

Detection of Complex Coincidences Using Coupled Learning Rules*

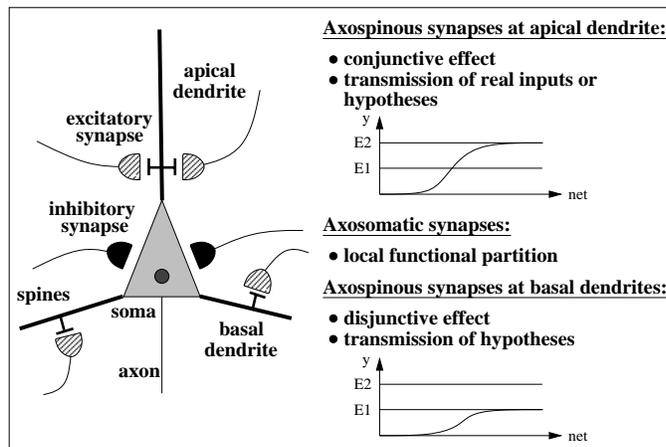
1 Introduction

In [MG93] a model of behaviour-based visual recognition is presented. It is based on the assumption that visual perception of shape is done by anticipating the sensory consequences of motoric actions in the cerebral cortex. Anticipatory hypotheses can only be set up when knowledge about relations between different sensory channels (e.g. visual and tactile) and motor commands had been integrated into an internal model. Relations between channels are reflected in coincident activation of the corresponding units. The learning rule system proposed here has been developed in order to detect complex coincidences in a recurrent network of spiking neurons.

2 Model

Basic assumptions

The neurons of our model network transmit 'real' input signals as well as hypotheses. In a HEBBian learning rule these two cases have to be distinguished: modification of synaptic efficacies should only be induced by input activity, not by hypotheses.



For this reason we postulate *separated activity ranges* for neurons, low activity for hypotheses and high activity for input. The character of a signal should be preserved through all processing levels, which is obtained by introduction of *separated pathways* — input information is transmitted via synapses at the apical dendrite of pyramidal cells, hypotheses via synapses at the basal dendrites.

Besides the excitatory synapses 'parallel' inhibitory pathways both at the apical and basal dendrites are assumed. These synapses (not shown in the figure) are provided by local inhibitory cells that are fed by pyramidal cells in the neighbourhood.

Learning rule system

The weight of a synapse trained by a HEBBian learning rule reflects the statistics of coactivation of the pre- and the postsynaptic neuron by input activity. If learning is restricted to this mechanism, only coincidences between two single channels can be detected. More general, *complex coincidences*, i.e. coactivation of *conjunctions* of signals should be detected, too. A conjunction of signals has to be expressed in synaptic weights, but only in the

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case when the conjunction of signals takes part in a coincidence, i.e. when the conjunction is *required* for the generation of an hypothesis. Basal and apical synapses are therefore provided with an additional function and different learning behaviour: basal synapses are trained in a HEBBian way using a pre-not-post rule, their effect on the postsynaptic neuron is *disjunctive*, whereas apical synapses are trained by a learning rule similar to [Mal73] with constant weight sum and hence show a *conjunctive* effect on the neuron. Both learning rules are *coupled*: a conjunction of signals at the apical path does only entail increased efficacies of activated apical synapses if the conjunction is a ‘cause’-part of a coincidence. Provided that basal connections are symmetrical, this condition is equivalent to the activation of one or more of the synapses at the basal dendrite of this neuron by high ‘input activity’ when the neuron is in a state of high activity — i.e. a tendency to increase weights of *basal* synapses influences the modification of the weights of *apical* synapses.

Basal learning and adaptation

Modification of synapses contacting basal dendrites is done by a pre-not-post learning rule, where weight modification is calculated from a product of a presynaptic term and a postsynaptic term with weight-depended balance point at the postsynaptic term [BKK90, HS93]. Post-not-pre rules with balance point at the presynaptic term are not suitable for the detection of cause-effect relations: if an effect can be brought about independently by different causes, a synaptic weight representing one of this relations is decreased during the presentation of one of the other relations. For the presynaptic term the high level portion of the membrane potential $m_{i_b}(t)$ at the spine head is used, the postsynaptic term is calculated from the high level portion of the joint membrane potential $M(t - \tau_0)$:

$$\Delta w_{i_b}(t) \sim \max\{m_{i_b}(t) - M_{E_1}, 0\} \cdot [\max\{M(t - \tau_0) - M_{E_1}, 0\} - c \cdot w_{i_b}(t - 1)]$$

The spine head potential results from a convolution of the presynaptic spike train with a synaptic response function, the joint potential is affected by all partial membrane potentials. Learning a time t depends on the spine potential at time t and on the joint potential at time $t - \tau_0$, because a spine potential set up by the firing of a presynaptic neuron which becomes active at the same time as the postsynaptic neuron is delayed for time τ but has to be brought together with the postsynaptic potential — this is necessary to enable the formation of symmetrical basal connections between two neurons. Basal contributions to the joint potential are limited to the low level ‘hypotheses’ activity whereas apical contributions are not. A fast *adaptation* behaviour in form of an integrative feedback was introduced to ensure that high level activation of a neuron is only temporarily, which is necessary to avoid the detection of coincidences that only occur due to long lasting activation of channels.

Apical learning and sensitivation

The update mechanism of apical synapses is a function of the high level portions of the joint membrane potential $M(t - \tau_0)$, of the basal influence expressed by $\Lambda_b(t)$ and of the spine head potential $m_{i_a}(t)$ of the apical spine which is concerned:

$$\Delta w_{i_a}(t) \sim \Lambda_b(t) \cdot \max\{M(t - \tau_0) - M_{E_1}, 0\} \cdot \max\{m_{i_a}(t) - M_{E_1}, 0\}$$

Weights are normalized after having updated all synapses. The basal term $\Lambda_b(t)$ is composed from the high level portions of the basal spine head potentials:

$$\Lambda_b(t) = \sum_{i_b} \max\{m_{i_b}(t) - M_{E_1}, 0\}$$

The effect of apical synapses onto the joint potential is modified by a sensitivation $S(t)$:

$$m_{i_a}^w(t) = [(1 - S(t - 1)) \cdot w_{i_a}(t - 1) + S(t - 1)] \cdot m_{i_a}(t),$$

If the represented conjunction of signals entails *counter-examples* of coincidences, the represented conjunction is not changed but the neuron becomes sensitive to other apical channels, too, to be able to change apical weights towards another conjunction that provides *examples* of coincidences. If examples are provided, sensitivation is kept on a low level, so the represented conjunction is stable. A post-not-pre rule is used for the modification of the sensitivation $S(t)$:

$$\Delta S(t) \sim \max\{M(t - \tau_0) - M_{E_1}, 0\} \cdot (e^{-\lambda \cdot \Delta_b(t)} - S(t))$$

A temporal sensitivation is in discussion; it could be necessary to discard represented conjunctions that never occur again.

Neuron function

The joint membrane potential with contributions from basal, apical and somatic synapses is compared with a dynamic noisy threshold; a spike is generated, when the joint potential exceeds the threshold. After emission of a spike, the neuron enters a period of absolute refractoriness ($1ms$) and then the threshold decays to its resting level (relative refractoriness). Noise has to be limited to a value which guarantees that low level ‘hypotheses’ activity is very unlikely to be transformed into high level ‘input’ activity by stochastic deviations.

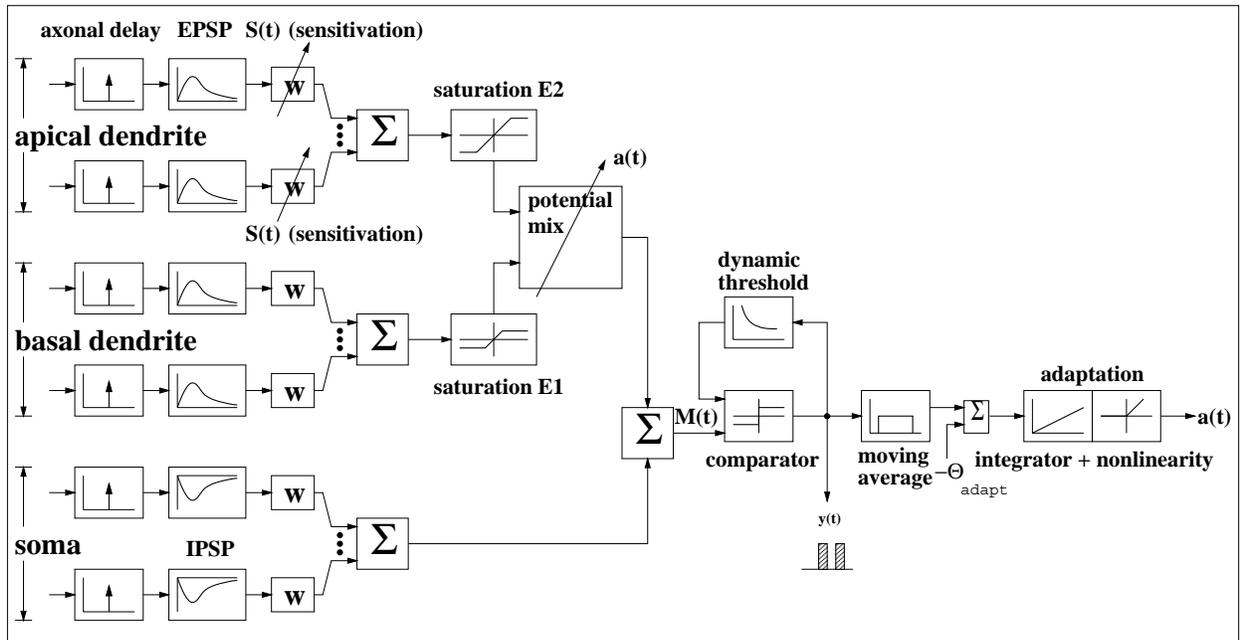


Figure 1: Block diagram of the neuron model. At apical dendrite and basal dendrites only excitatory synapses are shown.

Figure 1 shows the block diagram of the neuron model. Apical potential $M_a(t)$ and basal potential $M_b(t)$ are combined by a mixing function. This function has been designed to maintain the excitation levels of both pathways on one hand and to enable the interaction

of both potentials on the other hand. In the first few milliseconds after high level apical activation the activity of the neuron should not be changed by basal inhibition, otherwise hypotheses could generally disturb the learning process. After this time, however, it should be possible to suppress the output activity of the neuron by basal inhibition — even if the neuron is activated by the apical pathway — to enable the formation of an assembly sequence [Heb49, Pal82] that starts from the real situation and propagates to hypothetical situations without being disturbed by neurons representing the real situation. In figure 2 the mixing function $f_m(M_a(t), M_b(t), a(t))$ is shown for the non-adapted state of the neuron (first few milliseconds, low adaptation $a(t)$) and for the adapted state (high adaptation):

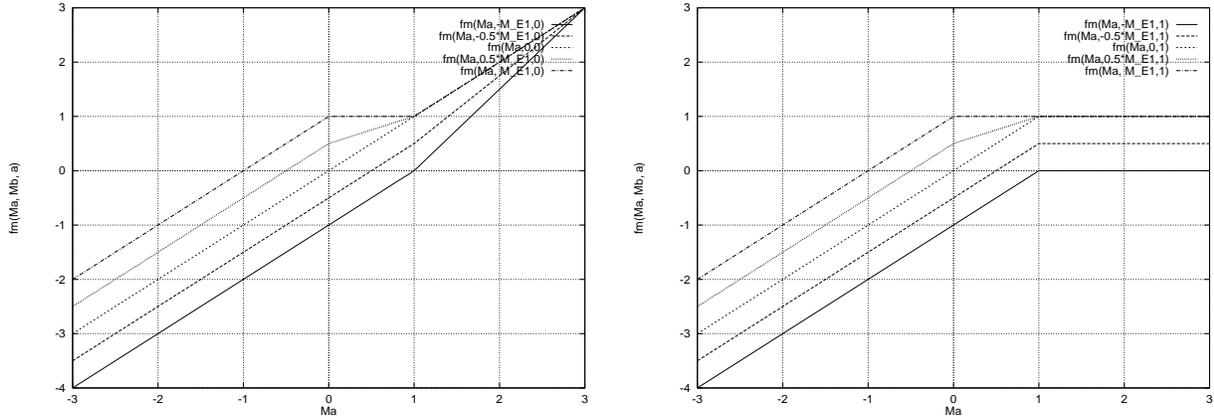


Figure 2: Mixing function of apical potential M_a and basal potential M_b . Non-adapted state ($a(t) = 0$) left, adapted state ($a(t) = 1$) right. In this case the limit potentials are $M_{E_1} = 1.0$ and $M_{E_2} = 3.0$. Parameter M_b from $-M_{E_1}$ (lower curve) to M_{E_1} (upper curve).

3 Simulation results

The effect of the learning rule system is demonstrated with a simple network. The upper picture of figure 3 shows the initial network state. Four input channels symbolized by the four input neurons in the lower part of the picture feed neurons A, B, C, and D immediately by apical synapses. A, B and C converge to E by apical synapses. A, B, C, and D are mutually connected by basal synapses as well as D and E. Initial weights are set to 1.0, but could be initialized with another value without changing the final state of the network. The input neurons of A, B, and C are activated randomly for 40ms approximately every 250ms with the maximum firing frequency. This independent activation is superimposed with a complex coincidence by simultaneous activation of A, B, and D for 40ms with a mean interval of 1000ms. After 30 seconds of simulation (30000 steps) the symmetrical coincidence between the conjunction of channels A and B and channel D results in the specialization of neuron E to the conjunction of A and B (apical synapses) and the formation of symmetrical connections between E (which now represents the conjunction of A and B) and D (basal synapses). Activity on channel A or B alone is not sufficient for activity on channel D — the corresponding connections became ineffective. A and B are not mutually coincident, so their mutual basal connections are suppressed. Because every time when E and D are activated A and B are activated, too, E and D project back to A and B. C is neither involved in any coincidence nor taking part in the conjunction at E — all connections from and to

C (except the fixed input connection) vanish.

4 Conclusions and future work

The way conjunctions of signals are integrated into the internal model of relations could be interpreted as a self-organization of representation of sensory information. Applied to the model of behaviour-based perception those conjunctions fulfil a special function: for the generation of an hypothesis of the form ‘What happens if I would do a certain action in the given situation ?’ the sensory situation has to be connected with a motor command in a conjunctive way to anticipate the resulting new situation that arises, if the motor command really would be executed.

Using the model presented above only those coincidences can be detected which are expressed in a *simultaneous* activation of channels. Relations with a fixed temporal structure should be detected, too, because causal connections of reality are often reflected by temporal relations. The introduction of neurons with a special timing behaviour will be examined.

References

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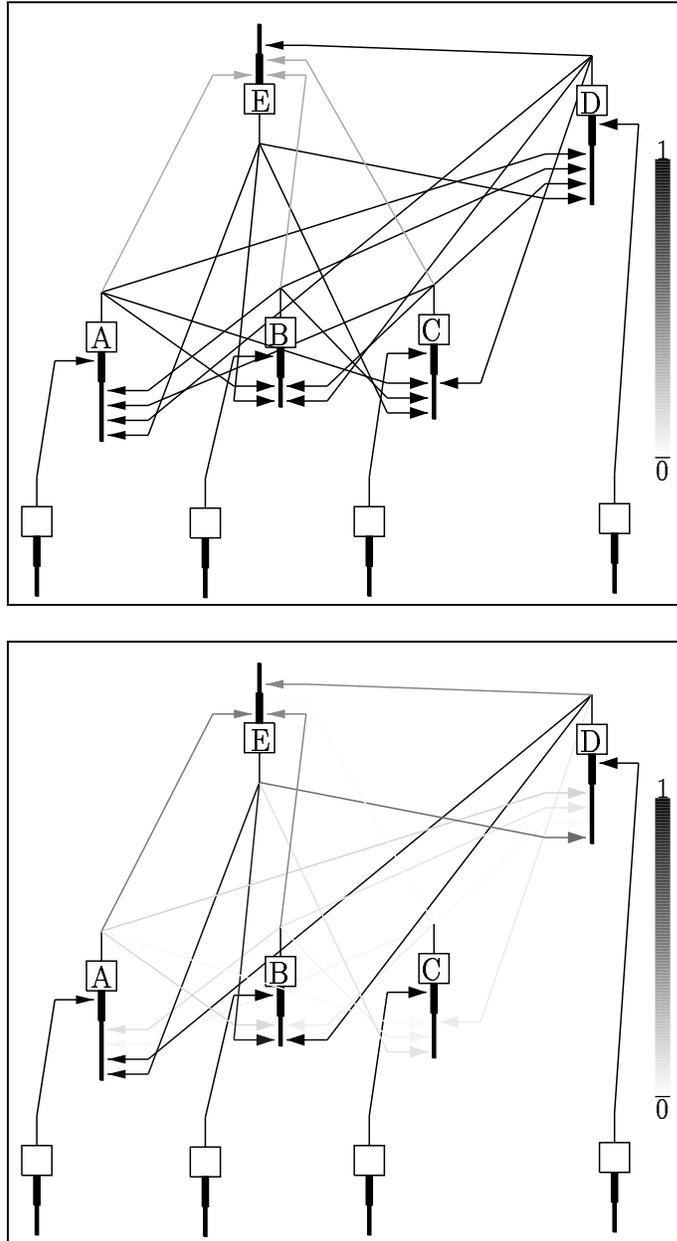


Figure 3: Initial state of a network (top) and state after 30000 simulation steps (30sec) (bottom). Lines symbolize axons, unfilled boxes somata, thick filled bars apical and thin filled bars basal dendrites. Weights are depicted in a linear gray scale (right). For explanation see text.