Learning a temporal code

Ph. Häfliger

Institute of Neuroinformatics UNIZ/ETHZ
Winterthurerstrasse 190
CH-8057 Zürich
Tel: ++41 1 634 27 99
e-mail: hafliger@ini.phys.ethz.ch

Abstract. The paper proposes a concrete information encoding for networks of spiking neurons. A temporal code is presented in which neurons respond to simultaneous spike releases of a particular group of neurons. The paper puts a spike-based learning rule in the context of that coding and shows how a network adapts to events experienced while observing an environment. Furthermore, correlations between events distant in time can be learnt. To demonstrate this, a net is simulated, the neurons of which become selective to moving bar stimuli after repeated presentations of samples.

1. Introduction

Temporal codes are an often examined phenomena in the neuroscience community [1, 2, 4, 9] and spike based learning is becoming more popular in neural modeling [6, 8, 7] and physiological evidence for it has been found [10]. However combinations of the two in a perceptive system are still relatively rare. The challenge met by this paper is to propose a concrete temporal coding that can be learnt by a spike based learning rule when receiving sensory input.

2. Coding by simultaneous spikes

We propose a particular temporal code: a network of neurons codes events, be they sensory or purely internal, as simultaneous spiking of a group of neurons. For example the simultaneous stimulation of adjacent optical receptors can encode the occurance of a bar. A neuron one step removed from the sensory level could be sensitive to such a bar event (figure 1 A). Simultaneous activity of a group of such orientation selective cells can signal the outline of an object. Other neurons could, via multi-synaptic connections, code for sequential occurances of events. For example a direction selective cell would need input from an orientation selective cell as well as from a group of cells that code for a bar position at some distance (figure 1 B). Activity in such a network looks like synfire chain [1] activity.

It is essential, that the weight vectors of these neurons are normalized, such that all the high weight inputs must be simultaneously active to trigger an action potential (AP), and the neuron must have a relatively short membrane time constant, so that it reacts as a coincidence detector.

To simplify the observations in the following simulations, the network is organized into levels is used in the network. Feed-forward connections between levels are then responsible for the binding of simultaneous activity in the previous level, whereas intra-level connections bind sequential occurances.

3. Algorithm

We implemented a particular network structure together with a spike based learning rule, the so called modified Riccati rule (MRR) [7]. Although we do not (yet) have a strong claim to biological plausibility, we tried to use physiologically realistic parameters when possible.

3.1. The neuronal model

We use leaky integrate-and-fire neurons with a firing threshold at 1. We chose a short membrane leakage time constant of 1.6ms. Therefore our neurons act like coincidence detectors. This is can be justified for average cortical neurons if one assumes a constant background activity that acts to increase the neurons' membrane voltage baseline above their reversal potentials. Then the time constant to bring a neuron back to that level is much reduced. Modeling of *in vivo* conditions in general show shorter effective time constants than *in vitro* experiments would suggest [3, 9].

3.2. The learning rule

The MRR has already been discussed in previous papers [8, 7]. It is a learning rule local to every synapse. The important property for its use in the context of our proposed coding scheme is its ability to make a neuron selective to input from synapses that tend to be active simultaneously, even if they cannot be distinguished from other synapses when only considering average frequencies [8]. It also implicitly normalizes a neurons weight vector to a constant length. Its definition is given in the Appendix. The parameters α and β are both 0.01, which will cause the weight vector length to be normalized to 1 ($\|w\| \approx \sqrt{\frac{\alpha}{\beta}}$) [7]. The time constant for the correlation signal's decay τ is set to 1.6ms, since only by having it the same as the membrane leakage time constant is the normalization accurate [7].

3.3. The network

A two layer network architecture with 9 neurons per layer is used. Four different bar stimuli are moved in a random sequence past the input layer. Neurons in
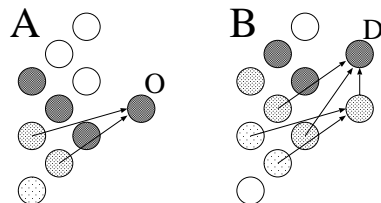
Figure 1: Two types of cells that can emerge in the experiments. The grey levels of the cells indicate recent activity. The darkest cells are spiking now. The lighter a cell is, the longer it has not spiked. The activations in the first (left) layer are caused by a passing bar-stimulus. (A) depicts an orientation selective cell in the second layer, marked with an 'O'. The strongest connections are feed-forward connections from aligned input cells. In (B) a direction selective cell is shown, marked with a 'D'. It receives inputs from aligned cells from the input layer too, but additionally from an orientation (or direction) selective cell that was active approximately one transmission delay earlier. This is a simple example of binding events that appear in sequence. Note that since the MRR normalizes the length of a neuron's weight vector to one, input from all major connections is necessary to trigger an action potential, regardless of their number. So in our particular example for the orientation selective cell in (A) only two inputs are needed, whereas three simultaneous inputs trigger the direction selective cell in (B).

that layer react to the passing of the bar by a single spike release. The Bars are parallel to the diagonals of the square formed by the nine input neurons and are moved orthogonally to their orientation. The bars are presented during 50 seconds of simulation time in 0.2 second intervals. The speed of the bars was such that the transit time from one line of neurons to the next matched the average axonal transmission delay. This maximizes the probability of obtaining direction selective neurons. If the speed is reduced, the numbers of direction selective cells will gradually decrease (figure 2 C). The input layer is fully connected to the next layer via learning feed-forward connections. In this next layer all neurons are connected to each other. Connection delays were randomized in an interval of 10ms±3ms in the first experiment and 3ms±3ms in a second simulation. The second setting is closer to biology (The delay of the earliest polarization in cortex after thalamic stimulation has been estimated to be between 1 and 5ms [5].).Initial weights were 0.45. An additional inhibitory neuron received inputs from all neurons in the second layer (weight = 0.45), and reduced all the neurons' membrane voltages by a fixed amount of -10 when active. This prevented the network from self sustained firing at the beginning of the experiment, when the learning had not yet normalized the weight vector.
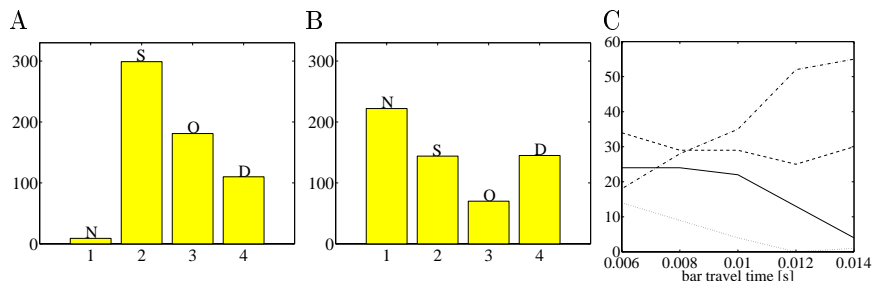
Figure 2: A&B: The numbers of members of selectivity-classes over 60 simulations. The first column shows the number of cells that were non-selective (N) because they responded to more than two stimuli, the second bar represents the cells that did not respond to any of the bars (S for silent). The third column shows the number of cells that were sensitive to orientation only (O; responding to two parallel stimuli) and the third is the number of direction selective neurons (D; responding to only one or (being direction sensitive without being orientation selective) to two orthogonal stimuli). A is the outcome of the simulation with 10ms base axonal delay. For B that base was 3ms. C depicts the influence of the bar transit time between rows of input neurons (x-axis) on the number of cells belonging to the above described classes (y-axis). The dotted line represents the non-selective cells, the dash-dotted line the silent ones, the dashed line the neurons sensitive to orientation and the solid one shows the numbers of direction selective cells. The sums over 10 experiments are shown. The axonal delay was 10ms

4.   Simulation results

A neuron in the second layer becomes tuned to a stimulation pattern that results in simultaneous arrival of presynaptic spikes at several of its synapses. Note that in contrast to time discrete Hebbian learning the term simultaneous is fuzzy and not biased by borders between time-slots. A neuron's choice of a stimulus depends on the set of stimuli and on the random offsets in the transmission delays from both layers. The preferences of a cell may therefore change when the preferences of others change, and neurons tend to choose similar stimuli, e.g. the example of a direction selective cell in figure 1 B is dependent on the existence of a cell that is selective to the same orientation. Still the coupling was not so strong as to always prevent the emergence of different orientation preferences in one run. In a bigger network with more local instead of full intra-layer connections several preference regions might develop, such as are observed in visual cortex for example.

   With the shorter axonal base delay (3ms) signals from subsequent bar positions could arrive simultaneously in the second layer. Therefore, as opposed to the example in figure 1 B, cells can become direction selective without another cell being orientation selective. Also the spike density is increased, which affects the coincidence detection property of the neurons and self sustained activity

was more probable. More cells remain non-selective (compare figure 2 A/B).

Mismatch between bar travel time and axonal base delay do not immediately destroy the network's ability to produce direction selective cells (figure 2 C, solid line). Even when the bar speed is reduced such that a direct input to the second layer must be faster than a two synaptic one from the previous bar position, one can still not rule out the possibility of a coincidence of a triple synaptic input from that formar bar position with a direct one, though the probability is very low. The number of orientation selective cells is independent of the bar speed (figure 2 C, dashed line). The number of silent cells (figure 2 C, dash-dotted line) increases with decreasing bar speed up to a point where only they and the orientation selective cells remain, whereas the number of non-selective cells declines to zero.

5.   Conclusion

A coding scheme has been put forward that is based on events of synchronous group activity. Spike based learning rules that reward causal relationships between pre- and postsynaptic spikes will tune a neuron to groups of synapses that receive coincident spikes and can therefore adapt a neuron to read this coding. Combining the learning and the coding scheme in a network can for example tune cells to the orientation and direction of moving bars. In more general terms such a network can bind features together that have appeared together in the systems experience. It can establish temporal relationships between features that tend to appear in sequence. This binding can appear recursively and so lead to representations of objects of increasing level of abstraction.

Appendix: The MRR

The following rule defines what happens at one synapse.

$$
c(t_{m,0}) = \begin{cases} e^{-\frac{t_{m,0} - t_{m-1,s}}{\tau}} c(t_{m-1,s}) & \text{if } s > 0 \\ 0 & \text{if } s = 0 \end{cases}
$$

$$
c(t_{m,1}) = 1
$$

$$
c(t_{m,n}) = e^{-\frac{t_{m,n} - t_{m,n-1}}{\tau}} c(t_{m,n-1}) + 1
$$
$$
\text{if}
$$
$$
n > 1
$$
$$
t_{m,n} \leq t_{m+1,0}
$$
$$
s = max\{v : t_{m-1,v} \leq t_{m,0}\}
$$
$$(1)$$

$$
w(t_{m,0}) = w(t_{m-1,0}) + \alpha c(t_{m,0}) - \beta w(t_{m-1,0}) \tag{2}
$$

where c is the 'correlation signal', 'remembering' recent presynaptic activity for a time determined by τ. w is the weight at this synapse, $t_{m,0}$ is the time of the m'th postsynaptic spike and $t_{m,n}$ $(n > 0)$ is the time of the n'th presynaptic spike after the m'th postsynaptic spike. s is the number of presynaptic spikes between the $(m-1)$'th and the m'th postsynaptic spike, so $t_{m-1,s}$ is the last event (presynaptic or postsynaptic spike) before the m'th postsynaptic spike; α and β are parameters influencing the learning speed and the weight vector normalization ($\|w\| \approx \sqrt{\frac{\alpha}{\beta}}$).

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