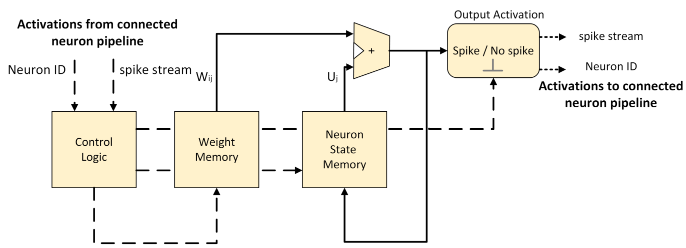


(a) Implementation of ANN



(b) Implementation of SNN

Fig. 1: Digital-hardware implementation of ANN and SNN update pipeline [21].

TABLE I: Power Consumption of Different Methods

Method	Platform	Latency	Power	Ref
ANN	Parallel ultra-low power platform	8.00 ms	1.004×10^4 µW	[29]
	NVIDIA Jetson Nano (Maxwell GPU)	3.80 ms	9.730×10^1 µW	[30]
	ARM Cortex M4	N/A	2.660×10^4 µW	[31]
	Edge TPU	2.96 ms	2.000×10^6 µW	[32]
SNN	DYNAP	N/A	1.190 µW	[33]
	DYNAP	N/A	5.000×10^1 µW	[34]
	Loihi	5.89 ms	1.000 µW	[30]
	SpiNNker	N/A	7.650×10^5 µW	[35]

ical plausibility of SNNs, which model neural dynamics and adapt through local learning rules like spike-timing-dependent plasticity (STDP) [24], enhances the robots' capacity to learn from user interactions and adjust their behaviour in real-time. Furthermore, by using spikes instead of continuous activation, SNNs closely mimic biological neural processes and require fewer multiplication operations in hardware than ANNs, as shown in Fig. 1, thereby reducing power consumption [25]. Table I further highlights the energy efficiency of SNNs over ANNs under similar tasks on neuromorphic hardware, making them ideal for resource-constrained systems [26]. In wearable robotics, some SNN reviews focus on analyzing human electrophysiological signals [27] (e.g., Electroencephalography (EEG), Electromyography (EMG), Electrocardiography (ECG)) or on specific robotic control tasks such as navigation [28], there is a noticeable gap in detailed exploration of HRI specifically for wearable robots.

In this paper, we aim to provide a comprehensive review of the latest advancements in SNNs and their applications in HRI for rehabilitative wearable robots. Our goal is to systematically analyze recent developments in SNN technology, including spiking neuron models, encoding methods, and learning mechanisms. We investigate how these advancements address the specific challenges faced by HRI, such as motion decoding, robotic control, and neuromorphic implementation. Literature was sourced from Google Scholar, IEEE Xplore, Scopus and Web of Science using keywords like SNN or Neuromorphic, HRI, and rehabilitation or rehabilitative wearable robot. Preferred publications were from 2014-2024 with some exceptions. Finally, this review highlights key areas for further research, focusing on how advancements in SNNs can be utilized to improve the effectiveness and usability of rehabilitative wearable robots. Fig. 2 provides a detailed overview of SNN implementation in wearable robotics.

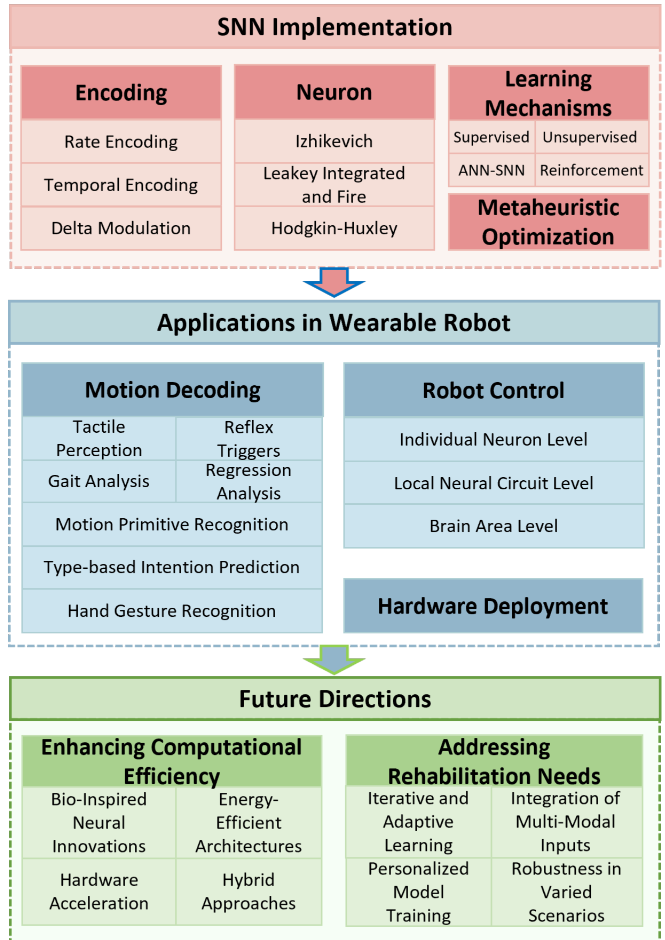


Fig. 2: An overview of SNN implementation and its applications in wearable robots.

II. SNN Models

A. Spiking Neuron Models

For SNN, several spiking neuron models have been developed. Some focus on biologically accurate, such as the Hodgkin-Huxley (HH) model [36], while others emphasize computationally efficient, such as the leaky integrate-and-fire (LIF) model [37], the Izhikevich model [38] and the spike response model (SRM) [39]. These models demonstrate a trade-off between biological accuracy and computational

TABLE II: Neurons in SNN

Neuron	Specific Model	References
LIF	Basic LIF	[26], [40]–[65]
	Improved LIF	[66], [67]
	AdEx	[33], [34], [68], [69]
	DEXAT	[70]
Izhikevich	Basic Izhikevich	[71]–[81]
SRM	Basic SRM	[82]

feasibility. Specifically, the HH model, though biologically accurate, is computationally intensive and rarely used in SNNs for HRI applications. Thus, this review highlights models as shown in Table II.

1) LIF Model and Enhancements: The Integrate-and-Fire (IF) model simply sums input signals until the membrane potential reaches a threshold. The model is enhanced by introducing a leak term, called L, representing the passive decay of the membrane potential toward the resting state. The LIF expressed by Eq. (1) simplifies the neuron model to a circuit-like analogy:

$$\tau \frac{dV(t)}{dt} = -(V(t) - V_{\text{rest}}) + RI(t) \tag{1}$$

$$\text{if } V(t) > \theta, \quad V(t) \leftarrow V_{\text{reset}} \quad last \quad t_{\text{ref}} \tag{2}$$

where τ is the membrane time constant, V_{rest} represents the resting potential, R is the membrane resitance, V_{reset} represents the membrane potential's reset value after firing, and t_{ref} is the refractory period. When the membrane potential reaches threshold potential θ, the neuron initiates a spike event, subsequently resetting the potential to the basic value. LIF's simplicity makes it the preferred choice for large-scale SNNs.

Current research mainly uses the basic LIF model with fixed v_{reset} and θ values which may lead to insufficient neuron firing and information loss. To address this limitation, an improved LIF model [66] introduces a dynamic reset potential mechanism that allows V_{reset} to vary with membrane potential fluctuations. This model significantly improves recognition accuracy, speeds up convergence and reduces information loss. An enhanced LIF model [67] addresses brain-computer interface challenges in wearable robots by dynamically adjusting θ. After each spike, θ increases and then decays back to baseline. This approach not only reduces the spike-firing rate but also improves classification accuracy, suggesting that the system's energy consumption is reduced while maintaining computational efficiency.

To better simulate the excitatory and inhibitory responses of neurons while also accounting for dynamic changes in membrane potential, the Adaptive Exponential Integrate-and-Fire (AdEx) model [83] was proposed. This model can simulate the properties of real neurons, making it highly scalable for practical applications. Moreover, the AdEx model can be deployed on DYNAP neuromorphic chips, facilitating its implementation in hardware. Building on the AdEx model, the Double Exponential Adaptive Threshold (DEXAT) model was proposed in [70]. Unlike the single adaptive mechanism of the AdEx neuron model, DEXAT controls threshold changes through two independent time constants, enabling it to better capture and process spatiotemporal information. The authors also discussed how to implement DEXAT neurons on Intel's Loihi neuromorphic chip [84] by simulating DEXAT behaviour using a multi-compartment structure. This approach improved gesture recognition accuracy and enabled the model's deployment on wearable devices using neuromorphic hardware.

2) Izhikevich Model: A simplified model which combines the biological implementation of the HH model with the computational efficiency of the LIF model was proposed [85]. Although it is less computationally demanding than the HH model, it is not as commonly chosen as LIF neurons when constructing SNNs. Two main differential equations govern the model: one describes the changes in the neuron's membrane potential and the other describes the dynamics of the recovery variable u.

$$\frac{dV(t)}{dt} = 0.04V(t)^2 + 5V(t) + 140 - u + I(t) \tag{3}$$

$$\frac{du}{dt} = a(bV(t) - u) \tag{4}$$

$$\text{if } V(t) \geq \theta, \quad V \leftarrow c, \quad u \leftarrow u + d \quad last \quad t_{\text{ref}} \tag{5}$$

where a, b, c and d are constants. u is a feedback mechanism for the membrane potential. After neuronal firing, this variable increases, temporarily reducing the neuron's excitability.

Some studies [71]–[77] have utilized the Izhikevich model to construct SNN models for predicting user intentions and facilitating HRI. Moreover, trained SNN models based on the Izhikevich model can be deployed on neuromorphic processors like ODIN [86], as demonstrated in the study by [30], achieving true neuromorphic applications. Additionally, other research has employed the Izhikevich model to convert data into spike signals, enhancing the sensory capabilities of prosthetic users [78]–[80] and improving the feature extraction from myoelectric control signals [81].

3) SRM: While LIF and Izhikevich models are effective for basic spike generation, the SRM offers a more flexible framework that incorporates refractoriness, adaptation, and spike history through linear filters and dynamic thresholds. The SRM dynamics can be described mathematically as follows. After the last spike at time $\hat{t}$, the membrane potential $v(t)$ evolves according to

$$V(t) = \eta(t - \hat{t}) + \int_{-\infty}^{+\infty} \kappa(t - \hat{t}, s)\, I(t - s)\, ds, \tag{6}$$

where η represents the spike-afterpotential, κ is the input kernel, and $\hat{t}$ is the time of the last spike. A spike is registered when

$$\text{if } V(t) \geq \theta \text{ and } \dot{V}(t) > 0, \text{ then } \hat{t} = t, \tag{7}$$

with an adaptive threshold defined as

$$\theta(t - \hat{t}) = \begin{cases} +\infty, & t - \hat{t} \leq \gamma_{\text{ref}}, \\ \theta_0 + \theta_1 \exp\left[-\dfrac{t - \hat{t}}{\tau_\theta}\right], & \text{otherwise.} \end{cases} \tag{8}$$

Here, γ_{ref} denotes the absolute refractory period, and θ_0, θ_1, and τ_θ define the baseline, magnitude, and decay rate of the dynamic threshold. Thanks to this explicit temporal structure, the SRM has also been used with reinforcement learning to solve control tasks like mountain car [82], highlighting its temporal decision-making capability.

B. Encoding Methods

The signal adapted from the real world can be processed by SNNs in the form of spikes. In this process, methods of spike encoding are necessary to process and transmit information effectively. These methods are divided into three major categories: rate encoding, temporal encoding and delta modulation, as illustrated in Table III.

1) Rate Encoding: Inspired by the performance of biological neural systems, rate encoding involves neurons conveying information about stimulus intensity by modulating the frequency of their spike sequences, with higher firing rates corresponding to stronger stimuli [91]. This method is widely used in models that require a direct relationship between stimulus intensity and neural response, playing a crucial role in sensory information processing and motor control.

For encoding muscle activity, Yang et al. [55] utilized a Smoothed Frequency Domain (SFD) encoder within rate encoding to generate spike sequences from smoothed signals. When the amplitude of muscle signals is higher, this method produces more frequent spikes, mimicking the biological principle that stronger stimuli lead to higher firing rates in neurons. Sreenivasa et al. [43], [44] used Poisson encoding to realistically simulate how sensory neurons transmit information about muscle length and velocity under different muscle states. This technique helps the model simulate complex neural control behaviours, playing a crucial role in the feedback of muscle closed-loop systems. On the other hand, Casellato et.al [54] used the Radial Basis Function (RBF) to encode joint angles or positions into spike patterns.

Population rate encoding offers a more effective method for representing complex signals compared to single-neuron encoding [92]. This method distributes information across many neurons, making it more biologically plausible, as information in the human brain is typically encoded within neural populations. Moreover, due to the collective activity of multiple neurons, this encoding method can average out noise, resulting in more robust signal encoding. Stochastic population encoding has been used to convert muscle activations into spike trains for controlling robotic hands [46], [47], [53].

2) Latency Encoding: Rate encoding can account for at most 15% of neuronal activity in the primary visual cortex (V1). If neurons indiscriminately defaulted to rate encoding, it would consume an order of magnitude more energy compared to temporal encoding [93]. Latency, or temporal encoding, focuses on the timing of spikes rather than the total number of spikes [94]. The greatest advantage of temporal encoding over rate encoding is its inherent sparsity. While this increases sensitivity to noise, temporal encoding significantly reduces the hardware power consumption.

Threshold encoding is a form of temporal encoding that rapidly converts continuous signals into spike sequences through a simple and efficient threshold setting. Behrenbeck et al. [57] not only utilized threshold encoding to process complex EEG and muscle activation signals, but also utilized Ben's Spike Algorithm (BSA) to encode finger force. Threshold encoding and BSA play different roles in this research: the former focuses on capturing the dynamic changes in signals, while the latter is used in scenarios requiring higher precision. To maximize the sparsity of neuronal firing, the Time-to-First-Spike (TTFS) method in temporal encoding can be employed. In this method, neurons encode their real-valued response to a stimulus by the time elapsed before their first spike in response to the stimulus [95]. Steffen et al. [60] utilized the TTFS encoding method to convert continuous depth data from depth sensors into spike sequences, enabling these data to be processed alongside event camera data by SNNs, thereby generating control signals. To further enhance neuromorphic implementation, Zanghier et al. [62] firstly introduced a method inspired by the cochlear model for hand kinematics regression. The artificial cochlea uses an event-based encoding technique that mimics natural auditory processing, enabling efficient signal handling.

Single-spike time encoding methods may lead to neurons that never fire due to the limited number of input spikes, which can be detrimental to the training SNNs. To address this issue, Bohte et al. [96] first proposed the population temporal encoding method. This approach used a set of overlapping and evenly spaced Gaussian receptive field functions. Liuy et al. [90] adopted this method to convert muscle activation signals into spike sequences. Cheng et al. [61] proposed an improved population temporal encoding method that integrates the concept of rank encoding to reduce information loss at the tails. This enhancement improves the accuracy and reliability of signal processing in SNNs, particularly for applications like hand gesture recognition in rehabilitation systems. In addition to Gaussian receptive field-based methods, Bucci et al. [73] introduced the concept of polychronous groups, which refers to a set of neurons that fire action potentials in a specific temporal sequence demonstrating the effectiveness of this method in processing tactile signals.

3) Delta Modulation: In Dynamic Vision Sensor (DVS) cameras, each pixel, and in silicon cochleas, each channel uses delta modulation to record changes in visual or auditory scenes. Inspired by these technologies and based on the concept that neurons thrive on change, delta modulation was proposed to process biological signals on neuromorphic hardware [97]. Notably, unlike rate and latency encoding which rely on absolute amplitude, delta modulation encodes temporal signal changes, enabling event-driven representations.

The enhanced delta modulation encoding method has been used in recent studies. For example, due to the large firing rate differences when processing signals of varying intensities with a fixed-threshold delta encoding method, an adaptive delta encoding method was proposed by [33]. This approach aims to maintain a relatively consistent firing rate across all channels. By introducing the adaptive delta encoding method, the system achieved balanced firing rates across different channels, thereby improving control performance while maintaining low power consumption. In [66], delta modulation was used for event-driven differential encoding. Unlike traditional

TABLE III: Encoding of SNN

Method	Encoded Property	Trigger Mechanism	Advantages	Amplitude Dependency	Specific Method	References
Rate Encoding	Amplitude magnitude	Firing rate (high amplitude $\rightarrow$ high frequency)	Intuitive and easy to implement	High	SFD Encoder	[55]
					Poisson Sampling	[43], [44], [87], [88]
					RBF	[54]
					Population Method	[46], [47], [53]
Latency Encoding	Amplitude $\rightarrow$ spike delay	Firing time (high amplitude $\rightarrow$ early spike)	Temporally sparse and energy-efficient	High	Threshold Encoding	[57], [59], [63], [89]
					BSA	[52], [57]
					TTFS	[60]
					Artificial Cochlea	[62]
					Population Method	[61], [70], [73], [90]
Delta Modulation	Signal change (Δ)	Firing when temporal signal change exceeds threshold	Hardware-friendly and noise-resilient	Low - only respond to changes	Basic	[26], [30], [34], [68], [69]
					Enhanced	[33], [66]

delta encoding, this variant generates a pulse when the signal's temporal variation exceeds a certain threshold but replaces negative pulses in delta encoding with zeros. This method helps increase the sparsity of the input signals and reduces floating-point operations between inputs and weights.

To better achieve hardware implementation, Corradi et al. [98] proposed an Analogue-to-Digital Converter (ADC) circuit for delta modulation, which has been widely used in biomedical circuits and wearable devices due to its low power consumption, low complexity, and high error tolerance [99], [100]. Ma et.al [69] used this delta modulation ADC circuit to implement an efficient signal encoding method. The application of this circuit also facilitated further processing on the neuromorphic processor DYNAP, demonstrating its great potential in real-time processing and wearable devices.

C. Learning Mechanisms

Training is a crucial process that enables SNNs to learn and perform various specific tasks. In the field of controlling assistive wearable robotics, the training techniques for SNNs can be categorized as follows: supervised learning, unsupervised learning, optimization and indirect training of SNNs involving their transformation from ANNs, as shown in Table IV.

TABLE IV: Learning Methods of SNN

Method	Specific Method	References
Supervised	BPTT	[26], [30], [40], [48], [51], [59]–[61], [64]–[66], [90], [101]
	PES	[46], [47]
	STDP & LMS	[102]
	STDP & SD	[53]
	Delta Rule	[34]
Unsupervised	STDP	[33], [45], [49], [50], [52], [57], [69], [71]–[76], [79], [89]
	CRITICAL	[63]
ANN to SNN	ReLU to IF	[88], [103], [104]
Reinforcement	Policy-Gradient Actor-Critic	[105]
	R-STDP	[79]

1) Supervised Learning: Supervised learning for SNNs is a significant area of research. Initially, traditional supervised learning algorithms could not be directly applied to SNNs because the internal state variables of SNN neurons and the error function between actual and desired output spike trains do not satisfy the property of being continuously differentiable. The introduction of surrogate gradient methods addresses the issue of non-differentiable spike functions, making it possible to apply gradient descent algorithms to SNNs [106]. Gradient-based learning algorithms, such as Backpropagation Through Time (BPTT), can be used in conjunction with surrogate gradient methods.

However, the traditional surrogate gradient descent method also brings computational complexity, leading to challenges in scalability, optimization and balancing model complexity with computational efficiency. To address this issue, a new approach can be combined with BPTT, namely stochastic gradient descent (SGD) [107]. SGD is often computationally more efficient than surrogate gradient methods because it involves smaller computational updates. Additionally, due to its inherent randomness, SGD helps improve model generalization and avoid local optima. The combination of SGD and BPTT, as shown in [59], enables the SNN to effectively learn from time-dependent data. Cheng et al. [61] utilized a modified version of SGD, which enhances the stability and efficiency of the training process, leading to faster convergence and more accurate models for real-time motion regression. Building on these ideas, Wang et al. [101] proposed Adaptive Smoothing Gradient Learning (ASGL) which dynamically learns the surrogate width and introduces stochastic pulse noise during training, enabling efficient and low-latency inference in SNNs. Gradient descent-based learning frameworks such as SpikeProp [96], SuperSpike [108], and SLAYER [109] have been proposed and applied in wearable rehabilitation robots [30], [48], [64], [90].

Additionally, a biologically plausible supervised learning method for training SNN, Prescribed Error Sensitivity (PES) [110], has been proposed. Unlike gradient descent, which relies on global information, PES converts global error signals into local error signals by limiting each neuron's encoder sensitivity to the error vector space. The PES method has been shown to effectively classify control signals and trigger robotic hand reflexes, demonstrating its feasibility and effectiveness in practical applications [46], [47]. Alternatively, Gyongyossy et al. [102] proposed a bio-inspired supervised learning method that combines STDP with the Least Mean Squares (LMS) algorithm, endowing it with supervised learning capabilities. This method was applied in gesture recognition scenarios, demonstrating its suitability for complex tasks in real-world applications. Tieck et al. [53] introduced the Selective Disinhibition (SD) mechanism building on STDP, which ensures that input signals are effectively associated with the desired teaching signals by inhibiting unwanted neuronal activity during the learning process. This method helps the network adjust synaptic weights more accurately, reducing noise interference in the learning process. Moreover, to promote the development of neuromorphic systems, the Delta rule was proposed [111] and demonstrated using Bump circuits [34].

2) Unsupervised Learning: For SNNs, unsupervised learning methods are based on biological mechanisms which enable more natural and efficient forms of computation. STDP [24] is the most commonly used method in training SNN. It modifies synaptic strength based on the precise timing of spikes between pre- and postsynaptic neurons, providing a biologically plausible and temporally precise learning mechanism for SNNs [112]. In addition to traditional STDP training mechanisms, several improved methods have been proposed to optimize STDP-based learning for specific applications. Ma et al. [33] combined STDP with the Winner-Take-All (WTA) mechanism to effectively extract features from input signals, using these features for action classification. The study's soft WTA approach allows multiple neurons to be winners, thereby improving the robustness of classification. Furthermore, by introducing a trace variable into STDP, Ma et al. [69] proposed a trace-based STDP learning method, and experiments showed that its biological plausibility makes it well-suited for direct implementation in online learning on neuromorphic chips.

Another typical type of unsupervised training method is CRITICAL method. Unlike STDP, which relies on precise spike timing, the CRITICAL method maintains activity near the critical point by adjusting branching factors, thereby ensuring network stability. In [63], the CRITICAL algorithm was applied in reservoir computing within SNNs to process myoelectric signals for gesture recognition which outperformed the STDP network. However, the CRITICAL algorithm-improved network increases computational complexity, making hardware implementation more challenging compared to the easier hardware deployment of STDP.

3) ANN-to-SNN Conversion: The ANN to SNN conversion is cost-effective because it avoids the non-differentiable spike activation in SNNs, requiring minimal training time and GPU resources during the training phase. The majority of methods dedicated to the conversion of ANNs to SNNs primarily focus on transforming ReLU activation function into IF neurons. Zhang et al. [88] used the error backpropagation algorithm to train an ANN model for analyzing myoelectric signals of amputee patients, replacing the ReLU units in the ANN model with IF neurons and directly mapping the trained connection weights to an SNN model with a corresponding structure. Although this method provides a solution for low-power motion classification in wearable devices, it still suffers from information loss during the conversion process. To address this issue, Wang et al. [104] introduced a two-stage framework that enables accurate and efficient SNN inference under ultra-low latency conditions, making it promising for real-time applications such as wearable robotics.

4) Reinforcement Learning: Reinforcement learning (RL), which enables online adaptation without explicit human models and optimizes long-term performance through reward-driven interaction, is well suited for personalized and efficient assistive control in dynamic HRI scenarios. Combined with SNNs, RL becomes particularly appropriate for wearable devices with strict power constraints. Tang et al. [105] demonstrated this by training a population-coded spiking actor network using policy-gradient methods to achieve continuous control in high-dimensional locomotion tasks such as simulated quadruped and biped walking. In addition to gradient-based methods, bio-inspired RL based on Hebbian plasticity has also been explored. Wang et al. [79] showed that SNNs trained with R-STDP can reproduce human-like heat-evoked withdrawal reflexes in upper-limb prosthetics, enabling reflex-level responses under low-power constraints. Although these approaches show promise, the integration of RL and SNNs in real-world HRI remains limited and presents a valuable direction for future research.

D. Metaheuristic Optimization

Over the past two decades, metaheuristic optimization techniques have gained significant popularity, such as Genetic Algorithm (GA) [113], Ant Colony Optimization (ACO) [114], and Particle Swarm Optimization (PSO) [115], becoming promising learning methods for training ANNs [116]. To overcome the limitations of traditional training methods in SNNs, applying metaheuristic algorithms to SNNs has emerged as a new research trend. For example, Wang et al. [77] employed the Cuckoo Search Algorithm [117] to adjust the weights of an SNN model, optimizing the network weight combination for superior performance in motor imagery tasks, thereby enhancing the network's accuracy and robustness. Yang et al. [55] utilized the Grey Wolf Optimizer [118] to effectively balance global and local search capabilities, fine-tuning SNN parameters to minimize the loss function, which ultimately led to improved action recognition accuracy.

III. Applications of SNNs in Human-Robot Interaction

HRI plays a crucial role in determining the performance of wearable robots. Given the limited computational resources of them, SNNs offer significant advantages. This section will provide a comprehensive overview of the application of SNNs in HRI, focusing on three critical aspects: motion decoding, robotic control, and neuromorphic implementation. The SNN-based framework is illustrated in Fig. 3, and the literature summary is presented in Table V.

TABLE V: Applications of SNN in human-robot interaction.

Function	Study	Acquired Signals	Performance	Application
Gesture Recognition	Rekabdar 2015 [71]	Visual information from video	83% classification accuracy	Applicable to upper-limb robotics
	Donati 2019 [34]	EMG from armband	74% accuracy while consuming only 0.05 mW on the DYNAP	Deployed on DYNAP
	Ceolini 2020 [30]	signals from EMG armband and DVS event camera	96% accuracy on Loihi	Deployed on Loihi
	Bezugam 2023 [70]	EMG from armband	90% accuracy with 77% fewer neurons, outperform GPUs by 983 times in energy and 19 times in speed	Deployed on Loihi
	Steffen 2024 [60]	Event data from event cameras and depth signals from depth cameras	91.48% accuracies for event data, and 80% for data fusion	Applicable to upper-limb robotics
Gesture Recognition & Force Estimation & Motor Imagery	Behrenbeck 2019 [57]	EEG from datasets, EMG from electrode devices, and force from sensitive resistors	75% accuracy in motor imagery, 1.29 N RMSE in force, and 77% accuracy for gesture on SpiNNaker	Deployed on SpiNNaker
Motion Primitive & Robot Control	Tieck 2020 [47]	EMG from armband	Pinky finger and no action reached 100% accuracy, the middle finger ranged from 60% to 64%	Control of a robotic hand
Motion Prediction	Hu 2014 [52]	EEG from a 14-channel device	86.67% classification accuracy	Applicable to upper-limb robotics
Motion Prediction & Robot Control	Kumarasinghe 2018 [119]	EEG from headset	Two subjects achieved 75% and 83.3% accuracies	Control of a prosthetic hand
	Zhou 2019 [72]	EMG from armband, EEG from headset and movement from motion capture systems	0.683, 0.852, and 0.894 F1 scores at 10%, 50%, and 100% action sequence	Control of a robot arm
	Feng 2022 [74]	Movement from motion capture systems	0.805 F1-score at 40% action sequence	Control of a robot arm
Reflex Triggers	Sreenivasa 2015 [43]	Joint positions from motion capture, EMG from wireless device, and force from bidirectional sensor	Difference are 1° in angles, 1-2 Nm in torque, 5-8 N in force, and 0.07-0.10 in activation	Applicable to upper-limb robotics
	Wang 2023 [79]	Temperature from robotic skin units	Near 1.0 reflex intensity at 50°C	Applicable to upper-limb robotics
Kinematic Analysis	Liao 2022 [51]	Spike-band power from V1 cortex	0.75 and 0.58 correlations with less memory	Applicable to upper-limb robotics
	Leroux 2023 [64]	EMG from NinaproDB8 dataset	MAE of 6.10±1.50 degrees	Applicable to upper-limb robotics
	Dewolf 2023 [62]	Movement from simulated sensors	0.29106 RMSE on Loihi, with two orders lower energy use	Deployed on the Loihi, with potential for 7-DoF robot arm
Tactile Perception	Bucci 2014 [73]	Hand movement from trackball sensor arrays	Close to 1 ROC curve	Applicable to prosthetics and rehabilitation gloves
	Follmann 2022 [58]	Force from force sensing resistor	100% accuracy in classifying sliding events	Applied in slip event detection for a prosthetic hand
	Hu 2023 [41]	Tactile from EvTouch-Objects and EvTouch-Containers	Improved accuracy on different datasets by 8.34% and 16.17%	Applicable to prosthetics and rehabilitation gloves
	Ali 2024 [40]	Tactile from a piezoelectric sensing system	A maximum classification accuracy of 92.1%	Deployed on Loihi, with potential for prosthetics
Tactile Perception & Robot Control	Sorgin 2020 [78]	Force from sensors and hand movement from leap motion	Improved user task completion efficiency and accuracy	Control of a robotic arm
Tactile Perception & Gait Event Detection	Prasanna 2023 [80]	Pressure from 16-photonic insole pressure sensors	87.5% accuracy for flat vs. uneven terrain and 62.5% for three types	Applicable to lower limb robots
Gait Event Detection	Argones 2021 [120]	Gait from IMU	2.16% ± 0.76% equal error rate with better energy efficiency	Applicable to lower limb robots
	Tao 2024 [121]	Spikes from DVS event camera	Over 96% accuracy on DVS128-Gait and EV-CASIA-B	Applicable to lower limb robots
Robot Control	Luque 2014 [42]	Angle and motion of robot Joints	Greatly reduce MAE	Control of a lightweight upper limb robot
	Dura 2015 [122]	Muscle length from a virtual musculoskeletal model	MAE was less than 2 degrees	Applicable to robotic arm
	Gilar 2018 [123]	Simulated joint angles and velocities	0.00417 ± 0.00096 mean square error	Applicable to two-link robotic arms
	Wei 2020 [124]	Visual information from cameras	Most sessions converged in 100-300 steps	Control of a 6-DOF robot arm
	Steffen 2020 [45]	Current-activated spikes of position neurons	0.021 to 0.041s path search time	Applicable to obstacle avoidance in wearable robots
	Perez 2021 [125]	Arm position and movement from simulated sensors	Adapted to changes within 1s	Applicable to prosthetics

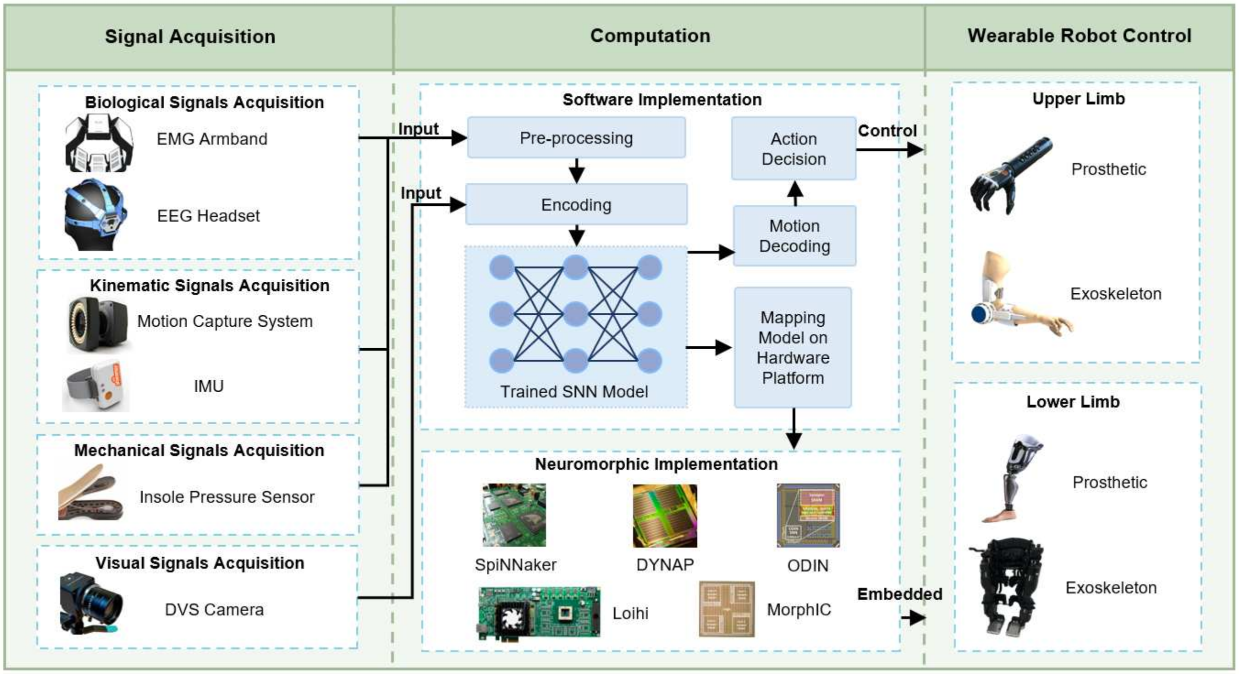


Fig. 3: SNN-based human-robot interaction for rehabilitative wearable robots.

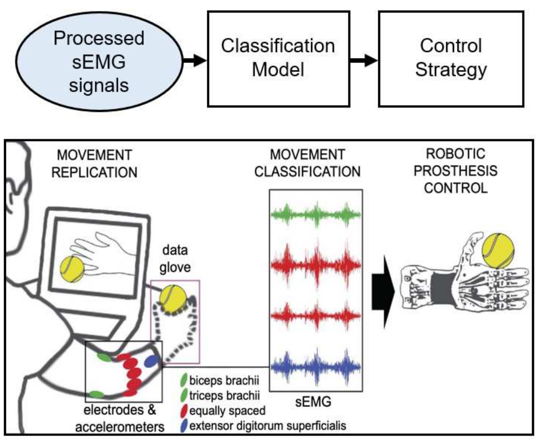


Fig. 4: Hand gesture recognition for robot control [126].

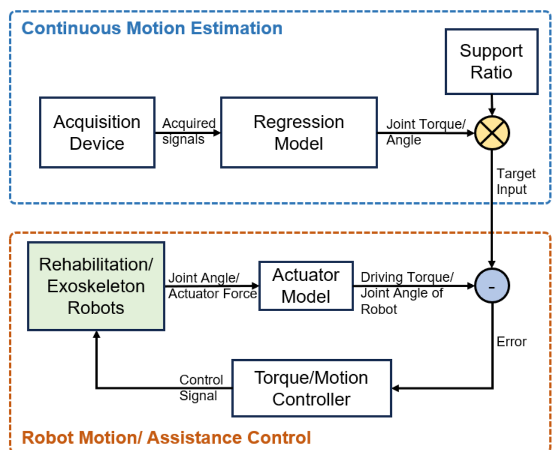


Fig. 5: Continuous motion estimation for robot control [127].

A. Motion Decoding

1) Hand Gesture Recognition: For the recognition of upper limb movements, numerous studies have focused on hand movement analysis based on EMG signals, as illustrated in Fig. 4, aiming to decode motion intentions for more natural control of prosthetics or exoskeletons. Several studies have employed SNNs to process EMG signals for hand movement classification [30], [34], [60], [66], [68], [70], [71], [103]. It suggests that rehabilitation robots could rapidly respond to the user's EMG signals. This allows for prompt feedback and assistance, significantly improving the user experience and the overall effectiveness of rehabilitation training.

2) Motion Primitive Recognition: In this category, SNNs have been employed to recognize different hand movement primitives (such as grasping, releasing, or moving) and map these primitives to robot control signals. For instance, Vasquez et al. [46] and Tieck et.al [47] used EMG signals, enabling precise control of each finger's reflex action. Tieck et al. also [53] utilized motion capture systems to generate movement primitives for controlling both finger and hand actions. Furthermore, tactile reflexes were integrated into the robotic hand to ensure safety during real-world operations. The generation of motion primitives using SNNs for robotic control is a cutting-edge and promising research direction, driving the development of wearable rehabilitation robots towards more efficient and intelligent systems.

3) Motion Type-Based Intention Prediction: For patients with mobility impairments, motion intention prediction enables robots to automatically understand and assist in completing necessary actions, thereby enhancing the collaborative aspect of HRI [128]. Hu et al. [52] classified activities of daily living (ADL) of the upper limbs using EEG data achieving a classification accuracy of 86.67% on test samples using SNN. Similarly, Zhou et al. [72] combined multiple signals, including EEG and EMG, to enable a robot to predict turn-taking intentions during task handovers. Remarkably, the performance of the proposed SNN surpassed human levels even with only partial observation data.

4) Reflex Triggers: Reflex activities are a critical area of research in the application of prosthetics. Sreenivasa et al [43], [44] combined realistic SNNs with musculoskeletal models to replicate physiological phenomena such as the stretch reflex of the human arm. They also explored the potential applications of these models in rehabilitation engineering, emphasizing their importance in enhancing prosthetic control and responsiveness in real-world scenarios. Wang et al. [79] introduced a bioinspired neuromorphic model designed to mimic the nociceptive withdrawal reflex of the upper limb triggered by thermal stimuli of robotic skin unit. This model offers a new approach to implementing thermal protection mechanisms in prosthetics and robotic systems, providing enhanced safety features for users.

5) Kinematic Regression Analysis: Continuous motion decoding is essential for achieving natural control of rehabilitative wearable robots. The classic control framework is illustrated in Fig. 5. Du et al. [48] was the first to use SNNs to decode elbow joint angles from preprocessed EMG signals, demonstrating the feasibility of this model. Leroux et al. [64] and Zanghieri et al. [62] further explored the regression of hand kinematics using EMG signals, predicting joint angles of the hand through SNN models. The former achieved a low mean absolute error (MAE) of 6.10±1.50 degrees and a fast inference time of 3.5 ms per time window, while the latter demonstrated significant advantages in memory usage, latency, and energy consumption. Compared to ANN methods, the memory footprint was reduced by approximately 9 times, latency by 10 times, and energy consumption by about 13 times. In addition to using EMG signals, EEG signals have also been employed for continuous motion decoding of the upper limbs. Kumarasinghe et al. [89] decoded and interpreted muscle activity and movement trajectories from EEG signals, showing that the proposed brain-inspired SNN model could achieve good predictive performance even with small-scale training data. Liao et al. [51] used SNNs to decode brain signals to predict finger movement speed, achieving a correlation coefficient level comparable to ANN decoders but with only 6.8% of the computational operations and 9.4% of the memory accesses required by ANNs.

6) Gait Analysis and Recognition: A key application of lower limb rehabilitation is gait reconstruction [129]. SNNs process data from various sensors, including IMU, ground reaction force, EMGs, and machine vision, in real-time, allowing for efficient decoding of gait information and providing a robust tool for gait analysis and recognition. Inspired by the way tactile data is processed in the brain, Lee et al. [130] designed a low-cost foot pressure sensor using conductive fabric, which detected events based on timing rather than pressure intensity. This approach used a two-layer SNN, where input neurons converted pressure signals into spikes using Izhikevich neurons, while output neurons identified specific gait events, and the synaptic kernel inverse method (SKIM) was applied to solve the weights of a discrete-time perceptron. This method achieved an accurate detection time of 1.2 ± 7 ms for heel strike events and 0.2 ± 14 ms for toe-off events, with a success rate exceeding 97%. Tao et al. [121] presented GaitSpike, which leveraged SNNs and a sparsity-driven event-based camera for gait classification. The SNN with three convolutional layers of LIF neurons and a fully connected layer was proposed to process the concise LIR images, using BPTT with a surrogate gradient function for learning. Argones et al. [120] addressed gait authentication using SNNs based on IMUs. The SNN training initially employed STDP to establish a baseline and subsequently utilized supervised backpropagation for further learning. It is suggested that the low power consumption of SNN hardware implementations, coupled with advancements in backpropagation techniques encourages further research into SNN applications.

7) Tactile Perception: In the field of rehabilitation, tactile training is often used for patients with sensory integration disorder and other neurodevelopmental disorders to improve their sensory processing and behavioral regulation abilities. To enhance the effectiveness of Sensory Integration Therapy (SIT), Bucci et al. [73] discussed the design and implementation of a neuromorphic robot named CARL-SJR (Cognitive Anteater Robotics Laboratory Spiking Judgment Robot) and successfully demonstrated the robot's ability to classify complex tactile patterns by using SNNs, offering new insights into the field of tactile perception.

Tactile perception can significantly enhance the ability of rehabilitation robots or prosthetic users to perceive and adapt to their surrounding environment [131]. For example, through tactile feedback, users can sense objects' hardness, temperature, or texture, enabling more precise manipulation in daily activities and improving their quality of life. Sorgini et al. [78] utilized SNN models to simulate the spiking patterns of neurons in the actual sensory system, converting force and motion information from the robot's end effector into tactile signals for the user's hand. The tactile feedback generated by the SNN allowed the system to more realistically mimic the response patterns of mechanoreceptor neurons beneath human skin, enabling users to experience robotic feedback more intuitively and naturally.

In addition, SNNs can be used to recognize and classify different objects and textures using tactile data. For instance, Hu et al. [41] proposed a model called Tacformer, a residualized graph self-attention SNN, for tactile object recognition, demonstrating that this model outperforms other benchmark models in object recognition tasks, particularly with small sample datasets. Similarly, Ali et al. [40] developed a sensing system that mimics human tactile biological processes, specifically for classifying texture features. This system employs a neuromorphic approach, using a PVDF-based sensing system to convert raw tactile signals into spikes, which are then processed by an SNN, achieving good classification accuracy under various experimental conditions.

Furthermore, tactile information can also be used to detect slippage events. Follmann et al. [58] collected data on slippage events by applying force with a mechanical finger equipped with pressure sensors and trained an SNN on this data. The results showed that the model could accurately detect slippage events, making it suitable for scenarios requiring real-time response and low power consumption, such as in prosthetics.

B. Robotic Control

By simulating the interactions between the nervous system and the musculoskeletal system using SNNs, researchers can model the propagation of neural signals and how these signals drive muscle contractions and skeletal movements. This approach offers new insights into the motion control of wearable robots, deepening the understanding of motor control in living organisms while also providing technical support for the advancement of bionic robots, neural prostheses, and rehabilitation devices. From a biomimetic perspective, SNNs used for robotic control in wearable rehabilitation robots can be categorized at various levels and scales based on the hierarchical organization of the nervous system, including the simulation of individual neuron behaviors, local neural circuits, and brain area functions.

1) Individual Neuron Level: SNNs emulate fundamental sensory processing by decoding bio-physiological signals, such as EMG, EEG, tactile data, etc. Pan et al. [132] utilized an SNN to encode intra-cortical micro-stimulation (ICMS) current and employed an auxiliary controller based on an MPC strategy to regulate the ICMS current. The encoded signal is fed into the PPV neuron, which senses the current position of the joint. Sorgini et al. [78] described an intuitive gesture-based system for remotely controlling a robotic arm with tactile telepresence, where neuronal spiking models generate vibrotactile feedback that is delivered directly to the palm of the hand. Since SNNs are primarily used for decoding information to interpret human intentions or analyze postures, this framework allows the robot's control algorithm to generate commands accordingly, enabling precise and responsive movement control.

2) Local Neural Circuit Level: SNNs replicate relatively complex motor control processes by modelling interconnected networks of neurons. By constructing a preset structure similar to reflex arcs using SNNs, Perez et al. [125] proposed a channel-based synaptic model and a control scheme based on the equilibrium point hypothesis to enhance the biological similarity of the controller. Wei et al. [124] developed a spiking neural circuit inspired by biological spinal circuits, utilizing dopamine-modulated STDP to adjust neural connections based on environmental feedback, enabling a robotic arm to autonomously learn how to reach or avoid specific positions. Meanwhile, local neural processing typically involves neural circuits that learn an inverse model of the non-linear dynamics, enabling them to infer the continuous-time command required to control a two-link arm along a desired trajectory [123]. Thus, these methods enable direct control of specific physiological responses or behaviours and allow for precise regulation of particular actions.

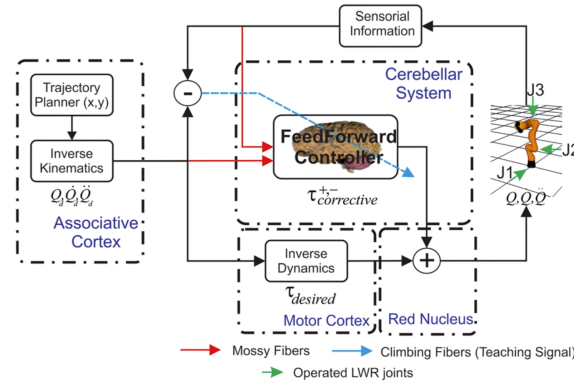


Fig. 6: Implemented cerebellar control loop [42].

3) Brain Area Level: SNNs simulate the functions of specific regions of the brain, such as the motor cortex or cerebellum, which are involved in higher-order tasks like motion planning, decision-making, and fine motor control, enabling wearable robots to implement more sophisticated capabilities. Luque et al. [42] demonstrated how integrating a cerebellar structure into the control loop as an adaptive feedforward model can learn to abstract the dynamics of manipulated objects, as shown in Fig. 6. This was achieved using an integrated simulation platform that combines a real-time spiking neural simulator with a simulated robot. Steffen et al. [45] presented a 3D path planning algorithm that employs an SNN of place cells. A wavefront initiated at the goal cell strengthened synapses through STDP, generating a vector field that directs the path from any cell to the destination. Dura et al. [122] developed a control system that integrates a cortical SNN with both a virtual musculoskeletal arm and a physical robotic arm. The SNN with STDP simulates the brain's process of coordinating motor commands through temporal patterns of neural spikes. The virtual arm, which mimics the dynamics of a real musculoskeletal system, receives commands from the SNN and translates them into joint control commands for the physical robotic arm.

C. Neuromorphic Implementation

In the field of robotic control, motion decoding and control signal computation are typically resource-intensive, leading to traditional devices that are both bulky and power-hungry [133]. This is particularly challenging for wearable robots, which require lightweight and energy-efficient solutions to minimize signal processing time [134]. Neuromorphic hardware offers a promising solution to this problem. Unlike traditional hardware optimized for the matrix-based computations of ANNs, neuromorphic hardware is a biomimetic computing system designed to replicate the structure and function of the biological brain. This hardware often relies on SNNs, which process and transmit information through sparse spiking activity, providing significant advantages in power consumption, computational latency and efficiency which is especially well-suited for wearable robots with limited resources.

Several neuromorphic processors have already been developed, with some of the prominent examples including SpiN-

Naker [135], Loihi [84], TrueNorth [136], BrainScaleS [137], DYNAP [138], Neurogrid [139], ODIN [86] and MorphIC [140]. In the field of rehabilitative wearable robotics, several studies have implemented applications of neuromorphic processors. Behrenbeck et al. [57] deployed the proposed SNN-based NeuCube framework onto the SpiNNaker platform to accomplish user motion decoding tasks. The study demonstrated that this hardware architecture enables the SNN model to achieve real-time processing under low-power conditions. Moreover, [33], [34], [68], [69] successfully deployed SNNs on the compact, ultra-low-power neuromorphic chip DYNAP to accomplish hand gesture discrimination tasks. These studies demonstrated the feasibility of implementing spiking models on the DYNAP neuromorphic chip and confirmed that such chips can perform complex neural network computations with extremely low power consumption, making them particularly suitable for wearable devices and other embedded systems. In addition to the neuromorphic processors mentioned above, the effectiveness of the Loihi for SNNs has also been demonstrated in practical applications. Dewolf et al. [133] deployed an SNN model on the Loihi to successfully perform complex nonlinear computations for controlling a 7-degree-of-freedom robotic arm. This control strategy highlighted the potential of Loihi in handling high-dimensional nonlinear control problems. In addition, Vitale et al. [26] and Bezugam et al. [70] implemented efficient gesture classification by running SNNs on the Loihi processor, demonstrating the potential of this neuromorphic processor in wearable devices and real-time computing. Ceolini et al. [30] explored multimodal data processing for gesture recognition by implementing SNN architectures not only on the Loihi but also on the ODIN + MorphIC. Their experimental data revealed that SNN characteristics vary across different neuromorphic platforms. Loihi is well-suited for more complex and larger-scale network architectures, particularly for handling high-dimensional visual data. In contrast, ODIN + MorphIC excels in low-power, small-scale tasks. These studies illustrated the potential and limitations of neuromorphic processors in practical applications, providing valuable insights for the future deployment of wearable devices based on neuromorphic hardware.

IV. Future Directions

A. Enhancing Computational Efficiency

The impulse-based mechanism of SNNs complicates the use of gradient computation and backpropagation algorithms, especially in large-scale networks, leading to the requirement of complex optimization strategies [141]. Wearable robots, with their limited computational resources, struggle with high computational complexity and training difficulty. While neuromorphic chips offer a potential solution, the technology remains immature, expensive, and limited in scale [142], significantly restricting the widespread adoption of SNNs in wearable devices. To address these challenges, future developments in SNNs should focus on several key areas to improve the feasibility of wearable devices:

1) Bio-Inspired Mechanisms and Neural Innovations: Leveraging new neural mechanisms and bio-inspired approaches may improve the sophistication and efficiency of SNNs. Key directions include integrating biologically inspired learning rules and incorporating neuromodulatory mechanisms like dopamine regulation to dynamically adjust learning processes. Developing adaptive synaptic models that reflect biological plasticity, optimizing algorithms for event-driven computation. Enhanced simulation and optimization tools tailored to these bio-inspired mechanisms will further support the efficient design and training of SNNs, paving the way for their practical application in wearable robots.

2) Hardware Acceleration: Future developments should focus on several key areas. First, advancing neuromorphic hardware, such as specialized chips designed to efficiently process spike-based computations. These chips need to be more scalable and cost-effective to support larger and more complex SNNs. Second, optimizing traditional hardware architectures, including GPUs and TPUs, to better handle the asynchronous and event-driven nature of SNNs. Third, integrating custom processing units that are tailored specifically for SNN operations, such as spike-time and synaptic weight updates, can improve real-time capabilities. Lastly, developing efficient hardware-software co-design strategies will ensure that SNN algorithms are fully optimized for the capabilities of new hardware, maximizing the potential of SNNs in real-world applications.

3) Hybrid Approaches: Integrating SNNs with traditional neural network techniques may be a promising direction. For example, combining SNNs with deep learning models can leverage the strengths of both paradigms: SNNs' event-driven efficiency and deep networks' advanced optimization capabilities. Additionally, incorporating reinforcement learning techniques like R-STDP [79] with SNNs can enable adaptive learning and optimization based on environmental feedback, further improving efficiency. Developing seamless interfaces and optimization algorithms that allow these hybrid models to function cohesively will be crucial for maximizing performance and resource utilization across diverse tasks.

4) Energy-Efficient Architectures: Employing energy-efficient neuron and synapse models that reduce the number of active components during computations can further lower energy usage. Techniques such as dynamic voltage and frequency scaling (DVFS) and adaptive clocking can be integrated to adjust power consumption based on network activity levels. By focusing on these design principles, SNNs can achieve substantial reductions in power requirements, thus extending the operational lifespan of wearable robotic systems.

B. Addressing Rehabilitation Needs

Human movement is continuous and highly complex, involving subtle variations and coordinated actions across multiple muscles and joints. In contrast, SNNs rely on spike-based communication, which is inherently discrete and event-driven. Accurately encoding these smooth, dynamic patterns into spikes demands sophisticated neural models and precise timing. This challenge is particularly relevant for rehabilitation needs, as SNNs must effectively capture the fluidity and variability of natural human motion to provide effective and responsive therapy. Furthermore, the diversity in individual rehabilitation needs adds further complexity, as SNNs must be able to adapt to a wide range of motor functions and conditions, often with limited data for each unique case. To overcome these challenges, future developments in SNNs may focus on the following important areas:

1) Iterative and Adaptive Learning: By delivering real-time feedback, SNNs continuously adapt to the user's movements and rehabilitation progress, presenting a promising approach for improving rehabilitation outcomes. This involves designing learning algorithms that enable SNNs to iteratively refine their synaptic connections and neural pathways based on ongoing interaction with the user. By implementing mechanisms that allow for rapid adaptation to changes in the user's condition, such as varying levels of motor function, SNNs can become more responsive and personalized. Additionally, incorporating adaptive learning strategies that adjust learning rates and synaptic plasticity in response to environmental feedback will help SNNs maintain high performance and accuracy over time, ensuring that the wearable robots provide effective and customized assistance throughout the rehabilitation process.

2) Integration of Multi-Modal Inputs: To enhance the effectiveness of SNNs in wearable robotics, future developments should focus on integrating multi-modal inputs to provide a richer, more comprehensive understanding of human movement. This involves incorporating diverse sensory data sources such as accelerometers, gyroscopes, EMG, and pressure sensors into the SNN framework. By fusing these multi-modal inputs, SNNs can better capture the complex and nuanced aspects of human motion, including subtle variations in muscle activity and joint dynamics. Developing effective fusion frameworks and adaptive filtering techniques will enable SNNs to process and interpret data from different sensors simultaneously, leading to more accurate and responsive control of wearable devices. For example, Jiang et al. [143] proposed a lightweight framework combining attention-based distillation and feature selection, offering valuable insights for SNN-based sensor integration under constrained conditions. Additionally, integrating real-time data streams with spike-based processing will allow the SNN to dynamically adjust its models and outputs based on immediate feedback, improving the system's adaptability and performance in varied rehabilitation scenarios. This multi-modal approach will enhance the SNN's ability to model and replicate intricate movement patterns, ultimately providing more effective and personalized assistance for users.

3) Robustness in Varied Scenarios: Future research should focus on developing SNNs that can maintain consistent performance despite changes in the environment and user behaviour. This involves designing SNN architectures that can generalize well to different contexts, such as varying terrains, motion speeds, and user-specific conditions like fatigue or injury. Implementing advanced generalization techniques, such as data augmentation, robust training algorithms and low-precision-aware learning strategies that tolerate quantization noise and hardware mismatch [144] will help SNNs adapt to diverse situations without significant loss in accuracy or reliability. Additionally, integrating context-aware mechanisms that enable the SNN to dynamically adjust its parameters in response to real-time changes can further improve robustness. By focusing on these areas, SNNs in wearable robots may become more resilient and effective, providing reliable assistance across a wide range of real-world conditions and rehabilitation scenarios.

V. Conclusion

This review highlights the significant potential of SNNs to advance embodied intelligence for human-robot interaction in rehabilitative wearable robotics. Recent advancements in SNN technology tackle critical challenges by enhancing real-time adaptation, sensory processing, and user interaction. However, challenges remain in optimizing SNNs for practical applications across diverse rehabilitation needs. Future research should concentrate on refining these technologies to maximize their effectiveness in rehabilitative wearable robots, further advancing the integration of embodied intelligence in robotics.

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