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Translation-invariant pattern recognition based on Synfire chains

Hans-Martin R. Arnoldi[1], **Karl-Hans Englmeier**[1], **Wilfried Brauer**[2]

[1] GSF-National Research Center for Environment and Health, Institute of Medical Informatics and Health Services Research, Ingolstädter Landstr. 1, D-85764 Neuherberg, Germany
[2] Technische Universität München, Institut für Informatik, D-80290 München, Germany

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Abstract. Most of current neural network architectures are not suited to recognize a pattern at various displaced positions. This lack seems due to the prevailing neuron model which reduces a neuron's information transmission to its firing rate. With this information code, a neuronal assembly cannot distinguish between different combinations of its entities and therefore fails to represent the fine structure within a pattern. In our approach, the main idea of the correlation theory is accepted that spatial relationships in a pattern should be coded by temporal relations in the timing of action potentials. However, we do not assume that synchronized spikes are a sign for strong synapses between the neurons concerned. Instead, the synchronization of Synfire chains can be exploited to produce the relevant timing relationships between the neuronal signals. Therefore, we do not require fast synaptic plasticity to account for the precise timing of action potentials. In order to illustrate this claim, we propose a model for translation-invariant pattern recognition which does not depend on any changes in synaptic efficacies.

1 Introduction

An explanation for translation-invariant pattern recognition in biological systems still poses a major challenge. Although structured neural network architectures (Fukushima and Myaki 1982) may solve the task for a limited number of objects, we still lack a conclusive understanding of the abilities of the brain. In the most common approach, a very specific feature detector is distributed spatially over all positions in the input layer (retina). All copies of this detector converge onto a single hierarchical higher cell in order to enable an invariant reaction. The combinatorial explosion of patterns in the stream of visual impressions, however, requires an astronomic number of different specialized detector cells. Therefore, this spatial convergence of a distributed detector may not be extended to real world situations and, very likely, does not reflect the strategy used in a biological visual system.

These considerations led Von der Malsburg (1981) to propose his correlation theory: Neurons in close proximity fire synchronously whenever they react to features of the same object. Therefore, these neurons bind their activity into a distinguished cell population or ensemble, which is characterized by its correlated discharges. This idea replaces the combinatorial number of feature detector cells because the short-term coherence of cells may switch with every new input pattern. For each different stimulus, a neuron may participate in another ensemble of cells, where it codes a feature common to several patterns. The correlated activity of the cell population itself forms a new characteristic signal associated with the pattern represented. Specialized neuronal circuits will easily detect such spatiotemporal patterns of action potentials.

In anatomical studies of the brain, synchronized action potentials often imply a strong excitatory synaptic connection between the neurons. Therefore, it is generally accepted that a synapse is labelled by correlated activities of the neurons involved. The correlation theory adopted the inherent assumption of this methodology and added an extension. According to correlation theory, the synapses between cells rapidly change their efficacies in the course of information processing. The short-term correlation of cell ensemble activities mirrors the strength of connectivity between neurons of the ensemble. For every new stimulus in pattern recognition, a tremendous change in synaptic effects is required. The new connectivity evolves through a so-called short-term synaptic plasticity in conjunction with random correlated discharges. Chance correlations are reinforced by a growing synaptic gain between the cells. Recent experimental evidence supports the idea of reversible short-term plasticity (Markram and Tsodyks 1996; Abbot et al. 1997; Magee and Johnson 1997; Markram et al. 1997).

Synchronized action potentials may evolve without anatomical synapses between the cells, as experimental

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Correspondence to: H.-M.R. Arnoldi

data (Aertsen et al. 1989; Vaadia et al. 1995) prove. The 'joint-peristimulus time scatter diagram' emphasizes the change in the correlation of action potentials whenever different stimulus configurations are used. This 'dynamic of effective connectivity' cannot be explained within the concept of a bridging synapse. Engel et al. (1991) report that varying stimulus configurations influence the correlations of action potentials. Spike time coordination was involved in auditory stimulus representation (de Charms and Merzenich 1996). The precise timing of coincidences in several experiments (Abeles et al. 1993a; Vaadia and Aertsen 1992) initiated an alternative explanation for synchronized action potentials. Abeles (1982, 1991) developed the theoretical concept of neuronal structures called Synfire chains. Within this concept, the correlated input from one ensemble of cells drives several other neurons simultaneously towards their firing threshold (see also Gerstner et al. 1993).

Based on the theory of Synfire chains, we developed a scheme to produce synchronized action potentials (Arnoldi and Brauer 1996). Two Synfire chains are coupled by synaptic connections as suggested in Bienenstock (1991). Due to the systematic interactions between both chains, their Synfire activities synchronize and proceed in a stable construct. Whenever two coupled chains are started within a time interval of about 40 ms, the activities in the last nodes of both chains are correlated. This effect was utilized to develop a system for translation-invariant pattern recognition. The central idea remains the same as in correlation theory. Within an ensemble, neurons signal their inner relationship through correlated discharges. When they fire together, two neurons include important information for further processing. This synchronized activity, however, is due to interactions of Synfire chains and not to reversible short-term synaptic plasticity. Therefore, it seems biologically more plausible.

Our system does not yet address rotation or size invariance, but the general principle might be extended similarly to implementations in dynamic link architecture (Lades et al. 1993). We chose a difficult example in pattern recognition where two patterns, a cross and a square, consist of the same very simple parts. These parts, however, are differently arranged for both patterns. This example also illustrates that coupled oscillators will fail to create a remarkable difference in responses to both patterns. With our system, we would like to draw attention to the capabilities of correlated activity as an information format. We therefore propose an alternative to reversible and drastic changes of synaptic efficacies on a short-term time scale.

2 Synchronization of Synfire activity

The concept of Synfire chains was introduced by Abeles (1982, 1991). A Synfire node consists of several neurons and represents the central entity within a chain. All neurons in a node fire together. Each neuron receives excitation from several neurons of the previous node and projects its action potentials onto several neurons in the next node. A structured neural network develops with this connection scheme where the signal from one neuron diverges onto several cells in the next node. At the same time, the signal from several neurons in one node converges onto one neuron of the next node. Coincidences in the first node of a chain are thus transmitted through the chain to the last node. In order to combine Synfire chains, Bienenstock (1991) extended this concept by adding synaptic connections between two chains in a systematic fashion. Node i in one chain projects to node $i+1$ in the other chain. The interchain connectivity therefore imitates the overall connection scheme within chains. The intrachain connectivity, however, is far more pronounced than those connections between chains. Two coupled chains do not simply combine into a bigger Synfire chain because each single chain may become active without the other.

Propagation of Synfire activity is generally assumed to involve a fixed time lag between the consecutive activations of nodes. According to this concept, all neurons within a node discharge synchronously and initiate neuronal responses in the next node after a given time interval (e.g., 1 ms). In contrast to a fixed propagation speed, Arnoldi and Brauer (1996) introduce the idea that each Synfire chain may propagate its activity at different levels of speed. The neuron model is based on the effects of conductivity G and capacity C at the membrane and uses a membrane time constant ($=C/G$) of 10 ms. Due to this membrane characteristic, the synaptic strengths of a connection between two nodes will severely influence the propagation time in a chain. In the simulations, the following 'integrate-and-fire' equation was used:

$$C\frac{dV(t)}{dt} = (Erev - V(t))G(t) + (Erest - V(t))G$$

Erev (0 mV for excitatory synapses or −70 mV for inhibitory synapses) denotes the reversal potential at a synapse and *Erest* (−70 mV), the resting potential at the membrane. The membrane potential $V(t)$ changes with every presynaptic spike according to an α-function $G(t)$ where the amplitude A represents the strength of a synaptic connection, and τ_0 ($\sim$1 or 3 ms) determines the time constant of the excitatory postsynaptic potential (EPSP).

$$G(t) = Ae^{-t/\tau_0}$$

The change in synaptic efficacies $G(t)$ influences a postsynaptic cell after a time delay of 1 ms, starting with the presynaptic action potential. Any cell fires whenever the membrane potential hits the firing threshold. This threshold fluctuates around −45 mV using a standard deviation of 5 mV. Additional refractory effects are simulated following each action potential. Figure 1 illustrates the simulation results in a chain of 500 nodes and stresses the large variability in propagation delays. Synfire activity will propagate within 500 ms through a chain of 500 nodes at maximum speed because each connection between two nodes must introduce a delay of 1 ms. With the time constant $\tau_0 = 1$ in $G(t)$,

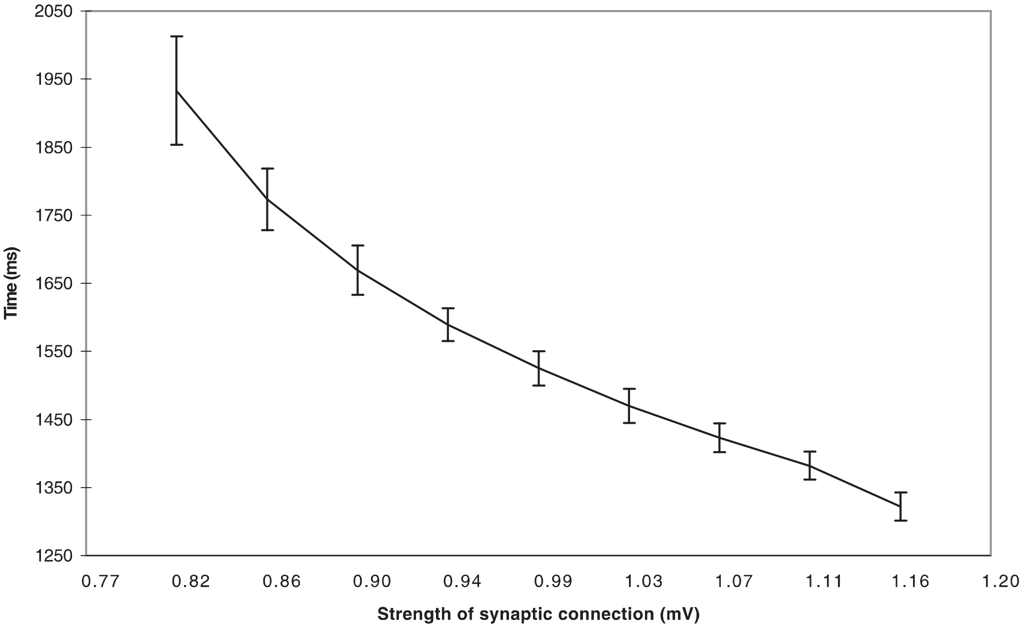

Fig. 1. Propagation time in Synfire chains. The y-axis denotes the millisecond delay after which the Synfire activity reaches node 500. The strength of a synapse between two neurons of consecutive nodes is given on the x-axis. A time constant of 1 ms is used for each EPSP. A Synfire chain with an EPSP amplitude of less than 0.82 mV cannot transmit a stable activity. Several simulations are averaged at each data point. *Bar* represents the standard deviation in arrival time, multiplied by 10, to visualize the decreasing variability with stronger synaptic connections

another millisecond delay between two nodes is added, when we assume that neurons in the following node fire when $G(t)$ reaches its amplitude value. Each node consists of 100 neurons where each neuron connects to 25 neurons in the following node. Using an EPSP amplitude within reasonable ranges (Fig. 1), the Synfire chains propagate the activity within 1300–2000 ms.

Two coupled Synfire chains will influence each other through their connectivity. A very important effect concerns the speed of propagation in the chains. Imagine two chains are started with a certain timing offset. Synfire activity in the earlier started (first) chain will increase the membrane potential of neurons in the second chain. This influence yields significant consequences. Neurons of the second chain receive excitatory input shortly before a Synfire activity reaches the respective node. Due to this depolarization, the node increases the speed of the Synfire propagation. Any positive deviation from the average membrane potential (−60 mV) introduces an effect on propagation speed in a node. In case of depolarization, this effect must be similar to an enhancement of synaptic strengths between the nodes. A node will transmit Synfire activity faster whenever the propagation process starts with a depolarized membrane. The excitation simply takes less time to hit the firing threshold. In a network of coupled Synfire chains, two Synfire activities will synchronize through this effect. The excitatory influence from the first chain speeds up Synfire propagation in the second chain. Therefore, the accelerated second chain will decrease the initial timing offset between the Synfire activities with every node, ending in a configuration in which both Synfire activities propagate together through the chains. Within a strict mathematical and statistical framework, Bienenstock (1995) proved this 'clued' propagation forms a stable construct.

In our neural network simulations, we tested the capabilities of the synchronization mechanism for different timing offsets with which the Synfire chains are started. For a positive simulation result, both Synfire activities had to reach the last node within a fixed time interval (e.g., 3 ms). Of course, this measurement of near-synchrony may be changed. For the simulation results in Fig. 2, we stress that no dependence on any other simulation parameter exists. The same noncyclic Synfire chains are used as in Fig. 1. The propagation time for the longest chain with 500 nodes is given there. One may therefore conclude that after 1.5 s a delay of 40 ms will be synchronized using two chains with 500 nodes. Two chains with 100 nodes will synchronize a 25-ms delay after 300 ms.

An explicit description of the synchronization mechanism is presented in Arnoldi and Brauer (1996), where it provides the first biologically plausible explanation for the development of correlated activity in the cortex.

3 The neural network architecture

Our network for translation-invariant pattern recognition consists of two main modules, namely a perceptual system (Sect. 3.1) and a memory structure (Sect. 3.2). The synchronization of Synfire chains will be exploited to correlate activities in one module with neuronal discharges in the other (Sect. 3.3). With this essential functionality, the synchronization of Synfire chains addresses the following problem in brain research: Few connections might regulate the interactions between

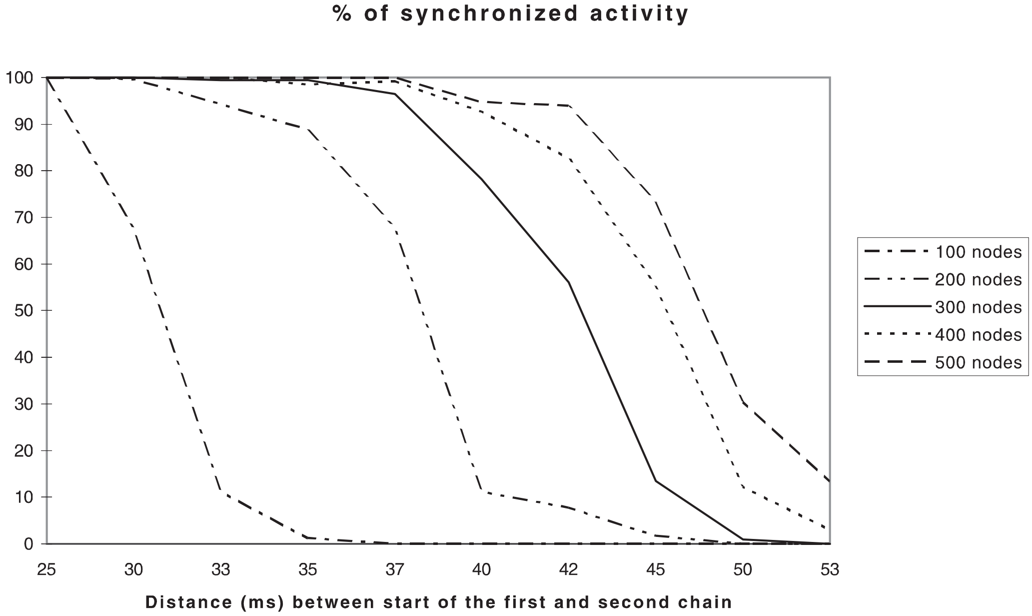

Fig. 2. Synchronization of Synfire activities. Timing offset at the start of both Synfire chains is given on the x-axis. Each line illustrates the results for a Synfire chain, using another number of nodes. Fluctuations of the membrane potential produce synchronization failures in several configurations. The y-axis reveals statistically in how many of 100 experiments the synchronization succeeded. Longer Synfire chains yield better results. This effect, however, seems to saturate with a length of 500 nodes. The gain from adding another 100 nodes is drastically reduced compared with the difference between a chain of 100 or of 200 nodes. The influence of excitatory postsynaptic potentials (EPSPs) has most probably disappeared after 40 or more ms. Therefore, chains started with this or a larger delay run independently

different cortex regions when structured in a systematic fashion. The example from pattern recognition represents an explanation of the formation of correlation-based information processing.

3.1 The detector cube for visual perception

The well-known design of orientation columns suggested the structure for the perceptual input system. Hubel and Wiesel (1968) reported a layered model for the visual cortex where the selectivity of cells gradually changes with the penetration of a microelectrode. Our perceptual network mimics the functional structure of the visual cortex found in textbooks (Kandel et al. 1991). It is primarily concerned with a systematic transformation of the visual world into neuronal signals. Cells react to light-dark contrasts on the retina and therefore code an object's 'Gestalt' with their activity. In the model, every point on the retina is filtered by several detector nodes. All detectors for horizontal edges are grouped in one layer. Activity in adjacent layers represents lines with a tilt of 45 or −45 deg, respectively. This principle of an increment of 45 deg produces a total of 8 layers. These layers have nothing in common with the anatomical layers (I–VI) of the visual cortex. They are inspired by a technical application of the hypercolumn concept. All layers together form a 3-dimensional cube which shall be called the detector cube in the following. The x- and y-coordinates in the detector cube determine the position of the receptive field which influences all neurons in a node. Following the z-axis of the cube, the optimal edge stimulus for each node gradually rotates around its center. Figure 3 illustrates the detector cube used in our network. Note that our detector cube implies a clear difference between a change from a dark region into a bright region and the opposite change. Most of the cells in visual cortex V1 ignore this distinction when they react to both the right and the left margin of an object. The difference in our model, however, seems to be neither critical nor fundamental. For technical disambiguation, slightly more specific features were revealed to be more convenient than those represented by simple line detectors. In theory, a Synfire node

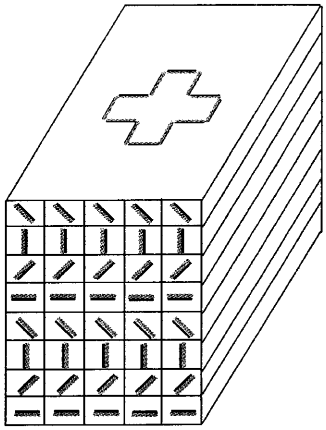

Fig. 3. Schematic view of the detector cube. The x- and y-coordinates of each node of neuron code the center of the receptive field on the retina. The z-axis determines the orientation selectivity of the node. The optimal line pattern gradually changes with each layer

consists of several neurons, each with a different response characteristic.

All eight feature detector nodes sharing their x- and y-coordinates represent a distinct group. They excite a common inhibitory neuron, and in turn they are inhibited by the action potential of this neuron. This inhibitory cell in our model corresponds to that 20% of stellate (inhibitory) cells in the cortex which act locally and rapidly. For information processing, this inhibition serves two functions. On the one hand, the negative feedback implements a winner-takes-all competition between edge detectors at the same position (or in one group). Only the optimally activated detector may react to the visual input. All other detectors at this position are silenced by negative feedback. On the other hand, the inhibitory neuron introduces an oscillatory component into neural processing. As inhibition acts on all detectors in a group, this includes the node of neurons which match the stimulus best (the winner). Therefore, this detector cannot produce activity for a fixed period of time. The duration of this silent interval may be adjusted through the time constant parameter of the inhibitory postsynaptic potential (IPSP) (Gerstner and van Hemmen 1992). A single but strong inhibitory potential decays over a very long time scale and prevents the excitatory neuron from firing again for an appropriate period of time. Therefore, an isolated inhibitory spike turns off the excitatory neuron. For the current model, an interval of 30 ms was chosen in accordance with experimental results in the visual cortex (Gray and Singer 1989).

The existence of oscillatory activity in the cortex still produces a controversy among experimentalists. Arnoldi and Brauer (1996) argue against an overall neural information processing based on coupled oscillators (see Discussion). In the connectivity of the visual cortex (or our detector cube), however, it might be more acceptable that the neurons show a periodical behavior due to the prevailing local inhibitory activity (Nischwitz and Glünder 1995). For the current technical application, namely translation-invariant pattern recognition, a scheme proved very useful where neurons fire reliably. Oscillatory interactions open a convenient framework for an application because they provide a very efficient method to synchronize activity in close proximity. One simply has to introduce several connections between nodes of the detector cube. With oscillatory activity in our detector cube, the neurons correlate their action potentials whenever coupled with excitatory synapses. These important couplings were chosen according to a well-known principle of the Gestalt theory (Wertheimer 1923; Rock and Palmer 1990): Two neighbor nodes share synaptic connections exclusively when both react to neighboring parts in the shape of a pattern. For example, a certain node detecting a horizontal dark-to-light contrast will exchange synaptic signals with its left and right neighbors in the same layer. Other detectors in this layer, however, which react to horizontal dark-to-light contrasts on top or on bottom of this node will not be connected to it. The visual world fails to include shapes consisting of two horizontal dark-to-light contrasts stacked on top of each other. The intention in this connection scheme may be replicated in all layers of the detector cube. Synaptic connections also exist between layers. A curved shape, for example, may be assembled from several straight lines which gradually change their orientation. All interlayer synapses, however, are limited to neighboring layers in the detector cube. The visual world and the existing shapes severely limit possible combinations of line segments in close proximity.

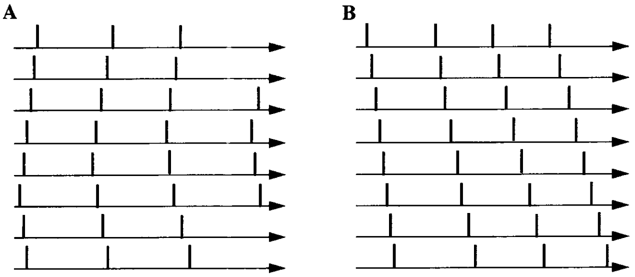

Fig. 4A,B. Action potentials in two different simulations using a pattern of 8 line segments (the octagon in Fig. 5). Each *arrow* symbolizes the time-axis in milliseconds, and a *bar* on this axis represents a cell signal. Neighboring cells (drawn on *neighboring arrows*) answer with correlated activity. **A** Chance correlations between the fourth and the last cell lose the exact temporal relationship in the course of time. **B** This spatiotemporal pattern was common in the simulations. Activity of the first and of the last cell is correlated as the activity pattern spreads over a time interval of 30 ms. Note that simultaneous and parallel sensory input does not imply synchrony at the level of action potentials in the higher cortices

Currently, several researchers support the hypothesis that Gestalt laws manifest in the correlated activity of visual cortex cells (Singer 1994). Our model transfers this idea into a possible architecture. Nevertheless, this transfer does not include that all neurons fire synchronously whenever they represent one shape. Instead, correlated activity is restricted to a limited neighborhood of shape segments. Figure 4 presents different spatiotemporal patterns of action potentials. Both patterns are produced by an object consisting of 8 line segments. In a visual shape, neighboring line segments have more in common than further distant ones. Different activity correlations of the respective cells express this fact. With such a code, the sequence of all spikes contains information about specific line segments and about the neighbor relationships of these line segments. This distribution of correlated activity covers more information compared with a synchronized burst of all the neurons concerned. Strict synchronization of all neuronal answers misses relevant information (e.g., how close two cells are related spatially). For recognition, an overall synchronization bears no information about the inner structure of the pattern.

3.2 The memory module

The second important component of the network is realized in the memory module which might be located in associative cortices. In contrast to the concept of the cardinal cell (Barlow 1972), we use a cell population to represent a pattern. Every node of cells in this population

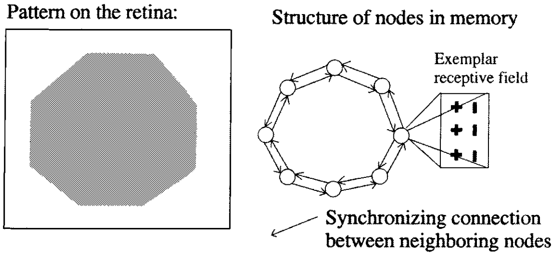

Fig. 5. Representation of an octagon in pattern memory. The system exclusively codes the shape (edges) of a pattern. For illustrative reasons, the population (structure of nodes) in memory is arranged similar to the respective feature detector nodes in V1. The nodes, however, may be distributed arbitrarily in any of the associative cortices. Neighboring nodes in pattern representation are connected by excitatory synapses

codes a short segment in the shape of the pattern. Therefore, each node's selectivity is reduced to simple edge detection. The underlying scheme is exactly the same as in the detector cube. A significant part of information stored about a pattern consists of the number and orientation of the line segments employed. Additional structural information about the pattern is incorporated in the synaptic connections within a population. Two nodes exchange excitatory synaptic potentials whenever they code neighboring line segments in the shape of the pattern. Figure 5 illustrates this memory module using an octagon as an example structure.

Every node in pattern memory is accompanied by an inhibitory neuron. The interactions with this cell produce oscillatory activity in the node. Activity in the node leads to a spike of the inhibitory cell. The resulting inhibitory synaptic potential silences the node. The time constant of this IPSP is again chosen to prevent activity in the node for a time interval of 30 ms. Therefore, the cells answer periodically.

Each neuronal population in memory stores a pattern. The topology of excitatory connections in a node population was explicitly constructed for the simulations. In principle, however, such a population and its topology will develop through Hebbian learning. In an initial network of neurons, all connected to each other, appropriate synaptic connections simply have to be reinforced to form a distinctive population. In the course of learning, one neuron might even participate in several memory storages. Note that a neuronal population does not constitute a Synfire chain. Synapses between memory nodes are far too weak to propagate a stable Synfire activity. These connections are meant to synchronize the action potentials of neighboring nodes but not to generate activity by themselves. Memory nodes correlate their activity through reciprocal synaptic connections. Most oscillator models (Sporns et al. 1989; König and Schillen 1990; Neven and Aertsen 1992; Ritz et al. 1994) propose that the respective neurons all fire synchronously. In our model, the correlation of activity is limited to neighboring line segments in the shape of a pattern. No synchronization is required for nodes at distant positions of the pattern. Tight synchronization of all memory nodes never occurred in the simulations. Few inhibitory synapses between distant nodes in the shape minimize correlations and prevent total synchronization very efficiently.

3.3 Application of Synfire synchronization

A detailed description of how the detector cube and the memory module are biologically realized has not yet been done because it seemed to be of minor relevance. The main contribution of the present work is given by the combination of neural activities in separated networks. The synchronization of Synfire chains is applied to match the spatiotemporal activity patterns of both our network modules.

For the recognition process, a well-known approach was chosen to compare a visual stimulus with a pattern in memory. Of course, all patterns in memory have to be matched successively in order to find the best fit. Our system shares this disadvantage with several more prominent pattern recognition systems. From the biological point of view, a 'deus ex machina' searching the memory system seems problematic. At the current state of simulations, conclusive data are missing, about how the system could utilize spontaneous activity in the memory module. A visual pattern might induce additional activity in memory through the Synfire connections. This results in a enhanced and concentrated activity in one pattern population. No change in the network architecture is required except for one reason. All neurons of the memory module must be tuned to conserve a constant and low spontaneous activity at a level of two spikes per second. This noise, however, must be a robust equilibrium, easy to change from outside but very stable to return to whenever an external influence ceases again. Using the Synfire connections, very weak influences from the detector cube might then be able to create an appropriate response in the memory module.

Let us turn to the recognition process. Neurons or nodes in the detector cube react with a characteristic spatiotemporal sequence of action potentials whenever a visual stimulus appears on the retina. At the same time, the system chooses a pattern with which it wants to compare the current input. Our implementation therefore uses a central controlling unit to serially step through a database of known patterns. This unit activates a population of nodes externally which represents a certain shape in pattern memory. These nodes also generate a typical spatiotemporal pattern of action potentials. In order to compare these signals, our system is designed to build up precise correlations between both spatiotemporal patterns. The result of this comparison will be intuitively positive when corresponding nodes in the cube and in memory fire together. In this case, a node coding a horizontal line in a pattern generates synchronous action potentials with a memory node representing the line segment at the same position. The temporal structure of neuronal answers produces an assignment between pattern memory and detector cube. Synaptic interaction within the detector cube or within the pattern memory also supports this assignment. In both network modules, neighboring nodes tend to correlate their activities. Imagine a node in the detector cube being correctly assigned to a memory node. The respective cells fire together, and at the same time these activities are correlated with spikes of neighboring nodes. Therefore, the synchronization process in the neighborhood of a correct assignment is tremendously facilitated. Once two partners are related, this assignment will spread to their local neighborhood. Nevertheless, a wrong assignment (e.g., a horizontal line in pattern memory with a vertical line in the cube) will also spread. Therefore, interactions within each network module must be tuned to act with similar force as interactions between detector cube and pattern memory. Then the comparison of spatiotemporal patterns is based on their structure as well as on their components. Incompatible components or a different arrangement of the same components both prevent stable correlations. Isolated line segments might form stable assignments, but the whole system remains in a state of low correlation. The interactions in the system signal a missing global affinity. Optimal resonance must be limited to those cases with an overall fit.

The realization of our matching mechanism is closely related to the synchronization of Synfire chains. Every node in the detector cube and in pattern memory starts a Synfire chain. These chains were designed in the implementation to feed back to their starting node after 10 nodes. The results of the following developmental process were therefore hard-wired into the network. For illustrative purposes, we pick node *A* with Synfire chain S_A. Remember that the respective neurons in the nodes fire periodically every 30 ms. After this time interval, the Synfire activity from S_A has reached node *B*. A simple 'Hebbian' learning will construct a feedback from *B* to the starting node *A*. A small but repeated change in synaptic efficacies produces a Synfire 'reverberation' (Abeles et al. 1993b) where Synfire activity in S_A runs in a closed loop. The transmission time of this loop is given by the repetition interval of node *A* activity. The Synfire chain is therefore tuned to reflect the periodic behavior of activity. More importantly, however, Synfire chains like S_A may bridge the gap between detector cube and pattern memory. With a few, systematically placed synapses in the network, Synfire chains started in the detector cube are connected to the respective chains from pattern memory and vice versa. A simple connection scheme, first proposed by Bienenstock (1991), is used for all synaptic interactions between Synfire chains: Node $i+1$ in one chain receives synaptic potentials from node i in the other chain (see Fig. 6).

The following synchronization process develops in our network: Two Synfire chains, one in the detector cube and the other in pattern memory, share synaptic connections and synchronize their activities. This synchrony feeds back to the starting points of both chains. Therefore, a node in the detector cube and one in pattern memory generate simultaneous action potentials. With these spikes, the nodes initiate Synfire activities which proceed together. The feedback results in a temporal assignment of the starting nodes. This correlation, however, must match the interactions with neighboring nodes. Synaptic influences within the cube or within memory always affect the exact timing of action potentials. A node in the cube repeatedly fires together with a memory node only if the respective neighbors also correlate their activities. Otherwise, the feedback of Synfire synchronization breaks down. Without a perfect match of both spatio-temporal patterns, a detector in the cube continuously receives contradictory synaptic influences which confuse the rhythm of its answers. A stable construct requires a cooperative resonance between Synfire feedback and neighbor interactions. Then the energy provided by the synaptic potentials settles into an optimal configuration.

The connectivity between Synfire chains is limited to chains representing similar features. A detector for

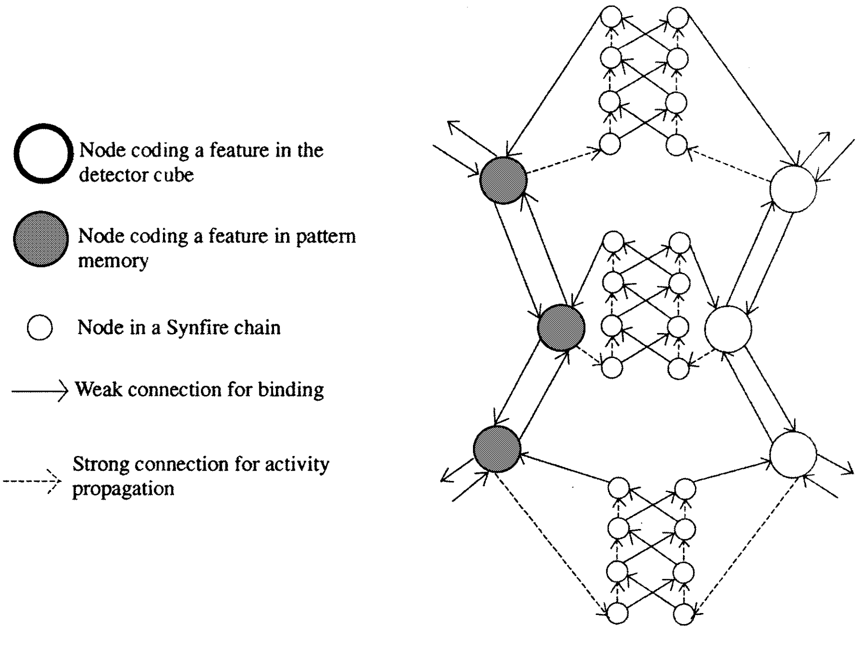

Fig. 6. Synfire chains are connected in a systematic fashion. Therefore, the chains synchronize their activities. Nodes in pattern memory start to fire synchronously with their partners in the detector cube due to the feedback of their Synfire chains. In both network modules, neighboring nodes also correlate their activities through excitatory synapses. As a consequence, coherent interactions develop

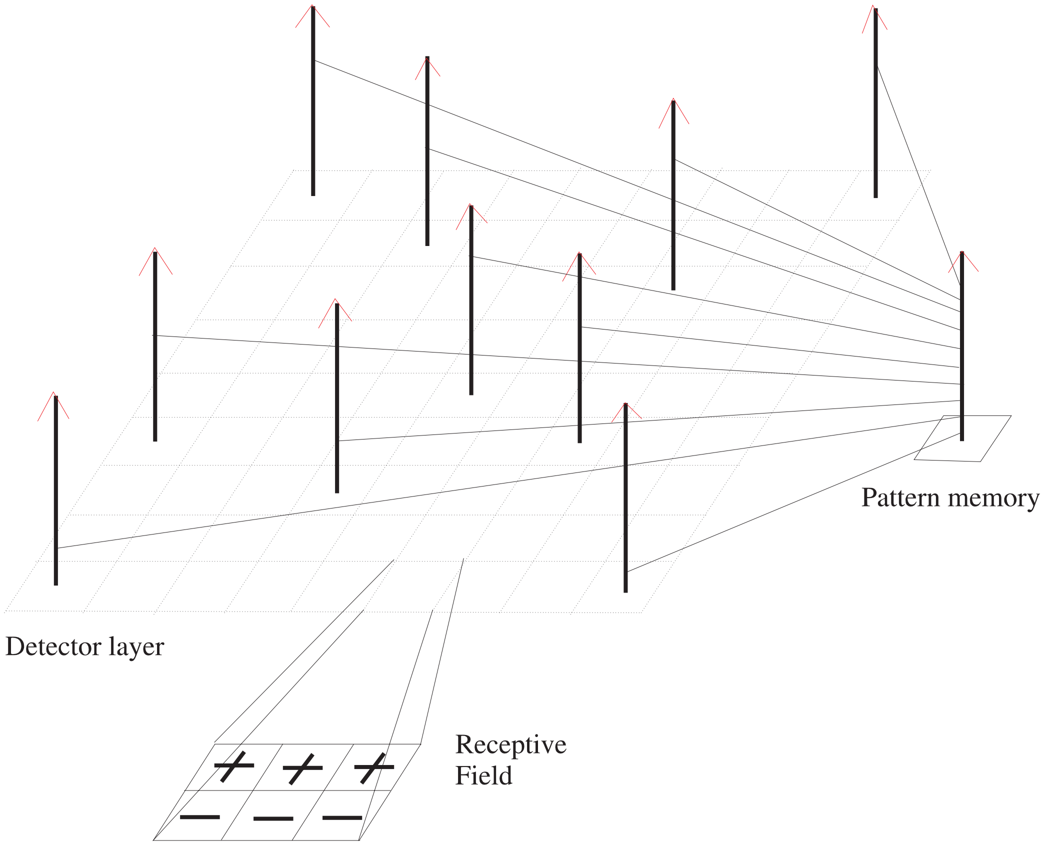

Fig. 7. Connectivity between detector cube and pattern memory. All nodes (*squares*) in one layer of the cube respond to a horizontal line. The node in pattern memory also represents a horizontal line. *Arrows* symbolize Synfire chains. This connection scheme enables the network dynamics to synchronize the activity of a single node with any of the activities in the layer. Binding through correlated activity may therefore happen translation-invariantly. Not all Synfire chains and their connections are shown. Note the important difference between a node and a grandmother cell: In a node, several cells with similar selectivity fire together. Each cell might participate in various nodes

horizontal lines in the cube may synchronize with a memory node coding a horizontal line which requires both of their Synfire chains to be connected. Nevertheless, a vertical line segment will not match a horizontal line, and therefore the respective Synfire chains shall not interact. The task of pattern recognition persists as ambiguous because each memory node may be mapped onto several detectors at different positions. A pattern may appear all over the retina and may excite different detectors of the same kind. Translation invariance requires the possibility of synchronizing a memory node representing a horizontal line with any of the horizontal line detectors in the cube. The connection scheme in Fig. 7 achieves this invariance. All Synfire chains from the same cube layer are connected to one Synfire chain from pattern memory. This connectivity between Synfire chains represents the gist of translation invariance in our system. The assignment of cell activities may vary dynamically with each new presentation of a pattern.

4 Simulation results

For introduction, a very simple pattern will illustrate the capabilities of our system. An octagon (see Fig. 5) provides an unique situation where exactly one detector in each layer of the cube will be activated. Eight nodes represent an octagon in memory. Cells in these nodes generate action potentials due to an external signal. They initiate eight different Synfire activities which shall bind to Synfire waves from the detector cube. The required assignment develops straightforwardly as every memory chain is connected to one active pendant only. Synchronization happens very rapidly, and neighbor interactions within the cube and within pattern memory support the resulting correlations. The system acts consistently as illustrated in Fig. 8.

A simple scheme should help to monitor the time course of correlations. A quantitative measurement ranging from 0 to 5 points separates different cases of ‘near synchrony’. The scheme rewards two nodes firing synchronously with 5 points. A delay of 1 ms reduces this reward to 4 points. An increasing delay further decreases the reward points. Finally, a correlation with a 5 ms distance does not contribute any points to the final sum. Eight pairs of nodes may generate 40 points with optimal synchronization. In Fig. 9, each data point comprises 4 cycles of periodic action potentials during 130 ms. With maximum performance, eight node pairs produce 160 points in this time interval. Figure 9 shows a system started randomly where correlations soon stabilize at a very high level. Each node pair fires

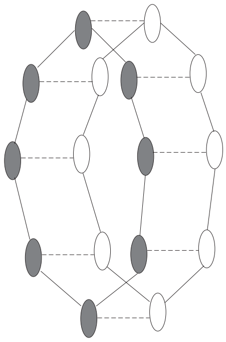

Fig. 8. Abstract result for an octagon pattern. *White circles* represent memory nodes, while *black circles* symbolize nodes in the detector cube. The octagon shape consists of eight edges, each with a different orientation. Every corresponding pair of edge representatives is connected through a *dotted line*. This line sketches two coupled Synfire chains which synchronize their activities

synchronously, which signals the success of the pattern recognition mechanism.

All nodes firing together also produce a high number of correlated spikes. This configuration, however, seems counterproductive as it destroys important information, namely the structure in the pairing of nodes. Few inhibitory synapses between distant cells in pattern memory avoid global synchronization. In the simulations, one may check the correlations of neighboring nodes for control. Eight neighbor pairs exist in pattern memory, and correlations should be limited there. Figure 10 illustrates the results in a simulation when all nodes in pattern memory are activated simultaneously. The time course of our artificial assessment scheme suggests that correlations drop from a very high level and stabilize at an intermediate value. At the same time, correlations between node pairs in the detector cube and memory develop according to Fig. 9. In conclusion, the system detects the similarity between the spatiotemporal patterns in memory and in the cube. Nevertheless, it does not repeat a single burst of action potentials.

Can we extend the proposed system for translation-invariant pattern recognition to more complicated patterns? Whenever several Synfire chains start from the same layer in the detector cube, the system may encounter difficulties in resolving the many-to-many mapping with chains from the memory structure. An important issue for the implementation of the network concerns the adjustment of synaptic connections between chains. The synchronization of Synfire activities works better the stronger the synapses are between the chains. Nevertheless, the influence of one chain must not generate Synfire activities in another chain by itself. Activities initiated through extremely strong interactions between chains destroy the information processing in the network. Therefore, adjusting the connectivity between Synfire chains has to satisfy two different conflicting objectives: Firstly, to provide a robust synchronization mechanism with strong synapses between the chains and secondly, to prevent any spontaneous Synfire activity with weak synapses between the chains. Finding the optimal configuration may require several try-and-error iterations or an adaptive process.

Imagine a network connectivity being adjusted so that synchronization between chains is working and none of the Synfire activities produces casual Synfire waves in any other chain. What happens when two or three active Synfire chains together project to a fourth chain? Several waves of activity will be generated, creating a situation where the search for optimal resonance between detector cube and memory system is disturbed. Another instance of the general normalization problem in neural networks might be discovered in this example. We would like to draw your attention to the nontrivial task for a neuronal structure to constantly keep activity

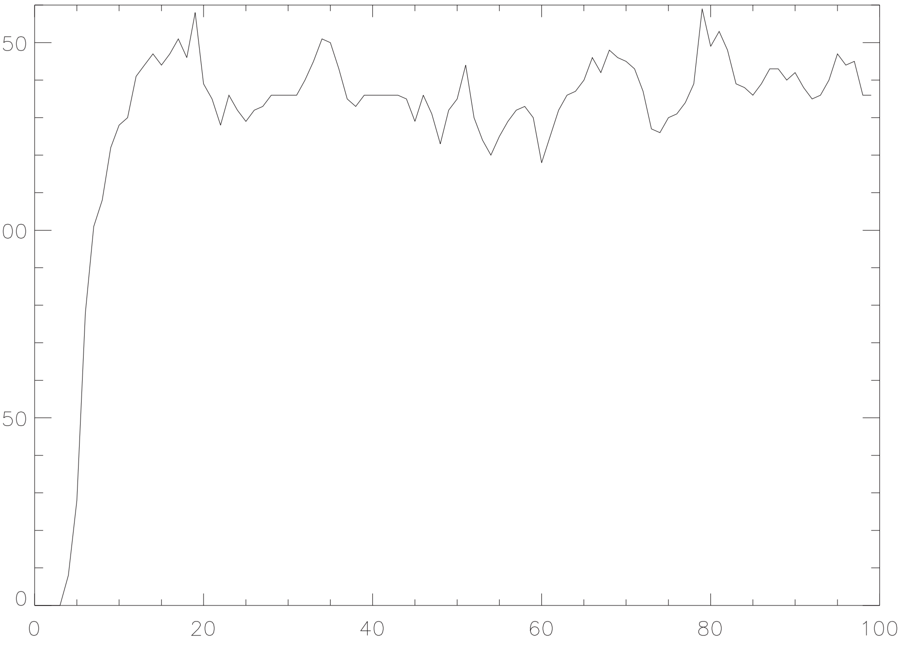

Fig. 9. Development of correlations with an octagon pattern. As the numbers on the axis represent artificial measurements, we did not label the axis. Altogether 13 s are shown because every point on the x-axis summarizes 130 ms of simulation. A node fires every 30 ms (four times in 130 ms). The system adds 5 points for perfect synchrony of a node pair. A millisecond delay corresponds to 4 points. The reward decreases until no points are added at 5 ms distance. Eight pairs in an octagon may gain maximally 160 points (the highest value on the y-axis) in a given time interval. In our example, the correlations develop very rapidly into a stable configuration with highly synchronized action potentials

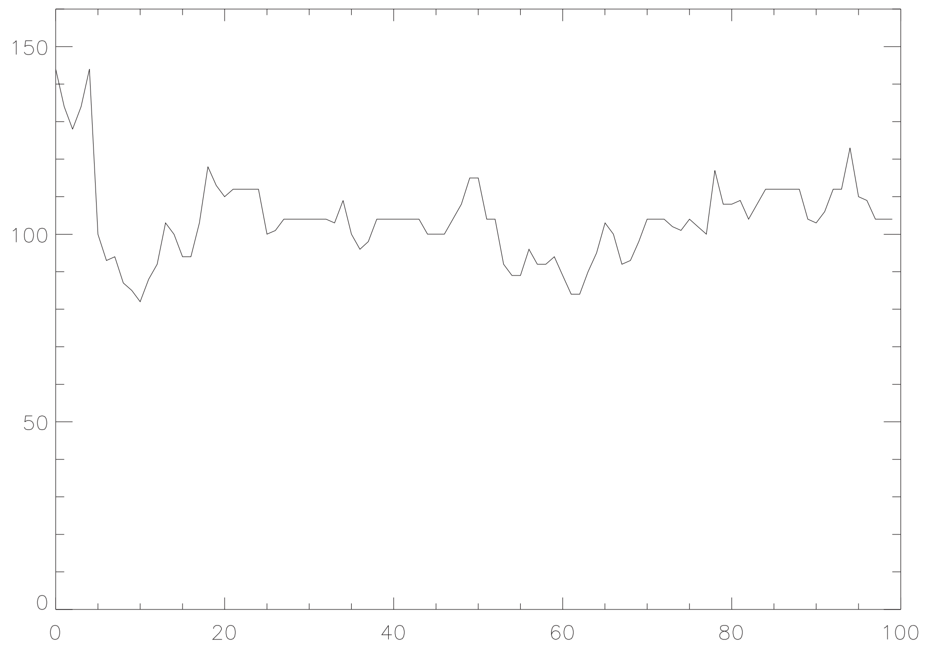

Fig. 10. Results for neighboring cells in pattern memory. The same artificial scale as in Fig. 9 is used on the *x*- and *y*-axes. At the beginning, all eight nodes fire together, which represent an octagon in memory. Therefore, the system starts from a very high level of synchronization. These strong correlations, however, drop drastically to an intermediate level around 100 points. After a while, neighboring nodes fire with a time delay of 1 or 2 ms. We may conclude that activity in the network differs from a trivial spatiotemporal pattern which consists of one synchronous burst

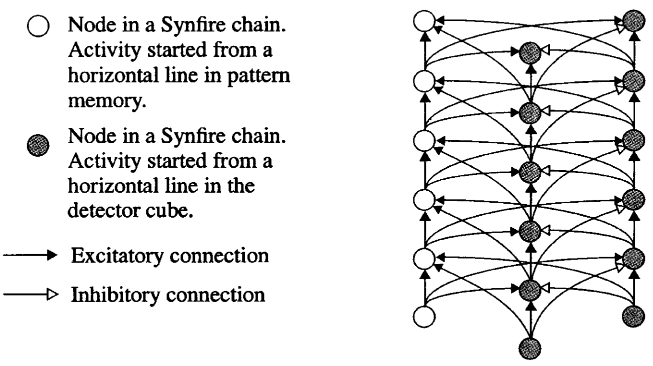

Fig. 11. Competitive connectivity between Synfire chains. Two chains (*gray*) are started in the same layer of the detector cube. Both chains compete to synchronize with the *white chain* from pattern memory. The winner of this competition propagates its activity together with the white chain. Through inhibitory connections between gray chains, all excitatory potentials from the white chain will be neutralized in that chain losing the competition

at a low level. Using a local process, the right amount of inhibition is hard to adjust. The importance of further investigations on this topic seems evident.

Our system chooses a straightforward approach to inhibition: a competition between Synfire chains accompanies the search for appropriate partners. All Synfire chains from the detector cube compete with each other when trying to bind with partners from memory. Inhibitory interactions between these competitors neutralize any excessive amount of excitation. Imagine one chain *A* out of the cube synchronizes with a memory chain *B*. All other Synfire chains emerging from the same layer of the cube receive excitation from memory chain *B*. The cube chain *A*, however, cancels through its inhibition this excitation from *B*. Within the group of competitors, the inhibitory potentials of chain *A* neutralize the excitatory potentials of its partner chain *B*. Simply copying the basic structure of the Synfire chains realizes this competition. The overall principle of Synfire chains also defines the rivalry between the nodes. Node *i* in a chain from the detector cube inhibits nodes $i+1$ in every other chain emerging from the same layer of the cube. Whenever two chains compete to bind with a partner, they exchange inhibitory signals in the typical Synfire mode: node *i* projects to node $i+1$. In pattern memory, all Synfire chains inhibit each other when attached to cells representing similar features. Figure 11 illustrates the connection scheme for two chains competing to bind with a third chain. The following example might help to illustrate information processing in such a structure. A visual pattern activates three nodes coding horizontal lines. At the same time, an external signal excites three nodes representing horizontal lines in memory. Therefore, six Synfire chains become active, and each receives excitation from three possible partner chains. Nevertheless, the inhibition from two competitors reduces the total amount of excitation in every chain. It cancels any excess input beyond the EPSPs of just one chain. Whenever two Synfire chains have bound together, both proceed synchronously. This construct, however, will not influence another chain and may therefore be ignored. In a stable composition, every chain compensates the excitatory potentials of its partner.

We now turn to an extremely difficult task in a neural network approach. The example is carefully chosen to stress an important advantage of our network architecture. Two patterns, a square and a cross in Fig. 12, represent different combinations of the same components. A significant change in the reaction of a cardinal cell (Barlow 1972) is very unlikely because both patterns share the same features. A rate-coded cell cannot distinguish between re-structured combinations in its input. In order to produce distinct response patterns for cross and square, new detector layers are required in the

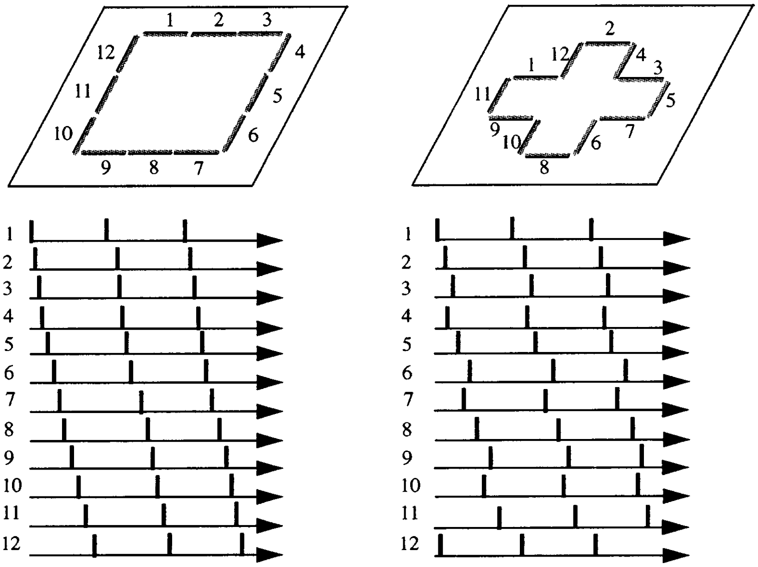

Fig. 12. Two visual patterns with identical features. *Below* one can see the center of action potentials for the respective detector nodes. The same subset of feature detectors generates a different spiking pattern for each stimulus. The arrangement of nodes determines the spatio-temporal activity pattern which clearly distinguishes between cross and square. A hierarchical higher neuron using rate coding or coupled oscillators, however, may not separate different combinations of the same components. It misses information about the spatial relationships of features within a pattern. Again we assume that in the higher cortices, parallel sensory input does not imply synchronous action potentials of the neurons concerned

network. Thus, several neural networks investigate an incremental improvement with new feature detectors. This includes the beginning of our own work (Waschulzik et al. 1990). A major counter-argument against such an approach is given by the combinatorial explosion of patterns. Our visual world contains too many different objects to reserve layers of feature detectors for each novel stimulus. Detectors in our system are therefore restricted to a minimal set for which experimental evidence exists. Difficult discrimination tasks may still be solved together with information about the spatial relationship of these detectors.

Critics might argue that coupled oscillators may achieve the same synchronization effects as our more complicated network. Substituting the Synfire chains through excitatory connections between oscillatory detector and memory nodes will fail, however, in the square and cross example. An oscillator approach misses the capability to synchronize the respective node pairs independently. Instead, all oscillators will produce a single burst of action potentials which destroys the possibility to distinguish cross and square answers. Looking at experimental results in neurophysiology, it seems rather implausible that such an oscillatory network codes pattern information in its oscillation frequency (its rate).

For the pattern recognition process, a population of neurons in the memory system is chosen and activated. At the same time, the retina reflects a square image. In reaction to this visual input, detectors in the cube start to produce a specific spatiotemporal spike pattern. Figure 13 presents the development of correlations

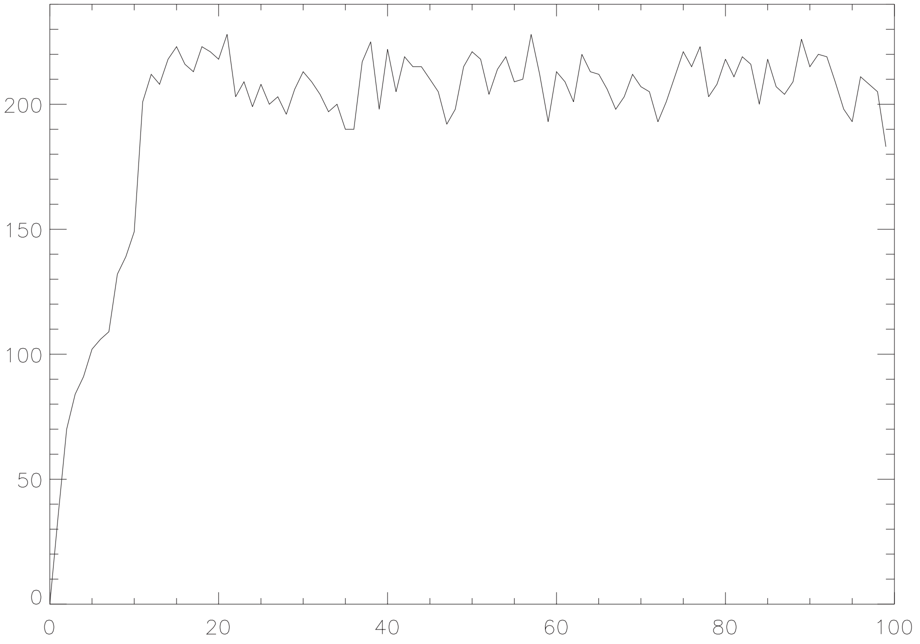

Fig. 13. Correlation result with a square. Figure 9 explains the artificial scale at the x- and y-axes with one difference: As 12 node pairs are involved, the best result is reached with 240 points. At the beginning, the correlations between nodes rise steadily to an enhanced level. This stable correlation value around 210 points proves an optimal resonance between action potentials in the detector cube and in pattern memory

between these spikes and action potentials of a memory population representing a square. The same evaluation scheme is used as in Fig. 9. With the square pattern, 12 node pairs may produce a maximum of 60 points per cycle. Every data point in Fig. 13 represents 130 ms or 4 cycles of simulation time. Therefore, the maximum correlation value is given at 240 points.

The system of inhibition meets high demands whenever a cross pattern is used. Line segments with identical orientation need absolutely independent processing. Any indirect couplings between Synfire chains from one layer contradicts this independence. Therefore, inhibitory interactions between Synfire chains from the same layer are required to function optimally. Due to these demands, some of our cross-simulations do not produce optimal correlations. The majority of node pairs is always correctly related, but sometimes several Synfire chains propagate without a partner. In these configurations, a lasting source of contradictory influences irritates a perfect harmony between nodes. Yet the contradiction generates a stable situation because the system first needs to decrease the number of node pairs, especially those correlated incorrectly before the optimal assignment between nodes might develop. Figure 14 illustrates the results in two different simulations, one including the perfect match between nodes and the other stuck in a local contradiction. In the later simulation, no total resonance develops between memory and cube. Some nodes receive contradictory signals from neighbors and from the feedback of their Synfire chains. That's why they cannot fit into an overall harmony with the rest of the network.

An analysis of the problem involving the cross pattern suggests several solutions. The network solves an optimization task in which synaptic energy ought to be exploited most efficiently. A standard approach like simulated annealing (Kirkpatrick et al. 1983) therefore prevents simulations trapped in local minima. Our model offers different possibilities to manipulate random influences during information processing. Fluctuations of the membrane potential with a standard deviation of 5 mV represent the standard noise level. In a straightforward extension of the simulation, one may start at a higher level and slowly decrease fluctuations in the course of processing. In biology, the random influences of distant neurons in the cortex also fade as the system reaches its equilibrium. The system also produces an 'annealing' effect by manipulating synaptic connections between Synfire chains. It starts with extremely weak synapses between the Synfire chains and automatically increases their influence. Excitatory as well as inhibitory synapses therefore reach their final value during information processing. This process was not simulated using excitatory and inhibitory learning mechanisms. Instead, a sequential procedure was used which increased the synaptic weights linearly. Both of the proposed strategies almost prevent any simulation trials terminating incorrectly. One out of a thousand cross simulations fails to generate perfect resonance between the detector cube and pattern memory. In all other simulations, the system finds the optimal correlations between nodes. It recognizes the pattern. The synchrony of the respective neuron pairs represents a perfect input for additional Synfire chains. In the simulations, we simply evaluated the correlations.

Of course, we also tried to correlate a cross on the retina with a square in memory and vice versa. The results are not worth mentioning (or an explicit display). None of these simulations produce significant correlations between the spatiotemporal patterns. Some Synfire chains synchronize with changing partners, but the existing interactions within the detector cube and within pattern memory destroy any lasting node pairs. The network produces contradictory signals and generates

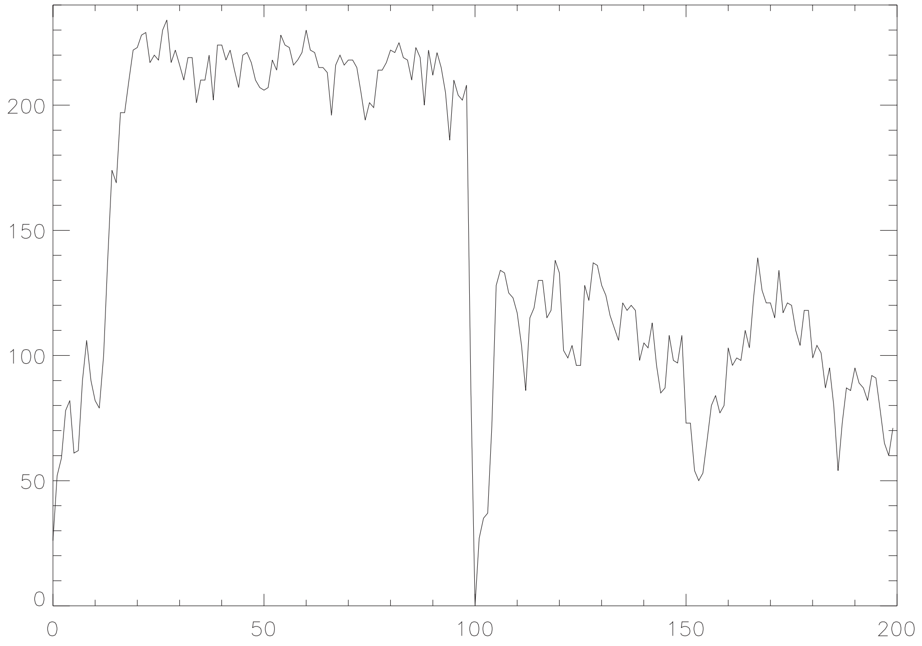

Fig. 14. Different simulation results with the cross pattern. See Fig. 9 for a description of the scale on the *x*- and *y*-axes. In the first trial (0–100), the network activity develops into a stable constellation. The neurons exchange their synaptic potentials optimally. In the second trial, the network activity enters a constellation with locally contradictory signals. Some nodes fire in synchrony, but others cannot fit into a coherent rhythm of action potentials. For an optimal constellation, the network activity is required to traverse a state with fewer correlations

an overall situation of dissonance at a persistently low level of correlations. The system is inconsistent.

Our system has not yet been tested with several other difficult tasks in pattern recognition. In particular, disturbed and nonclosed patterns present a major challenge. Preliminary simulations with occlusion, overlapping patterns, or missing parts suggest that the performance of recognition will be reduced. However, we experienced a graceful degradation and not a total breakdown. In addition, it is always possible to structure a pattern into several closed subpatterns. With appropriate connections of subpatterns in memory, the system easily constructs more complicated spatiotemporal patterns. Therefore, the system might be extended with arbitrary combinations of patterns.

Pattern recognition has to work in close symbiosis with pattern segmentation. A lack of feedback between both tasks introduces persistent difficulties in any real-world application. This knowledge and the idea of reconciling recognition and segmentation requirements dominated the design of our system. The final simulations test the success of these efforts. An octagon and a square are simultaneously projected onto the retina. At the same time, the respective structures in pattern memory are activated. At the beginning, all nodes fire randomly but with time the correct node pairs emerge from the interactions between Synfire chains and between neighbor nodes. A major obstacle in this process is closely linked to the question of activity control in the network. In some simulations, inhibitory interactions fail to regulate the development of activity, and the number of action potentials in the Synfire chains explodes. The Synfire interactions somehow ignore the security mechanism of inhibition. Additional inhibitory cells help to control network activity. With this extension, the simulations produce an error in three out of a thousand simulations. Segmentation is therefore included in our system. The automatic regulation of activity, however, represents a key issue requiring further investigations in neural network simulations. Otherwise, information processing is always vulnerable to ‘epileptic’ attacks during which all neurons burst uncontrollably.

5 Discussion

No conclusive theory exists about how translation-invariant pattern recognition can be accomplished in vision. Neural network simulations offer an interesting methodology to investigate this task. Most neuronal simulation architectures, however, depend on the questionable premise that a neuron’s firing rate codes the relevant information transmitted. There are several theoretical reasons against this approach. Firstly, the combinatorial explosion of patterns in the world implies an astronomical number of neurons exclusively dedicated to the task of pattern recognition. Any relevant coding scheme needs to take the relationships of subpatterns into account in order to cope with the growth of possible combinations. Rate-coded neurons require a new cell for any slight change in such a relationship. Secondly, those capabilities responsible for translation invariance must somehow develop during an adaptive process. Up to now, all neural networks simulating this process either include shared weights between neurons or require an exhaustive training of each pattern at every position. Thirdly, we would like to stress the need for a close feedback between segmentation and pattern recognition. Neural network models using a rate code persistently fail to implement this important interaction.

Von der Malsburg (1981) proposed the correlation theory to overcome some of the limitations inherent in rate coding. According to this theory, two neurons create a novel relationship whenever they generate simultaneous action potentials. Correlations between neuronal signals on a millisecond time scale create a new information format. In correlation theory, synchronous action potentials imply a very strong synaptic connection between the cells involved. These synapses produce simultaneous discharges of the cells, and the efficacy is rapidly adapted to the requirements of individual constellations in pattern recognition. In its current form, the theory heavily depends on short-term plasticity on a millisecond time scale in order to generate appropriate correlations.

The Synfire concept (Abeles 1982, 1991) offers an alternative option for precise correlations of action potentials. Within this concept, Arnoldi and Brauer (1996) develop a scheme to provoke and manipulate synchronous activities with similar capabilities as fast synaptic changes. This scheme is applied to the general idea of correlation theory, namely to code relevant information in the timing of action potentials. Our model of a translation-invariant pattern recognition system compares two spatiotemporal patterns of action potentials generated by a sensory and a memory module. The system enters a state of optimal resonance when very similar patterns are involved. In this state, the synaptic energy at work is exploited most efficiently. Sequences of action potentials created by different visual patterns, however, cannot find a global affinity for each other.

Rate-coded neural network models as well as coupled oscillators must fail at a discrimination task where the same features are arranged differently. A cross and a square pattern illustrate this situation. The synchronization of Synfire chains produces distinguishable spatiotemporal activity patterns for both visual inputs. Thus, our system may recognize cross and square independently, solving an important issue in pattern recognition.

The system incorporates several discrepancies compared with the situation in neurobiology. A major point of controversy concerns the oscillatory nature of the neuronal signals. From a technical point of view, a regularly repeating signal like an oscillation represents a very advantageous tool. A modeler is inclined to use the resulting design principle, although several experimental reports do not confirm the periodic character of cortical signals in visual areas. In general, cell activity in the cortex is well-known to correspond to a Poisson process without rhythm. We adopt the argumentation that each cell fires irregularly but that certain populations of cells may produce answers in regular intervals whenever their signal is isolated. Starting from this hypothesis, several problematic features of our model receive more credibility. Firstly, a Hebbian learning process combined with rhythmic activity explains the development of Synfire reverberations. Secondly, the population concept justifies the nature of units in our detector cube. In the visual cortex, most cells respond to the orientation of a change from dark to bright and vice versa. These cells react to the left and the right margins of a pattern. A detector node in our model consists of a cell population forming a special subset of all simple cells. The synchronous activities of these cells form a new characteristic signal which strictly distinguishes between left and right margins.

In addition, the population idea solves an extremely important task, namely to reconcile correlation coding with rate coding of neuronal signals. In particular, peripheral areas dedicated to sensory or motor tasks are famous for their graded responses reflecting the intensity of a stimulus or a motor command. König et al. (1995) discovered optimally and suboptimally stimulated cells, all of which synchronize their action potentials. Those cells with stronger stimulation systematically lead in the regular outbursts of simultaneous activities. In the model, each cell generates a single spike every 30 ms. Theoretically, this response may vary between a burst of spikes at every synchronous event and a few action potentials separated by 60 or 90 ms. Technically, a graded signal offers useful options for information processing. Most applications in computer vision fail due to signal noise or significant changes in illumination. In real world images, most filters produce boundary contours all over a pattern, or they miss detecting important gray level changes. For each position, interactions between segmentation have to determine the probability of an edge. The number of synchronized answers in a cell population may reflect the degree of uncertainty.

The proposed system shares an important disadvantage with many pattern recognition approaches including dynamic link architecture (Lades et al. 1993). For recognition, all known patterns have to be stored in a database. In order to find the optimal fit, every item in this database is successively compared with a pattern on the retina. Psychophysical experiments imply that the brain does not follow such a strategy. A casual resonance between detector cube and memory system, however, may extend our system. We propose looking for an appropriate connectivity of the representational structures in memory. Then the stimulation in the detector cube and interactions between Synfire chains should be able to activate the correct population in pattern memory. For this task, we hypothesize an ongoing weak activity to be required in the memory module. Therefore, more efforts will be concentrated on the task of creating a persistent weak activity in memory. This activity resembles those random and 'useless' spikes in associative cortices.

In summary, two important features of our model are worth mentioning in comparison with similar approaches. First of all, the system is inherently parallel. The resonance between the respective spatiotemporal pattern develops by distributed and parallel interactions once the activity in the detector cube and in pattern memory is initiated. The timing of cell activity results from simultaneous synaptic inputs of several EPSPs. In contrast, dynamic link architecture (Lades et al. 1993) requires an attentional and therefore sequential mechanism to set up the proper assignment between a pattern and its stored pendant. Furthermore, our system addresses one of the key issues in a vision task. It incorporates segmentation and pattern recognition in a continuous feedback. For this purpose, both perceptual processes share the same information code. Correlation of cell activities represents the basis of this code. Synchronization of Synfire chains offers a tool to manipulate its signals.

The current network was neither aimed at presenting a persuasive explanation of biological pattern recognition nor at competing with other technical applications of recognition systems. Biological systems require 150 ms (Thorpe et al. 1996) for recognition and therefore put severe constraint on any model. Instead, our work introduces an alternative to fast synaptic changes in correlation theory (Von der Malsburg 1981). Synchronization of Synfire chains might serve for this purpose. More importantly, our network addresses the important issue of how different cortical areas might interact with another. An example architecture is presented of how neuronal information in one part of the brain might be combined with information elsewhere. Different specialized regions for color, shape, and movement may communicate through correlated activity and thus fuse distributed activity into a coherent whole.

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