Oscillatory Neurocomputers with Dynamic Connectivity

Project Report

Submitted by

Satyam Mohla

Krishna Subramani

Under the guidance

of

Prof. Udayan Ganguly

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Neuromorphic Engineering

Department of Electrical Engineering

IIT Bombay

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Abstract:

When someone mentions the name of a known person we immediately recall her face and possibly many other traits. This is because we possess the so-called **associative memory** . Tasks, which are deemed computationally hard, such as pattern recognition, or speech recognition amongst others, can be success fully performed. The main inspiration such a computing architecture is the insight that the brain processes information generating patterns of transient neuronal activity excited by input sensory signals.

The two fundamental components that a neural network, capable of associative memory needs, are neurons and synapses, namely connections between neurons. Ideally, both components should be of nanoscale dimensions and consume/dissipate little energy so that a scale-up of such circuit to the number density of a typical human brain (consisting of about 10^{10} synapses/cm2) could be feasible. While one could envision an electronic version of the first component relatively easily, an electronic synapse is not so straightforward to make. The reason is that the latter needs to be flexible (”plastic”) according to the type of signal it receives, its strength has to depend on the dynamical history of the system, and it needs to store a continuous set of values (analog element).

We use Kuramoto's model to illustrate the idea and to prove that such a neurocomputer has oscillatory associative properties. We demonstrate by simulation the behaviour and evolution of the non-linear dynamical neural network, both spatially and temporally.
We in the latter half of the project also extend the analysis to comment on the hardware implementation of said network using an <u>*emerging class of highly nonlinear, nanoscopic, and ultrabroadband, low power wave oscillators, a spintronic oscillator.*</u>

The phenomenon of synchronization pervades everyday experience. Some examples are hardly surprising, like the synchronization of the front and back wheels of a bicycle, as they are highly coupled as compared to synchronisation in circadian rhythms observed in animals, and even in the subtle synchronization of the heartbeat to music.
Associative memory- the ability to correlate different memories to the same fact or event is a fundamental property is not just limited to humans but it is shared by many species in the animal kingdom. Arguably the most famous example of this are experiments conducted on dogs by Pavlov whereby salivation of the dog's mouth is first set by the sight of food. Then, if the sight of food is accompanied by a sound (e.g., the tone of a bell) over a certain period of time, the dog learns to associate the sound to the food, and salivation can be triggered by the sound alone, without the intervention of vision.

Today there is mounting evidence that the periodic and synchronised neuronal firing have a necessary role in neural information processing, especially in associative memory formation, visual perception and olfaction. The interactions of many excitatory and inhibitory neurons are responsible for the rhythmic behaviour. However most of today's focus in neural networks is on neurons having equilibrium dynamics, modelled as neurons having non-linear function with varying weights which in principle can model any transfer function. There is no temporal behaviour.

Oscillatory Neurocomputers, unlike conventional von-Neumann Machines, rely on their auto-associative memory to recall the output when presented with a corrupt input (Pattern Recognition).

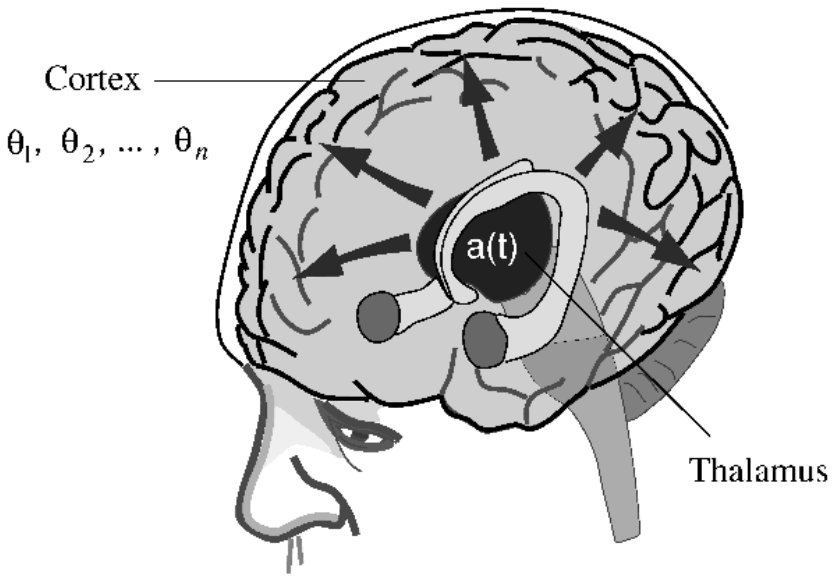

Fig. 1: *We treat the cortex as being a network of weakly connected autonomous oscillators q1,..,qn forced by the thalamic input a(t).*

Neurocomputing is a recently introduced, bioinspired computational paradigm that exhibits state-of-the art performance for processing empirical data. There are still classes of computational problems, such as data classification and pattern recognition, where conventional digital computers perform very poorly compared to the elementary skill of human intelligence. For these applications, it is expected that neurocomputing characterized by a massive parallelism could lead to significant advances.

Among various neural networks, the most promising are **oscillatory neural networks (ONN)** because they take into account **rhythmic behavior of the brain**. Arrays of weakly coupled oscillators represent a promising approach to unconventional computation. It has been proved that oscillator arrays can implement computational tasks such as pattern recognition and associative memory by exploiting their natural attitude to synchronization.
In these oscillator arrays, data information is commonly encoded in the relative phase differences achieved at synchronization, which makes computation robust against intrinsic noise of circuit implementation.

To demonstrate our concept, we have chosen the widely studied Kuramoto oscillator. The model of this dynamical system is modelled by the Kuramoto's dynamical equation. We now demonstrate by simulation, the capability of our single nonlinear dynamical node to identify corrupted digits (pattern recognition). The primary architecture used is that of a Hopfield-Grosberg paradigm, which is a kind of Recurrent Neural Network (RNN) Architecture.

Unlike conventional neural networks which work on backpropagation (training data), a Hopfield Network is a Dynamical System.

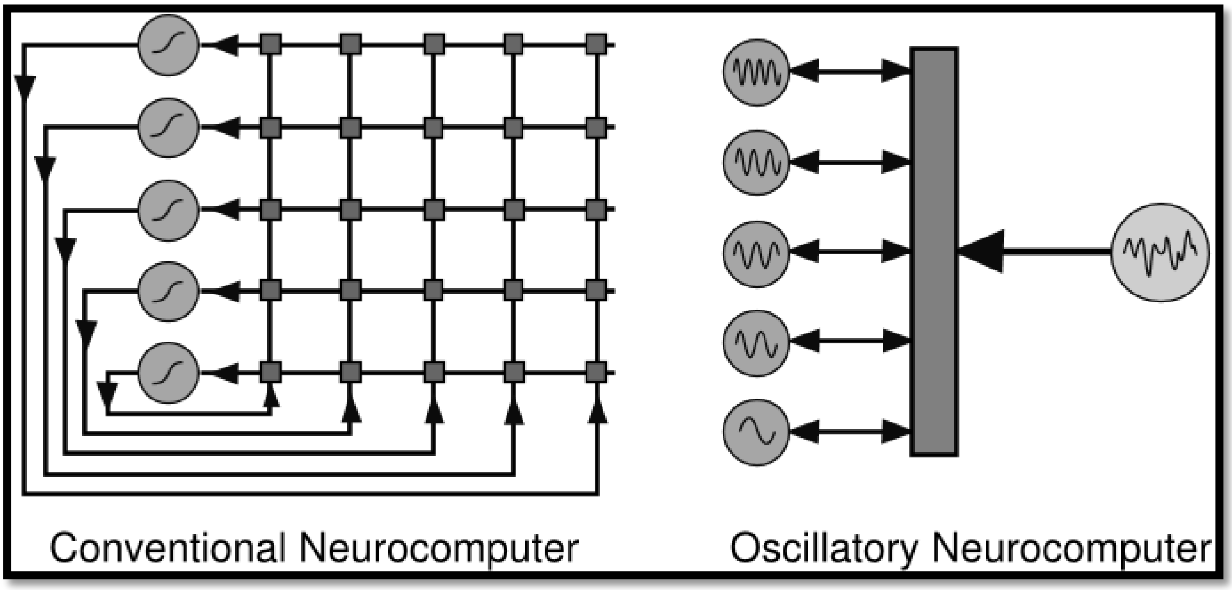

Fig 2.: *Conventional neurocomputer having n neurons (circles) would have n2 connections (squares). An oscillatory neurocomputer with dynamic connectivity imposed by the external input (large circle) needs only n connections.*

Through adjustment of its internal parameters (connection weighs), it leads to the system evolving from the input state(Corrupted Image) to the output state(Image pattern stored in memory) leading to identification. Addition of Oscillatory behaviour leads to cycle attractors as opposed to fixed point attractors in a conventional Hopfield Networks. Each oscillator plays an active role in the synchronization of coupled nonlinear oscillators is a common natural phenomenon. The coupling is typically the resulting synchronized state.

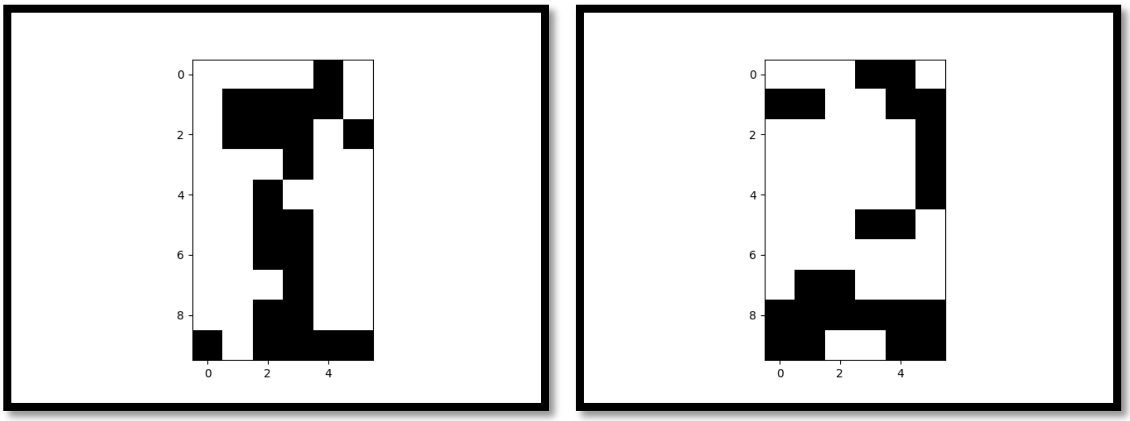

***Fig 3**:* The Corrupted image to be resolved- **Digit 1** and **Digit 2**

The method followed is as follows :

- In the **initialisation** phase, the network is initialized with the fundamental states (stored patterns) and the corrupt image to be recognized is fed to the system in the form of connection weights. The system is evolved & directed by the energy minimisation feature of kuramoto's ODE leading the system to converge to the state corresponding to the corrupted image.

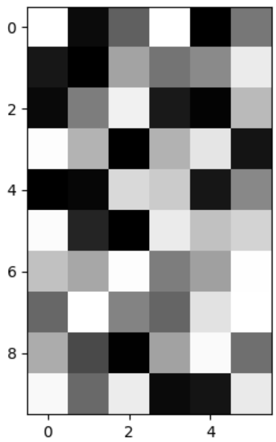

Fig 4: <u>**Phase State** of the ONN after being **initialised with corrupted image of 1.**</u>
<u>**ONN is of 60 neurons (6x10)**</u>

- In the **recognition** phase, the **Hebbian Learning rule** is introduced and the weights are set as per this HL equation. Now the system is in the the corrupt image state and the system is again left to evolve to, the state which is closest to the corrupt image, thus giving the output as the uncorrupted image.

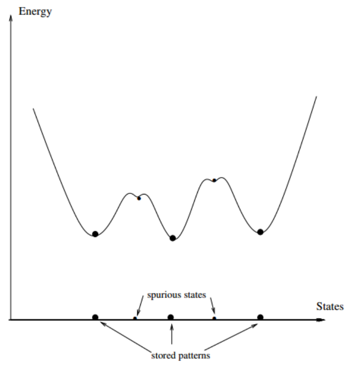

Fig 5: <u>Energy-State Diagram of the **ONN for different convergent states**</u>
(*Note that in our case the states are namely 'digit 0' and 'digit 1' respectively.)*

Simulation Results:

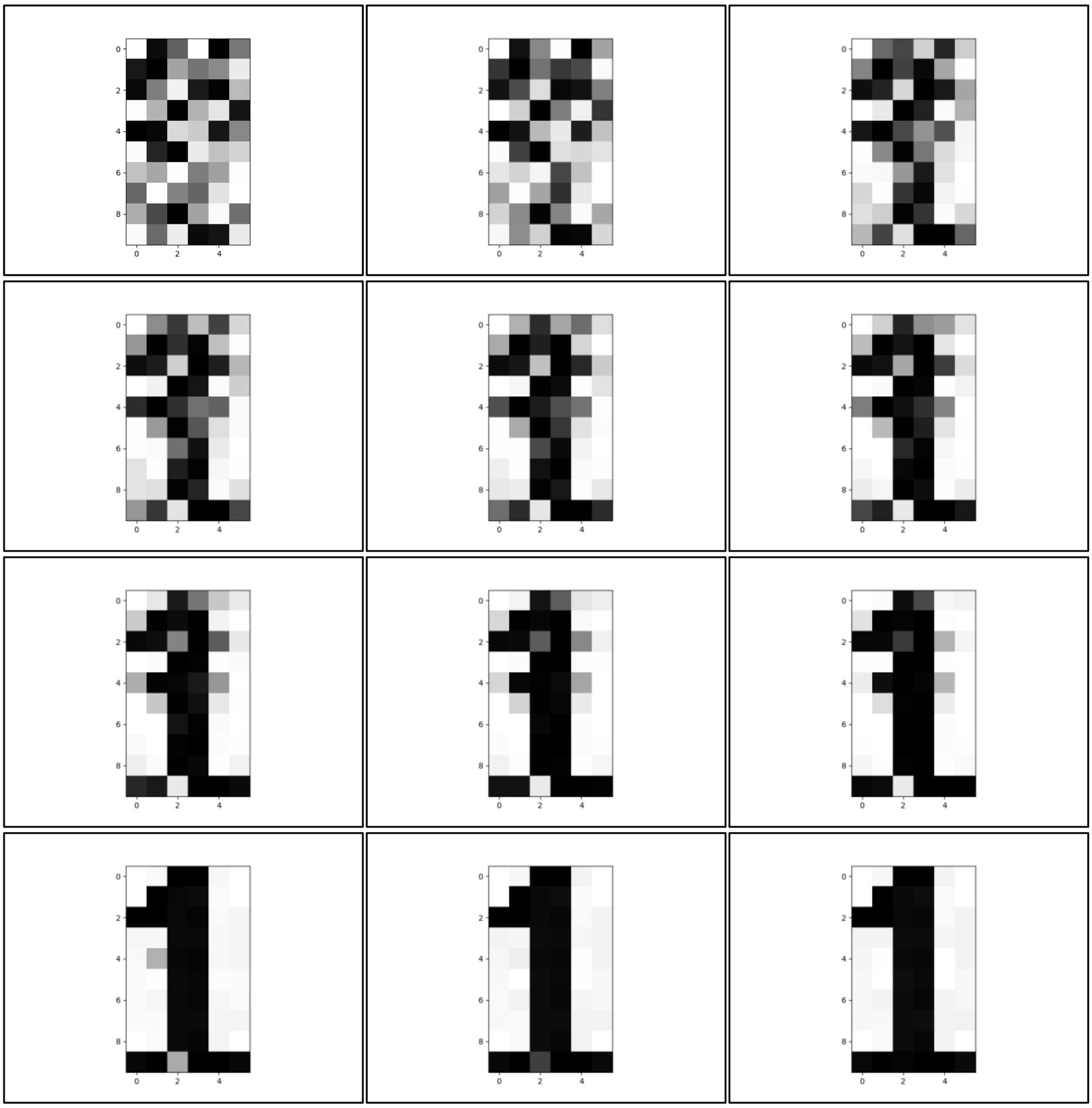

Fig. 6-17: The time **evolution** of the **ONN** is shown above.

Here, note that the state at t=0 is the system's corrupted image state as earlier. The time difference between each step is 5s until 10 states (t=0 to t=50s). Last two states are at t=100s and for a very large t (t=200s).

RESULT:

We have verified through numerical simulations the pattern recognition behaviour of an interconnected oscillatory neural network using units (referred to here as oscillatory neurons) performing simple nonlinear transformations in parallel, underlining the feature of associative memory. Our brain also recalls memories in a similar fashion. Thus, the above architecture works very well for Pattern Recall and Recognition type problems, as minimal training (in our case, just one sample) is needed. It is believed that a new generation of computers will employ these principles of the human brain for faster computation.

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