Invariant Recognition of Spatio-Temporal Patterns in The Olfactory System Model

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Abstract. This paper presents a model of a network of integrate-and-fire neurons with time delay weights, capable of invariant spatio-temporal pattern recognition. Spatio-temporal patterns are formed by spikes according to the encoding principle that the phase shifts of the spikes encode the input stimulus intensity which corresponds to the concentration of constituent molecules of an odor. We applied the Hopfield's phase shift encoding principle at the output level for spatio-temporal pattern recognition: Firing of an output neuron indicates that corresponding odor is recognized and phase shift of its firing encodes the concentration of the recognized odor. The temporal structure of the model provides the base for the modeling of higher level tasks, where temporal correlation is involved, such as feature binding and segmentation, object recognition, etc.

Key words. integrate-and-fire neurons, olfactory cortex, phase shift encoding, spatio-temporal pattern recognition

1. Introduction

1.1. OLFACTION

In the olfactory bulb odor stimulus information is encoded into a periodic spatio-temporal pattern of oscillatory neural activity (Hoshino et al., 1998 Skarda and Freeman, 1987; Laurent and Davidowitz, 1994; Laurent, 1996). Specific spatial patterns of synchronized firing are correlated to a certain constituent molecules of the applied odor. Relative time advances of the appearances of these spatial patterns are correlated with the concentrations of the molecules. This spatio-temporal correlation enables odor recognition and concentration estimation in the olfactory cortex (Hopfield, 1995; Hoshino et al., 1998). The olfactory epithelium of a nasal cavity contains hundreds (say n) of receptors sensitive to various types of molecules (Ressler, 1994). Thus, epithelium perceives odors, basically, as the mixtures of their components (different molecules). It is convenient for the odors to be represented by the concentration vector $C = \{c_1, c_2, \ldots, c_n\}$, where c_j is the corresponding concentration of the jth odor component.

During sniffing constituent molecules of an odor cause receptor neurons (that are equally distributed in the olfactory epithelium) to fire, producing spikes (Duchamp-

Viret et al., 1998; Ressler, 1994). A firing pattern in the receptor field is then mapped to the olfactory bulb. Axons from the same receptors of olfactory epithelium go to the corresponding ensembles of the neurons in the olfactory bulb (Ressler, 1994). So, each ensemble of neurons in the olfactory bulb represents a corresponding constituent molecule of the odor. Once they receive impulses from the receptor level, the neurons in the ensembles synchronize their activity. They fire synchronously within each ensemble, and with the time shifts between different ensembles (Hoshino et al., 1998; Laurant and Davidowitz, 1994). As a result, the odors at the bulbar level are presented by the sequence of firing of different neural ensembles, where the specific neural ensembles represent the odor constituent molecules and the time shifts of the firing of these ensembles represent the concentrations of the constituent molecules (Hoshino et al., 1998; Duchamp-Viret et al., 1996).

The larger is the concentration c_j of a constituent molecule, the earlier the corresponding ensemble gets excited and synchronized (Campbell and Wang, 1998) and the greater is the time φ_j the jth ensemble fires in advance of the moment of the maximum of its subthreshold activation, which serves as a reference time (Hopfield, 1995). So, the corresponding concentrations c_j of n constituent molecules can be encoded as time advances $\varphi_1, \varphi_2, \ldots, \varphi_n$ of ensemble's firing presented as:

$$\varphi_j = t_j - t^{(r)} \tag{1}$$

where t_j is the time of the ensemble's spike and $t^{(r)}$ is the reference time mentioned above. The relationship (2) between input concentrations c_j and corresponding time advances φ_j has been proposed in the Hopfield's model (Hopfield, 1995), where each time advance is proportional to the logarithm of the corresponding concentration, α is a coefficient and δ is a scale factor.

$$\varphi_j = \alpha \ln(c_j/\delta) \tag{2}$$

The logarithmic scaling makes the relative phase pattern invariant to the different concentrations of the same odor. In this case, not the relative, but the entire pattern is shifted when the odor concentration is changed.

1.2. OLFACTORY PATTERN RECOGNITION MODELING

In most of the functional olfactory models reported in the literature the authors focus on the spatio-temporal pattern formation at the olfactory bulb level. The basic principles of pattern formation presented above are more or less understood and they are supported by the biological experiments (Duchamp-Viret et al., 1998; Hoshino et al., 1998; Laurent and Davidowitz, 1994; Laurent, 1996). However, the mechanism by which these spatio-temporal patterns (Figure 1(a)) are recognized and then processed at the next, olfactory cortex level, remains, basically, unknown.

One of the plausible biological mechanisms of spatio-temporal pattern recognition is a system with an appropriate set of delays stored in synaptic memory followed by coincidence time detectors that receive these appropriately delayed (and now synchronized) signals. Recognition of a stored odor can be indicated by firing of the

corresponding coincidence time detector neuron (Hopfield, 1995; Natschlager and Ruf, 1998; White et al., 1998). The question that arises is how the concentration of the recognized multi-component odor is represented at the olfactory cortex?

Experimental evidence indicates that time shift encoding of stimulus intensity occurs not only at the bulb level, but at olfactory cortex level as well (Duchamp-Viret et al., 1996, 1998). This supports the idea that time shift encoding is also used at the 'output level' of the olfactory system, i.e. at the olfactory cortex. It also indicates that the mechanism of this encoding could be similar to the one at the olfactory bulb.

However, most of the olfactory pattern recognition models do not make use of temporal encoding and temporal processing. In such models the patterns to be recognized are ordinary time independent vectors that represent certain odor qualities. Those vectors are then recognized by one of the classical pattern recognition techniques, which do not have much in common with biological temporal processing.

Temporal encoding and temporal processing have only recently been included in the olfactory pattern recognition modeling. Significant progress in this direction has been made by White et al. (1998). In their model vapor identity is encoded by the spatial code across output units, and vapor intensity is represented by response latency. The system is not only biologically relevant (at some extent), but also proved to be more effective than classical neural networks models. Its percentage of correctly identified test patterns was higher than the one of the feed-forward neural network with hidden layer (82% and 71% correspondingly) (White et al., 1998).

However, the model of White et al. is not complete. Odor intensities are encoded just qualitatively: shorter response latency signifies greater concentration (and vice versa), but no precise functional correspondence exists between response latency and odor concentration. Moreover, the model as it is shown in (White et al., 1998) works only in the very narrow range of relative concentrations. Our proposed model implements precise functional encoding of the pattern intensity, that is odor concentration, with the phase shifts of the output neuron firing. The odor recognition remains invariant within broad range of concentrations due to the Hopfield's logarithmic intensity encoding.

2. Model

Our network consists of one layer of m leaky integrate-and-fire neurons fully connected with n temporal inputs. These inputs simulate spatio-temporal patterns formed in the olfactory bulb (Figure 1(a)), and the neural layer (Figure 1(b)) corresponds to the olfactory cortex that receives and recognizes those patterns. The periodic inputs $s_j(t)$ for $j = 1, \ldots, n$ are expressed by Dirac delta function:

$$s_j = \beta \sum_{k=1}^{\infty} \delta(t + \varphi_j - kT) \tag{3}$$

where T is the period of the signal's oscillation. The time advance φ_j of a periodical input spike can be expressed in terms of its phase advance ϕ_j related to the reference
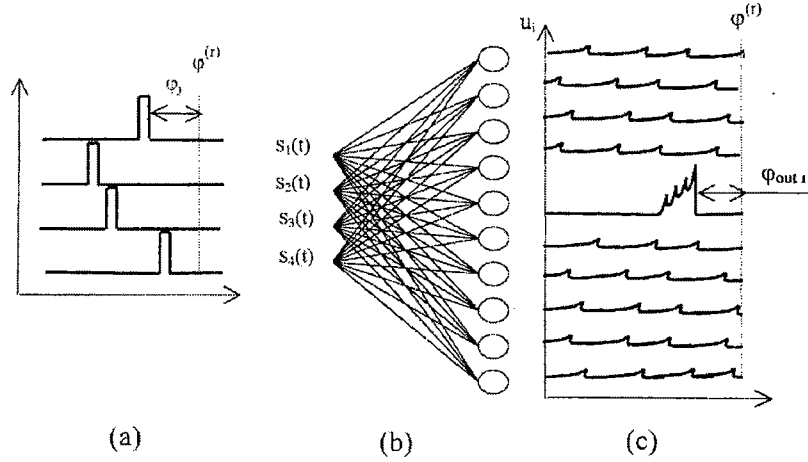
Figure 1. Pattern formation and encoding in the olfactory system model: (a) synthetic input pattern where $s_j(t)$ are the input signals, φ_j – phase shift of the input signals, $\varphi^{(r)}$ – reference phase as in Equation (1); (b) network of integrate and fire neurons; (c) output pattern: u_i – membrane potential of the output neurons.

phase $\phi^{(r)}$ (which corresponds to the zero time advance) as: $\varphi_j = \phi_j/\omega$, where $w = 2\pi/T$. In order to distinguish periodical time advances of the input spikes from the constant time delays stored in the network, further in the paper we will call the time advances φ_j as the phase shifts φ_j, related to the reference phase $\varphi^{(r)}$. Thus, the phase shifts φ_j of the signal's spikes encode concentrations of the n corresponding constituent molecules (2). An example of input pattern is shown at Figure 1(a).

During each cycle the spikes arrive to the neural layer with the delays equal to their phase shifts φ_j. Then the spikes acquire additional time delays d_{ij} stored in the synaptic connections. So, the total time delays of the signals that arrive to ith neuron are equal to $\varphi_j + d_{ij}$.

Each neuron in the layer (Figure 1(b)) is characterized by its state–membrane potential u_i, $(i = 1, \ldots, m)$. Every time a neuron receives a spike, its potential u_i is increased by the weighted value of that input spike: $w_{ij}s_j(t - d_{ij})$. At the same time the potential u_i is constantly decreasing with decay coefficient k as follows:

$$\frac{du_i(t)}{dt} = -ku_i(t) + \sum_{j=1}^{n} w_{ij}s_j(t - d_{ij}) \tag{4}$$

When the potential of a neuron reaches its threshold value u_{thresh}, neuron fires (Figure 1(c)), and its potential u_i is instantly reset to 0 as shown below.

$$u_i(t^-) = u_{thresh} \Rightarrow u_i(t^+) = 0 \tag{5}$$

The coefficient β in (3), that is equal to u_{thresh}/n, scales the value of input spikes. So, only all spikes added together are able to increase the value of potential to u_{thresh}. As well as the membrane potential u_i is constantly decreasing (4), the spikes that arrive with big time intervals one after another fail to significantly increase the potential's

value. They have to arrive within a narrow time interval (almost simultaneously) to the neuron in order to increase its value to u_{thresh}. Odor patterns are stored in the network memory by the delays d_{ij} between inputs and the neurons. The delays are set in such a way to make each of n spikes arrive simultaneously to the neuron if the applied pattern is equal to the pattern stored:

$$d_{ij} = \varphi_{st\,j}^{(i)} - \min_j\{\varphi_{st\,j}^{(i)}\} \tag{6}$$

where $\varphi_{st}^{(i)}$ is a phase vector of ith stored pattern.

When a stored odor pattern is applied, the total input $\sum_{j=1}^{n} w_{ij}s_j(t - d_{ij})$ to the neuron i has to be equal to or more than u_{thresh} in order to increase the membrane potential u_i by this value and make it fire (Figure 1c). So the weights have to be determined as follows:

$$w_{ij} \geqslant \frac{u_{\text{thresh}}}{\sum_{j=1}^{n} s_j(t - d_{ij})} \tag{7}$$

The neuron fires simultaneously with the last arriving spike, so the phase shift of the output spike is equal to the minimal input phase shift (or phase shift of the weakest component), as shown in Figure 2.

If the pattern applied is not close enough to any of stored odor patterns (of any concentration) spikes arriving with significant time intervals will not make output neuron fire because of its exponential decay. Output potentials in Figure 1(c) show a superthreshold firing of neuron #5 with the phase shift $\varphi_{\text{out}\,i}$ and subthreshold activity of all other neurons. This indicates that odor #5 with some concentration is recognized.

Due to logarithmic scaling in Equation (2) the global phase of the entire pattern is shifted when the odor concentration is changed, while the relative phase shifts remain
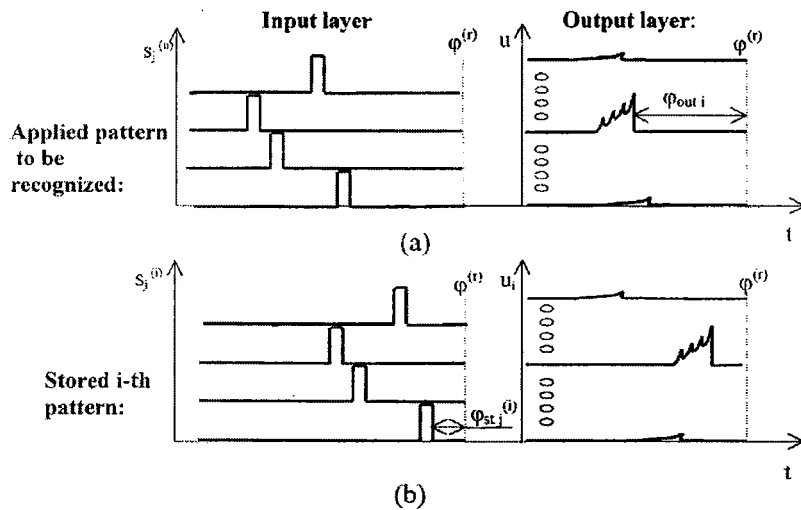

Figure 2. Recognition of the patterns of the same odor with different concentrations.

the same. This makes pattern recognition of the model invariant to the different concentrations of the same odor. Figure 2 shows an example of two patterns of the same odor with different concentrations. Phase shift of the entire pattern (a) is greater than of the pattern (b), though the pattern itself is the same. Thus, the output spike phase shift at (a) is greater than at (b). So, the odor concentration of the pattern (a) is greater.

Concentration of entire odor $c_{\text{out } i}$ is defined as relative concentration of odor applied to the corresponding odor stored. This concentration is decoded from the output spike phase shift $\varphi_{\text{out } i}$ and the minimum phase shift of the corresponding stored pattern $\min_{j}\{\varphi_{st\,j}^{(i)}\}$ (Figure 2) by the inverse function of Hopfield's encoding.

$$c_{\text{out } i} = \delta \exp[(\varphi_{\text{out } i} - \min_{j}\{\varphi_{st\,j}^{(i)}\})/\alpha] \qquad (8)$$

3. Simulation Results

In our computational simulation the stimuli are 4-dimensional ($n = 4$) concentration vectors C (as defined above). Four input neurons produce the spatio-temporal patterns that correspond to the applied stimuli. 10 output neurons ($m = 10$) correspond to 10 stored odors. The concentration of their components varied from 1 (threshold concentration) to 10. Concentration of the components of the odors tested varied from 1 to 70.

Two basic parameters were to be optimized during the simulation: exponential decay coefficient k (4) and corresponding weights w_{ij} (7). The system is quite sensitive to both of them. With w_{ij} determined by Equation (7) with the equality sign, or with decay coefficient $k \gg 1$, the system can recognize undistorted stored patterns only. When weights increase or k decreases the network becomes more flexible (the receptive regions of the neurons get larger). However, the greater the receptive region, the worse the system accuracy is. So, certain compromise had to be found. For our system the highest success rate of recognition (shown in Table I) was achieved with $k = 6.3$, and $w_{ij} = 1.32$, $\forall i, j$. Period T and threshold u_{thresh} were arbitrary selected as follows: $T = 50$, $u_{\text{thresh}} = 1$. The coefficients α and δ define the scale of the transformation (2). They were chosen as: $\alpha = 10$, $\delta = 1$, that makes the maximum phase difference of the spikes (that is $T = 50$) correspond to the relative concentration of the odor components equal to 150.

Example of a simulated input pattern is shown at Figure 3(a). This signal is a repeating sequence of four spikes corresponding to applied odor $\{63, 96, 48, 10\}$

Table I. Characteristics of the model performance

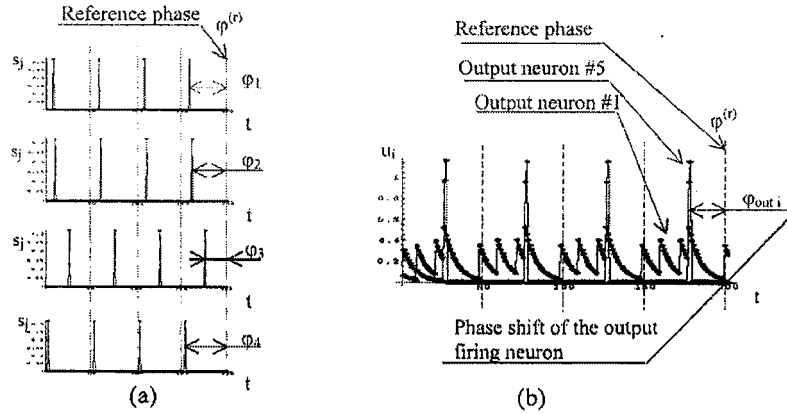|	
Patterns applied	5000
Odors recognized	10.3%
Successful recognition	81%
Incorrect recognition	19%

Figure 3. Simulated input and output patterns: (a) input pattern of an example odor {63, 96, 48, 10}; (b) Output patterns of the 1st, and 5th neurons (both are shown on the same picture). There is a super-threshold firing of the neuron #5, and substhreshold activity of neuron #1. Odor #5 is recognized.

which was chosen for illustration purpose. Figure 3(a) shows the activity patterns of two neurons. Only neuron #5 reaches the threshold and fires. This indicates successful recognition of odor #5. Neuron #1 does not reach the firing level, so the odor #1 is not recognized.

In our experiment 5000 randomly generated test odors have been presented to the system. A total of 89.7% of them caused the output neurons to produce the sub-threshold activity only (odors were not recognized). A total of 10.3% of the test-stimuli provoked superthreshold firing of output neurons (odors were recognized). A total of 81.0% of them were recognized correctly (both odor and concentration), with allowed concentration error equal to 20%.

For the sake of testing the proposed model, each applied odor is projected onto the distance–concentration coordinate system. The purpose of the test is to determine if our model correctly classifies an input odor as resembling one of the stored odors, or leaves the input odor unclassified if it does not resemble any of them. The resemblance is expressed using a metric introduced in the Appendix. The stored odors have a certain distribution in the concentration space. The distance D between the arbitrary input odor and its closest neighbor amongst the stored odors allows for testing our model.

The inputs that caused an output to fire are indicated as points in Figure 4(a). Majority of these points are gathered in the region of small D with various concentrations. This indicates that the odors which caused an output to fire were indeed close to one of the stored odor patterns. The concentration level of the input odor does not affect the models ability to classify the input as one of the known odor patterns.

On the other hand, all other input odors which did not cause an output to fire are shown as points in Figure 4(b). These points tend to have large values of distance function D. Any input odor that is too far from all of the stored patterns fails to
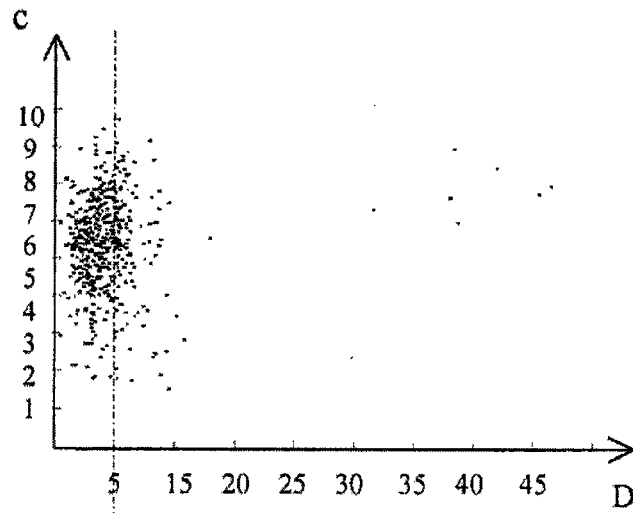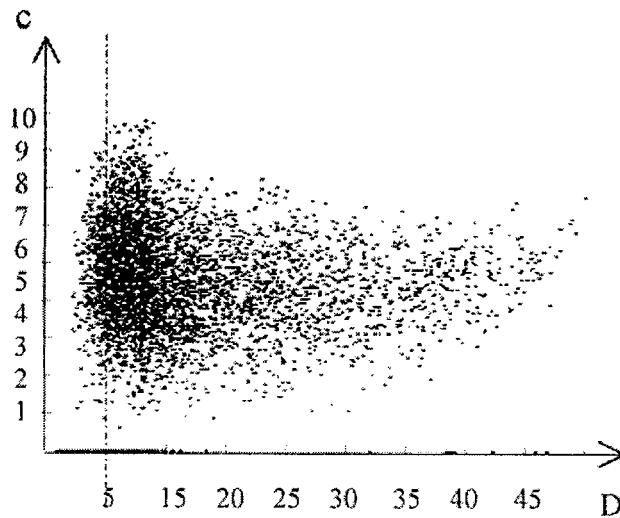
Figure 4. Distribution of the simulation results. (a) Patterns correctly recognized. (b) Patterns that are not recognized.

activate the model outputs. Even strongly concentrated odors stay unclassified if they lack resemblance to one of the stored patterns.

In order to compare Figure 4(a) and (b) a vertical division line is drawn. The line separates the classified points from the unclassified ones in terms of the distance

value D. Points to the left from the line manifest a resemblance to one of the stored pattern odors and hence activate the output of the model. Most of the points stay on the right side of the division line, as no stored pattern claims such resemblance. Remarkably, the division line is vertical, which means that Hopfield's principle works well separating the odor 'flavors' from their concentrations.

4. Discussion and Conclusion

Recognition of a single pattern is only one of the first stages of sensory information processing. The higher-level problems of multi-pattern processing, such as object recognition in real world, feature binding and segmentation, object-background separation, attention focusing, etc. are much more difficult to model and they are far from being handled by modern computational methods. However, all these tasks are efficiently performed by cortical neural networks of animals and humans, where different temporal correlation types are believed to be the underlying principle of these abilities (Campbell and Wang, 1998; Malsburg and Buhmann, 1992; Malsburg and Schneider, 1986).

Temporal correlation plays an essential role in olfactory systems as well. Experimental results prove that several odors in a mixture are separated temporally from each other at some of the higher levels (Jinks and Laing, 1999). One of the possible ways to do such a temporal segregation is using temporal correlation and competition of output neurons (or neural ensembles) and inhibitory top-down feedback to input level in order to temporally segregate recognition of different odors, suppress noise or irrelevant inputs and focus attention on the necessary odor (Campbell and Wang, 1998; Malsburg and Buhmann, 1992; Malsburg and Schneider, 1986). Phase encoding, that is a specific example of temporal correlation is the basic principle of our model and we believe it provides the base for the solution of the higher level processing tasks presented above.

Appendix

This section introduces the transformation of odor vectors to the distance-concentration space. Each component c_j of applied odor vector, C, is logarithmically transformed as in (2) to the corresponding components φ_j of phase vector φ. In the same way m stored vectors $c_{st}^{(i)}$, $i = 1, \ldots, m$ are transformed to m vectors $\varphi_{st}^{(i)}$, where $\varphi_{st}^{(i)} = \{\varphi_{stj}^{(i)}, j = 1, \ldots, n\}$.

Vectors $\varphi_{st}^{(i)}$ and φ are normalized in the phase space in the following way:

$$\varphi_{st}^{(i)*} = \{\varphi_{stj}^{(i)} - \min_j\{\varphi_{stj}^{(i)}\}, j = 1, \ldots, n\} \tag{9}$$

$$\varphi^* = \{\varphi_j - \min_j\{\varphi_j\}, j = 1, \ldots, n\} \tag{10}$$

Each applied and then normalized phase vector $\varphi^* = \{\varphi_j, j = 1, \ldots, n\}$. is characterized by its distance D to the closest of the $\varphi_{st}^{(i)*}$. This distance D is defined as:

$$D = \min_i \{\|\varphi^* - \varphi_{st}^{(i)*}\|\} \tag{11}$$

Thus D defines distance in the phase space from the vector applied to the closest of the stored vectors.

Acknowledgements

References

Campbell, S. and Wang, D.: Synchrony and desynchrony in integrate-and-fire oscillators. *Proceedings of the IEEE International Joint Conference on Neural Networks*, Anchorage, Alaska, **2** (1998), 1498–1503.

Duchamp-Viret, P. and Palouzier-Paulignan, B. and Duchamp A.: Sensory information processing in the frog olfactory pathways. Experimental basis for modeling studies. *Biosystems*, **48** (1998), 37–45.

Duchamp-Viret, P. and Palouzier-Paulignan, B. and Duchamp A.: Odor coding properties of frog olfactory cortical neurons. *Neuroscience*, **74** (1996), 885–895.

Hopfield J.: Pattern recognition computation using action potential timing stimulus representation. *Nature*, **376** (1995), 33–36.

Hoshino, O. and Kashimori, Y. and Kambara, T.: An olfactory recognition model based on spatio-temporal encoding of odor quality in the olfactory bulb. *Biological Cybernetics*, **79** (1998), 109–120.

Jinks, A. and Laing, D.: Temporal processing reveals a mechanism for limiting the capacity of humans to analyze odor mixtures. *Cognitive Brain Research*, **8** (1999), 311–325.

Laurent, G. and Davidowitz, H.: Encoding of olfactory information with oscillating neural assemblies. *Science*, **265** (1994), 1872–1875.

Laurent G.: Dynamical representation of odors by oscillating and evolving neural assemblies. *Trends in Neuroscience*, **19** (1996), 489–496.

Malsburg, C. von der, Buhmann, J.: Sensory segmentation with coupled neural oscillators. *Biological Cybernetics*, **67** (1992), 233–242.

Malsburg, C. von der, Schneider W.: A neural cocktail-party processor. *Biological Cybernetics*, **54** (1986), 29–40.

Natschlager, T. and Ruf, R.: Spatial and temporal pattern analysis via spiking neurons. *Network*, **9**(3) (1998), 319–332.

Ressler, K. and Sullivan, S. and Buck, L.: Information coding in the olfactory system: evidence for a stereotyped and highly organized epitope map in the olfactory bulb. *Cell*, **79** (1994), 1245–1255.

Skarda, C. and Freeman, W.: How brains make chaos in order to make sense of the world. *Behavioral and Brain Sciences*, **10** (1987), 161–195.

White, J. and Dickinson, T. and Walt, D. and Kauer, J.: An olfactory neuronal network for vapor recognition in an artificial nose. *Biological Cybernetics*, **78** (1998), 245–251.