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 (VO2) and synapses based on molybdenum disulfide (MoS2) memristors to emulate synaptic plasticity.

KEYWORDS
ONN, Neuromorphic circuit, Beyond-CMOS, VO2, MoS2 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 VO2 and MoS2 materials allow compact and configurable ONN circuit design using few components for low energy operations [2]. We harness phase change transitions of VO2 material to design compact relaxation oscillators [2]. We bias a two-terminal VO2 device with a transistor in series, such that the load line intercepts the VO2 Negative Differential Resistive (NDR) region to produce oscillations (Fig.1C). For large scale ONNs, we couple oscillators with MoS2 memristors (Fig.1B) to emulate synaptic plasticity from weak coupling (large MoS2 resistance) to strong coupling (small MoS2 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 ΔΦzi = 0° and ΔΦzi = 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 MoS2 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 VO2 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].

4 CONCLUSION

We have showcased a beyond-CMOS ONN composed of VO2 neurons and MoS2 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.

REFERENCES