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Energy Efficient Neuromorphic Computing with beyond-CMOS Oscillatory Neural Networks

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ABSTRACT

Oscillatory Neural Networks (ONNs) are non-von Neumann architectures where information is encoded in phase relations between coupled oscillators. In this work, we present the concept of ONN based on beyond-CMOS devices to reduce the energy footprint of neuromorphic circuits. We investigate oscillating neurons made of vanadium dioxide material (VO_2) and synapses based on molybdenum disulfide (MoS_2) memristors to emulate synaptic plasticity.

KEYWORDS

ONN, Neuromorphic circuit, Beyond-CMOS, VO_2, MoS_2 Memristor

1 COMPUTING IN PHASE

ONN encodes information in phase relations between synchronized analog oscillating circuits (Fig.1A) interconnected by electrical components to emulate synapses (Fig.1B). ONN is a non-linear system where synaptic currents flow in parallel through the network to achieve high-speed computing. Computing with ONN consists of 1) setting an initial phase state, 2) letting the ONN settle, and 3) measuring the final phases with respect to a reference (first oscillator) [1]. Inference efficiency is of interest for edge devices with limited power and memory resources that run AI algorithms.

2 ONN DESIGN FROM DEVICES, CIRCUITS TO ARCHITECTURE

Beyond-CMOS devices based on VO_2 and MoS_2 materials allow compact and configurable ONN circuit design using few components for low energy operations [2]. We harness phase change transitions of VO_2 material to design compact relaxation oscillators [2]. We bias a two-terminal VO_2 device with a transistor in series, such that the load line intercepts the VO_2 Negative Differential Resistive (NDR) region to produce oscillations (Fig.1.C). For large scale ONNs, we couple oscillators with MoS_2 memristors (Fig.1.B) to emulate synaptic plasticity from weak coupling (large MoS_2 resistance) to strong coupling (small MoS_2 resistance).

3 IMAGE RECOGNITION WITH ONN

By associating oscillator *i* to a single pixel, one can interpret ONN phase state as a binary image where $\Delta\Phi_i = 0°$ and $\Delta\Phi_i = 180°$ correspond to a white and a black pixel, respectively [1]. When oscillators are fully connected like in Hopfield Neural Networks [3] (Fig.1D), ONN associates a noisy input to a stored image for recognition. We train the ONN using the Hebbian rule [1], and we map synaptic coefficients to coupling resistances implemented by MoS_2 memristors [4]. For ONN inference, we apply a noisy input image, and we run transient circuit simulations (described in [4] and [5]). ONN settles to the correct state in only 4 cycles in average and associates the input image to one of the stored patterns (Fig.1E). With VO_2 oscillators running at 20 MHz and @ 0.3 V supply voltage [2], an image recognition task would dissipate 4x50 fJ/neuron/oscillation=200 fJ/neuron, which is 6x less than state-of-the-art ONN in 28 nm CMOS technology [6].

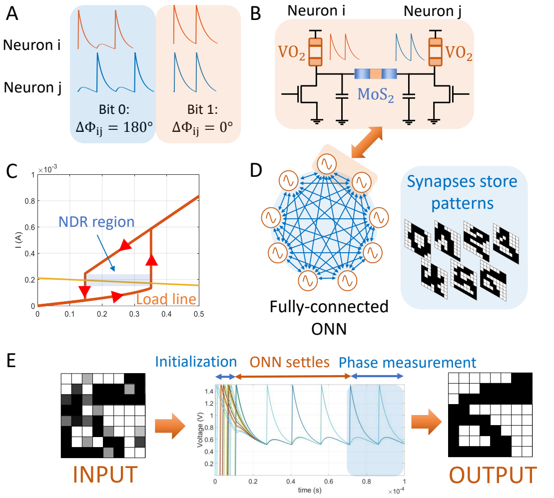

Figure 1: A) Phase encodes information in ONN. B) Two VO_2-oscillators coupled by a MoS_2 memristor. C) VO_2 IV curve and load line in the NDR region to obtain oscillations. D) ONN in a fully-connected network as a HNN. E) Example of 8x8 ONN inference.

4 CONCLUSION

We have showcased a beyond-CMOS ONN composed of VO_2 neurons and MoS_2 synapses. Circuits compactness and ONN parallelism bring a promising alternative to the von-Neumann architecture for real-time AI workloads such as image recognition at the edge.

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