Oscillatory Neural Networks: A digital implementation

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Abstract

The traditional Von Neumann computing paradigm struggles to keep pace with the exponential growth of data, leading to the exploration of novel computing paradigms. Oscillatory Neural Networks (ONNs), utilize **oscillators** for computation, offer a promising alternative by enabling efficient **neuromorphic computing**. In this work, we present an **FPGA-based fully digital implementation** of ONNs for pattern recognition.

Introduction

- Smart edge devices are becoming prevalent across industries, but face constraints in power, memory, and bandwidth. While AI applications using **deep neural networks** are increasingly effective, they demand significant resources and **struggle to run efficiently on small edge devices**.
- In addition, privacy and security concerns would recommend the data to be stored locally. This creates a challenge for **edge computing**.
- This has led to research into alternative computing paradigms like neuromorphic systems.

Biological inspiration

- ONNs use **coupled oscillators** to mimic **neural oscillations** of brain, **encoding information in phase** relationships between oscillators. This allows for fast, energy-efficient parallel computation, making ONNs promising for AI at the edge.
- Contrarily to the classical computation based on voltage amplitude to determine a logic "1," or "0," in ONN we use the phase relations to determine the logic **"1" (out-of-phase 180°) or "0" (in-phase 0°)**.

Associative memory

- ONNs exhibit associative memory properties similar to Hopfield Neural Networks. They can store patterns and associate inputs with the closest stored pattern[1].Stored patterns represent the minima of an energy function toward which the network evolves.

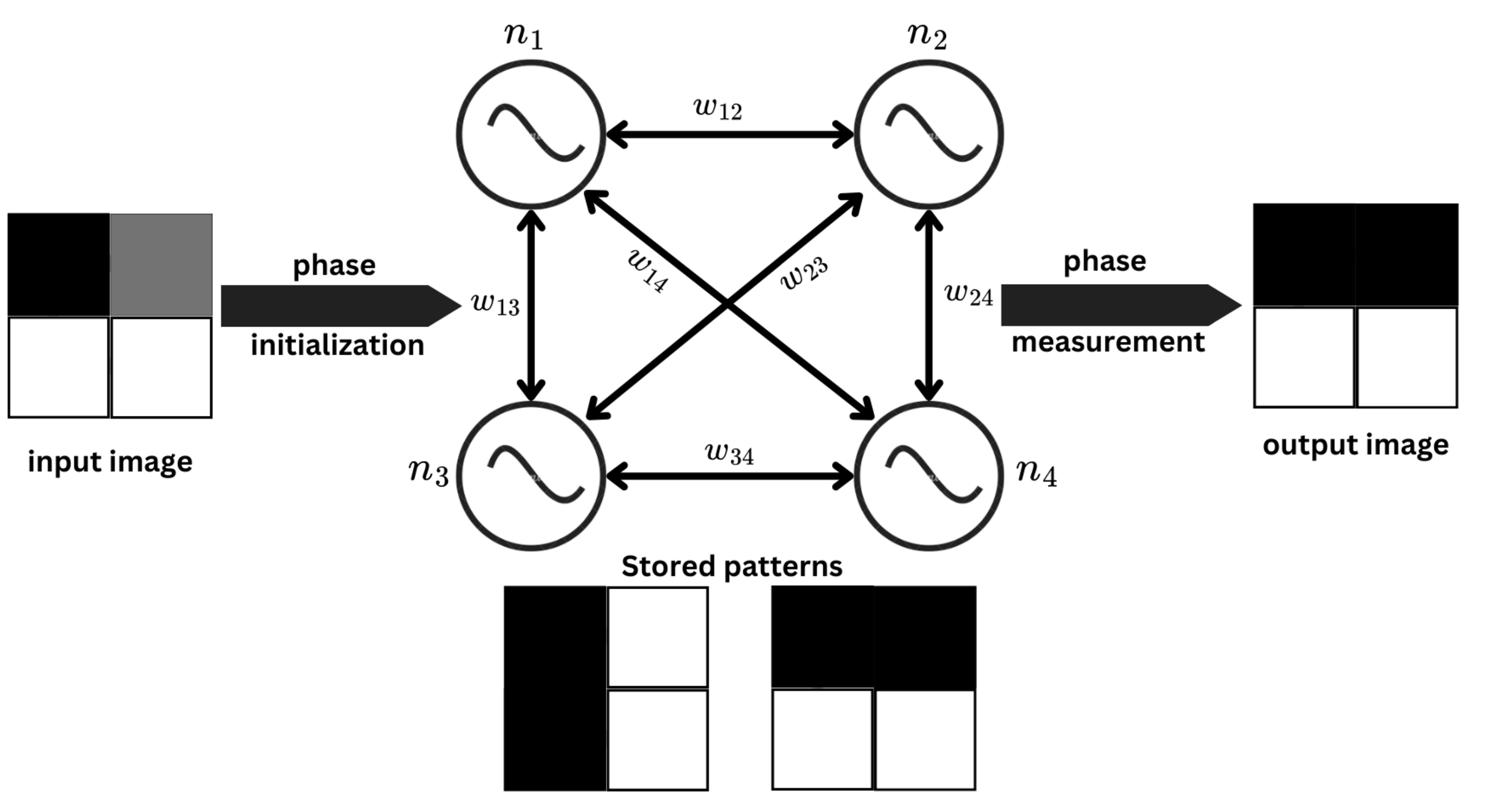

Figure 1. ONN with 4 neurons using associative memory capability to perform image recognition

Materials and Methods

ONN learning

- The **Hebbian learning rule** is one of the most popular learning algorithm to calculate synaptic weights for bipolar-valued $(-1/1)$ stored patterns[2].

$$w_{ij} = \sum_k \xi_i^k \xi_j^{kT} and \quad w_{ij} = 0 \quad \forall \quad i = j \qquad (1)$$

where w_{ij} = synaptic weight between neuron n_i and neuron n_j.
ξ^k = vector of k-th stored pattern

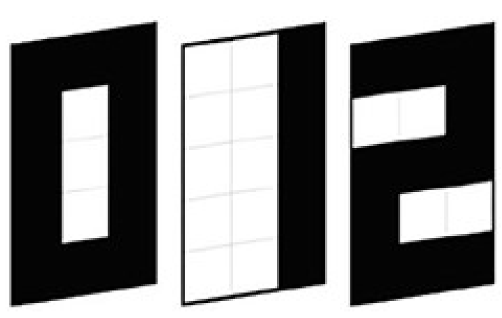

Figure 2. Reference patterns for 5 x 3 ONN

- Corrupted inputs are supposed to converge to the most similar stored pattern based on **Hamming distance**(HD).The HD between two patterns ξ_i^v and ξ_i^u of i elements is:

$$HD = \frac{1}{2}\sum_i (\xi_i^v - \xi_i^u) \qquad (2)$$

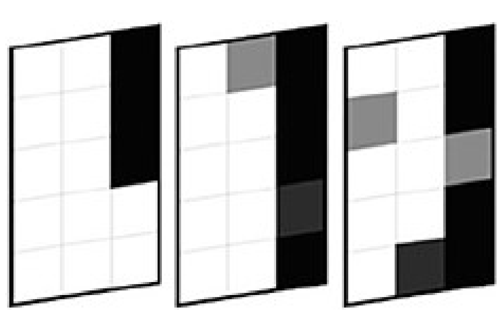

Figure 3. Corrupted test patterns of digit 1

Phase controlled oscillator

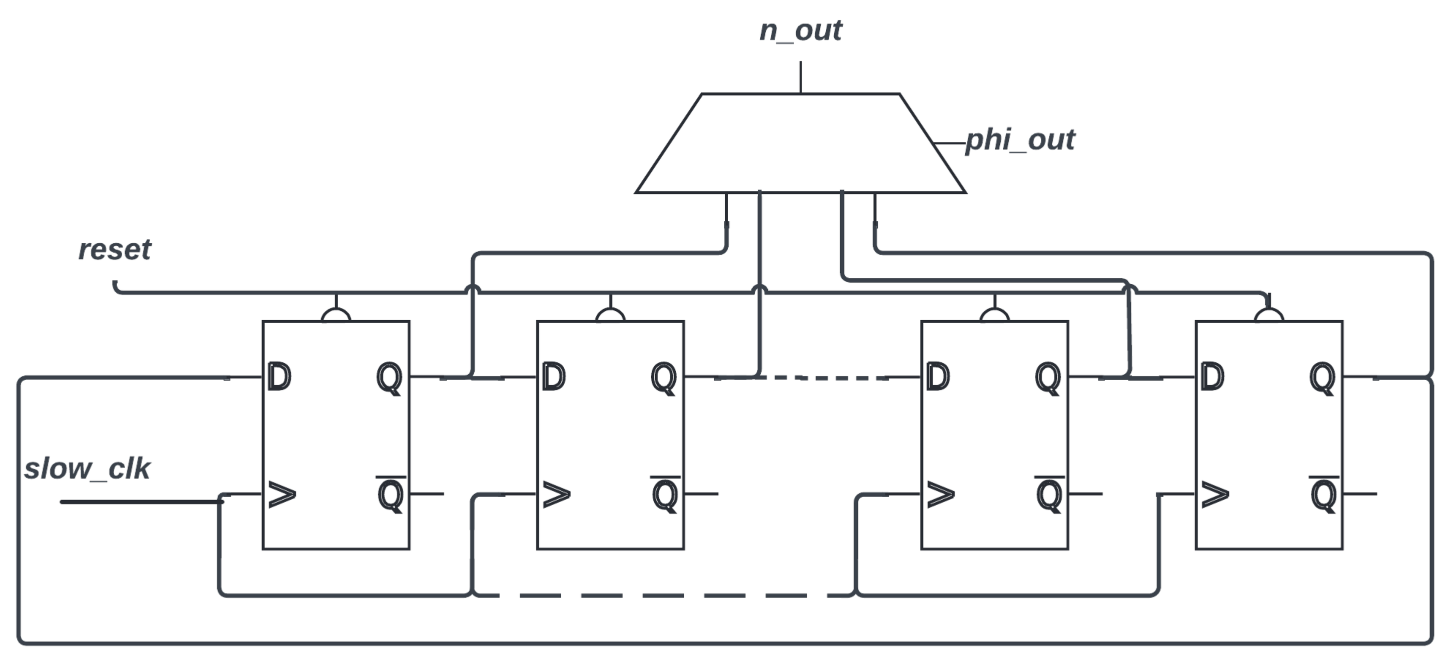

Figure 4. The 16-bit pattern [1111111100000000] cycles continuously in the circular shift register

Digital ONN design

Arithmetic logic circuit in the synapses block generates the input signal to the i-th neuron as: $n_{in}[i] = sign(\sum_j w_{ij} - \sum_k w_{ik})$

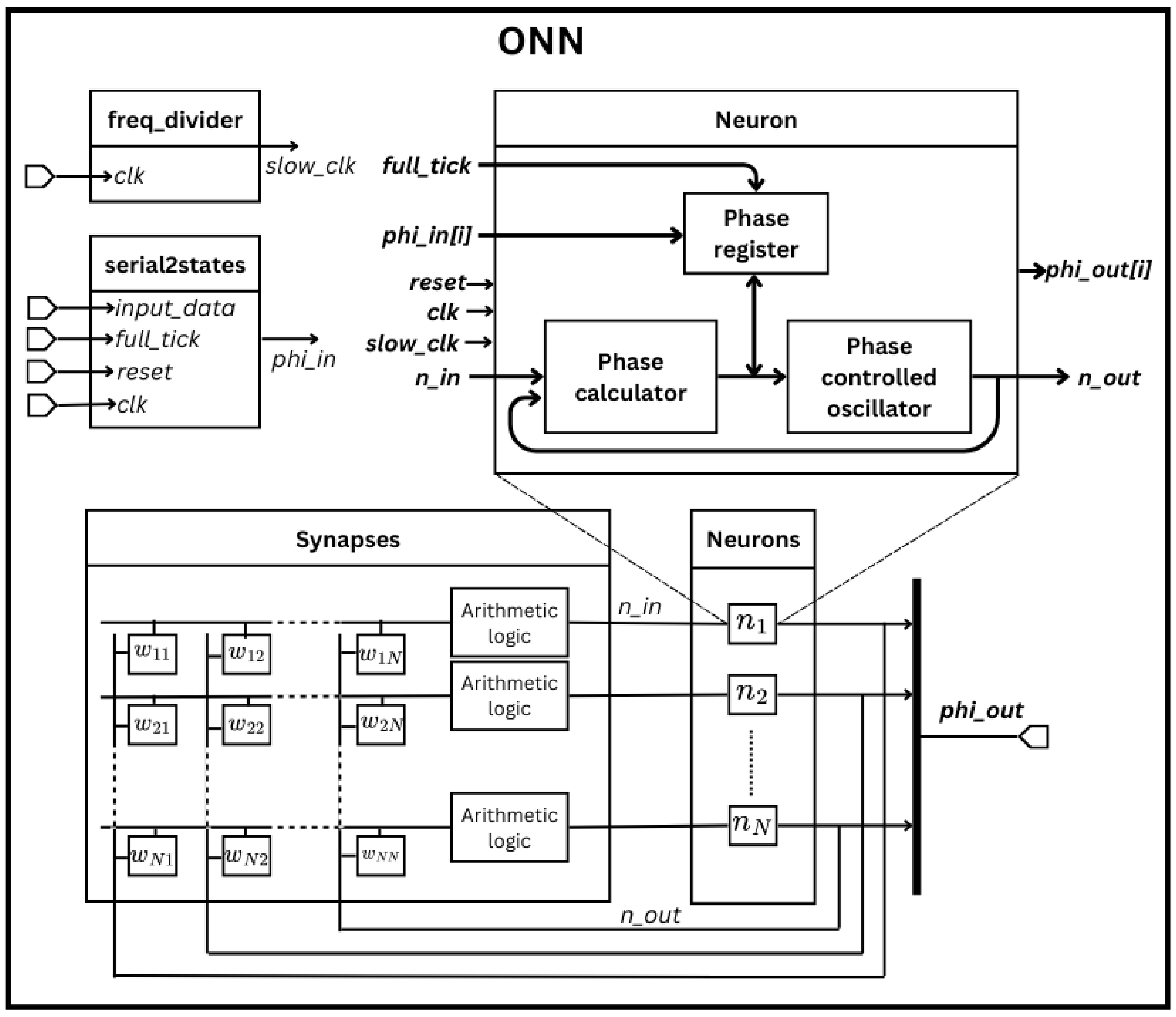

Figure 5. Fully parallel digital ONN architecture

Results and discussion

ONN size	Synapses	Stored patterns	Comp. time, avg (μs)	FFs
5 x 3	225	0,1	5.03	851
10x6	3600	0 to 5	5.16	1982
28x28	616656	0 to 9	5.9	39984

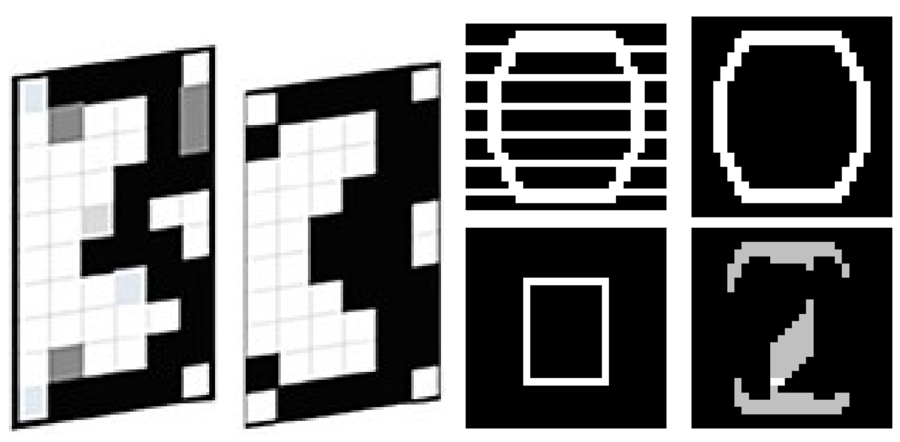

Figure 6. (right)ONN timing performances and resource utilization, (left) Test results

We observe ONN computation time remains nearly constant as network size increases, a **key feature** of the ONN concept.

Conclusion and Future directions

ONNs offer a promising alternative computation paradigm due to their parallel behavior enabling fast computation independent of network size despite limitations in retrieval capacity (can be improved with enhanced learning rules). ONNs are still in their infancy for comparison with benchmarks which is the focus of future works

References

[1] Frank C Hoppensteadt and Eugene M Izhikevich.
Pattern recognition via synchronization in phase-locked loop neural networks.
IEEE Transactions on Neural Networks, 11(3):734–738, 2000.

[2] Richard GM Morris.
Do hebb: The organization of behavior, wiley: New york; 1949.
Brain research bulletin, 50(5-6):437, 1999.