Large scalable electro-optical spiking neural network

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Summary. Photonic neural networks are currently a highly sought after area of research. Comprehensive studies and experiments have laid a strong foundation for future high-performance complex computing. In artificial neural networks, neurons are simple, nonlinear maps. On the contrary, information transmission and computation in biological neurons occur through spikes, where spike time and/or rate presumably play a significant role. We developed the first large-scale spiking photonic neural network that comprises of more than 30,000 excitable neurons, which serves as an excellent proof of concept experiment for novel bio-inspired learning concepts.

Photonic hardware integration of neural networks can benefit from the inherent properties of parallelism, high-speed data processing and potentially low energy consumption. Considering this, we designed a photonic reservoir computer (RC) [1] based on photonic recurrent spiking neural networks (SNN) [2], i.e. a photonic liquid state machine (see Fig 1 (a)). Fig 1(a) shows that, the optical field $|E_i^0|^2$ is homogenized by a beam homogenizer and after getting transmitted through the polarizing beam splitter (PBS) and a half waveplate, a microscope objective MO_1 focuses it to illuminate the spatial light modulator (SLM) . Our neural network's state is encoded in the pixels of the SLM, which makes the SLM function as the substrate of our neurons. The half waveplate positioned after MO_1 is oriented in a way that enables the SLM to operate in the amplitude modulation mode. After being reflected from the SLM, the optical field is transmitted through the polarizing beam splitter (PBS) where it acquires nonlinearity and is subsequently modulated as follows:

$$E_i = E_i^0 cos(2\pi \frac{x_i^{SLM} + \Phi}{\kappa^{SLM}}) \tag{1}$$

where, x_i^{SLM} is the gray scale value of the SLM pixel i, Φ is gray scale offset and a device constant and κ^{SLM} is the conversion factor between the polarization angle and the gray scale values of the SLM pixels. A diffractive optical element (DOE) is introduced in between the PBS and the camera. The spacing between the diffractive orders corresponds to the spacing between the SLM pixels. The beam reflected from the PBS, passes through the DOE, establishing recurrent coupling between the photonic neurons. Finally, the camera positioned at the focal plane of the microscope objective MO_2, record the neuron response. The signal (i.e. optical intensity) recorded by the camera can be represented as :

$$I_i^{CAM} = \beta(\left|\sum_{j=1}^{N} W_{i,j}^{DOE} E_j\right|^2) \tag{2}$$

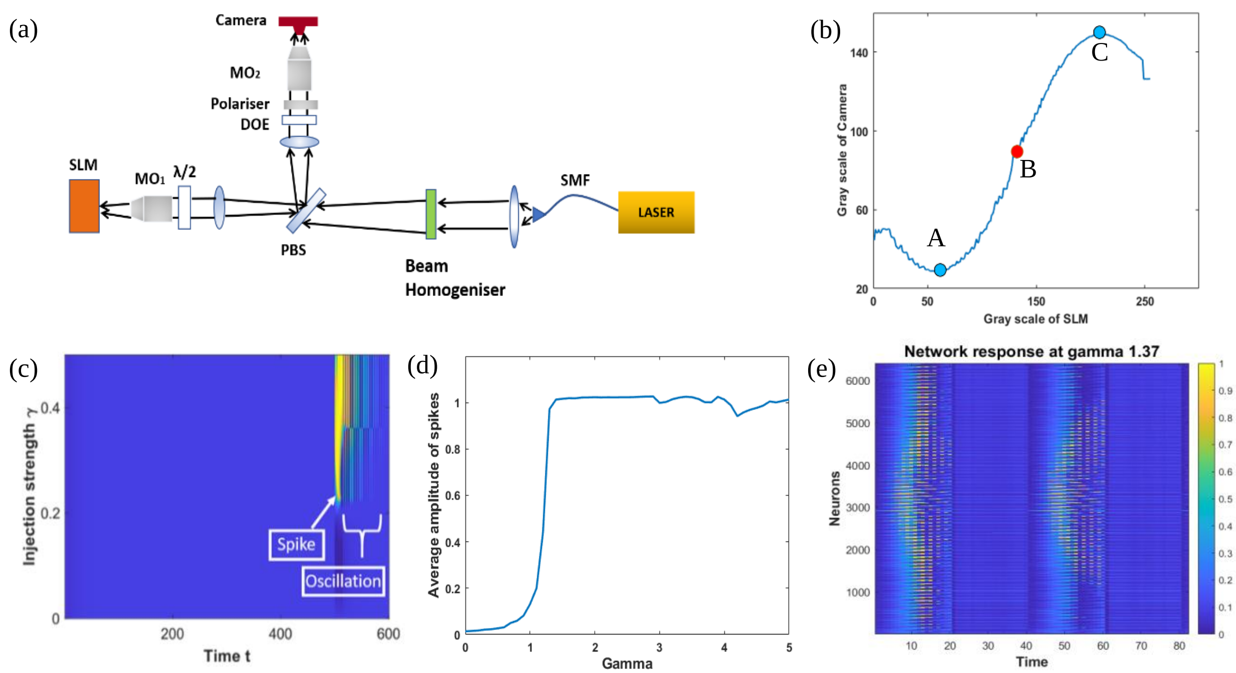
where, W^{DOE} is the DOE created coupling matrix. Therefore, the recurrent loop is closed when the camera images the SLM pixels (i.e. neurons), since the SLM is driven by the recorded images as electronic feedback. So, the Ikeda map which can be used to define the state of our recurrent neural network (RNN) can be represented as:

$$x(t+1) = -\delta * y(t) + sin^2\left(\pi\left(\alpha * x(t) + \gamma * u(t+1)\right) + \theta\right) \tag{3}$$

where, $x(t+1)$ is the SLM state sent to the SLM via MATLAB, β is the feedback strength, γ is the signal strength of the input signal sequence $u(t+1)$ (this contains elements normalized between 0 and 1. We go beyond and create excitability of our electro-optical neurons by including a high-pass filter (given by Eq. (4)) in the electronic feedback loop and experimentally demonstrate the neuron's all-or-nothing spiking response to input stimuli.

$$y(t+1) = 0.995 * y(t) + x(t+1). \tag{4}$$

When at rest, the system resides in its lower stable fixed point, labelled A in Fig. 1(b). External input then pushes the system across unstable fixed point B, resulting in an excursion to the upper stable fixed point C. There, slow forcing governed by the high-pass dynamics of Eq. (4) projects it back to the lower stable fixed point A. This enabled us to demonstrate experimentally all-or-nothing spiking response (see Fig. 1(c)) to the input stimuli. Fig. 1(d) shows the average network response amplitude with increasing injection strength (Gamma). Fig. 1(e) shows the spatio-temporal response of our network when two MNIST digits are given as input to our system.



- **Fig. 1** Spiking photonic neural network. (a) Schematic diagram of the experimental setup. (b) Non-linearity curve of the SLM. (c) Shows a characteristic response of one of our 36.000 photonic neurons. (d) Average network response amplitude. (e) Spatio-temporal network response with two MNIST digits as input. This shows that the neurons respond differently depending on the average value of the 784 pixels of each digit.

To conclude, our electro-optical system uses more than 30,000 excitable neurons [3-4], which is the first proof-of-concept system that allows to implement learning in large scale photonic SNNs. Currently, we are training our system on the MNIST datasets for handwritten digit recognition and explore different learning concepts.

References

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