VCSEL Based Neuromorphic Computing

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Abstract: We report on Vertical-Cavity Surface-Emitting Lasers (VCSELs) for high-speed and energy-efficiency systems for photonic neuromorphic computing, yielding excellent performance in complex processing tasks whilst benefitting from hardware-friendly implementations and full compatibility with optical communication technologies.

1. Introduction

Neuromorphic (brain-like) computing technology is undergoing major research effort worldwide for novel, more efficient hardware for future information processing and artificial intelligence (AI) platforms. Photonic technologies thanks to their unique properties (e.g. high bandwidths, low cross-talk, reduced power consumption and high-speed) are attracting increasing interest for novel light-enabled neuromorphic processing systems (see [1] for a review). Amongst these, approaches based on semiconductor lasers, especially Vertical-Cavity Surface-Emitting Lasers (VCSELs) have received growing attention. Thanks to their compact structures, vertical light emission, low cost and technology maturity, VCSELs are ubiquitously deployed for disparate uses, spanning from optical communications, to automotive sensors and supermarket barcode scanners, etc. The widespread deployment of VCSELs added to their unique inherent attributes, e.g. high modulation speeds, low energy operation, high coupling efficiency to optical fibres, ease of integration in 2-dimensional arrays, nonlinear dynamical operation make them exciting candidates for future neuromorphic hardware implementations (see [2] for a review). Here we present our research on VCSEL-based neuromorphic processing systems, including our work on VCSEL-neurons for spike-based processing tasks [3-7], our implementation of VCSEL-based photonic reservoir computers (RC) [8], and a novel approach for the development of the first generation of VCSEL-based photonic spiking neural networks (SNNs) [9].

2. Neuromorphic Computing Systems built with VCSELs

2.1. Information Processing with Spiking VCSEL Neurons

VCSELs with emission at key telecom wavelengths have recently generated reports of neural spiking responses at sub-nanosecond speeds [2-4] and their use as spiking photonic neurons for spike-based processing functionalities has been described [2-5]. Fig. 1 shows our recent results demonstrating successful operation of VCSEL spike-processing systems across different tasks, e.g. pattern recognition and image processing. Fig. 1a shows the performance of a single VCSEL-neuron in the recognition of 4-bit data patterns (at 80ps per bit) [5]. The left plot in Fig. 1a shows (input/output) time-traces from the VCSEL-neuron showcasing the system's ability to recognize a target 4-bit pattern (pattern C, '1001') with the firing of an optical spike (approx. 100ps long). The right plot in Fig. 1a plots a confusion matrix illustrating the successful system operation in detecting distinct 4-bit data patterns. We have also worked on systems of spiking VCSELs for image processing tasks, e.g. image edge-feature detection [6]. In this technique, kernel operators are applied to the source images prior to their injection into the VCSEL-neuron. With this approach the system fires (100 ps-long) optical spikes in response to specific target edge-features. Fig. 1b shows experimental results demonstrating that a single VCSEL-neuron can retrieve all edge-feature information from images from the MNIST handwritten digit dataset. Moreover, the output from this photonic edge-feature detection system was fed to a software-implemented Spiking Neural Network (SNN) demonstrating successful classification of these images (96.7% accuracy). Single VCSEL-neuron systems have also shown the capability to rate-coding the pixel colour information of RGB images in the (GHz) firing rates of their elicited optical spike trains [7]. This shown in Fig. 1c where the spiking rates of the VCSEL-neuron are assigned to different colour intensities, thereby acting as a spike-timing dependent encoder of the colour information in RGB images.

2.2. Information Processing with VCSEL-based Photonic Reservoir Computers (RC)

Another promising research avenue for VCSEL-based neuromorphic photonic computing systems is the implementation of photonic reservoir computers (RC) with these devices [8]. These use the inherent nonlinear dynamics in VCSELs when subject to external optical injection and/or feedback to process information. Recently, our group has reported and analyzed in detail the performance of a VCSEL-based RC system using the time-delayed reservoir architecture (TDR), shown in Fig. 2a. This creates an interconnected network of virtual nodes using a single VCSEL and an optical delay line (with a round trip time of τ). Input information is weighted (using a temporal weight mask) and optically injected into the VCSEL, which acts as a non-linear element transforming inputs and feedback signals continuously. The continuous output of the VCSEL is sampled at time slots (θ) to read the state of the nodes of the output layer of the system. A set of weights, calculated during an offline training procedure are applied to the output layer nodes, which are then linearly combined to deliver the final state of the RC. Fig. 2b shows the experimental setup used to demonstrate the VCSEL-based RC system, using a hardware-friendly platform utilizing a single 1550nm-VCSEL subject to external optical injection and delayed feedback. This VCSEL-based photonic RC system delivered state-of-the art performance at benchmark complex tasks, such as the Mackey-Glass time-series prediction task, as shown in fig. 2c. The latter also shows that this photonic RC system, thanks to the intrinsic polarization properties of VCSELs, provide additional avenues to enhanced performance via the control of light polarization in both injection and feedback channels [8].

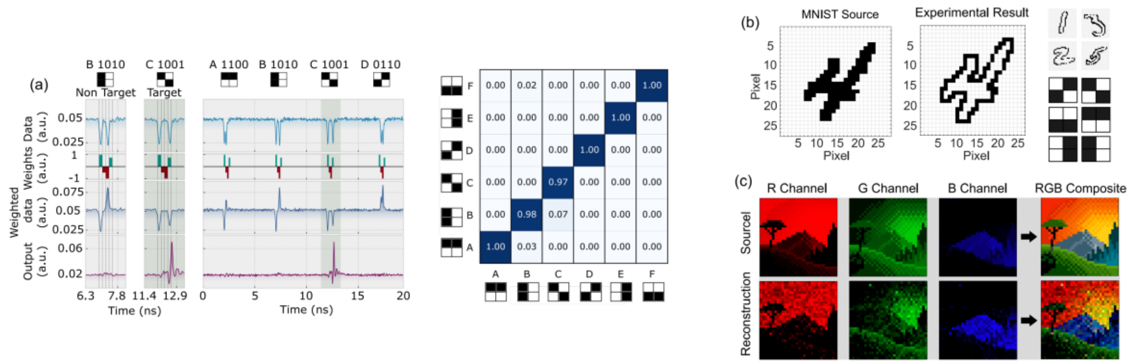

Fig. 1. Spike-based processing systems built with a single telecom-wavelength VCSEL-neurons. (a) 4-bit pattern recognition system (80ps/bit) [5]. (Left) Input/Output time-series recorded from the VCSEL-Neuron demonstrating the detection of a target pattern ('1001'). (Right) Confusion matrix demonstrating accurate pattern recognition. (b) Image edge-feature recognition system at ns/pixel rates [6]. (c) System for the rate-coding of pixel image information in RGB images at ns/pixel rates [7].

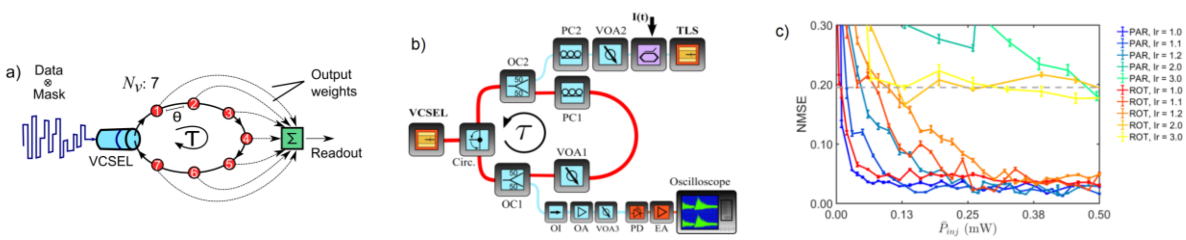

Fig. 2. Photonic Reservoir Computer (RC) built with a VCSEL. (a) Network architecture of the VCSEL-based time-delayed reservoir forming the photonic RC. (b) Experimental Setup. (c) Performance of the VCSEL-based photonic RC system in the Mackey-Glass time-series prediction task (for different values of optical injection power) showing very low error (NMSE) overall for different configurations of polarized optical injection and feedback (parallel-PAR and orthogonal-ROT) [8].

2.1. Photonic Spiking Neural Networks (SNNs) with VCSELs

We have also recently developed the first generation of VCSEL-based full photonic Spiking Neural Networks (SNNs) [9]. Our approach merges the spiking dynamics of a VCSEL-neuron (section 2.1) with the RC paradigm (section 2.2.). This permits us to describe a radically new class of high-speed, hardware-friendly and fully-operational photonic SNNs using just one VCSEL. Fig. 3a shows the simple setup used to build the photonic SNN with a single 1300 nm-VCSEL and off-the-shelf optical components. This system uses neural-like optical spikes for computation, thus yielding a truly neuromorphic processor. In our approach, the optical output of a spiking VCSEL, is time-multiplexed into multiple (virtual) spiking nodes. This creates a full photonic SNN with the spiking (virtual) nodes interconnected through the non-linear integrate-and-fire dynamics and refractoriness of the excitable spiking responses of the VCSEL [9]. Fig. 3b illustrates the architecture of the VCSEL photonic SNN, showing the input time-multiplexed weighted input data entering the VCSEL, the mechanism by which consecutive (virtual) spiking nodes are coupled to yield networking operation, and the readout of the VCSEL's output optical spiking patterns. Only the latter are subsequently trained offline (the input and hidden-layer network nodes are fixed) to provide the output state of the photonic SNN. We have showed successful operation of this VCSEL-based SNN in the complex nonlinear Iris Flower Classification task. This requires to classify individual flower specimens in three different classes (Iris Setosa, Iris Virginica, Iris Versicolor) based on input data consisting of 4 features (petal and sepal widths and lengths). Fig. 3c shows exemplar optical input (top plot) and spiking output (bottom plot) time-traces from the VCSEL photonic SNN. Fig. 3d plots a 2D temporal map merging in a single plot the optical spiking output from the SNN in response to all 150 input data points of the Iris Flower Dataset. The photonic SNN was configured with a total (virtual) node count of 1024, which at 250ps time per node yields a total processing time per data point of only 256 ns. Fig. 3d reveals that different spiking patterns are produced by the VCSEL photonic SNN in response to different input flower classes, allowing the use of the distinct spiking regimes to produce an accurate classification. Fig. 3e depicts the obtained confusion matrix revealing 100% accuracy (with a 1024 node photonic SNN) in the classification of the Iris Flower species, thus showcasing its powerful computational performance. At last, fig. 3f plots the classification error of the VCSEL SNN (with 1024 nodes) as a function of the size of the training dataset. Fig. 3f reveals another remarkable feature of this new photonic SNN, its ability to yield excellent performance even when very small training data set sizes are used (<5 data points per flower class).

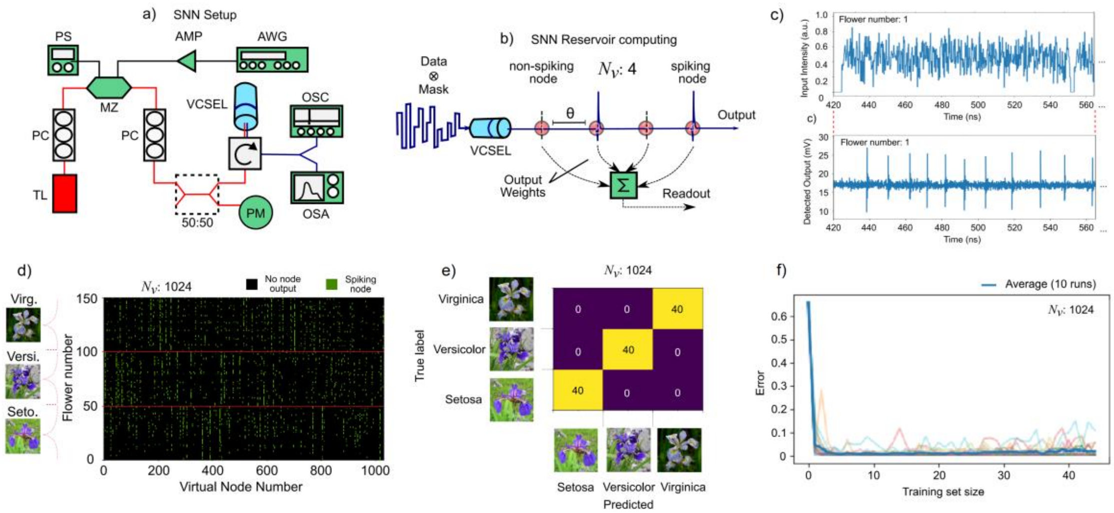

Fig. 3. VCSEL-based photonic Spiking Neural Network (SNN). (a) Experimental Setup. (b) SNN architecture. (c) Time-series for the optical input data (top plot) and optical spiking output from the SNN (bottom plot). (d) Temporal map plotting the spiking patterns from the photonic SNN in response to all 150 points of the Iris Flower dataset. (e) Confusion matrix showcasing 100% accuracy of the photonic SNN (with 1024 virtual nodes) in the Iris Flower classification task. (f) Error performance of the SNN versus training data set size (for the Iris Flower task) [9].

3. Conclusions and Outlook

In summary, we present our work on the use of VCSELs for novel neuromorphic photonic computing systems. We report first on different photonic spike processing systems based upon VCSELs for use across different tasks, e.g. pattern recognition, image processing. We also report on VCSEL-based photonic reservoir computing systems, able to solve complex tasks with state-of-the-art performance, whilst allowing high-speed (GHz rate) and energy-efficient operation. At last, we demonstrate a novel approach for the development of hardware-friendly photonic spiking neural networks (SNNs) using a single telecom-wavelength VCSEL and offering excellent performance in a complex nonlinear classification task. These results open exciting new avenues towards ultrafast, low-power VCSEL-based photonic systems for future high-performance neuromorphic computing and AI platforms.

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3. References

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