A review on photonic spiking neural network algorithms

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***Abstract*—The use of artificial intelligence is becoming increasingly widespread, but the power consumption during training and inference of neural networks is very high, and current research directions continue to improve artificial neural networks by adopting the characteristics of the biological brain, an advance that has led to the emergence of third-generation spiking neural networks (SNNs). It is capable of more energy efficient and accurate computing, while also making more faithful use of biological properties to provide higher processing power. This paper reviews the algorithmic implementation of optical devices for spiking neurons. The biological background of the SNN learning algorithm is first reviewed. Important elements of learning algorithms, such as biological and photonic neuron models, synaptic plasticity and information encoding are presented. Then some discussions on the currently existing learning algorithms for photonic pulsed neural networks are presented, and finally the challenges and opportunities in the field of SNN are analysed.**

***Index Terms*—photonic synapse, spiking dynamics , spiking neural network (SNN), STDP, VCSEL.**

I. Introduction

IN recent years, artificial intelligence (AI) has developed rapidly and is being used in a wide range of fields and industries, changing people's lives to a large extent. As an important implementation of AI, artificial neural networks can "learn" and perform complex operations in different environments, and are widely used in many fields such as computer vision, facial recognition and voice translation. However, as the volume of data increases year by year, more complex neural network models and huge amounts of training data are needed to solve more advanced problems, and modern computer systems based on Moore's Law and conventional Von Neumann architectures run into "memory walls" and "power bottlenecks" and are gradually unable to cope with the huge amounts of data processing. The so-called 'memory wall' refers to the physical separation of the central processing module and the storage module, and the difference between the fast computing power of the central processing module and the slower storage speed of the storage module; and the "power bottleneck" refers to the problems of power loss and heat dissipation as the processing power of computers with conventional von Neumann architectures increases.

In contrast, brain computing shows great advantages: the average speed at which the adult brain performs operations is 10^{16}/sec and the energy required is only about 20W [1]. In contrast, synapses play a major role in rapid information processing, with approximately 9×10^{10} neurons and 10^{14} synapses in the brain [2]. The brain combines a computational module and a storage module into one, and information is transferred between neurons by electrical impulses called spikes, reducing the amount of energy needed for transmission. To meet the growing demand for computing, so brain-like neural computing based on non-Von Neumann architectures has attracted research and discussion from a wide range of researchers, and it promises a new computational platform with high speed and low loss [3].

This new field, which has been expanded from artificial neural networks and also has some biological significance in neuronal modelling, is known as spiking neural networks (SNN). SNN uses pulsed neurons as computational units to simulate the encoding and processing of information in the human brain [4]. It transmits information through precise moments of a pulse sequence, which consists of a series of discrete pulses rather than continuous values. Precise spike timing has a higher capacity for encoding information in a small group of spiking neurons [5]. In addition, when a neuron receives a pulse, the pulsatile neuron integrates the input into the membrane potential and issues a response pulse when the membrane potential reaches a threshold, passing down the line so that event-driven computations can be performed. Due to the sparsity of event-driven computations and pulse events, SNNs have excellent power efficiency and are considered to be the neural network of choice in brain-like neuromorphic architectures [6].

Over the past two decades, researchers in the fields of neurobiology and computational neurology have worked on learning algorithms for SNNs [7]. The research efforts focusing on two main directions: unsupervised training and supervised training using temporal information. The spike timing-dependent plasticity (STDP) observed in biological synapses is a general unsupervised learning rule [8], which is closely related to biological learning mechanisms [9]. It adjusts synaptic weights according to the time difference between pre-synaptic and post-synaptic spikes, with synapses having excitatory connections (weights greater than zero) and inhibitory connections (weights less than zero). The weight is enhanced when the pre-synaptic pulse is delivered before the post-synaptic pulse within a specific time window (STDP window), and is diminished in the opposite direction.

For supervised learning, the SNN is first trained with samples, and then the trained model is tested and used for data inference. Common supervised learning algorithms include SpikeProp [10], Tempotron learning rule [11], ReSuMe [12], etc. In addition, supervised learning algorithms for multilayer SNNs or deep SNNs have also attracted increasing attention [13]. These supervised learning algorithms are mainly based on gradient descent, STDP mechanisms or spike sequence convolution. In particular, the STDP mechanism has also been widely used to design biologically sound supervised learning [14]. However, these neural network algorithms are results obtained from simulations on computational systems based on the Von Neumann architecture. Not all the advantages of SNNs have been fully realised. Meanwhile, many research teams are working on new hardware architectures with hardware-friendly algorithms in the hope of coming up with more reliable computational solutions for biological neuro-morphology [15].

The first section of this paper briefly describes the development and applications of SNNs, the second and third sections briefly describe the biological and optical contexts in which SNNs are used, the fourth section describes the principles of information transfer in biological synapses and is also an important learning mechanism for optical pulse neural networks, and the fifth section describes the common photonic pulse neural network learning algorithms currently available. Section 6 then summarises the challenges and opportunities currently faced by researchers. Finally, the paper ends with a conclusion in section 7.

II. Biological Background

A. The LIF neuron model

Neuronal models in turn contain several types of neuronal models, and although the Hodgkin-Huxley model can be better explained from a biological point of view, but the reality is that it is often impossible to apply this model due to the difficulty (or high cost of measurement) of measuring all aspects of the parameters of the nerve cell to exact values [16]. Therefore the leaky integrate-and-fire (LIF) neuronal model is currently widely used. Where leaky indicates the presence of leakage currents in the model; Integrate indicates that the system is capable of accumulating currents, for example in the role of capacitors in a circuit; and Fire indicates that the membrane voltage generates a sudden spike when the input current is sufficiently high. It has been shown that the LIF model is a valid model of biological neurons that can describe a variety of different biologically observed phenomena. Its main structures include dendrites, axons, cell bodies and nuclei. The main role of the dendrites is to receive signals and summarise them, both from connected neurons and their own neurons. The nucleus acts as a low-pass filter, integrating the signal over a period of time. The role of the axon is to transmit signals that exceed the threshold of the neuron. The main role of the axonal thalamus is to provide a threshold of excitation for the neuron. The biological LIF neuron model is simplified to a general topology as shown in Fig 1. It basically implements the basic function of the LIF model: in a state of internal activation, with N inputs $x_n$with synaptic weights (w_i) and one output y(t), the integrated input signal can be expressed as:

$$\sum_{i=1}^{N} \omega_i x_i(t-\tau_i)$$

Where τ_i indicates the delay in the signal transmission process. Figure 2 illustrates the peak dynamics in LIF neurons.

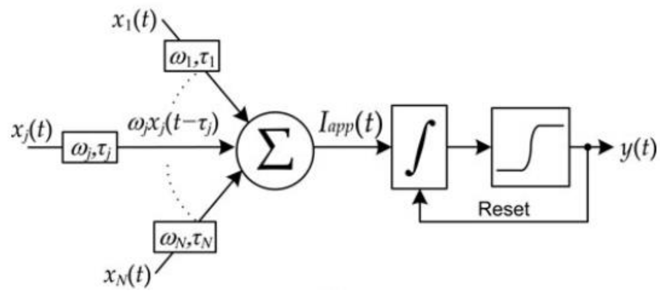

Fig. 1. A functional description of the LIF neuron model [17]

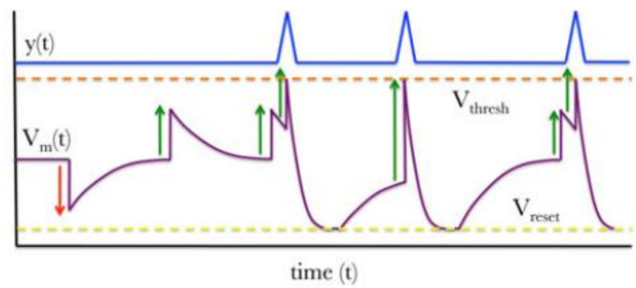

Fig. 2. Illustration of peak dynamics in LIF neurons [17]

B. Neuronal signalling

Neurons are the basic units of the biological nervous system. For individual neuronal cells, the membrane potential of the cell body changes in response to stimulation by an injected current, and when the membrane potential reaches or exceeds the threshold voltage of the neuron, the neuron generates an action potential, i.e. emits a short electrical spike signal. Where the axon of a neuron comes into contact with the dendrites or cytosol of other neurons is the synaptic structure of the neuron. When the pre-synaptic neuron transmits a signal, the post-synaptic neuron undergoes a potential change due to the synapse. Usually the neuron generates an action potential in the initial segment of the pre-synaptic neuron and the action potential is subsequently transmitted to the axon terminal where the release of neurotransmitters is evoked. The binding of the neurotransmitter to the post-synaptic membrane causes the opening of ion channels in the post-synaptic membrane and an influx of ions from outside the neuron's membrane into the membrane, resulting in a change in membrane voltage. A change in membrane voltage at one location in the neuronal membrane will in turn cause ion channels to open or close in neighbouring neuronal membranes, leading to a change in membrane voltage at the neighbouring location and ultimately to the conduction of nerve impulses. As shown in Fig. 3.

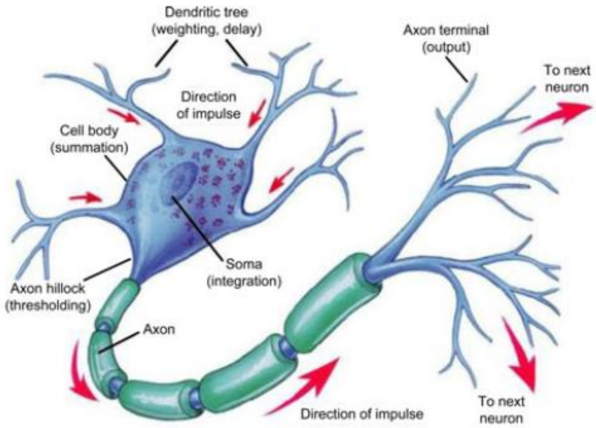

Fig. 3. Neuronal signaling processes [17]

III. Photonic Background

Many of the physical processes in photonic devices exhibit strong similarities to the biological neuron model of information processing, and both can be described within the framework of non-linear dynamics. Photonic neurons are the functional devices underlying optical domain computing systems, whose primary function is to receive and integrate incoming information and to complete information transfer. The difference is that while biological neurons are influenced by the chemicals in the organism, photonic neurons are primarily determined by the semiconductor properties of the optical device itself. In the past decade, photonic neurons have undergone a transition from being based on non-linear discrete devices to being based on integratable laser devices. In 2009, a team of researchers at Princeton University first proposed a cumulative emission (LIF) photonic neuron based on a semiconductor optical amplifier (SOA) and improved it in 2011 to obtain a fully functional LIF photonic neuron [17].

In addition, similar to the above neuron structures are photonic neurons based on electro-absorption modulator (EAM) [18]. However, discrete components built from SOA have the drawbacks of large size, low cost and high power consumption, making it difficult to implement functionally complex optical neural computing systems, so researchers have turned their research to semiconductor lasers with rich nonlinear dynamics. The commonly used semiconductor lasers are vertical cavity surface emitting lasers with saturable absorbers (VCSEL-SA), semiconductor ring lasers [19] and distributed feedback lasers with saturable absorbers (DFB-SA) [20]. Among them, VCSEL-SA has the advantages of low cost, small size and low energy consumption compared to other lasers, thus making it an ideal candidate for photonic neurons.

A. Photonic neuron model

VCSEL is a new type of semiconductor laser and is one of the most promising lasers for optical communication systems. It has many advantages over other lasers, such as easy two-dimensional integration, low power consumption, low cost, small size and long service life. The VCSEL-SA is a model of a photonic neuron embedded in a saturable absorber. The structure of the VCSEL-SA photonic neuron is a saturable absorber SA embedded in a VCSEL cavity, consisting mainly of a front plane mirror, a gain region, an absorber region, a rear plane mirror and a base. The gain region, among others, consists mainly of two quantum wells of indium gallium arsenide/ aluminium gallium arsenide. The main material in the absorption region is also indium gallium arsenide/ aluminium gallium arsenide. The main objective of the resonant cavity is to produce a signal at the desired wavelength [21], as shown in Fig. 4.

When an external signal is injected into the gain region of the VCSEL-SA photonic neuron, the carrier concentration in the gain region will change, and when it reaches a certain threshold and the saturated absorption region reaches saturation, it will enter a transparent state, while the VCSEL-SA will excite a spike signal. After excitation, the carrier concentration in the gain region decreases rapidly and the neuron gradually enters a stable output state. If the VCSEL-SA photonic neuron is stimulated again within a short period of time, the neuron will not stimulate the spike again. This is because the photonic neuron cannot return to a steady state within a short period of time, and therefore the neuron cannot respond normally to the second stimulation, which is a characteristic of the neuron's under-stimulation period.

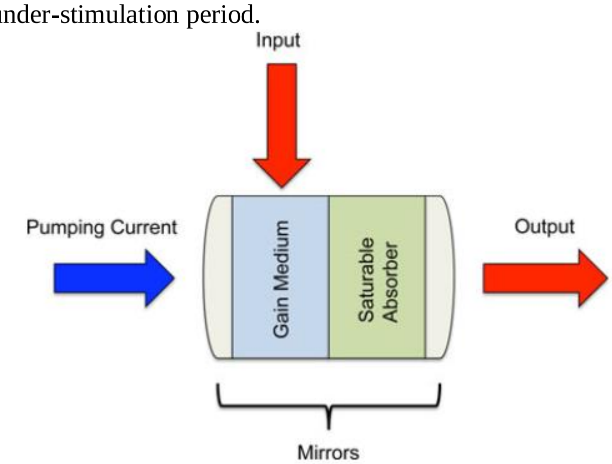

Fig. 4. A simple schematic of an SA laser. The device is composed of (i) a gain section, (ii) a saturable absorber, and (iii) mirrors for cavity feedback. In the LIF excitable model inputs selectively perturb the gain optically or electrically [17].

B. VCSEL-SA photonic neuron undershoot period

In spiking neural networks based on VCSEL-SA photonic neurons, the refractory period is the period after the first excitation of the spike during which the VCSEL-SA cannot re-excite the spike. At the same time, the refractory period is the key property that leads to the symmetry breaking phenomenon and allows spikes to achieve unidirectional stable propagation. From a signal processing point of view, the final processing speed of an optical or electronic system depends on the refractory period when excitable logic, cognitive processing or pulse shaping are taken into account. In neuronal physiology, spikes can be specifically divided into absolute refractory period and relative refractory period. In the absolute refractory period, inhibition is complete, whereas in the relative refractory period, the spike can be excited given a sufficiently large perturbation intensity, and the spike power of the second spike is less than that of the first spike due to inhibition.

C. Dynamic properties of VCSEL-SA photonic neurons

The Yamada model can describe the self-spiking phenomena of the laser. And it can also be used independently as a model to describe the dynamics of the gain and absorption regions of the laser. We based the modified Yamada model to accurately describe the non-linear dynamics of VCSEL-SA neurons [22], with relevant parameters referenced to the Prucnal research team [23], to numerically simulate the gain of light injected into the VCSEL-SA, as shown in Fig. 5.

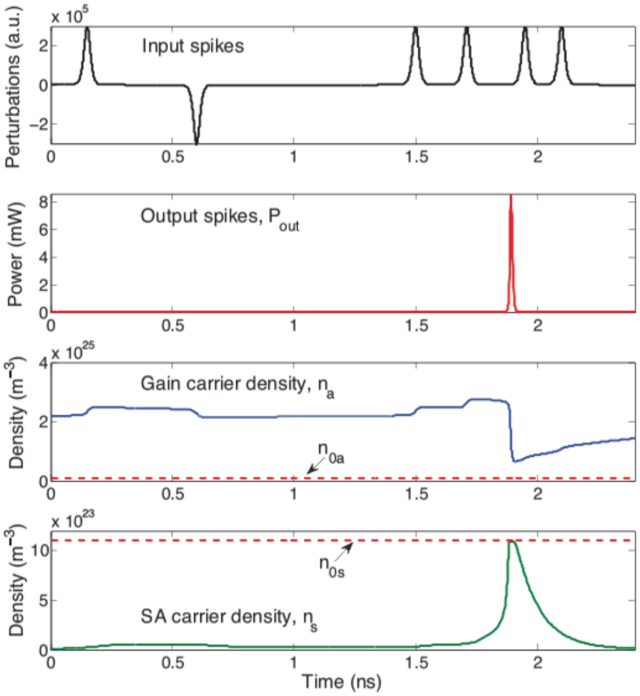

Fig. 5. Dynamic properties of VCSEL-SA photonic neurons [24]

In this case, the spike input perturbs the carrier concentration in the gain segment of the laser, with positive and negative pulses causing gain depletion and enhancement respectively. Given sufficient stimulation, this eventually causes the laser to enter fast dynamics and release a pulse, a behavior that belongs to the LIF neuron model.

D. VCSEL-SA-based coding

In biological neural networks, the processing and transmission of signals generally takes the form of spike signals. A spike signal that is analogue in time and digital in intensity. Because it is analogue in time and has spikes when there is a signal and no spikes when there is no signal, so it is energy efficient. As the signal is digital in intensity, the spikes are less likely to accumulate noise during transmission and can overcome noise during transmission. It is also possible to shape signals of different strength sizes, which is more conducive to signal transmission in neural networks. So we need to encode the analogue or digital signals used in the communication process into the form of spike signals. This is more bionic and more conducive to signal transmission, processing, computation, and storage in the neural network [25].

In the coding process, we use frequency coding and time coding. Frequency coding is the coding of the signal strength into different frequency and number of spikes. Time coding refers to the use of the time information of the spike to represent the information of the signal, etc. Time coding includes first spike time coding, spike interval coding, etc. For example, first spike time coding means that the length of time from the time of signal injection to the time of generating the first pulse represents the specific information of the signal.

1) VCSEL-SA based frequency coding

The VCSEL-SA analogue neuron encodes the signal. Assuming that the input analogue signal is a rectangular pulse, we can encode the rectangular analogue signal as a pulsed signal at this point without considering the effect of the refractory period. Let us assume that a rectangular pulse of strength $k_e=1$ and a rectangular pulse of duration Δt=2ns produces a spike signal from the laser, we can assume that this analogue signal is encoded as a spike signal; continuing with a rectangular pulse of the same strength, but with a longer duration, to a rectangular pulse of duration Δt=20ns, the laser can produce five spikes. This means that the longer the duration of the analogue signal, the greater the number of spikes that can be encoded at the same strength of the analogue signal. And the original analogue signal can be recovered to some extent based on the spike pulse signal generated [26].

The duration of the analogue signal is important information for coding, and likewise the strength of the analogue signal is important information for coding. It has been found that different strengths of the analogue signal will produce different numbers of spike pulses [27]. We still assume that the analog signal is represented by a rectangular pulse, and at this point, the duration of the rectangular pulse is specified Δt=5ns, and the intensity of the rectangular pulse is varied. When the rectangular pulse intensity is k_e=0.5, the laser cannot generate spikes; increasing the rectangular pulse intensity so that k_e=2, the laser can generate two spikes. And so on, indicating that larger intensities of rectangular pulses can produce more spikes. After studying the encoding of pulses of different intensities, it was found that if the duration is given, the recovery of the analogue signal can be achieved to some extent depending on the number of spikes. In Fig. 6 shows the number of pulses generated at different k_e and $\Delta\tau$.

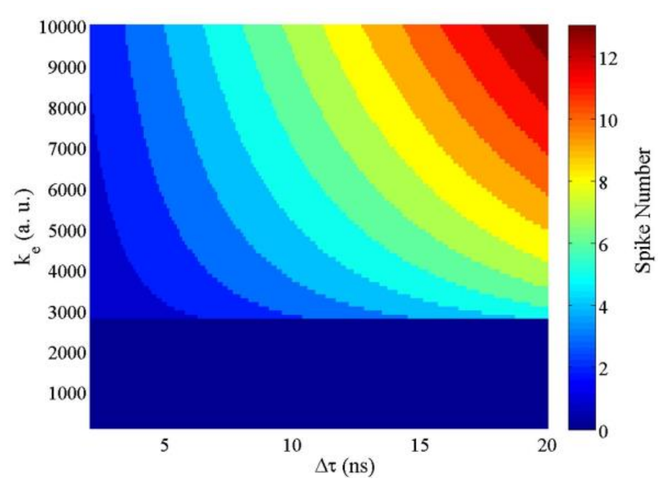

Fig. 6. Two-dimensional map of the number of output spikes in the parameters k_e and $\Delta\tau$ [26]

When the cause of the spike pulse is determined, we can encode the spike, the spike signal is encoded as "1", no spike signal is encoded as "0", so as to achieve the successful encoding of the digital signal [25]. It can be seen after the coding of good spike signal can be accurately recovered from the digital signal, that is, each spike signal represents a unit of high level signal [17].

2) VCSEL-SA based time coding

One of the more important concepts in spike coding is the coding time window, which refers to the length of time it takes for a neuron to convert external input into a sequence of impulses, and determines the output performance of a neural network. The length of the spike sequence corresponds to the single symbols in the neural code. The longer the coding time window, the larger the number of digits in the binary string corresponding to the single neural symbols in the neural code, and the larger the number in the neural code. With further research in neuroscience, the precise timing of spikes holds much neural information, and most neural systems have high demands on the response time of stimuli. Currently available methods for encoding based on spike timing are mainly time delay encoding and order encoding.

Latency coding is another abstraction of the temporal properties of the spike signal, where The information is encoded into the time to first spike release delay [28], and the delay of different spikes represents the different strengths of the external input stimulus. The earlier the moment of the output spike, the stronger the external stimulus that caused the spike; the later the moment of the output spike, the weaker the external stimulus that caused the spike.

Rank order coding (ROC) encodes the information carried by the first pulse by encoding the relative order in which pulses are delivered between neurons. The desensitization mechanism used in the rank order coding scheme implies that for a given stimulus neuron should be selective and that the synapse that delivers the pulse first should be given a greater weight [29]. Thus, during natural learning, synapses that activate early are enhanced, while synapses that activate late are inhibited. To demonstrate this coding scheme, for neurons A, B, C, D and E in Fig. 7, the spiking peaks are ordered as C > E > D > A > B [30].

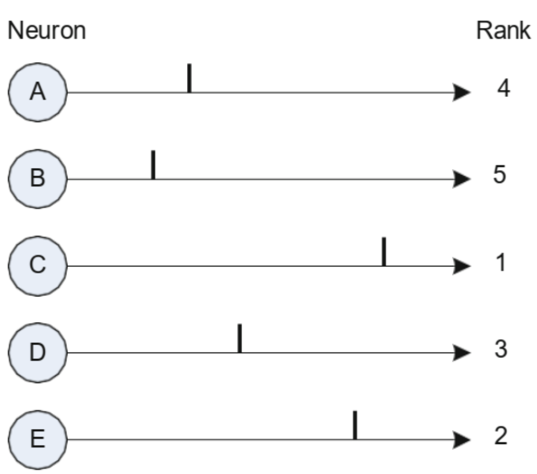

Fig. 7. Ranking of spikes in a ROC encoding method [30]

IV. Learning Methods For Impulsive Neural Networks

There is biological evidence that synaptic latencies are not always constant and can be modulated during the transmission of impulse signals [7]. This property of synapses that are constantly changing, remodelling and renewing as neurons transmit impulse signals through them in order to adapt to the functional needs of the body is synaptic plasticity. Synaptic plasticity is the basis for important functions of the nervous system such as development and learning and memory. And the main learning approach of SNNs is based on this. In biological neuronal networks, the temporal information carried by the pulse sequences is extremely important when learning. In general, learning in SNNs can be defined as a process of parameter adaptation and learning rules as a process of weight adjustment. learning in SNNs is dominated by unsupervised learning, while supervised learning algorithms are another hottest research area in SNNs [31].

A. Hebbian Learning

Based on long-term experimental studies, neuropsychologist Donald Hebbian proposed a basic law for synaptic operation during learning: when neurons at both ends of a given synapse are activated synchronously (either by the same excitation or by the same inhibition), the strength of that connection is enhanced and vice versa, known as the Hebbian hypothesis [32]. Hebbian's rule laid the foundation for the learning algorithm for SNNs and can be condensed into the following equation:

$$\Delta\omega_{ij} = C_{ij}V_iV_j + C_{ii}V_i^2 + C_{jj}V_j^2 + b_iV_i + b_jV_j + \alpha$$

where V_j is the pre-synaptic neuron firing rate; V_i is the firing rate of the post-synaptic neuron; ω_{ij} denotes the amount of change in the connection weights from pre-synaptic neuron j to post-synaptic neuron i during the learning cycle T; C_{ij}, V_i, V_j denotes the correlation between pre-synaptic and post-synaptic neuron activity; C_{ij}, V_{i2} and C_{ij}, V_{j2} are usually omitted.

B. STDP learning rules

Current biological neuroscience researchers have identified spike timing dependent plasticity (STDP) learning rules in the neural loop systems of many organisms. And, STDP can be seen as an extension of Hebb learning in the temporal dimension [33]. Synapses in biological nervous systems are divided into two main categories according to the distinction of neurotransmitters: excitatory synapses and inhibitory synapses. Assume that the pre-synaptic neuron is j, the post-synaptic neuron is i, and the connection weight between the pre-synaptic neuron j and the post-synaptic neuron i is W_{ij}. If the spike generated by the pre-synaptic neuron j reaches the post-synaptic neuron i before the post-synaptic neuron i delivers the spike, i.e., Long-term Potentiation (LTP), then the connection between the neurons W_{ij} will be enhanced. In contrast, if post-synaptic neuron i delivers a pulse before the arrival of pre-synaptic neuron j, i.e., Long-term Depression (LTD), the synaptic W_{ij} between neurons is weakened. The synaptic change between neurons can actually be seen as a function of the temporal relationship, and the process of synaptic change is called the STDP learning mechanism, as shown in Fig. 8.

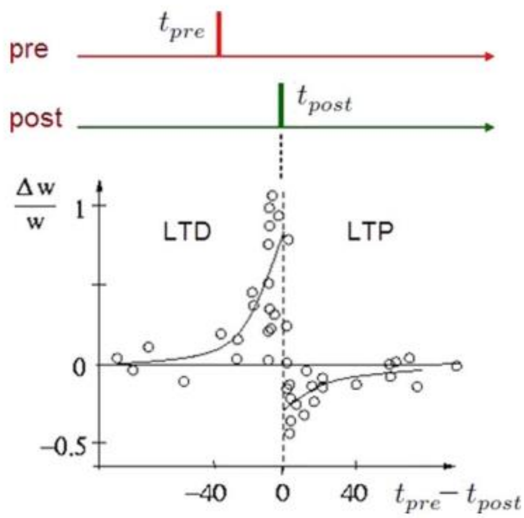

Fig. 8. STDP Learning Mechanism [34]

The update of synaptic weights takes place within a time window, and with the action of the neuron issuing pulses before and after the synapse, the time window function can be expressed as follows: A_+ and A- are both greater than zero representing the maximum value of the change in synaptic weights, t_+ and t- are both membrane time constants, and t represents the time difference between two firing moments: $s = t_j^f - t_i^f$. STDP learning time window. If the posterior neuron discharges after the pre-synaptic peak, the synaptic connection weight increases from the pre-synaptic neuron to the post-synaptic neuron. The magnitude of the change increases with A_+e^{-t/τ_+}. The opposite order leads to a decrease in synaptic weight with A_-e^{t/τ_-}.

V. Photonic Pulse Neural Network Learning Algorithm

As a synaptic plasticity learning mechanism, spike timing dependent plasticity (STDP) has a wide range of applications in the fields of pulsed machine learning and adaptive control. STDP determines the amount of weight change based on the sequential timing of pre-synaptic and post-synaptic spikes, and its optical implementation relies heavily on the non-linear characteristics of the optical device.

A. Optical STDP based on SOA and EAM

Fok's team was the first to implement an optical STDP [35], in which the optical STDP synapse is implemented via SOA and EAM. The post-synaptic and pre-synaptic spikes are each generated simultaneously by a mode-locked laser, injected into the coupler and distributed unevenly. More of the post-synaptic spike energy goes into the SOA, and more of the pre-synaptic spike energy goes into the EAM. The stronger post-synaptic light spikes cause a gain loss effect in the SOA, affecting the weaker pre-synaptic light pulses that enter during a certain time interval, so that the gain gained increases with the time interval, and the pre-synaptic light pulses are extracted by the corresponding optical filter, which then observes their light intensity through a photodetector and is used to adjust the synaptic weight, thus achieving the synaptic weight suppression effect in the STDP mechanism. Similarly, stronger pre-synaptic light spikes cause a saturation absorption effect in the EAM, affecting the post-synaptic light spikes so that the gain obtained is smaller with increasing interval time and is extracted by the corresponding optical filter, which also observes the light intensity and adjusts the weight through the photodetector, thus achieving the synaptic weighting enhancement effect in the STDP mechanism.

In the structure of Fig. 9, the parameters of the STDP (learning window width and height) can be adjusted by the input current magnitude of the SOA/EAM and the pre-synaptic and post-synaptic signal light intensity ratio; the STDP inhibition and excitation module parameters are controlled independently by the SOA and the EAM, but the advanced pulse learning algorithm cannot be implemented due to the need for the researchers' own adjustment and the lack of a feedback adjustment mechanism.

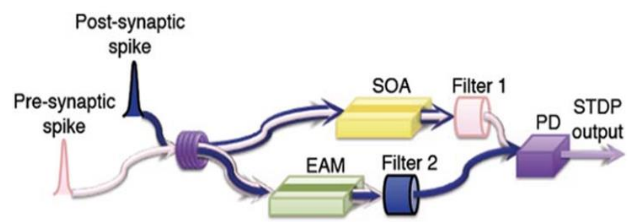

Fig. 9. Optical implementation of STDP based on SOA and EAM [35]

B. Single SOA based implementation of optical STDP

A photonic implementation of STDP characteristics was designed and experimentally demonstrated in a single semiconductor optical amplifier (SOA) using nonlinear polarisation rotation (NPR) and cross-gain modulation (XGM), improving photonic STDP circuits that require multiple electro-optical devices [36]. The shaded dashed box in Fig. 10 shows the experimental setup part of the optical STDP, with the rest of the circuit used to generate pre-synaptic and post-synaptic spikes. The two beams pass through the polarisation controller and then enter the SOA as pre-synaptic and post-synaptic spikes. If the pre-synaptic spike lags behind the post-synaptic spike, due to the XGM characteristics of the SOA, the optical gain of the output pre-synaptic spike parallel to the input polarization direction is smaller at short pulse intervals and increases with increasing time intervals; if the post-synaptic pulse lags behind the pre-synaptic pulse, due to the polarization rotation caused by the birefringence change of the SOA, the optical gain of the output post-synaptic pulse perpendicular to the input polarization direction is larger at short pulse intervals and decreases with increasing time intervals.

The output spectrum of the SOA passes through the polarisation beam splitter (PBS) into the polarisation parallel channel CH1 and the polarisation perpendicular channel CH2, where the STDP inhibitory properties can be obtained by filtering out the pre-synaptic light pulses through CH1 and measuring them for comparison; the enhanced properties can be obtained by filtering out the post-synaptic light pulses through CH2 and measuring them for comparison.

Since only the input current of the SOA can affect the STDP in this structure, the inhibition and excitation of the STDP are correlated and cannot be adjusted independently. Moreover, the output optical power of the excitation module of the NPG effect is much smaller than the output optical power of the suppression module using the XGM effect, so optical amplification of the signal is required at a later stage. Furthermore, the introduction of the concept of optical polarisation increases the complexity of the experiment and makes the conditions more demanding.

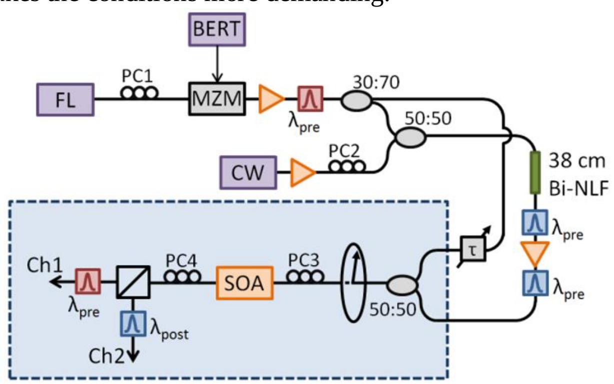

Fig. 10. The setup of optical STDP with single SOA [36]

C. SOA-based implementation of optical multiplication STDP and reward learning

In biological nervous systems, STDP synapses are usually regulated by boundary regulation mechanisms to prevent weights from becoming too small or too large, and it can be regulated by external factors to achieve reward-based augmented learning [37]. The weight updates in STDP can be classified as either additive or multiplicative [38]. Related studies have shown that additive STDP is simpler in processing models, but its robustness is not as good as multiplicative STDP. But overly simple model processing that does not involve neuro-modulation, optical STDPs cannot provide reward learning, and reward learning mechanisms are a necessary consideration in neural system morphology, which is closely related to synaptic plasticity and machine learning [39]. On this basis, local and global feedback with the introduction of SOA currents were implemented for multiplicative STDP as well as reward-based augmented learning, respectively. As shown in Fig. 11.

In Fig. 12, a mode-locked fiber ring laser is used to generate two ultrashort pulse beams as pre-synaptic and post-synaptic peaks. The relative time delay between the two beams is achieved by a variable optical delay line (ODL), and the pre-synaptic and post-synaptic spikes are separated by a non-uniform coupler, with the larger part of the pulse serving as the SOA signal spike and the smaller part as the detection spike. If the signal spike enters the SOA before the detection spike, it will be amplified normally and is not affected by carrier loss; if the signal spike enters the SOA after the detection spike and is within the relative refractory period of the detection spike, the output signal will be weak relative to the normal case. We thus subtracted the two spikes to achieve a link between reward learning and feedback signals: if the difference was positive, STDP inhibitory and excitatory module currents were positively correlated with reward; if negative, inhibitory module currents were negatively correlated with reward, enhancing the influence of the inhibitory module on synaptic modulation, while conversely, excitatory module currents were positively correlated with reward, weakening the influence of the excitatory module on synaptic modulation. To avoid too large synaptic weights w, a variable attenuator (VA) can be used as a weight adjustment device. By setting the maximum and minimum values of the attenuator as bounds for the weight update, the normalised w can be restricted to the interval [0,1] when integrating over the weight change Δw [40]. The mechanism by which this synaptic weight modulation is influenced by reward is similar to that of bio-augmented learning. The result of training is that the output spike sequence learns the target pulse sequence.

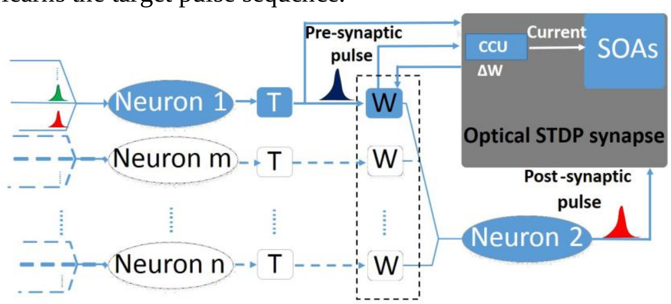

Fig. 11. Two photonic neurons are connected with an optical STDP synapse. W - variable weight adjusting device, T - variable delay line, SOA - semiconductor optical amplifier, CCU - current control unit [40].

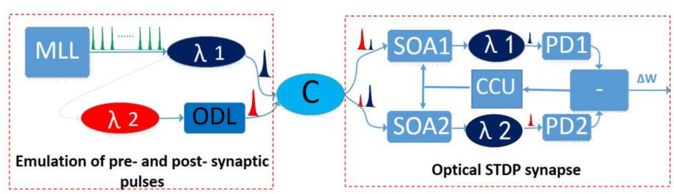

Fig. 12. Optical implementation of weight-dependent STDP. MLL-mode-locked fiber ring laser, λ1/λ2 - optical bandpass filters, ODL - variable optical delay line, PD – photodetector [40].

VI. Challenges and Opportunities

In the above cited articles, many basic principles and techniques related to SNNs are presented, and many optimisation algorithms are proposed and applied. In photonic pulsed neural networks, photonic neurons, optical pulsed neural network learning algorithms and photonic integrated neural network architectures are the three most important parts, and there are still many challenges in the development of each of them. The biggest problems in photonic impulse neural networks are currently integration and storage. In terms of optical integration, as most nonlinear optical devices are discrete devices not in integrated form, integration is difficult and the training process of the algorithm still requires the use of a computer to calculate the amount of synaptic weight change. Although there have been important breakthroughs in the research of all-optical chips, optical neural network chips that can really be used for bionic computing have not yet been introduced [41]. So integrated optical SNN algorithms are still extremely challenging.

There are also some problems with the unsupervised pulse recognition algorithm: a post-synaptic neuron can only recognize the first pulse of a spike pulse pattern at the same time, which does not allow for the recognition of multiple spike pulses, and a photonic SNN with multiple post-synaptic neurons and a lateral inhibition mechanism still needs to be proposed as a better solution. If combined with the inhibitory mechanism of photonic neurons, selective inhibition or time-division multiplexing of multiple spike pulses can be considered for pattern recognition.

This paper focuses on the training approach based on synaptic plasticity, which can better simulate brain-like computing as impulsive neural networks are a class of computational models that are closer to the biological nervous system. However, this type of algorithm is mainly applicable to the learning of single neuron or single layer neural networks and cannot be introduced for the back propagation mechanism of synaptic plasticity. Finding a biologically logical and implementable algorithm for training SNNs is a huge challenge because back-propagation is biologically implausible, the training approach does not mimic the human brain, and the non-linear and discontinuous nature of SNN activity makes it difficult to implement SNN training in this way. However SNN activity incorporates the presence of a temporal model, and although discrete pulses increase the difficulty of learning algorithms, as a new feature of the model energy efficient algorithms based on local event analysis can be considered.

VII. Conclusion

This paper mainly discusses the encoding methods and learning algorithms of common photonic pulses. The above-mentioned neuron models and training algorithms in photonic pulse neural networks show diversity, and for different models and computational requirements, we can use the corresponding algorithmic models, and the STDP algorithm is obviously a better algorithm for SNN applications at present, and also discusses the characteristics and problems of various experimental setups using different numbers of SOAs and computational methods.

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