Neuromorphic Photonics for RF Signal Processing

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Abstract—**Neuromorphic photonics use light to imitate the neural models and systems of nature for solving complex human problems that are challenging for conventional electronic approaches. Neural algorithms are natural designs that govern the survival of the organism, therefore, are highly effective for the designated tasks. In this paper, we review two small-scale neural algorithms – spike timing dependent plasticity process for learning and jamming avoidance response in Eigenmannia, discuss the marriage of those neural algorithm and photonics, as well as explore their real-life applications in human society.**

Keywords—neuromorphic photonics, biomimetic photonics, photonic neuron, bio-inspired signal processing, neural algorithm

I. Introduction

Animals and plants have unique neural algorithms that are critical for their survival. Those neural algorithms undergone billions of years of evolution and have been extremely efficient in performing their designed tasks. By closely examining the nature, we could find lots of neural algorithms that could be the natural solutions towards the critical challenges that we are facing in modern technologies. Discovering those hidden treasures, understanding them, and using photonics to mimic the useful neural algorithms is a new and exciting field.

In the last ten years, intensive research efforts have been made in neuromorphic photonics. Spike processing devices [1]-[17] using semiconductor optical devices, silicon photonics, and excitable lasers have been proposed and experimentally demonstrated. The photonic based spiking devices mimic the spiking process in a biological neuron, including summing and weighting, integration, thresholding, and spiking, but can also be operated at a tens of picosecond time scale. Photonic synapse [18]-[20] has also been demonstrated for potentially mimicking the brain's approach to simultaneous processing and storage of information. Artificial neuron networks [21]-[24] have been demonstrated using semiconductors and silicon photonics. Furthermore, photonic implementation of small neural circuits has also been explored. For example, crayfish tail-flip escape response [25] has been demonstrated using two semiconductor optical amplifier (SOA) based neurons and has been used for pattern recognition. Spike timing dependent plasticity (STDP) - a biological process that adjusts the interconnection strength between neurons has been mimicked using a SOA [26] and SOA with an electro-absorption modulators [28]. STDP is an important process for learning, and a photonic implementation of supervised learning based on STDP has been demonstrated experimentally [28]-[29]. Furthermore, research on machine learning based on neuromorphic photonics [30]-[34] has draw a lot of research interest in recent years.

In this paper, we focus on reviewing our recent progress on the applications and photonic implementation of small scale neural algorithms. First, we will introduce the STDP neural learning algorithm and discuss the use of STDP function for angle-of-arrival detection and localization [26]-[27]. Next, we will explain the jamming avoidance response found in a genus of electric fish – Eigenmannia [35]-[38], and discuss the photonic implementation of the jamming avoidance response [38] and how it can be used in a phase locked loop [39].

II. Spike Timing Dependent Plasticity (STDP)

One of the most interesting and powerful capabilities of neuron are its abilities to both learn and adapt. The fundamental element of adaptability, learning, and memory in neural systems is synaptic weight plasticity, which enables neural systems to adjust the strength of synaptic connection between neuron to adjust how information is being processed based on the spiking activities. Among various synaptic weight plasticity model, spike timing dependent plasticity (STDP) is the most popular one in which strengths of connections between neurons are based on the temporal relationship between pre-synaptic and post-synaptic activity. STDP often being referred as "Neuron that fire together wire together". Over the last few years, several photonic approaches [28]-[29] have demonstrated the STDP behavior with a time scale of hundreds of picosecond. Supervised learning [28]-[29] can be implemented based on photonic based STDP.

A. Biological model

In STDP algorithm, the strength of the synaptic connection between two neurons are adjusted based on the relative timing between the neuron input and output, i.e. pre-synaptic spikes and post-synaptic spikes. Increase in synaptic connection strength occurs when the post-synaptic spike is caused by the pre-synaptic spike. On the other hand, the connection strength decreases when the post-synaptic spike fires before the arrival of the pre-synaptic spike. The amount of synaptic connection strength increment/decrement depending on the precise timing difference between the pre-synaptic and post-synaptic spikes of the neuron, i.e. the smaller the time difference the larger the change in synaptic connection strength, described by Fig. 1.

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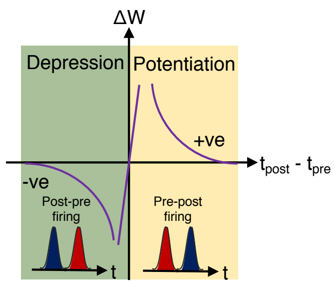

Fig. 1. Theoretical spike timing dependent plasticity curve. Pre-post firing: post synaptic spike fires shortly after the pre-synaptic spike; Post-pre firing: post synaptic spike fires before the pre-synaptic spike. t_{post}-t_{pre}: time difference between the firing of the post- and pre-synaptic spikes.

B. *STDP Algorithm for Angle-of-Arrival Detection and Localization*

Besides using STDP algorithm for its designated neural functions, STDP process can be utilized for advancing different aspects in engineering. Here, we will describe the application of STDP in angle-of-arrival (AOA) detection and localization. Fig. 2 shows the STDP-inspired AOA system [27], consists primarily of two laser source at λ_{pre} and λ_{post}, two impulse generators, two Mach-Zehnder intensity modulators (MZMs), two microwave antennae, and a STDP system [26]-[27]. The target object emits a microwave signal at a frequency f_{RF}, and is received by two antennas at the AOA system. Due to the path difference between the target and the two antennas, a time delay Δt between the two received signals is resulted. The unique STDP curve is able to convert both the positive and negative values of Δt into a positive or negative amplitude. The ability to distinguish negative and positive values of Δt eliminates the ambiguity arising from the measurement of signals arriving from opposite directions but at the same angle relative to the antenna array. The normalized STDP output has a direct correspondent to a particular delay, therefore, the angle-of-arrival can be determined through the relationship $c\cdot\Delta t = d\cdot\cos\theta$, where c is the speed of light, Δt is the time delay between the two received signals, d is the separation of the two antennas, and θ is the resultant angle-of-arrival value.

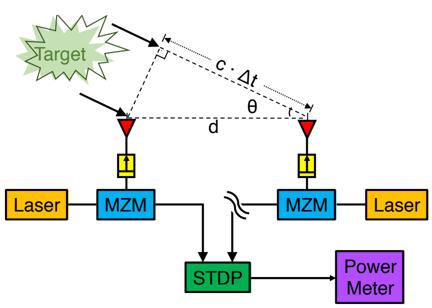

Fig. 2. Experimental setup of STDP based AOA measurement. MZI: electro-optic intensity modulator; STDP: spike-timing dependent plasticity circuit.

Fig. 3 shows the angle-of-arrival system simulation results. The red curve corresponds to an arrival angle between 0º to 90º, while the blue curve corresponds to an arrival angle between 90º to 180º. The target object is at an arbitrary location, and the observed STDP outputs for different nodes are shown by the blue outlined circles, while the red filled circles corresponds to the expected STDP output without errors. Since this angle of arrival system is mainly for indoor use, unit displacement with 1-mm error and laser power error of 0.003 dBm are considered.

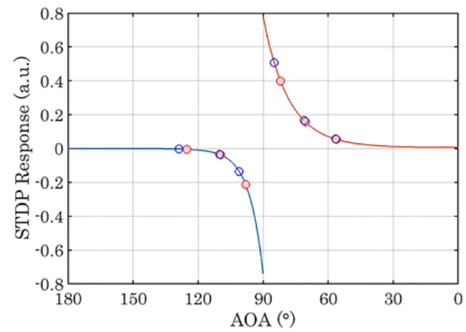

Fig. 3. Angle-of-arrival measurement based on STDP curve. Comparison of expected (red) and observed (blue) STDP outputs for various arrival angles.

With the use of three or more STDP based angle-of-arrival systems, a 3D localization scheme can be implemented, as depicted in Fig. 4. In our simulation, the localization system consists of three STDP-based AOA nodes, each positioned on a Cartesian axis at $(x_a,0,0)$, $(0,y_b,0)$, and $(0,0,z_c)$ at points a, b, and c, respectively. Each node has a transmitter that provides one third of the location information to the user at *p*. Based on the angle-of-arrival value of each node, conical surfaces for each axis are resulted. The common intersection of the three conical surfaces gives the exact location of the user.

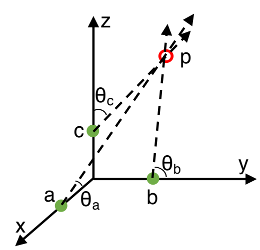

Fig. 4. Basic 3D AOA localization schematic with three nodes uncovering three directions, θ_a, θ_b, θ_c.

Root mean square error (RMSE) of the STDP based localization system has been investigated for various sceneries. Two sceneries are shown in Fig. 5, by considering a maximum location error of 1 mm and laser instability of 0.003 dBm for each node. With the transmitter location at $x_a = y_b = z_c = 1$ m, a maximum RMSE is just over 1 m, which can be significantly reduced by relocating two of the nodes to $y_b = z_c = 5$ m, to result in a maximum RMSE of 0.4 m. The maximum RMSE is further decreased to 0.3 m if the nodes are relocated to $x_a = y_b = z_c = 15$ m. The demonstrated STDP based localization approach provides a simple but accurate solution to indoor positioning systems, where existing systems usually require large networks of measuring units [15-17]. The possibility of outdoor positioning has been explored by setting the nodes at $x_a = y_b = z_c = 5$ m and user location could be over 100 m away. A RMSE of about 9.7 m is resulted for outdoor positioning.

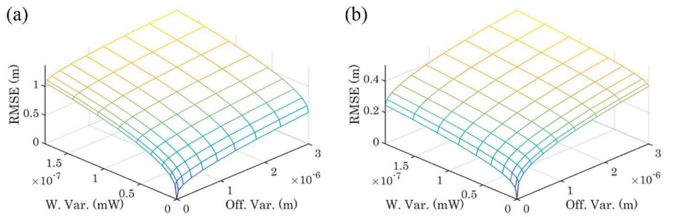

Fig. 5. Error plot for detecting a transmitter at (10,10,10) (a) with nodes at $x_a = y_b = z_c = 1$ m; (b) with nodes at $x_a = 1$ m, $y_b = z_c = 5$ m.

III. Jamming Avoidance Response in Eigenmannia

Another neural algorithm that will be discussed is the jamming avoidance response (JAR) in Eigenmannia [40]-[44], a genus of electric fish that lives under the deep ocean. Eigenmannia generate and use electric fields for specialized active sensing that enable navigation, communication, and prey capture in the dark. When two nearby Eigenmannia are emitting electric fields that are very similar in frequency, interference could occur and endanger the Eigenmannia. Eigenmannia has a very efficient neural algorithm, JAR, that always regulate the frequency of the Eigenmannia away from the other electric fish if a similar frequency is detected, and they will never cross their frequency.

A. *Biological model*

Neuroscientists have dissected the JAR and they found out that the ability for the Eigenmannia to avoid jamming from another electric fish is based on the phasor phenomenon [40]-[44], which can be explained in Fig. 6.

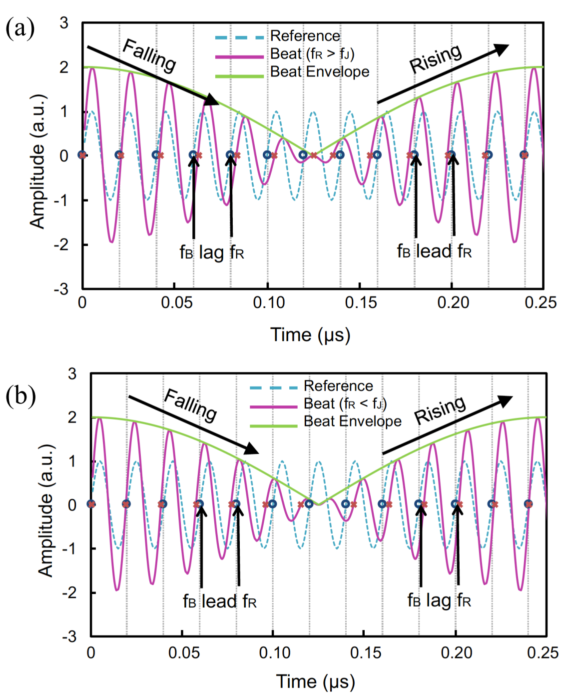

Fig. 6. Principle of the jamming avoidance response (JAR) in Eigenmannia. (a) When $f_R > f_J$, phase of beat signal is lagging the phase of the reference signal at the falling edge of the envelope, while it is leading at the rising edge. (b) When $f_R < f_J$, the phase of beat signal is leading the phase of the reference signal during the falling portion of the envelope, while it is lagging during the rising portion.

In JAR, the first Eigenmannia receives the jamming signal f_J alongside its own signal (reference signal) J_R (blue dash curve), generating a beat signal at f_B (magenta solid curve). The envelope of the beat signal is represented by the green solid curve in Fig. 6. It is observed that when the jamming signal f_J is at a lower frequency than the Eigenmannia's own signal f_R, i.e. Fig. 6(a), the phase of the beat signal is lagging that of the reference signal at the falling edge of the beat signal envelope; while it is leading the phase of the reference signal at the rising edge of the envelope. On the other hand, when the jamming signal f_J is at a higher frequency than the Eigenmannia's own signal f_R, i.e. Fig. 6(b), the phase of the beat signal is leading that of the reference signal at the falling edge of the beat signal envelope; while it is lagging the phase of the reference signal at the rising edge of the envelope. Therefore, by examining the relationship between the instantaneous amplitude and phase of the Eigenmannia's own signal and the beat signal, the JAR algorithm in the Eigenmannia can tell whether it should tune its emitting frequency to a higher or lower frequency to avoid jamming.

B. *Optical implementation of JAR*

The jamming from neighboring Eigenmannia is similar to inadvertent jamming in our wireless system. Inadvertent jamming is aimless and unforeseen, but it is as harmful as intentional jamming [45]-[46]. Therefore, there is a critical need to identify an effective solution to tackle inadvertent jamming, which convention solution for intentional jamming will not work. Turning to nature for a solution, JAR in Eigenmannia is exactly what we need. The JAR in Eigenmannia mainly consists of four functional blocks, as shown in Fig. 7 [35]-[38]: (1) Zero-crossing point detection unit (ZeroX unit), the (2) Phase detection unit (Phase Unit), the (3) Amplitude unit, and the (4) Logic unit. The ZeroX unit locates the positive zero crossing points in the reference signal. Then the Phase unit takes the identified positive zero crossing points from the ZeroX unit and compares it with the beat signal, to determine if the phase of the beat signal is leading or lagging that of the reference signal. Then, the Amplitude unit takes the envelope of the beat signal, and identifies the rising and falling slopes. Finally, the Logic unit takes the phase and amplitude information from the Phase unit and Amplitude unit and determines if the emitting frequency should be remained, increased, or decreased.

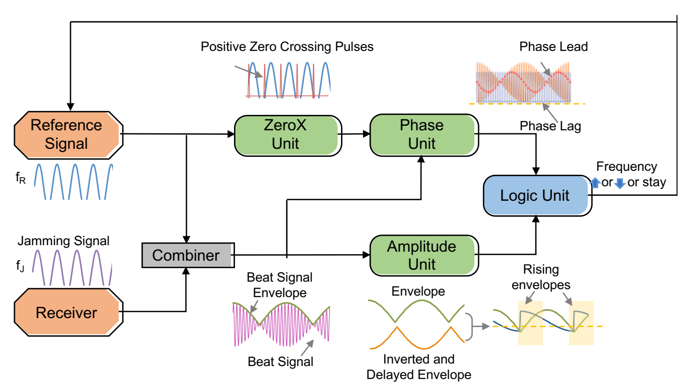

Fig. 7. Illustration of the JAR design and the four functional units – ZeroX unit, Phase unit, Amplitude unit, and Logic unit in JAR.

The photonic implementation of the JAR circuit is mainly based on the use of semiconductor optical amplifiers (SOA) – the same component that has been used as a photonic based neuron. Various optical phenomena are used in the SOA. The photonic JAR works well for frequency from hundreds of MHz to tens of GHz. First, ZeroX unit uses self-phase modulation in SOA and offset filtering for positive zero crossing points extraction (Fig. 8(a)). Then, cross-gain modulation in SOA is used in the Phase unit for generating a "1" or "0" output to represents phase leading or phase lagging (Fig. 8(c)-(d)). Lastly, the Amplitude unit uses signal inversion capability in SOA for generating a signal for "subtraction" and an optical delay line for temporal delay, such that a "1" is generated for rising envelope and "0" is generated for falling envelope (Fig. 8(b)).

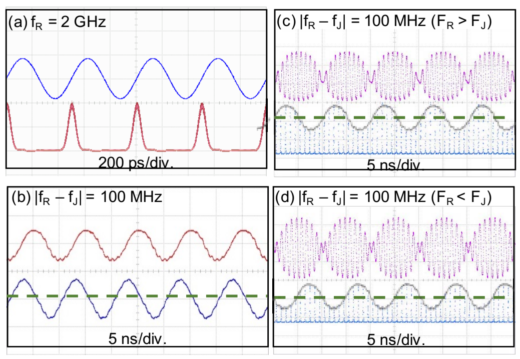

Fig. 8. Experimental results of the photonics based JAR. Top curve: input; bottom curve: output. (a) ZeroX unit – positive zero crossing points of the reference signal are identified and represented by the bottom red pulses. (c)-(d) Phase unit – the output amplitudes are high for phase lag and a low for phase lead. (b) Amplitude unit – rising and falling in beat signal envelope amplitude are distinguished, a high output represents rising in amplitude and a low output represents falling in amplitude.

By taking both the amplitude and phase information, an Arduino Due is used to implement the Logic unit that perform a XOR logic for determining if the emitting frequency should be increased or decreased. Arduino Due is used instead of photonic based XOR because of the low frequency nature of the Phase unit and Amplitude unit outputs – they are usually in the range below 200 MHz, determined by the frequency difference between f_R and f_J. Once the frequency adjustment is in process, the Logic unit also responsible to determine when to stop, i.e. once the jamming signal is out of the jamming frequency range of the Eigenmannia. Fig. 9 shows the spectral waterfall measurement of the photonic JAR in action. The jamming signal is approaching the Eigenmannia from either lower or higher frequency and the JAR helps the Eigenmannia to keep its emitting frequency to be out of the jamming frequency range.

It is worth noticing that the ZeroX unit and the Phase unit can be used for phase difference detection in a phase locked loop. An experiment has been performed [39] with the photonic based ZeroX unit and Phase unit, and the experimental results show that this bio-inspired optical microwave phase lock loop has significantly suppressed the phase noise of a voltage controlled oscillator (VCO) by 25 dB.

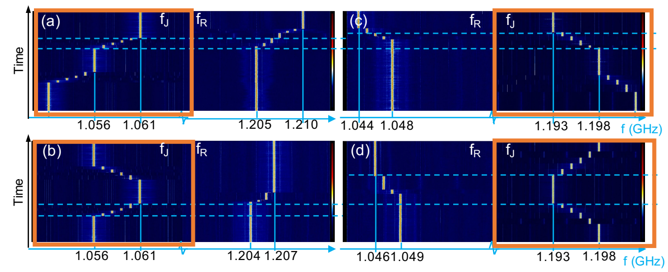

Fig. 9. Spectral waterfall measurement of the photonic JAR in action with sinusoidal reference signal f_R and jamming signals f_J = 150 MHz. (a) f_J is approaching f_R from the low frequency side and triggers the JAR, (b) f_J is approaching f_R from the low frequency side and triggers the JAR, and then is moved away, (c) f_J is approaching f_R from the high frequency side and triggers the JAR, (d) f_J is approaching f_R from the high frequency side and triggers the JAR and then is moved away.

IV. Summary and Discussion

This paper briefly summarize the recent progress on neuromorphic photonics. In just a short ten years, spiking neuron, synapse, neural network, and various small scale neural algorithms have been dissected and mimicked by photonics, moving the processing time scale from millisecond in biological neuron to picosecond in photonic implementation. Neural algorithms have find its value in various RF signal processing applications due to its efficient, accurate, and task-specific capabilities, including angle-of-arrival measurement, indoor localization, phase-lock-loop, and jamming avoidance in wireless systems. The implementation of those neural algorithm using photonics enables the system to operate from hundreds of MHz to tens of GHz range. There are still lots of hidden treasure in the nature that could be an effective solution to the challenges we are facing in the modern society.

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