Synaptic device-based neuromorphic computing in artificial intelligence

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Abstract. The application of synaptic device-based neuromorphic computing in artificial intelligence is an emerging research field aimed at simulating the structure and function of the human brain and realizing high-efficiency, low-power, and adaptive intelligent computing. This paper reviews the principles, growth and challenges of neuromorphic devices based on synapses computing and its applications and perspectives in artificial intelligence fields like an image processing as well as natural language processing. The paper first introduces the basic concepts, properties and classification of synaptic devices, as well as the basic framework and algorithms of neuromorphic computing. Then, the paper analyzes the advantages and difficulties of neuromorphic computing based on synaptic devices, including the preparation, testing, modelling and integration of the devices, as well as the system's architecture, programming and optimization. Then, this paper gives examples of the applications and effects of synaptic device-based neuromorphic computing in artificial intelligence fields such as image processing and natural language processing, including image denoising, image segmentation, image recognition, text classification, text summarization, and text generation. Finally, this paper summarizes the current research status and future synaptic device-based neuromorphic computing trends. It puts forward some research directions and suggestions to promote the development and innovation in this field.

Keywords: Neuromorphic Computing, Synaptic Devices, Artificial Intelligence, Synaptic Plasticity, Efficient Computing

1. Introduction

Artificial Intelligence (AI) is an important driving force in today's technological development, which involves a number of disciplines and fields, such as computer science, electrical engineering, mathematics, physics, biology, psychology, philosophy, and so on. Artificial intelligence aims to enable machines to simulate and surpass human intelligence, and realize autonomous, efficient and flexible information processing and decision-making. The application of AI has widely penetrated into various aspects, such as healthcare, education, transportation, entertainment, security, etc., bringing great convenience and value to human life and social progress.

However, AI also faces some challenges and limitations, one of which is the traditional computing model based on the von Neumann architecture, which is centered on logical operations and data storage, and performs computation in a serial, synchronous, and deterministic manner, which is very

DOI: 10.54254/2755-2721/65/20240511

different from that of the human brain. The human brain is based on neurons and synapses as the basic unit and calculates in a parallel, asynchronous, and stochastic way, with a high degree of plasticity, adaptivity, and energy conservation. Therefore, how to borrow and simulate the computational mode of the human brain is a crucial research direction of artificial intelligence.

Neuromorphic computing is a new computing paradigm that mimics the computational model of the human brain, which aims to realize efficient, low-power, and adaptive intelligent computing. The key to neuromorphic computing is synaptic device, which is an electronic device that can mimic the function of synapses with the characteristics of non-volatility, adjustability, polymorphism, etc., and can realize the functions of synapses, such as learning, memory and transmission. Neuromorphic computing systems based on synaptic devices can realize the construction and operation of large-scale neural networks and the processing of complex intelligent tasks.

The research objective of this paper is to explore the applications and effects of synaptic device-based neuromorphic computing in artificial intelligence, as well as the problems and challenges it faces. The research questions of this paper are whether Neuromorphic computing of synaptic devices based on synaptic devices can improve the performance and efficiency of artificial intelligence, and how to optimize and improve the design and implementation of neuralmorphic computing based on synaptic devices systems. The research hypothesis of this paper is that synaptic device-based neuromorphic computing can improve the performance and efficiency of artificial intelligence to a certain extent. Still, it also needs to solve some technical and theoretical problems and challenges. The research framework of this paper is: firstly, to review the principle, growth and challenges of neuromorphic devices based on synapses computing; secondly, to introduce the application and effect of synaptic device-based neuromorphic computing in artificial intelligence fields like an image processing as well as natural language processing; and finally, to summarize the current status of neuralmorphic computing based on synaptic devices and the future trend, and to put forward some research directions and suggestions.

2. Basic concepts, properties and classification of synaptic devices

2.1. Characterization of synaptic devices

A synaptic device is a technological gadget that can replicate the capabilities of a synapse, which is the basis and core of neuromorphic computing. Synapses are connection points between neurons, which enable the transmission and regulation of neural signals, as well as learning and memory in neural networks. The main function of synaptic devices is to simulate the change in resistance of synapses, i.e., synaptic plasticity, which is the information storage and processing mechanism in neural networks.

2.2. The properties of synaptic devices

The properties of synaptic devices [1] include the following:

1. Non-volatile: the synaptic device can maintain its resistive state, i.e. memory state, after power failure, realizing long-term information storage.
2. Adjustability: The synaptic device can dynamically change its resistive state, i.e., synaptic weight, according to the strength, frequency and time of the input signal, realizing short-term information processing.
3. Polymorphism: Synaptic devices can realize different synaptic plasticity according to different operating modes, such as long time-range enhancement (LTP), long time-range depression (LTD), short time-range plasticity (STP), etc., to realize diverse information encoding and decoding.
4. Low power consumption: synaptic devices can operate under low voltage and low current conditions, realizing low energy consumption for information storage and processing.

2.3. Classification of synaptic devices [2]

There are mainly the following types:

1. Classification by material: synaptic devices can be divided into metal oxide synaptic devices, organic molecule synaptic devices, carbon-based synaptic devices, nanowire synaptic devices and so on, according to the type and composition of their materials.

2. Classification by structure: synaptic devices can be classified into planar structure synaptic devices, three-dimensional structure synaptic devices, heterogeneous structure synaptic devices and so on according to the form and characteristics of their structure.

3. Classification by mechanism: synaptic devices can be classified into electron-migration synaptic devices, ion-migration synaptic devices, phase-change synaptic devices and so on, according to the physical and chemical mechanism of its resistance change.

2.4. Applications of various synaptic devices and their advantages:

Electrically Stimulated Synaptic Devices [3, 4]: - Advantages: complete simulation of synaptic functions, device scalability and good durability. - Applications: Mainly used to simulate the functions of excitatory synaptic current (EPSC), inhibitory synaptic current (IPSC), long time-range potentiation (LTP), long time-range depression (LTD), and synaptic plasticity related to timing-dependent plasticity (STDP). Figure 1 shows the basic functions of some kinds of photoelectric synaptic devices. Electrically stimulated synaptic devices can induce neuromodulatory effects within the sensorimotor cortex through continuous whole hand sensory electrical stimulation. This stimulation reduces the activity of inhibitory neural circuits and strengthens excitatory synapses, which promotes the formation of long-term potentiation mechanisms (LTP), affecting cortical plasticity. This synaptic plasticity is essential for neuronal activity-dependent changes that can be induced by electrical stimulation, thus positively affecting neurorehabilitation. The advantage of electrically stimulated synaptic devices is their ability to induce neuroplasticity, enhance cortical excitability, and positively impact the recovery of motor function. Through stimulation, the excitability of the motor cortex can be increased and the recovery of motor function can be facilitated. In addition, electrical stimulation can be used to treat neurological conditions like Parkinson’s illness and multiple sclerosis, as well as diseases such as neuropathic pain.

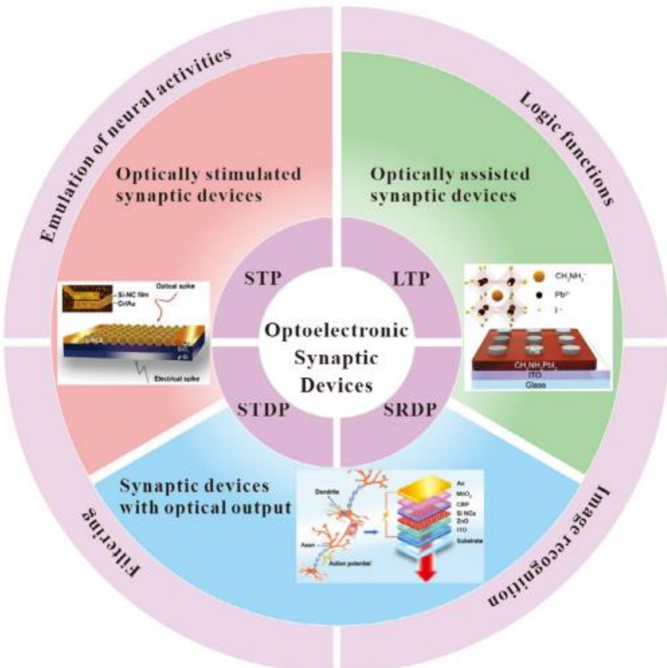

Figure 1. Overview of this Review. Optoelectronic synaptic devices have basic functionalities such as STP, LTP, STDP, and SRDP. These devices can be categorized into optically stimulated synaptic devices [4].

DOI: 10.54254/2755-2721/65/20240511

Optically stimulated synaptic devices [5]: - Advantages: High bandwidth, quick transmission, and the ability to replicate eyesight directly for color identification. - Applications: mainly used for optical simulation and color recognition. Synaptic devices activated by light have several benefits and applications. First, they are able to reduce the computational burden by performing in-sensor preprocessing during image data acquisition. This preprocessing includes contrast enhancement and image filtering of the image, which helps improve the accuracy of image recognition. In addition, photostimulated Synaptic mechanisms can imitate human synaptic properties, like long- and short-term memory, to achieve photon-triggered synaptic plasticity. These properties make optically stimulated synaptic devices potentially useful in machine vision systems. For example, photostimulated synaptic devices can be used for image contrast enhancement, producing preprocessed images that help improve image recognition accuracy. In addition, these devices can be used for moving object detection by filtering the image to extract certain characteristics from the picture data, like edge detection and image relief. In addition, optically stimulated synaptic devices can be applied to artificial sensory systems, such as simulated pain receptors, for timely detection of potentially dangerous damage. These applications indicate that synaptic devices activated by light have a wide range of potential applications in image processing and perception.

Optical synergistic synaptic devices [4]: - Advantages: 1. Wide bandwidth: Optical synergistic synaptic devices are characterized by wide bandwidth and can receive both optical and electrical stimuli. 2. low impedance and capacitive delay: these devices have very low impedance and capacitive delay, enabling fast signaling. 3. global regulation: optoelectronic synergistic synaptic devices can globally regulate multiple synaptic devices, offering the advantage of global regulation. 4. Mixing visual perception, signal processing, and memory: This is important in the context of neuromorphic computing because humans acquire most of their information through the biological visual cortex system. APPLICATIONS: 1. simulation of neural activity 2. image recognition 3. signal filtering 4. logic functions This example is about the application of near-infrared quantum dot emitting diodes of light (NIR QLEDs) as optoelectronically synergistic synaptic devices. As shown in figure 2, these NIR QLEDs have a multilayer structure including Ag/ZnO/Si NCs/PFN/P3HT/PEDOT:PSS/ITO/glass. this structure allows these devices to mimic important synaptic plasticity. Among them, the Si NCs layer is the key functional layer miming synaptic plasticity, while the PFN layer blocks the electron escape from the silicon QDs layer. These NIR QLEDs emit light at a peak wavelength of 850 nm, which allows them to operate in the near-infrared spectral range. In addition, the P3HT layer has a high carrier mobility, which helps to balance the carrier injection in the device. The application of these devices demonstrates the potential applications of optoelectronically synergistic synaptic devices for image recognition and memory, especially in modeling important synaptic plasticity. The design and application of such device structures provide important examples for developing optoelectrically synergistic synaptic devices in neuromorphic computing and image processing.

There are benefits to electrically triggered synaptic devices in modeling synaptic function, while Advantages of optically stimulated synaptic devices in large bandwidth and quick speed of propagation. Optically synergistic synaptic devices have combined visual perception, signal processing, and memory functions for neural activity simulation, image recognition, and so on. These devices have many applications in neuromorphic computing and artificial neural networks.

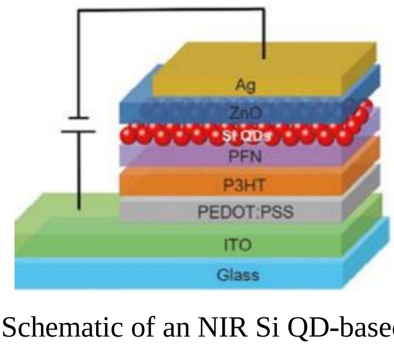

Figure 2. Schematic of an NIR Si QD-based QLED [4].

3. Basic framework and algorithms for neuromorphic computing

3.1. Characterization of Neuromorphic computing

Neuromorphic computing is a computational paradigm that mimics the human brain and aims to realize highly efficient, low-power, and adaptive intelligent computing. The basic framework of neuromorphic computing is a neural network composed of synaptic devices, which can realize large-scale parallel, distributed, event-driven information processing. The basic algorithm of neuromorphic computing is a learning rule based on synaptic plasticity, which can achieve self-organization, self-adaptation and self-optimization of neural networks [6].

3.2. The basic framework of neuromorphic computing consists of the following main components:

1. Neuron: the basic unit of a neural network responsible for receiving, integrating and distributing neural signals. Various neuron models exist, such as impulse neuron, membrane potential neurons, etc., which are selected according to the application requirements.
2. Synapse: the connection point between neurons, responsible for neural signaling, network learning and memory. Synapse models include linear and nonlinear synapses, which are selected according to learning rules and goals.
3. Neural network: an information processing system composed of neurons and synapses, capable of realizing complex intelligent tasks. Various network structures, such as fully connected, convolutional, and recurrent networks, are chosen according to data characteristics.

3.3. The basic algorithms for neuromorphic computing include the following:

Unsupervised Learning Based on Synaptic Plasticity [7]: unsupervised learning according to synaptic plasticity refers to the neural network automatically adjusts the weights of the synapses according to the statistical characteristics of the input data to realize feature extraction and clustering of the data and so on. Typical algorithms of unsupervised learning based on synaptic plasticity are Haibu learning, competitive learning, self-organizing mapping, etc., which can realize the self-organization and self-adaptation of neural networks. This paper introduces A new unsupervised learning rule inspired by the brain called voltage-dependent synaptic plasticity (VDSP) for online implementation regarding neuromorphic computing hardware. The synaptic conductance is updated by the VDSP learning rule only on the impulses of the postsynaptic neurons, which reduces the number of updates and does not call for more storage space. The rule also adapts to the input signal frequency, eliminating the need to manually adjust hyperparameters. The study achieved good accuracy by training a solitary layer impulse neural network (SNN) to recognize handwritten digits. This suggests that the VDSP learning rule has potential for application in challenges involving the perception of spatial patterns. Future research will take into account more complex tasks and explore the scalability of VDSP in larger networks. As an example, the experiments in this paper show that the VDSP learning rule exhibits similar performance to the STDP learning rule in handling the handwritten digit recognition task, while being robust to the input's temporal dynamics signals and eliminating the requirement that adjust the hyper-parameters of the input signals for distinct frequency ranges. This suggests that the VDSP learning rule has potential applications in dealing with real-world problems.

Supervised Learning Based on Synaptic Plasticity [8]: supervised learning according to synaptic plasticity refers to the neural network that automatically adjusts the weights of the synapses according to the error in between the input data and the intended result data to realize the classification and regression of the data and so on. Typical algorithms of supervised learning based on synaptic plasticity include back propagation, perceptron, support vector machine, etc., which can realize self-optimization and self-learning of neural networks. Supervised learning based on synaptic plasticity is a learning method for pulsatile neural networks (SNNs), where synaptic plasticity means the strength of the connection between synapses can be adjusted according to the temporal correlation between neurons. In this paper, researchers used a long-term memory SRM (spike response model) to implement under supervision based on synaptic plasticity. They conducted experiments on four UCI

DOI: 10.54254/2755-2721/65/20240511

datasets, including the PIMA, Iris, WBC, and Liver datasets. The researchers conducted their experiments by normalizing and converting the feature values to frequency intervals and then encoding each frequency value as a pulse training using a linear coding approach. They compared their proposed algorithm with other algorithms, including SpikeProp, SWAT, and multi-ReSuMe. The experimental results showed that their method achieved higher classification accuracy on these datasets. For example, their method achieves an average classification accuracy of 69.5% per sample on the PIMA dataset, compared to 67.7% and 66.7% for the other methods, respectively. On the WBC dataset, their method's average per-sample classification accuracy was 68.1%, while the classification accuracies of the other methods were 62.4% and 61.7%, respectively. These results indicate that the supervised learning method based on synaptic plasticity achieves good classification performance on these datasets.

Reinforcement Learning Based on Synaptic Plasticity [9]: Learning reinforcement through synaptic plasticity refers to a neural network that automatically adjusts the weights of the synapses according to the rewards or penalties between the input data and the environmental feedback to realize decision making and control of the data, among others. Typical algorithms for reinforcement learning based on synaptic plasticity are Q-learning, policy gradient, actor-critic, etc., which can realize self-exploration and self-adaptation of neural networks. Reinforcement learning based on synaptic plasticity is an approach that mimics how the biological brain learns by adjusting synaptic weights to maximize the expected reward. This paper introduces a synaptic plasticity-based reinforcement learning rule called Synaptic Plasticity with Online Reinforcement Learning (SPORE). The rule modulates synaptic updates via global reward signals to maximize the expected reward. Specifically, SPORE does not converge to local maxima of synaptic parameter vectors, but continuously samples from solutions that are likely to yield high rewards. In addition, SPORE uses temperature parameters to modulate the distribution of solutions so that they can be highly explored or highly utilized. Examples in this paper include the use of SPORE to learn two visuomotor tasks: reaching and lane following. It is shown that SPORE is able to learn and perform these tasks in a simulated environment. In addition, the study notes that regulating the learning rate and controlling the temperature of the stochastic processes that regulate the dynamics of synaptic learning are critical to improving performance. Finally, the study also discusses how deep reinforcement learning techniques can be drawn upon to enhance SPORE's functionality in visuomotor tasks.

4. Applications and perspectives of synaptic device-based neuromorphic computing in artificial intelligence

The application and outlook of synaptic neuromorphic computing in artificial intelligence through devices is the focus and difficulty of this paper, which involves several fields and aspects, such as image processing, computer vision, pattern recognition, machine learning, and natural language processing, speech recognition, natural language generation, and so on. The main contents of Applications and Perspectives of Neuromorphic Computing in Artificial Intelligence based on Synaptic Devices are:

The application cases and effects of synaptic device-based neuromorphic computing in artificial intelligence are the core part of this paper, which can demonstrate the advantages and potentials of synaptic device-based neuromorphic computing, as well as its roles and values in solving real-world problems and improving performance and efficiency [6]. In this paper, we will select some typical application areas and cases, such as image processing, natural language processing, etc., introduce the application methods and processes of synaptic device-based neuromorphic computing, as well as its comparison and analysis with the traditional artificial intelligence methods, and demonstrate the application effects and advantages of synaptic device-based neuromorphic computing, such as image denoising, image segmentation, image recognition, text classification, text summarization, text generation, etc.

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5. Conclusion

The problems and challenges in the application of synaptic device-based neuromorphic computing in artificial intelligence is a key part of this paper, which can reveal the limitations and shortcomings of synaptic device-based neuromorphic computing, as well as its difficulties and obstacles in realizing a high level of artificial intelligence. In this paper, we will analyze the application problems and challenges of synaptic device-based neuromorphic computing in artificial intelligence from both technical and theoretical aspects, such as preparation, testing, modelling and integration of synaptic devices, architecture, programming and optimization of neuromorphic computing systems, and scalability, reliability and interpretability of neuromorphic computing.

The current status and future trends of synaptic device-based neuromorphic computing in AI is the concluding part of this paper, which summarizes and evaluates the achievements and contributions of synaptic device-based neuromorphic computing in AI, as well as its potential and prospects in advancing the AI development and innovation, as well as its potential and prospects. In this paper, we intend to summarize the state of affairs now and in the future trends of synaptic device-based neuromorphic computing in AI from both academic and industrial perspectives, such as the research progress and hotspots of neuromorphic computing based on synaptic devices, the market demand and application scenarios of neuralmorphic computing based on synaptic devices, and the direction of synaptic device-based neuromorphic computing development and challenges.

References

[1] Yuhan Shi, Scott W. Fong, H.-S. Philip Wong, et al. Synaptic devices based on phase-change memory[M]Neuro-inspired Computing Using Resistive Synaptic Devices. Springer, Cham, 2017: 20-21.

[2] Wen Huang, Xuwen Xia, Chen Zhu, et al. Memristive artificial synapses for neuromorphic computing[J]. Nano-Micro Letters, 2021, 13: 3-5.

[3] Golaszewski, Stefan, et al. Synaptic Plasticity by Afferent Electrical Stimulation[M]. Synaptic Plasticity. IntechOpen, 2017: 2-13.

[4] Pham, Phuong V., The-Hung Mai, Huy-Binh Do, et al. Integrated Graphene Heterostructures in Optical Sensing[J]. Micromachines, 2023, 14(5): 1060.

[5] Minkyung Lee, Hyojin Seung, Jong Ik Kwon, et al. Nanomaterial-Based Synaptic Optoelectronic Devices for In-Sensor Preprocessing of Image Data[J]. ACS omega, 2023, 8(6): 5209-5224.

[6] Catherine D. Schuman, Shruti R. Kulkarni, Maryam Parsa,et al. Opportunities for neuromorphic computing algorithms and applications[J]. Nature Computational Science, 2022, 2(1): 1-2.

[7] Nikhil Garg, Ismael Balafrej, Terrence C Stewart, et al. Voltage-dependent synaptic plasticity: Unsupervised probabilistic Hebbian plasticity rule based on neurons membrane potential[J]. Frontiers in Neuroscience, 2022, 16: 983950.

[8] Xianghong Lin, Mengwei Zhang, and Xiangwen WangSupervised learning algorithm for multilayer spiking neural networks with long-term memory spike response model[J]. Computational Intelligence and Neuroscience, 2021, 2021.

[9] Jacques Kaiser, Michael Hoff, Andreas Konleet al. Embodied synaptic plasticity with online reinforcement learning[J]. Frontiers in Neurorobotics, 2019, 13: 81.