Photonic Spiking Neural Network with Resonant Tunnelling Diode Optoelectronic Neurons

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Abstract: We report high-speed, energy-efficient artificial optoelectronic spiking neurons based upon resonant tunnelling diodes (RTD). Using these, we demonstrate a photonic spiking neural network (perceptron) numerical model for classification of spatiotemporal pulse patterns with 94% accuracy.

1. Introduction

Driven by recent significant advances in the fields of artificial intelligence (AI) and machine learning (ML), alternative computing approaches are gathering increased interest in both academic and commercial sectors. By promising higher energy efficiency and faster operation rates for the algorithms that AI & ML rely on, neuromorphic (brain-like) computing aims to deliver information processing systems inspired by the computational power and architecture of the brain. Additionally, given the numerous desirable properties of optical and photonic components, e.g. low-loss waveguiding, high speeds, wavelength division multiplexing, etc., research efforts are now focusing on realising light-enabled, brain-inspired computational systems. As a result, a wide range of photonic systems based upon different technologies, e.g. silicon photonics [1], lasers [2,3], phase-change materials [4] have been recently reported for use in neuromorphic computing.

2. RTD-based optoelectronic node models

Double-barrier quantum well (DBQW) resonant tunnelling diodes (RTDs) are a class of semiconductor devices capable of operating at ultra-high frequencies at room temperature. Due to the presence of resonant quantum tunnelling states in the DBQW, RTDs exhibit highly nonlinear I-V characteristics with regions of negative differential conductance (Fig. 1a) as well as excitable dynamical responses [5] (Fig. 1b). This is a key functionality used in this work for operation of the RTD-based nodes as high-speed (>GHz rate) excitable sources in optical spiking neural networks. To realize the optoelectronic nodes, the RTD excitable circuit is combined either with a laser diode (LD), forming a spiking "master" (RTD-LD or RL) node, or with a current-coupled photodetector, forming a spiking "receiver" (PD-RTD or PR) node. For full details on the numerical model and parametric values used see [6].

The spikes in the RTD-spikeSLP model are analog-in-time and digital-in-amplitude (as used by biological neurons), allowing the system to natively operate with temporally represented data.

2.1. The RTD-spikeSLP neural network

The RTD-based spiking optoelectronic neural network realised in this work, a single-layer perceptron (abbreviated as RTD-spikeSLP), has an N-to-1 (or generally N-to-M) feed-forward topology with two types of RTD optoelectronic nodes. The nodes in the first layer consist of RTD-LD (E/O) nodes, which translate analog electronic signals into spike-based data representation in the optical domain. The optical spiking signals are then propagated to a downstream optoelectronic neuron via weightable, unidirectional, feed-forward links. The downstream (output) neuron is realized as a PD-RTD (O/E) node, performing signal summation on the photodetector of weighted (attenuated) optical pulses arriving from the upstream nodes. Once the total optical power on the PD at any moment exceeds a given threshold, an excitable electric spike is triggered in the RTD of the output node. By properly configuring the weights in the network, the system can successfully recognise spatiotemporal data patterns fed to the input nodes.

We have successfully tested the proposed RTD-spikeSLP network model with a 5-to-1 architecture (Fig. 1c), for classification of 5-bit spatiotemporal pulse patterns. During the learning phase, an off-chip learning rule allows for

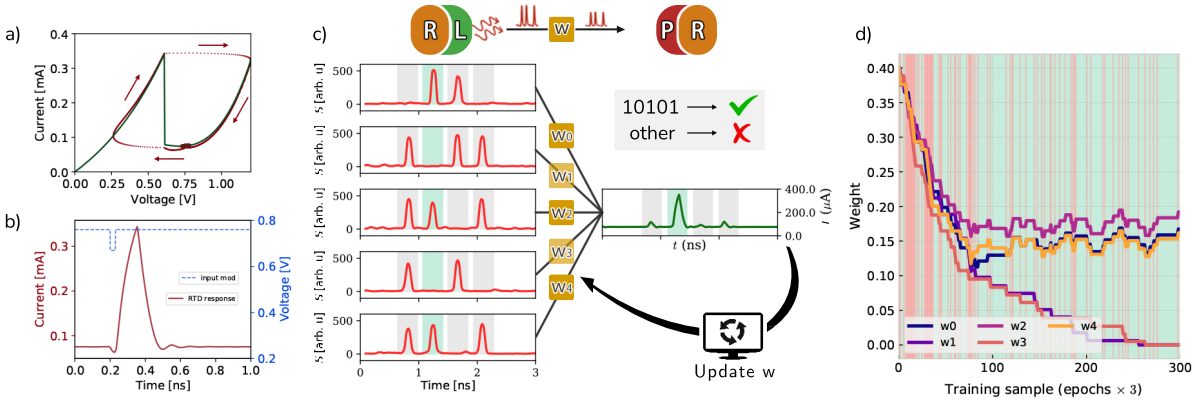

Fig. 1: **a)** Highly nonlinear I-V characteristic of the RTD (green) biased at 0.75 V with phase space limit cycle trace of a single spiking event (red). **b)** Small, super-threshold input electrical perturbation (blue) resulting in strong, excitable electric spike (red). **c)** Network operation diagram, illustrating how input patterns elicited in upstream nodes propagate to the downstream (output) node using weighted connection. The output node performs summation (on the PD) and thresholding, resulting in excitable events for particular spatiotemporal pattern, here [1 0 1 0 1] (highlighted in green shading). **d)** Evolution of network weights during the learning phase, where an off-chip algorithm gradually updates the weight matrix with a spike-timing based learning rule.

automated weight readjustment during (Fig. 1d), utilizing a modified spike-timing dependent plasticity (STDP) training algorithm [6]. By properly training and configuring the network weight matrix, the optoelectronic network is capable of recognising target pulse patterns with equal number of ON-bits, with total classification accuracies surpassing 94% [6]. Fig. 1c depicts inference procedure for multiple 5-bit patterns processed in sequence during a single network simulation step (epoch), with approx. 420 ps temporal spacing between patterns, yielding a system with spiking rates higher than 2 GHz. It can be seen that only one pattern (here [1 0 1 0 1]) results in the downstream node firing a full spiking response, while it remains quiescent (non-spiking) for other input patterns.

3. Conclusions

We combine excitable, high-speed, low-energy RTDs with PD and LD elements to obtain high speed (>GHz rate) optoelectronic neurons. Utilizing these, we demonstrate a spiking neural network model with optical signalling and master-receiver interconnectivity. Using the optoelectronic neural network, we perform recognition of 5-bit spatiotemporal pulse patterns with high accuracy. This work provides a first demonstration of the viability of RTD-based neurons for use in high-speed spiking photonic neural networks for neuromorphic computing

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