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Spiking neural network research based on brain-inspired computing

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Abstract. With the shortcomings of deep learning in training cost, generalization ability, interpretability, and reliability, increasing attention was concentrated on the novel neuromorphic devices. A spiking neural network can better simulate the information transmission mode of biological neurons, and has the characteristics of strong computing power and low power consumption. Therefore, this study provides an overview of the pulse neural network from the perspective of its fundamental structure and operating principle. In terms of structure optimization, there is a summary of the aspects of the encoding mode of a spiking neural network and topology structure. In addition, the deficiency and development of the spiking neural network are analyzed. Pulsed neurons work by integrating the mechanism of firing, exchanging information with the time of the signal, and transmitting signals to adjacent neurons only when the membrane potential reaches a threshold. Spiking neural network (SNN) still lags behind traditional Artificial neural network (ANN) in accuracy, has large computational capacity and is inefficiently trained due to the complexity of pulsed neuron models. Future developments lie in bionics, deeper studies of the complex dynamics of the human brain, and synaptic connections in the human brain.

Keywords: spiking neural network, brain-inspired computing, topology structure, deep learning.

1. Introduction

With the constant deepening of artificial intelligence research and development in various fields, deep learning has experienced the first stage of the perceptron and the second stage of multi-layer artificial neural network development, making deep learning in pattern recognition, automatic control, system, prediction, intelligent robot and biomedical fields more widely used and mature. Brain-like intelligence research inspired by brain science is expected to promote the development of the next generation of artificial intelligence technology and the new information industry [1].

Spiking neural network (SNN) is a new generation of artificial neural network inspired by the biological brain for information processing based on event-driven sparse computing [2]. The research on the brain and neuroscience has given many important inspirations in the field of artificial intelligence research. The two intersect, and understanding the characteristics of the biological midbrain can promote the development of the field of artificial intelligence. Based on these factors, the pulsed neural network is summarized and this paper intends to figure out the future advantages of spiking neural networks over other neural networks. This paper expounds the basic principles of

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pulsed neural networks, summarizes the improvement of the pulse network model, summarizes the defects and development of pulse neural network, lists the application of pulsed neural network, and summarizes the network.

2. Analysis of spiking neural system

The human brain is a complex network structure composed of more than 80 billion neurons connected by millions of synapses. In the network, neurons receive the information transmitted by other neurons, and then transmit the information to the next neuron through the axon. Spiking neural network as the third generation of artificial neural network, compared with the first generation of neural network and the back propagation algorithm represented by the second generation of neural network, through more accurate imitation of biological neurons, information transmission, etc., enhances the ability to process space and time data and spatial information, in a powerful computing environment at the same time and has the advantage of low power consumption, low latency [3].

The pulsed neural network is composed of the input layer, coding mode, pulse neurons, synaptic weight learning rules, and output layer, with a multi-layer network topology similar to biology [4]. SNN takes time and spatial sequence as the coding mode; spiking neurons take pulse excitation time as the input and output; multiple spiking neurons construct different kinds of topology, learn through certain learning rules, and finally get the output results. Spiking neural networks reduce the gap between neuroscience and machine learning by using the model of biological neuron mechanisms for computing, which can better simulate biological neurons, and then become the basis of brain-like computing.

Inspired by the neural science experiments, the typical deep ANN has a multi-level hierarchical structure [5]. After a lot of image training, the convolution operation gains the same abilities as neurons in the retina and other visual systems. In recent years, ANN has made important breakthroughs in visual information, such as in image recognition and classification, segmentation, and detection, which have surpassed the human level [6]. However, ANN obtains image features through end-to-end methods, so it is difficult to explain the meaning of the underlying network features. The spiking neural network uses the firing time of the spikes as the information processing mode of the network, which increases the time domain information and improves the computing power of the network. At the same time, its event-driven and dynamic characteristics can effectively reduce the power consumption and have good biological interpretability. Compared with ANN, SNN has the following characteristics and advantages:

1)Information encoding and representation. The SNN encodes information as pulse trains using a temporal coding scheme, while the ANN encodes information as a scalar using rate-coding. In contrast, SNN has more powerful information representation capabilities when processing complex temporal or spatial-temporal data.

2)Computing unit and simulation. The basic computing unit of ANN is the artificial neuron, where the input is processed by the activation function; the basic computing unit of SNN is the pulse neuron, represented by the differential equation. The simulation strategy of ANN is a step-by-step simulation process, and SNN is mainly based on the clock-driven and event-driven simulation processes.

3)Synaptic plasticity and learning. The synaptic plasticity mechanism of the SNN emphasizes the pulse time-dependent plasticity between presynaptic and postsynaptic neurons, while the ANN mechanism generally satisfies the Hebb rule. Unlike the ANN error back propagation algorithm, the biggest difficulty in SNN's current research is the training problem caused by the discontinuity and non-differentiable problems of network gradients in back propagation.

4)Parallel and hardware implementation. SNN enables rapid and massively parallel information processing, while ANN is relatively weak. SNN uses discrete pulse sequences instead of analog signals to transmit information, which is more suitable for hardware implementation with low energy consumption.

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3. The structure of the optimization

3.1. Encoded mode

Brain neurons transmit information by all-or-nothing pulse encoding. Information is propagated between neurons through action potentials and synaptic structures. Current neuroscience research suggests that the brain is likely to have two codes based on pulse release frequency and timing [7]. The spiking neural network simulates the processing mode of brain information transmission. By encoding external stimuli with certain methods, stimulating neurons completes information processing and issues a series of pulse signals under certain conditions to realize information transmission. So far, SNN coding mode has 12 typical kinds: frequency coding, time coding, bursting coding, group coding, adaptive coding, Gaussian differential receptive field coding, single pulse time coding, convolutional share weight nuclear coding, step coding (SW), rank order coding (ROC), new ROC and first pulse time coding.

3.2. Spiking neurons

The most basic component of the SNN is pulse neurons, which transmit information by sending and receiving action potentials [8]. The two vital variables of spiking neurons are membrane potential and activation threshold. When the information passes through the pulsed neurons, by encoding the information with an action potential, the neurons in the network are activated only when the potential accumulation reaches a certain threshold. The activated neurons produce a pulse and the other neurons remain silent. The strength of the connection between two neurons is determined by the pulse signal intensity of the presynaptic neuron. Due to the binary nature of information representation, SNN outperformed ANN in terms of energy and efficiency [9]. SNN has superior capabilities in integrating information coded in time, phase and frequency, and in processing large amounts of data in an adaptive and self-organized manner.

Five models commonly used in SNN network construction are the Hodgkin-Huxley model (H-H), the integrate and fire model (IF), the leaky integrate and fire model (LIF), the spike response model (SRM), and the Izhikevich model.

The H-H model more realistically simulates the properties of biological neurons but the disadvantage is that the expression form is complex and cumbersome, which cannot be used for large-scale network architecture [10]. IF and LIF models have the advantages of simple computation and are suitable for hardware implementation [11]. They are the most widely used neuronal models in spiking neural networks. The Izhikevich model has a good trade-off between biological rationality and computational efficiency [12]. Overall, the most commonly used spiking neuron models are the LIF and Izhikevich models, the LIF neuron mode is expressed as

$$\tau_m \frac{dV}{dt} = V_{res} - V + R_m I \tag{1}$$

τ_m is the membrane time constant, V_{res} is the resting potential, R_m is the cell membrane impedance and I is the input current. The Izhikevich neuron model is expressed as

$$\frac{dy}{dx} = a(bV - u) \tag{2}$$

u is the sodium inhibitory variable and the potassium activation variable; V is the neural membrane potential; a is the membrane potential attenuation rate, and b is the sensitivity of the activation variable to the membrane potential change.

3.3. The sketch of the topology structure

At present, from the perspective of the complexity of topology structure and the update and iteration speeds of network parameters, the topology of pulse neural networks is mainly divided into three types: feed-forward spiking neural networks, recurrent spiking neural networks and hybrid spiking neural

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networks. The model construction of the topology of an SNN network can influence the choice of an SNN learning algorithm. We summarized the improvement direction of pulse network topology from the perspective of structure application improvement. There are 5 main methods: locally connected pulse neural networks, integrated pulse neural networks, high parallelism inception-like SNNs and spiking inception structures.

4. Defects and the development of spiking neural networks

ANN is inspired by the biological brain, but compared with the real brain, the biological system is highly abstract and in capturing biological neurons, processing complex system with timing and dynamic characteristics is insufficient. In the data acquisition process, structure, learning algorithm and learning rules have fundamental differences with the human brain, leading to deep learning bottlenecks in recent years. Brain-like computing event-driven features can reduce running power consumption. The SNN algorithm theory can be well understood biologically, and temporal domain information has more processing power. On the other hand, traditional frame-based static data has gradually been unable to meet the requirements of SNN applications, and SNN has weak information expression ability on the encoded static data, which is not conducive to SNN model learning and reasoning. The Dynamic Vision Sensor (DVS) neuromorphic data set, which has the advantage of hardware realization, has broad applications in optical flow estimation, target tracking, and action recognition. It also features asynchrony, low power consumption, minimal data redundancy, and low delay. Complicated calculation process, time-consuming, generally ineffective training, and lack of good training algorithms are urgent problems to be solved for spiking neural networks.

5. Development direction of brain-like computing

Brain-like computing is the intersection of brain science, cognitive science, information science, computer science and technology, artificial intelligence and other disciplines, and is the simulation of the essential laws of brain activity. The cranial nerve and its cognitive system are complex systems, and there are some limitations in the research in this field. The future research directions for brain-like computing based on pulse neural networks are as follows:

The first is the investigation into the novel brain-like computer model. In order to truly achieve autonomous learning, class brain computing models should be built based on the fundamentals of the brain's information processing mechanism rather than on some superficially similar brain details and structures. These models should explore how the brain can use the body environment to adapt and dynamically adjust the calculation model.

The second is research on integrated brain-like computing methods. The pulse neural network-based class of brain computing research can take into consideration a variety of methods of integration, class brain computing methods such as pulse neural network and deep neural network, the combination of the pulse neural network and inspired by the biological learning process, enhance the combination of learning methods, etc., through a variety of methods of integration and get a more effective and good generalization of brain learning training algorithms.

The third is to develop a practical brain-like morphology chip. To realize the brain robot and achieve a higher level of intelligence, brain intelligence is the foundation. For more typical pulse neuron models, nerve synapse, learning algorithm for practical neural form chip, can be applied to the robot drone system, and autonomous vehicle driving system brain chip.

6. Conclusion

First, the fundamental ideas behind pulsed neural networks are presented in this paper. Finally, a summary of the use of SNN in brain-like computing is provided after explaining the advancement in structure, summarizing the flaws, and developing spiking neural networks and brain-like computing. Deep learning's modeling of a second-generation neural network is now utterly insufficient to imitate the organization of the brain's connections and the representation of biological information. Although the data-driven mode and 2-dimensional solidified structure are useful in training, they also act as a development block. Hence, event-driven and pulsed information representation mode based spiking neural networks have a more promising future. By utilizing the information memory of the network architecture and connection strength and achieving the integration of memory and processing, it is possible to develop robust artificial intelligence.

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