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MODEL ARCHITECTURE FOR PATTERN RECOGNITION AND DISCRIMINATION IN A NEURAL NETWORK OF SPIKING NEURONS

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A living being interacts with the world receiving external stimuli like light, sound or chemical molecules. The whole set of possible stimuli must be encoded and identified by the brain. Encoding has been the subject of several experimental works that relate responses from animal brains to external influences [1, 2]. However, knowledge about the way information is handled by the neural network remains incomplete.

Experimental results relate stimulus to response with no wiring specification, that is, without details about the encoding process. In this work, we propose a simple one-layer neural encoding system based on Hebb's rule. The odors (or any other external stimulus), intended to be recognized and discriminated by the system, are represented by random activation patterns. The model network recognition capability is evaluated through a configuration space reduction method. The main question we address is whether the simple wiring model linking realistic neurons proposed here is able to produce the same kind of stimulus-response relationship observed in experiments.

It is widely accepted that, in order to recognize an external stimulus, neurons within a network activate/deactivate each other via chemical synapses. Our construction starts following the simple hypothesis established by Hebb [3]: neurons responding similarly to a given stimulus have probability C of being connected to each other via excitatory synapse. This is extended to the negative form: neurons that do not respond similarly to a given stimulus have a probability D of being connected through inhibitory synapses.

In order to formally implement the connection hypotheses above, we introduce the concept of pattern as a neuron set responding to a specific external stimulus. For simplicity, neurons are assumed to respond to each stimulus with a homogeneous probability a. This means that, since the whole network has N neurons, each pattern is coded approximately by aN neurons.

We propose that the net effect of chemical synapses on each neuron pair is a superposition of excitatory and inhibitory currents. Each neuron belonging to a pattern excites, on average, $\sim NaC$ neurons and inhibits, on average, $\sim N(1-a)D$ neurons due to this pattern. Furthermore, we want to handle excitation and inhibition between two neurons independently. This requires the definition of two synaptic matrices: an excitatory and an inhibitory. If neurons i and j respond to a specific pattern while neuron k does not, neuron i excites j with probability C and inhibits k with probability D. In addition to the long-range chemical synapses, a neuron also interacts through gap junctions with its close neighborhood.

In order to investigate the network ability for pattern recognition we follow a simple strategy: the external stimulus activating a pattern is simulated by choosing a fraction $P_{ext} < 1$ of neurons, among those encoding the pattern, to receive external input. That is, a pattern is presented to the network only through $aP_{ext}N$ neurons. This way we may test if the network is able to identify different stimuli to a given pattern. The current injected in one of the chosen $aP_{ext}N$ neurons follows a Poisson process: at each iteration, the neuron has probability p_c to start receiving a short external current pulse. The method intend to simulate the input coming from other network layers by excitatory synapses.

The network was analyzed using the frequency multidimensional space. We define the i^{th} component of a firing rate vector $\mathbf{M}_j$ as the number of spikes that neuron i produced in a specific time interval j. After the simulation, Principal Component Analysis (PCA) [5] is applied to the resulting frequency space in order to obtain a highly informative low-dimensional subspace. PCA consists in a linear transformation of the matrix $\mathbf{M}$ resulting in a new one whose components are ordered so that the first few retain most of the variation present in all of the original components.

Figure 1 shows PCA projection space trajectories corresponding to the simulations using Rulkov neurons [4] for the following parameter values: $N = 1024$, $a = 0.3$, $C = D = 0.1$, $P_{ext} = 0.5$, $p_c = 0.2$ and 20 patterns to build the synaptic connections. The axes correspond to the first and

third principal components (in this specific case, the first and second axes describe the trajectory while the third one discriminates the patterns). Each circle corresponds to a 50 iterations time bin, used to build the $\mathbf{M}_j$ vectors (Rulkov model is a discrete one, with 1 iteration $\approx$ 1 ms). Full circles and thick lines represent input time intervals. The system starts from the quiescent baseline state (Q), follows a loop under the presentation of the external stimulation and returns to the baseline state. There are three loops in each figure, numbered from 1 to 3, corresponding to three stimulations. Pattern 1 is presented along a time interval (loop 1). Then, after a period without external input, pattern 2 is presented followed by a period without external input (loop 2). Finally, pattern 1 is presented once more, but now to a different choice of neurons (loop 3). In the absence of connections (Figure 1a), the three loops are uncorrelated, only representing the activation paths of neurons receiving current injection. In the connected network (Figure 1b), loops numbered 1 and 3 are much closer to each other than loop numbered 2, since the formers follows stimulation of pattern 1. This means that the network is able to recognize pattern 1 and to distinguish it from pattern 2, even if the neurons receiving current injection are different.

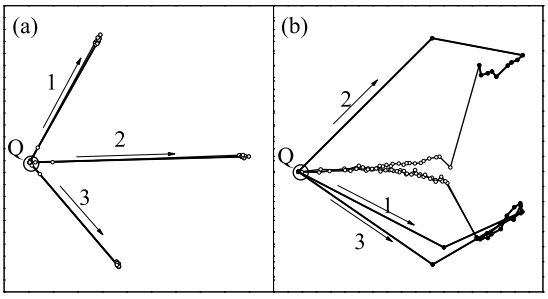

Figure 1 – Plot of the first and third principal components from the Principal Component Analysis of the frequency vectors $\mathbf{M}$. In (a), simulation without connections; in (b), both chemical and electrical connections. Each circle corresponds to a 50 iterations time bin with external input during 500 iterations. Full circles and thick lines correspond to input time intervals.

We also investigated the system stability against different injection times. Figure 2 shows four simulations using external stimuli on the same neurons, but with different input time intervals Δt. In (a) $\Delta t = 100$, in (b) $\Delta t = 800$, in (c) $\Delta t = 1600$ and in (d) $\Delta t = 3200$ iterations. Squares and thick lines represent the input time interval. As can be seen in the figure the trajectory remains nearly the same and, as the injection time increases, there is an accumulation of points around a fixed point (FP). In the absence of current injection this fixed point destabilizes and the system returns to the baseline state (Q), following the same trajectory, independently of the injection time. This way we recover the same features of the trajectories observed in the work by Mazor *et al.* [2] and Lin *et al.* [1].

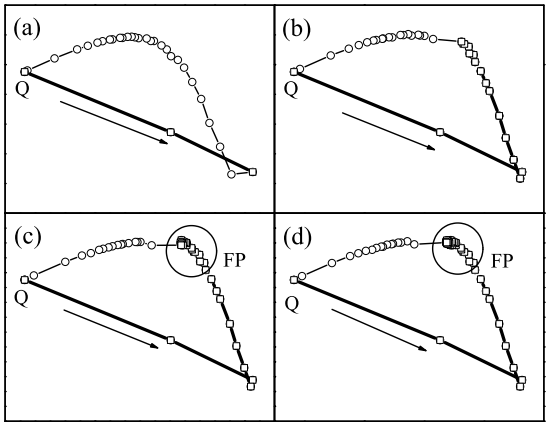

Figure 2 – Plot of the first two principal component from Principal Component Analysis from four simulations. The external input is into one pattern and into the same neurons, differing only in the time input interval (Δt). In (a), (b), (c) and (d), $\Delta t = 100$, $\Delta t = 800$, $\Delta t = 1600$ and $\Delta t = 3200$ iterations, respectively. Squares and thick lines represent the input time intervals. Number of circles increase with the increase of Δt. In (c) and (d) the regions with accumulation of circles, indicated as FP, are the fixed points of this pattern.

A synaptic architecture providing pattern recognition abilities to a network of spiking neurons is proposed in this work. PCA analysis of simulations shows that the synapses modify the trajectories in the frequency space in a way that trajectories corresponding to the same input pattern are close to each other, while injection corresponding to some other pattern describes a very different trajectory. This means that the network has clear discriminative capabilities. The response to different current injection times was also investigated showing the presence of a fixed point. This scenario is consistent with two alternatives: either the recognition of a pattern is more related to describing a trajectory than just reaching a fixed point, or the fixed point itself is the discriminative element for the pattern.

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