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Self-Sustaining and Self-Silencing Activity in Spiking Neural Networks

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Memory in the brain is generally considered as being supported by structural plasticity. Alternatively, research in rate based neural networks have shown that the dynamics of multiple neurons can be sufficient to encode a memory. It is nevertheless difficult to transfer this result to real brains as the dynamics of the neurons are different. Our work approaches the idea of non-plastic memory using spiking neural networks, a model closer to the dynamics of the brain. Using genetic algorithms, we evolved a network capable of retaining its activity despite the absence of external stimuli for a fixed amount of time, but also capable of silencing itself. This constitutes a first step toward the study of biologically plausible non-plastic memory.

1. Introduction

Spiking neural networks are a class of neural networks which have been created to tightly model the functioning of real neurons[Maass 97]. Those differ from more traditional neural networks in the particularity that the information transferred between neurons is based on events called spikes. Spikes can be seen as a discharge of electricity resulting from the accumulation of electric currents originating from afferent neurons. Over the past years, spiking neural networks became the preferred model for exploring in silica the functioning of the brain.

In rate based neural networks, it has been known that learning can be obtained without the need of synaptic plasticity[Tuci 03]. Learning was obtained by exploiting the inherent dynamics exhibited by the neural model. In spiking neural networks, this has yet to be shown it can be done, and subsequently, it is not yet known if the brain could possess any kind of memory relying exclusively on non-synaptic plasticity. Our goal with this work is to begin exploring the possibility of non-synaptic memory in spiking neural networks.

There is no definition of learning, but a functional definition has been widely used instead: "A system possesses memory if after encountering a set of stimuli or situation, it reacts differently subsequently when encountered again.". To start our exploration, we based ourselves on this functional definition in order to create a system that could maintain a memory. One additional aspect we were looking for is the capacity of this memory to disappear on its own. Indeed, without forgetting, a system would not be able to return to its previous state and react to the same event again.

1.1 An Experiment in Self-Sustainability

The system we developed is a spiking neural network which can maintain its activity without external inputs and naturally become silent after a specific amount of time. This by itself would not represent a memory because it is not embedded within a functional framework, such as a robotic task, but it constitutes the neural basis for one.

After an initialisation period of 1s where the network receives external stimulation, its task is to maintain neural activity for 2s without any external input. After those 2s, the network must by itself stop its activity. This could represent a memory of 2s activated by an external event lasting 1s, and forgot after 3s.

The next section will describe the setup required to obtain such a self-sustaining and self-silencing network. Section 3. will present our results and section 4. will discuss them.

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2. Experimental Setup

The spiking neural model we rely on is the Izhikevich neuron which became a standard in neural modelling for its computational lightness combined with its relative accuracy to real neurons[Izhikevich 03, Izhikevich 04]. This model relies on a system of two differential equations:

$$v' = 0.04v^2 + 5v + 140 - u + I \quad (1)$$

$$u' = a(bv - u) \quad (2)$$

where v is the membrane potential of the neuron, u its membrane recovery variable, I the external stimulation from pre-synaptic neurons. a and b are parameters tuning the regime of the neuron and decided experimentally. The membrane potential describes the accumulation of energy received from other neurons, while the membrane recovery implements a negative feedback pushing the membrane potential toward its resting state. When the membrane potential reaches a threshold of 30mV, a spike is emitted and transmitted to post-synaptic neurons connected to it, and the parameters are reset to $v = c$ and $u = u+d$, where c and d are parameters describing the regime of the neuron. a, b, c and d have been provided by Izhikevich for different types of neurons. In our case, we chose to use the regular spiking model with parameters $a = 0.02$, $b = 0.2$, $c = -65mV$ and $d = 6$.

The network used in the following experiment is composed of 1 input, 60 hidden neurons and 1 output. The input is represented by 5 neurons receiving identical external stimulation in order to increase its potency on the other nodes. All the nodes are interconnected without recurrent connection. The strength of the synapses, and the excitatory or inhibitory nature of each neuron, is tuned by a genetic algorithm(GA)[Holland 75].

The task required from the network is to maintain spike activity on the output neuron for 2s. Afterward, no activity should be recorded. The experiment lasts for 7s, divided into three periods: 1s of training where the input receives a regular external stimulation, followed by 2s during which no external stimulation is provided and the spike activity of the output neuron is monitored to ensure it does not remain silent, and finally 5s during which the output neuron should not display any activity.

At the end of the 7s, the fitness of the network is computed using the following equation

$$\text{fitness} = \begin{cases} \exp\left(\frac{(x-s)^2}{2*(0.35*s)^2}\right) & \text{if } x \leq s \\ \exp\left(\frac{(x-s)^2}{2*10^6}\right) & \text{if } x > s \end{cases}$$

where x is the time of the last spike emitted by the output neuron and s the time when the output is expected to stop spiking. In our experiment, we use a simulation time step of 0.1ms which gives us $s = (1+2)/0.0001$.

3. Results

The genetic algorithm was run for 5000 generations with a population of 100 individuals, which resulted in the evolution of a neural network capable of solving the task. Figure 1 shows the spiking pattern over time of all the neurons within the network, with the input neuron ranging from neuron 0 to 4, the output neuron being 5 and the rest being hidden neurons. We can see that the activity of the network stops after 3s as expected. We can also notice the difference in activity pattern before and after 1s, which corresponds to the moment where the external input is stopped and the network self-sustains its activity.

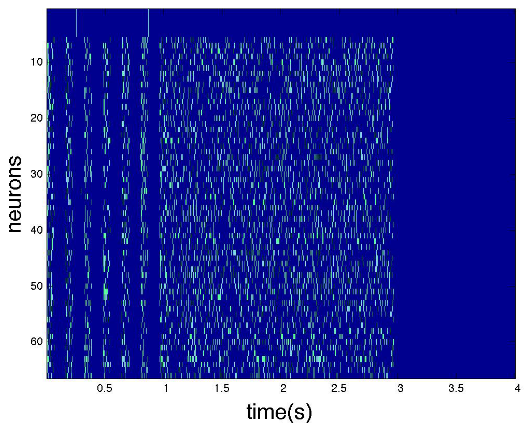

図 1: Activity of a successfully evolved network for the first 4s. The x-axis is the time in second, and the y-axis represents the neurons. The green squares represent spike activity.

The dynamics behind the network activity has not yet been uncovered. What we have understood so far is that the initial conditions of the network are important for this particular network. Indeed, the network cannot be reactivated after its activity has been stopped. This could be resolved by randomising the initial conditions and evolving again a new network. We also found out that every node possess different roles at different times through pruning experiments. For instance, a node might be a promoter of activity at time step t, but might become the opposite at time step t+1. This means that the role of the nodes within the network might depend on the timing of their interaction with other nodes.

4. Conclusion

With this work, we wanted to study the possibility of having a memory encoded within the dynamics of a spiking neural network. The rationale behind this goal was that not all memory need to be based on structural plasticity, and enough neurons interacting with each other can be sufficient to support a memory. The network shown in this work has all the properties required to implement a memory: it is activated by an external signal, retain its activity for a fixed amount of time and stops naturally without any external intervention.

As it is, this network could be embedded within an artificial life system and act as a short term memory, remembering a specific event for a short amount of time. Unfortunately, it does not yet support enough of the brain specificities to be convincing as a replacement for synaptic memory. To make it more biologically plausible, a study of its robustness and the addition of noise in the system would be important. It would be also interesting to study what kind of dynamics can create such a network, and what properties encode the duration of the self-sustaining period. This knowledge might provide useful information on how the brain encodes time.

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