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Oscillatory model of novelty detection

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Abstract

A model of novelty detection is developed which is based on an oscillatory mechanism of memory formation and information processing. The frequency encoding of the input information and adaptation of natural frequencies of network oscillators to the frequency of the input signal are used as the mechanism of information storage. The resonance amplification of network activity is used as a recognition principle for familiar stimuli. Application of the model to novelty detection in the hippocampus is discussed.

(Some figures in this article are in colour only in the electronic version; see `www.iop.org`)

1. Introduction

Current opinion about information processing in the brain presumes that biological memory systems constantly make decisions concerning the storage of incoming information (Squire 1992). One important attribute for deciding whether information should be stored or not is its novelty to the organism. Novelty detection gives a living organism the possibility of avoiding storage of redundant information and concentrating on processing new stimuli, which may be important for survival.

Novelty detection can be thought of as a differential response of some parts of the brain to a stimulus depending upon the relations between the incoming and previously stored information. One well-known manifestation of novelty detection is the change in activity in the hippocampus during the orienting response (Sokolov 1975, Vinogradova 1995). The long (tonic) theta activity that appears in the hippocampus after presentation of a new or significant stimulus is changed to a short (phasic) reaction during repeated presentations of the same stimulus. This process is referred to as habituation. An important fact is that the tonic reaction is immediately restored when a stimulus with different characteristics is presented.

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Recently, Borisyuk and Hoppensteadt (1998, 1999) developed an oscillator network model of memory formation in the hippocampus. The model network is a chain of locally coupled oscillators that receive two periodic input signals coming from two brain structures (the entorhinal cortex and the medial septum). The dynamics of the network is determined by phase relations between input signals. Depending on these relations, particular regions of the network are activated by a stimulus, and the memory is created through Hebbian modification of connections between oscillators.

Our model inherits the idea that memory storage is controlled by phase relations between several input signals, but this idea is generalized in two respects. First, we consider multidimensional input signals (the dimension is more than two) with random phase shifts. This results in sparse distribution of high activity in the network during each stimulation and hence in sparse distributed coding of stimuli in the network memory. Second, different stimuli are supposed to be coded at the input by signals of different frequencies. This restricts the population of oscillators participating in coding a stimulus to those oscillators whose natural frequencies are similar to the frequency of the input signal. Thus, the memory in the network appears as a result of the transformation of a time–frequency code at the input of the network into a space–frequency code in the network memory. In addition, the following new features appear in the model:

- memory storage by appropriate modification of natural frequencies of oscillators;
- memory retrieval by resonance of network oscillatory activity in response to an external input.

The idea of learning and memorizing by forming an ensemble of frequency-tuned oscillators is traditional in the field of oscillatory neural networks. This mechanism is hypothesized to be one of the general principles of information processing in the brain (Singer and Gray 1995). While connectionist theory assumes that an ensemble of synchronous (in-phase) oscillators is formed via strengthening connections between the oscillators in the ensemble, we suggest an alternative mechanism of memorization through adaptation of natural frequencies of oscillators. We suppose that the input signal synchronizes the activity of some oscillators in the network, resulting in a ‘learned’ pattern; that is, some oscillator frequencies are gradually tuned by network dynamics to the frequency of the input signal. Eventually, a population of recruited oscillators, now having identical dynamical properties, is formed.

The hypothesis that adaptation of oscillation frequencies in the brain can be used as a learning mechanism appeared in the neurophysiological works of Ukhtomsky and his school (Ukhtomsky 1978) and John (Thatcher and John 1977). Some neural network implementations of this mechanism have been suggested by Torras (1986) and Hoppensteadt (1992).

The important feature of such oscillatory memory is that memory formation in a network of N oscillators requires only N modifiable parameters (these are the natural frequencies of oscillators). Note that the number of modified parameters (adjustable connections) in a Hopfield network of associative memory is about $0.5 \times N^2$.

Another component of our model is a frequency resonance between the input and some network oscillators. Suppose that oscillatory signals of the frequency ω are channelled in parallel with different time delays to a set of oscillators working with a variety of natural frequencies, so that each oscillator receives n signals. Those oscillators whose input signals arrive approximately in-phase and whose natural frequencies are near ω can be most easily phase-locked by the input. The permanent coincidence of the oscillator phase with the phases of the input signals results in a sharp increase in oscillation amplitude while amplitudes of other oscillators decay (on average). (A similar resonant recall has been considered in Hoppensteadt (1992) by passing both the input and oscillator signals to a correlating cell and obtaining the output frequency increase with higher correlation.) In our model, the resonance is used to get a dynamical label for those oscillators that should participate in memory storage and retrieval.

The idea of resonance interaction is not new in novelty detection modelling. It has been efficiently exploited in adaptive resonance theory (ART) networks to distinguish between the objects belonging to a learned category and the objects belonging to a previously unseen category (Carpenter and Grossberg 1987a, b, Grossberg 1999). While our model is worked out in the paradigm of oscillatory neural networks, ART-networks are traditional neural networks whose information storage abilities are based on the modification of coupling strengths between elements of the network.

We develop our model as a network of oscillators. It is assumed that each oscillator represents a population of locally coupled excitatory and inhibitory neurons. The activity of an oscillator represents the average activity of the population (local field potential). We suppose that the interaction between oscillators can be described in terms of a phase-locking procedure. Such networks have been useful in engineering applications and in mathematical neuroscience when a qualitative mathematical representation of phase-locking is needed. In our model, an oscillator is described by three variables: the oscillation phase; its natural frequency; and its amplitude. Such an oscillator can be considered as a generalization of a phase-locked loop oscillator. It is known that the explicit extraction of the oscillator phase as a variable describing the dynamics of oscillator activity simplifies the analysis of conditions that ensure the entrainment of oscillators. This has been confirmed by the mathematical analysis of networks of phase oscillators with different connection architectures (Kuramoto and Nishikawa 1987, Daido 1988, Strogatz and Mirollo 1988). Phase-locked loop oscillators have been successfully used to model neurophysiological data related to phase-locking and synchronization of neural activity in the brain (Kammen *et al* 1990, Sompolinsky *et al* 1990, Schuster and Wagner 1990, Kuramoto *et al* 1992, Ermentrout and Kopell 1994, Kazanovich and Borisyuk 1994, 1999, Hoppensteadt 1986, Hoppensteadt and Izhikevich 1997, Wu and Gao 1999, Denham and Borisyuk 2000).

2. Model description

The model for novelty detection is a network of oscillators with a loop of inhibitory feedback control (figure 1). The oscillators are combined into groups $G_j (j = 1, \ldots, m)$ with q oscillators in each group. The oscillators belonging to the same group are coupled by all-to-all connections. For simplicity, there are no connections between oscillators of different groups.

There is an n-dimensional input channel that delivers the information about a stimulus to each oscillator in the network. The input signal is $C = (C_1, \ldots, C_n)$ with the components $C_i = \sin(2\pi\omega_0 t + \psi_{ij})$ $(i = 1, \ldots, n,\ j = 1, \ldots, m)$. Thus, each stimulus is coded at the input by a set of periodic oscillations with parameters ω_0, ψ_{ij}, where ω_0 is the frequency of oscillations and ψ_{ij} are phase shifts that imitate different time-lags during signal transmission to a particular group of oscillators. The values of ω_0 are taken from some range $(\omega_{\min}, \omega_{\max})$ and the phase shifts ψ_{ij} are supposed to be randomly distributed in the range $(-\tau, \tau)$.

At the initial moment (before the network stores any information) each group G_j contains oscillators whose natural frequencies are distributed in the whole range $(\omega_{\min}, \omega_{\max})$ of input frequencies. During information storage these natural frequencies may change depending on the parameters ω_0, ψ_{ij} of the input signal.

The network is trained by a sequence of stimuli. The presentation of each stimulus results in the appearance of an oscillatory input signal during time T. The natural frequencies of oscillators obtained after previous stimulations are used as initial values of natural frequencies

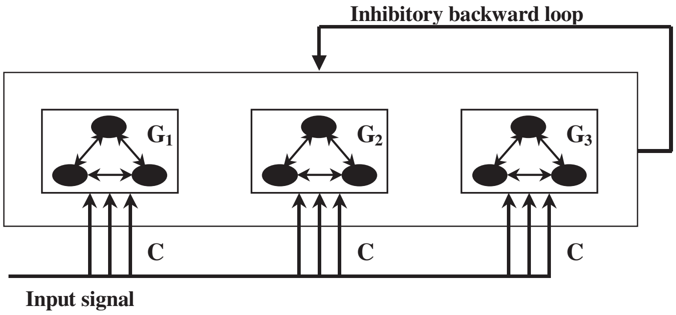


Figure 1. Network architecture (the case $m = 3, q = 3$ is shown). The oscillators are combined into groups G_j with all-to-all connections between oscillators in the groups. There are no connections between oscillators of different groups. Each oscillator receives a multi-dimensional input signal C. The inhibitory backward loop stops the activity in the network after the number of resonant oscillators exceeds a threshold level.

at the beginning of a new stimulation (no memory decay). These modified natural frequencies are the only information stored by the network about the stimuli. The amplitudes and phases of oscillations are assigned zero values at the beginning of each stimulation (amplitude and phase reset).

A basic assumption of our modelling is that an oscillator reaches and keeps a high level of activity (high amplitude) if the signals that are supplied to this oscillator arrive in-phase, that is if the values of ψ_{ij} are approximately the same for the given j. Due to a random choice of the values of ψ_{ij} for each stimulus, this implies that the presentation of a stimulus results in high oscillatory activity at only a small number of randomly chosen locations (groups), where an appropriate coincidence of input signal phases takes place. The activity in other parts of the network is low. Such of activity appears during both memorization and recall. We call it a sparse representation (coding) of the stimuli in the network activity. The important feature of sparse coding is that if the number of groups in the network is large relative to the number of memorized stimuli, then different stimuli (even those that are labelled by the same or similar frequencies) will activate different (though possibly overlapping) regions in the network. Therefore, different stimuli are memorized in different locations of the network.

Memory storage is conditioned by the dynamics of oscillators and the related adaptation of their natural frequencies. The formal description of the dynamics is presented in appendix A. Here we describe it in a non-formal way, focusing on the algorithms embedded in the network.

The oscillators' dynamics are controlled by a phase-locking procedure (1). Analytical description of conditions for phase-locking of an oscillator in the case of a multi-dimensional input signal C are presented in appendix B. Phase-locking is also used as the mechanism of interaction between oscillators. The peculiarity of this procedure in our model is that the amplitudes and natural frequencies of oscillators are not constant in time. The amplitude of an oscillator depends on the synchrony of its oscillations with the input signals. This causes a selective amplification of the activity of some oscillators.

The following two principles were applied to control the activity of an oscillator.

Principle 1. The amplitude of oscillations sharply increases if most of the input signals arrive at an oscillator in-phase with its own oscillations (equation (2)). This implies that this oscillator is synchronized with the input and operates with the current frequency ω_0. We consider this increase as a resonant response of an oscillator to properly tuned input signals. The amplitudes of those oscillators that do not work in-phase with C are kept at a low level or decrease.

By definition, an oscillator is in a resonant state if its amplitude is greater than a given threshold. In simulations we put this threshold a bit lower than the maximal possible value of the amplitudes (for details see appendix A).

Principle 2. The natural frequency of an oscillator tends to the value of its current frequency (equation (3)). To avoid rapid jumps of natural frequencies during transitional stages of phase-locking, the dynamics of natural frequencies is made slow relative to the rate of phase-locking.

Let us describe how these principles are embedded in network dynamics control.

Suppose that a stimulus is presented at the input of the network. According to principle 1, under the influence of the signal C some oscillators of the network increase their activity and reach a resonant state. The amplitudes of other oscillators are kept low.

The interaction between oscillators in the network is organized in such a way that only an oscillator in a resonant state has an effective influence on the other oscillators of its group. In fact, such an oscillator plays the role of a central element for the whole group in the sense as introduced in Kazanovich and Borisyuk (1999). The dynamics of oscillators in this case has been termed as partial synchronization. During partial synchronization, the current frequencies of oscillators have a tendency to be entrained at the frequency of the central element or at least to approach this frequency. Therefore, the natural frequencies of oscillators in a group that contains a resonant oscillator will be moved in the direction of ω_0. The speed of movement depends on how far the natural frequency of an oscillator is from ω_0. The oscillators whose natural frequencies are in a close neighbourhood of ω_0 will change their natural frequencies to ω_0 (and, hence, will reach a resonant state) in a short enough time. If the natural frequency of an oscillator is far from ω_0, a number of repeated stimulations by the same stimulus will be needed to modify this natural frequencies to ω_0.

This is the basic mechanism for memory storage in the network: a stimulus is coded in the network memory by a sufficiently large population of oscillators with natural frequencies nearly identical to that of the input. Such a population is formed as a result of two processes. First, some oscillators in the group (with natural frequencies near ω_0) are phase-locked by other oscillators that are already in a resonant state. Second, this phase-locking results in these oscillators 'learning' the new frequency ω_0 (due to principle 2) and become resonant (due to principle 1).

After several oscillators in a group reach a resonant state, they combine their efforts to recruit other oscillators of the group to synchronization and resonance. The array of natural frequencies that have been formed during stimulation is conserved and later these frequencies are used as initial natural frequencies of oscillators during presentations of other stimuli. Note that the memory in the form of adapted natural frequencies is of a static type in the sense that it is supposed to be unchanged in the periods between stimuli presentations when the network is silent.

The inhibitory feedback loop (mentioned at the beginning of this section) is used to stop further changes of network parameters when the memory for a given stimulus is formed. In a session of repeated stimulations by the same stimulus, the population of resonant oscillators (the oscillators whose amplitudes exceed a certain level) gradually increases its size. We suppose that memorization of this stimulus is finished if the size of the population of oscillators in a resonant state exceeds a certain threshold level H. As soon as this event takes place, all the activity in the network is shut down by the inhibitory loop (the amplitudes and phases of all oscillators are kept equal to zero) until a new stimulation begins.

Let T_H be the time from the beginning of stimulation until the moment the threshold H is reached (by definition, $T_H = T$, the duration of stimulus presentation, if the threshold has not been reached during the current stimulation). We say that a network is in the *active* state during the time interval $(T_0, T_0 + T_H)$, where T_0 is the moment when some stimulation has started. In the active state the dynamics of the network are governed by equations (1)–(3). We say that a network is in the *passive* state during the time interval $(T_0 + T_H, T_1)$, where T_1 is the moment when the next stimulation has begun. In the passive state the phases and amplitudes of the oscillators are zero and the natural frequencies of the oscillators are unchanged.

During memorization of a given stimulus in repeated stimulations, T_H gradually decreases. We use this fact to formulate a criterion to distinguish between new and familiar stimuli. A stimulus is considered to be a new one if $T_H > T_{\text{cr}}$ and $T_{\text{cr}} < T$, where T_{cr} is a given threshold (critical time). If $T_H \leqslant T_{\text{cr}}$, a stimulus is considered to be familiar. In network simulations we put $T_{\text{cr}} = T/2$.

By computer simulation we show that it is possible to choose the parameters of the learning control in such a way that this criterion for novelty detection is satisfied. More precisely, in a sequence of presentations of the same stimulus, the stimulus will be recognized as a new one during the first few presentations, but from a certain presentation the stimulus will be recognized as familiar.

3. The simulation

As stated in the previous section, each stimulus is coded by both a frequency and a set of phase shifts. To make the computations less time consuming, we separate the consideration of stimuli coded by the same frequency and stimuli coded by different frequencies. In the first case, we simulate a large network with many groups of oscillators and show how different stimuli are coded in different locations of the network depending on the phase shifts. In the second case, we restrict the consideration to one group and show how different populations of oscillators in the group are involved in coding stimuli with different frequencies.

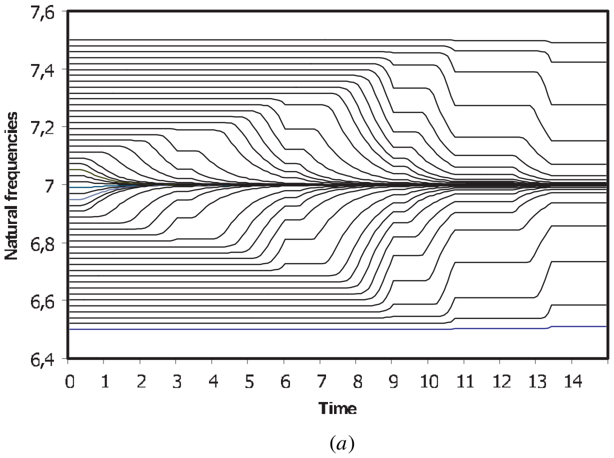
The learning procedure is the same in both cases. Four stimuli are presented in succession. Each stimulus is repeated five times at the moments $sT (s = 0, 1, \ldots, 4)$ (we denote by 0 the moment when stimulation by a new stimulus begins). The duration of each stimulation is $T = 3$, so learning of a stimulus takes 15 time units.

At the initial state (before learning) the natural frequencies of the oscillators in each group of the network are distributed with a fixed step in the range $(\omega_{\min}, \omega_{\max})$ so that $\omega_1 = \omega_{\min}$, $\omega_q = \omega_{\max}$, $\omega_{i+1} - \omega_i = \text{const}$.

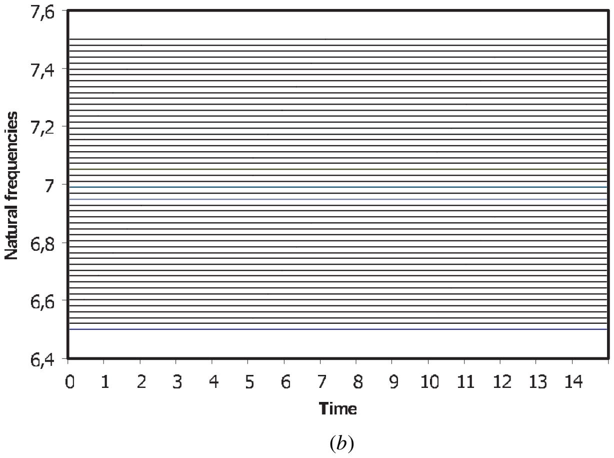
3.1. The case of identical input frequencies

We consider a network with the following parameters: the number of groups is $m = 500$, the number of oscillators in each group is $q = 50$, the range for distribution of initial values of natural frequencies of oscillators is (6.5, 7.5), the frequency code of all stimuli is $\omega_0 = 7$, phase shifts ψ_{ij} are randomly distributed in the range $(-\pi/2, \pi/2)$. In the criterion for novelty detection, we put $H = 450$ and $T_{\text{cr}} = 1.5$. Other parameter values are presented in table 5 of appendix A.

The parameters of the network have been chosen in such a way that five presentations of a stimulus are sufficient to memorize this stimulus. More precisely, for each stimulus the network reacts on its first P presentations $(1 \leqslant P < 5)$ as if to a new stimulus and the network reacts to the presentations $P + 1, \ldots, 5$ as if to a familiar stimulus. Usually, the number of groups with resonant oscillators involved in coding each stimulus in the simulation experiments was about 10–20, which is more than one order lower than the number of groups m. This ensured sparse coding of the stimuli in the network.



(*a*)

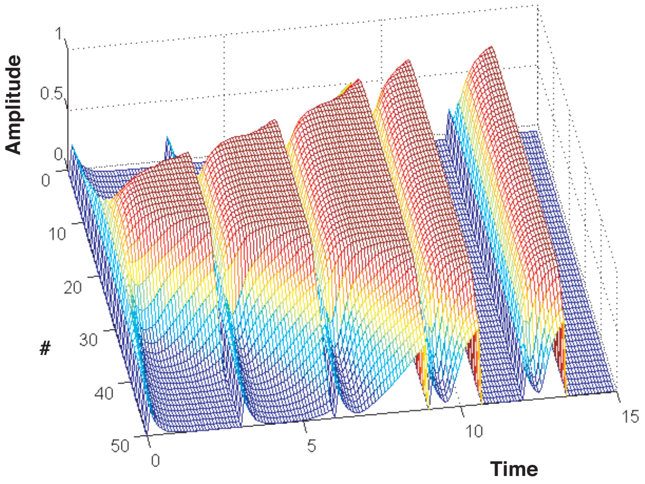


(*b*)

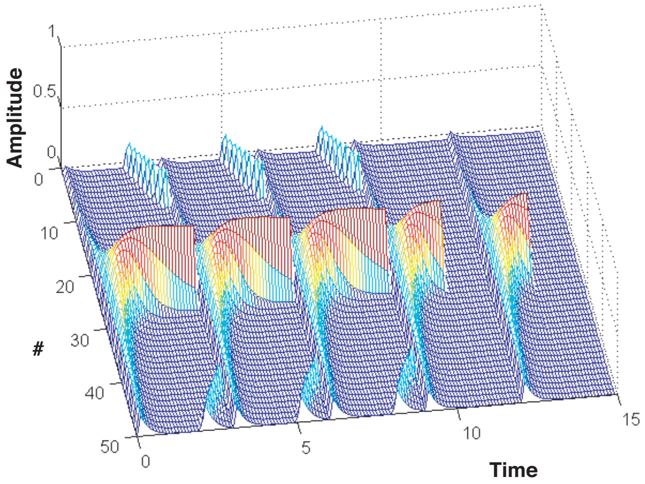
Figure 2. Evolution of the natural frequencies of the oscillators in two groups that receive coherent (*a*) and incoherent (*b*) input signals, respectively. In the first case, the oscillators tune their natural frequency to the frequency of the input signal. In the second case, the oscillators keep their natural frequencies unchanged. The same stimulus has been repeated five times at the moments 0, 3, 6, 9, and 12. The frequency code of the stimulus is $\omega_0 = 7$.

The results of the simulations are presented in figures 2–4. Figure 2 shows an example of the evolution of the natural frequencies of the oscillators in two groups during five presentations of the same stimulus. Figure 2(*a*) shows a group where resonant activity appeared in response to the given stimulus. Figure 2(*b*) shows a group where no resonant activity took place in response to the given stimulus. The adaptation of the natural frequencies is induced in the case of figure 2(*a*) only. The values of the natural frequencies in figure 2(*b*) do not change. In figure 2(*a*) the adaptation of the natural frequencies of those oscillators that were close to ω_0 started earlier and was faster. The size of the population of tuned oscillators in the group increases with repeated presentations of the same stimulus. Finally, nearly all oscillators of the corresponding group achieved approximately the same natural frequency.

Figure 3 shows the evolution of the amplitudes in the same groups. Those oscillators in figure 3(*a*) that have been synchronized with the input signal sharply increase their activity, while the oscillators in figure 3(*b*) work with a relatively low level of activity which does



(*a*)



(*b*)

Figure 3. Evolution of the amplitudes of the oscillators in the groups shown in figure 3: (*a*) resonant increase of amplitudes for coherent input signals; (*b*) low values of amplitudes for incoherent input signals. During the fourth and fifth stimulations, the activity of oscillators is shut down for a short time after stimulation begins due to recognition of the stimuli as familiar.

not reach the resonance level. In figure 3(*b*), a relatively small increase in amplitudes can be seen for those oscillators whose natural frequencies are near $\omega_0 = 7$. These oscillators are phase-locked by the input signal, but they do not reach resonance due to poor coincidence of phases in the input signal for this group of oscillators. There are also short spurious increases of amplitudes of those oscillators with low values of natural frequencies (in the neighbourhood of the value 6.5). Such effects take place at the moments when the phases of these oscillators reach the best coincidence with the phases of the input signals. In figure 3(*a*), the size of the

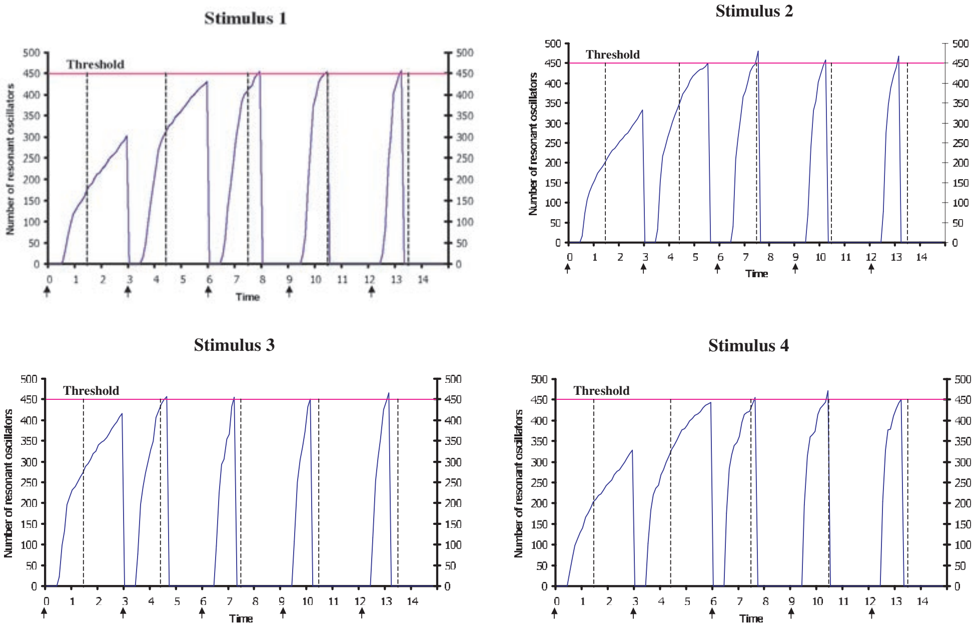


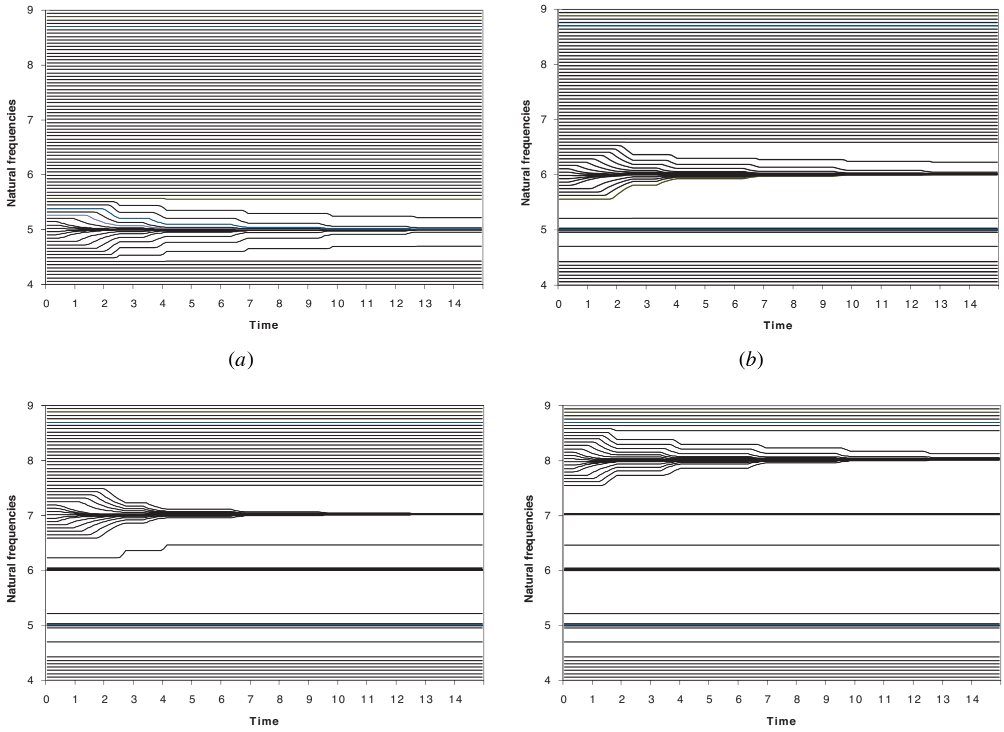
Figure 4. Graphics of the number of resonant oscillators in the network under stimulation by four stimuli. Each stimulus has been repeated five times. The moments when stimulations begin are shown by arrows. The vertical dashed lines show critical moments 1.5 time units after beginning a stimulation. A stimulus is detected as familiar if the number of resonant oscillators exceeds the threshold before the critical moment.

population of the oscillators with high amplitudes gradually increases from one stimulation to the other. During the fourth and fifth stimulations, the activity in both groups (in fact, in the whole network) is shut down before time T has past. This is the result of the fact that during these two stimulations the number of resonant oscillators exceeds the threshold H.

Figure 4 presents the behaviour of the number of resonant oscillators in the network for four stimuli. Dashed vertical lines show critical moments when discrimination between new and familiar stimuli is made. As can be seen from the figure, the number of resonant oscillators increases from one stimulation to the other and for the first time exceeds the threshold level H during the second or the third stimulation by the same stimulus. After that, the time T_H gradually decreases until it becomes smaller than T_{cr}. This is the moment when a stimulus is detected as familiar. In the given example, the number of repetitions of the same stimulus to make it familiar is 5, 4, 3, and 4, respectively.

3.2. The case of different input frequencies

To illustrate the memorization of stimuli coded by different frequencies, we need a larger number of oscillators in the groups and a larger range of distribution of their natural frequencies. We put $q = 250$, $\omega_{\min} = 4$, $\omega_{\max} = 9$ and consider a network with one group only ($m = 1$). This is enough for illustrative purposes because in a network with many groups the mechanism of memorization is the same for each group where resonant oscillations appear. To ensure the appearance of resonance in the group, we narrow the range of phase shifts of a stimulus to $(-0.4, 0.4)$. The number of resonant oscillators in the group is restricted by the threshold $H = 50$. This allows the possibility of memorizing several frequencies since each stimulus



(*a*) (*b*)

(*c*) (*d*)

Figure 5. Evolution of natural frequencies of oscillators in one group under stimulation by four stimuli coded by different frequencies (83 out of 250 oscillators are shown). The frequencies of input signals are 5 (*a*), 6 (*b*), 7 (*c*), and 8 (*d*), respectively. Each stimulus has been repeated five times at the moments 0, 3, 6, 9, and 12. Note that each stimulus indices the evolution of natural frequencies in its own population of oscillators, leaving the natural frequencies of other oscillators unchanged.

of a given frequency is memorized by its own ensemble of oscillators. The frequency codes ω_0 of the four stimuli are 5, 6, 7, and 8, respectively. Other parameter values are presented in table 5 of appendix A.

The results of the simulations are presented in figures 5, 6. Figure 5 shows an example of the evolution of the natural frequencies of the oscillators during the stimuli presentations (each stimulus is repeated five times). Figure 5(*a*) corresponds to the first stimulus with the frequency code $\omega_0 = 5$. It can be seen that presentation of this stimulus results in a gradual adaptation of the natural frequencies of those oscillators whose initial values of natural frequencies were located in the neighbourhood of $\omega_0 = 5$. After several presentations of the first stimulus, a population of oscillators with frequencies approximately equal to five is formed. This population codes the stimulus in the network memory.

In a similar way, figures 5(*b*)–(*d*) show the formation of ensembles of tuned oscillators corresponding to other stimuli. Note that the presentation of the next stimulus does not corrupt the memory that has been formed already. The natural frequencies in a population of tuned oscillators formed by one stimulus are kept unchanged during presentations of the other stimulus if the frequency codes of these stimuli are far away from each other.

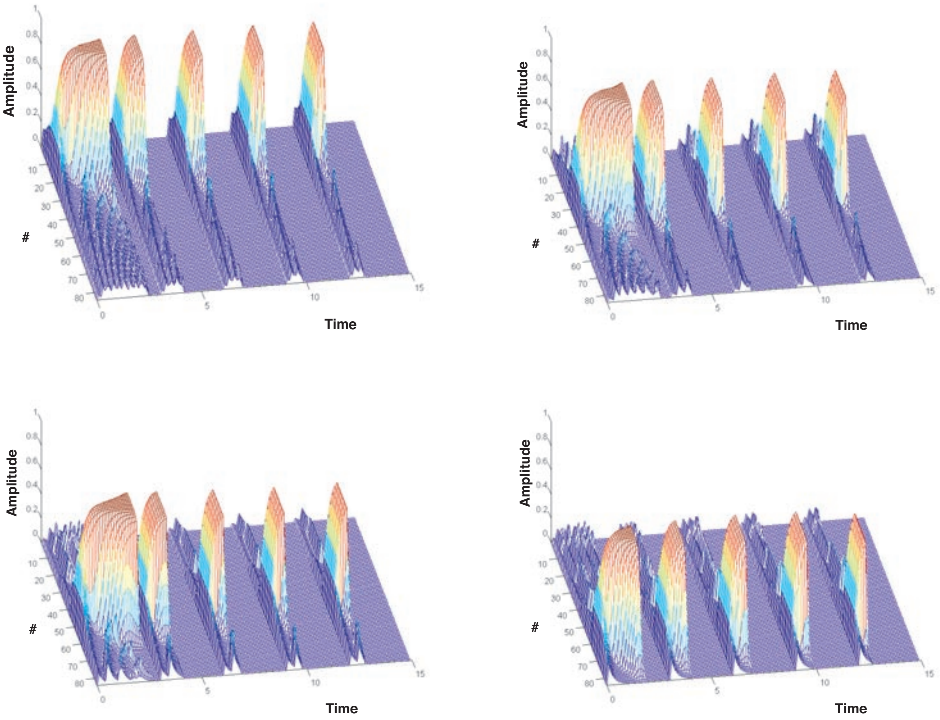


Figure 6. Evolution of amplitudes of the same oscillators as in figure 5. Note the correspondence between resonant increase of amplitudes of oscillators in the figure and adaptation of natural frequencies of oscillators shown in figure 5.

Figure 6 shows the evolution of the amplitudes of the oscillators. Those oscillators that have been working in-phase with the input signal sharply increase their activity, while other oscillators work with a relatively low level of activity. The size of a population of tuned oscillators increases and the time T_H gradually decreases with repeated presentations of the same stimulus. As expected, for each stimulus a resonant increase in the amplitudes and an adaptation of the natural frequencies occur in the same oscillators.

After four stimuli have been presented, four populations of tuned oscillators are formed, each population being tuned to the frequency of the corresponding input signal. Such a population is used as a code of the stimulus in the frequency domain. The presentation of the learned stimulus results in rapid synchronization of the oscillators of the population coding this stimulus, therefore the number of resonant oscillators quickly reaches the threshold level H and after that the activity in the network is stopped.

In a network with one group of oscillators, the memorization in the frequency domain is possible only if the difference between the input signal frequencies is sufficient to make the coding populations of oscillators non-overlapping. Due to the restricted range of frequencies, a limited (and relatively small) number of different stimuli can be coded in the frequency domain. However, a combination of both space and frequency codes, as described in section 3, makes the memory capacity potentially unlimited when the number of groups in the network increases.

4. Estimation of novelty detection reliability

Consider a sequence of r different stimuli presented in succession to a network for novelty detection, each stimulus being repeated K times. Three results of presentation of a particular stimulus of the sequence may appear: (a) a stimulus has been recognized as familiar during its kth presentation $(1 < k \leqslant K)$, (b) a stimulus has been recognized as familiar during its first presentation, (c) a stimulus has never been recognized as familiar during all K presentations. Case (a) corresponds to a correct processing of the stimulus during novelty detection. Cases (b) and (c) correspond to errors in novelty detection. In this section we are going to present some results on the estimation of the number of errors during novelty detection. Since different sequences of stimuli can give a different number of errors, to get an idea of how reliable the network is for novelty detection, we compute the average number of errors made after the presentation of a sample of randomly chosen sequences with r different stimuli. Every presentation of a sequence of stimuli starts with 'empty' network memory, that is, all the natural frequencies of the network oscillators are in the initial state. Averaging is done via the size of the sample of sequences used in the network testing. We denote by E_r the average number of novelty detection errors and will consider this value to be a measure of the novelty detection reliability.

In what follows, we present some results on estimating E_r by Monte Carlo simulations. Our simulations are limited to the case of stimuli coded by a fixed frequency (considered in section 3.1) and therefore this study should be considered as a first step in a more detailed investigation of novelty detection characteristics.

For the simulations, we have used a network with the same parameter values as defined in section 3.1 (see also table 5 in appendix A). The only difference with respect to this subsection is that a sequence of $r = 20$ different stimuli (each stimulus being repeated $K = 5$ times) has been presented to the network and a sample of ten such sequences has been processed by the network. For each stimulus, its time delay codes have been chosen randomly and independently from other stimuli.

The following simulation results were obtained. The full number of errors was 18. All errors were of type (b), that is, in all 18 cases a new input pattern was mistakenly detected as familiar at the first presentation of a stimulus. Since the whole number of stimuli in the sample of sequences was 200, this gives, on average, 9% of errors. About 6% of these errors were made during the detection of the last ten of the 20 input stimuli. This is reasonable, because the probability of an error increases as the network memory is filled.

Let us consider the source of errors in more detail. Since the number of oscillators tuned with the frequency ω_0 of the input signal monotonically increases during memorization, in the limit all oscillators of the network will have their natural frequencies equal to ω_0. Then, presentation of any stimulus will result in its detection as familiar. (Note, that similar effects of memory overflow that limit the number of memorized stimuli take place for networks with associative memory.) In an intermediate case, an error may appear if a new stimulus evokes resonant oscillations in the groups already associated with a previously learned stimulus. Then if the number of tuned oscillators in these groups exceeds the threshold H, an error in detection will occur.

With some simplification, this reasoning can be approximated by the following probabilistic model. Consider m empty boxes. Let us call a trial a random distribution of s balls in the boxes in such a way that each ball occupies a separate box $(s < m)$. If there is a sequence of trials, we suppose that the trials in the sequence are made independently. This means that during a trial the balls may fall into the boxes that have been occupied already on previous trials. u denotes the number of balls in a trial that fall into occupied boxes. Thus, u

Table 1. Normalized number of errors e_r in novelty detection; $r = 0.03m$, $p = 0.0$.

	s							
m	1	3	5	7	9	11	13	15
100	0.011	0.084	0.21	0.34	0.47	0.55	0.61	0.64
300	0.012	0.11	0.28	0.43	0.58	0.68	0.74	0.80
500	0.016	0.12	0.28	0.45	0.60	0.71	0.77	0.82
700	0.016	0.12	0.28	0.46	0.60	0.71	0.78	0.83
900	0.014	0.12	0.29	0.46	0.61	0.72	0.79	0.83
1100	0.014	0.12	0.29	0.46	0.61	0.72	0.79	0.84
1300	0.016	0.12	0.29	0.47	0.62	0.72	0.79	0.84
1500	0.014	0.12	0.29	0.47	0.62	0.72	0.79	0.84

is a random value that depends on the number of boxes filled on previous trials. Therefore the probability that u will take a greater value increases with the number of trials. If u is greater than a given constant p, we say that an error in balls distribution has appeared during the trial. E_r denotes the average number of errors that appear in a sequence of r trials (averaging is carried out for all sequences of r trials). Than the average value of the probability of making an error in one trial is $e_r = E_r/r$. Below we present some results on the estimation of e_r for different values of m, s, r, and p obtained by Monte Carlo simulation. In the computations, averaging has been carried out for 1000 sequences of trials for each value e_r.

The correspondence between the above probabilistic model and the problem of estimation of novelty detection reliability is evident. The m groups of the network are associated with the m boxes in the model. Memorizing a stimulus that is coded by the oscillators of s groups is associated with a trial (distribution of s balls among m boxes). So, if a group j of oscillators participates in coding the stimulus by tuning the frequencies of these oscillators, we associate this event with the occupation of the box j by a ball. Our assumption about random distribution of the balls in a trial follows from random distribution of input signal phase shifts. An error in the distribution of balls is associated with an error in novelty detection.

The simplifications introduced in the probabilistic model are the following. First, it is assumed that the number of groups s that participate in coding a stimulus is constant. In fact, this value varies for different stimuli. Second, it is assumed that memorizing a stimulus after a sufficient number of stimulus presentations gives one of the following two results for a group of oscillators: (1) all oscillators of the groups are tuned to the frequency ω_0; (2) no oscillator of the group changes its frequency in response to the given stimulus. In fact, the number of oscillators in a group that codes the stimulus depends on how good the coincidence of input phase shifts is at this group. Due to such simplifications, the estimation of E_r cannot be considered as a rigorous approximation of memory reliability. Yet, such an estimation sheds some light on what kind of reliability can be expected in the network. In particular, by these results we can judge under which parameter values the novelty detection can be of any use.

Tables 1–4 show the values of e_r for the following cases. Each table represents the values of e_r obtained for different values of m (m varies between 100 and 1500) and s (s varies between 1 and 15). Tables 1, 2 correspond to $r = 0.03m$. Tables 3, 4 correspond to $r = 0.05\,m$. In other words, the number of memorized stimuli is 3 or 5% of the number of groups of oscillators, respectively. Tables 1 and 3 correspond to the case $p = 0$. In this case no overlapping between the groups coding different stimuli is allowed. Tables 2 and 4 correspond to the case $p = [s/2]$, when half of the groups coding a stimulus may overlap with the groups coding previous stimuli.

Table 2. Normalized number of errors e_r in novelty detection; $r = 0.03m,\ p = [s/2]$.

	s							
m	1	3	5	7	9	11	13	15
100	0.011	0.0047	0.0013	0.0020	0.0023	0.0047	0.006	0.007
300	0.013	0.0062	0.0061	0.0044	0.0069	0.0072	0.014	0.020
500	0.012	0.0067	0.0055	0.0065	0.0072	0.011	0.013	0.022
700	0.016	0.0066	0.0055	0.0050	0.0061	0.0094	0.014	0.021
900	0.015	0.0070	0.0053	0.0060	0.0076	0.0093	0.015	0.022
1100	0.015	0.0058	0.0055	0.0066	0.0079	0.0110	0.015	0.023
1300	0.015	0.0068	0.0058	0.0061	0.0077	0.0110	0.016	0.023
1500	0.014	0.0068	0.0057	0.0066	0.0082	0.0110	0.016	0.024

Table 3. Normalized number of errors e_r in novelty detection; $r = 0.05\ m,\ p = 0.0$.

	s							
m	1	3	5	7	9	11	13	15
100	0.022	0.16	0.37	0.54	0.66	0.73	0.77	0.79
300	0.022	0.180	0.41	0.60	0.73	0.81	0.85	0.88
500	0.023	0.19	0.42	0.61	0.74	0.82	0.87	0.89
700	0.023	0.19	0.42	0.62	0.75	0.82	0.87	0.90
900	0.023	0.19	0.42	0.62	0.75	0.82	0.87	0.90
1100	0.024	0.19	0.42	0.62	0.75	0.83	0.87	0.90
1300	0.024	0.19	0.42	0.62	0.75	0.83	0.88	0.91
1500	0.025	0.19	0.42	0.62	0.75	0.83	0.88	0.90

Table 4. Normalized number of errors e_r in novelty detection; $r = 0.05\ m,\ p = [s/2]$.

	s							
m	1	3	5	7	9	11	13	15
100	0.021	0.012	0.014	0.023	0.032	0.043	0.08	0.13
300	0.021	0.016	0.021	0.027	0.042	0.066	0.10	0.14
500	0.024	0.016	0.019	0.029	0.045	0.069	0.10	0.15
700	0.026	0.018	0.021	0.027	0.046	0.068	0.11	0.15
900	0.024	0.018	0.021	0.031	0.046	0.071	0.11	0.15
1100	0.025	0.019	0.020	0.031	0.046	0.073	0.11	0.15
1300	0.023	0.018	0.021	0.030	0.048	0.072	0.11	0.15
1500	0.024	0.018	0.021	0.031	0.046	0.072	0.11	0.15

In terms of network memory reliability, the tables illustrate two trivial and two non-trivial facts. Firstly, considering tables 1 and 3, one can see that the values of e_r in table 1 are smaller than the values in the same cells of table 3. The same is true for tables 2 and 4. Note that the only difference between these pairs of the tables is the value of r/m, which is smaller for tables 1, 2 than for tables 3, 4. This reflects an intuitively obvious fact that the probability of making an error in novelty detection increases as the memory is filled with a larger number of memorized stimuli.

Secondly, permitting an overlap between the groups coding different stimuli decreases the relative number of errors. For example, if $p = 0$ and $s \geqslant 5$ (tables 1, 3), the values of e_r exceed 0.2. Such a large number of errors is too high for novelty detection to be of any use.

Yet, if overlapping is permitted, the probability of making an error becomes much smaller. All the values of e_r in tables 2, 4 are smaller than 0.1, excluding the last two columns in table 4.

The other two facts are not so obvious. Looking at the columns of the tables, one can notice that for higher values of m, the values of e_r show a tendency to increase to an asymptotic level. This can be interpreted as an asymptotically linear increase of memory capacity when m increases. Note that the number of parameters in the network used for memorization (the natural frequencies of oscillators) is $n = qm$. Thus, the memory capacity is of the same order as the number of modified parameters n. This memory characteristic is better than the one known for associated memory of a Hopfield type, where the memory capacity is of the order of $\sqrt{n}$, where n is the number of modified parameters (connection strengths).

Looking at the rows, one can see that the values of e_r in tables 2 and 4 do not show a tendency to increase monotonically as in tables 1 and 3. This means that in the case where overlap is permitted there is an optimal value of s (greater than 1) that gives the minimum probability of errors. This optimal value of s is rather small relative to the number of groups m. This confirms that only sparse coding of stimuli in the groups of the network is efficient. In our network model the number of groups participating in coding a stimulus is controlled by the parameter ξ_2 in equation (2) of appendix A. Increasing this parameter results in decreasing the number of groups involved in stimulus coding.

5. Discussion

We have developed a new approach to modelling memory formation and novelty detection. This approach is formulated in terms of oscillatory mechanisms realized by an oscillatory neural network with an inhibitory backward control loop. For information storage instead of the traditionally used modification of connection strengths, we consider modification of the natural frequencies of oscillators. In relation to this new approach to memory formation we suggest a new encoding scheme that is based on the phase–frequency characteristics of the input signal.

We assume that a stimulus is coded at the input of the network as an n-dimensional vector, whose components are periodic oscillations of identical frequencies and different phases. A similar idea of information encoding is used in a phase modulation scheme suggested by Hoppensteadt and Izhikevich (1998) for their oscillatory neural network implementation of the FM radio. The differences in-phase shifts of the input signals result in different responses of the oscillators. Those oscillators that receive coherent (nearly in-phase) input signals and that are phase-locked with a small phase shift relative to the input, start to generate high amplitude (resonant) oscillations, while other oscillators are silent or work with low amplitudes of oscillations.

The resonant oscillators modify their natural frequencies to the frequency of the input signal. Thus, memorization of a stimulus results in the formation of groups of oscillators tuned to the frequency of a given stimulus frequency code and distributed in different locations of the network.

Resonant oscillations play a crucial role in this mechanism for novelty detection. If the frequency of the input signal coincides with the natural frequency of an oscillator and if this oscillator receives coherent input signals, the amplitude of oscillations in this oscillator rapidly increases. Such rapid and simultaneous increase of activity of a critical number of oscillators is detected by the inhibitory backward control loop. Thus the dynamics of the network can be organized in such a way that the activity of the network continues for a long time in the case of a novel stimulus (tonic reaction) and the activity is shut down much faster in the case of a familiar stimulus (phasic reaction).

Some ideas used in this paper for the model of novelty detection have already appeared in our previous publications:

- phase–frequency encoding of the input information (Borisyuk and Borisyuk 1997);
- phase coincidence as a mechanism for choosing memory storage location (Borisyuk and Hoppensteadt 1998, 1999);
- partial synchronization as an important type of dynamics for tuning neural oscillators (Kazanovich and Borisyuk 1994, 1999).

Frequency adaptation as a mechanism for memory storage has been suggested in the paper (Torras 1986), where the author presented a network of biologically plausible neurons for the storage of information about two stimuli in frequency domain. Our approach can be considered as a generalization of this result to memorization in the space–frequency domain. The main advantage of our approach is in the combination of space and frequency coding of information in the network memory so that stimuli coded by the same frequency are stored in different regions of the network. As a result, the network memory is potentially unlimited.

The memory that we model is a temporary type. In terms of the model, we assume that the oscillator tuning is not kept forever. Without constant repetition of the same stimulus the oscillators that code this stimulus gradually return to their initial natural frequencies, i.e. 'recall' their original natural frequencies. Thus, the memory about this particular stimulus is freed for the storage of other stimuli.

The oscillatory neural network model developed in this paper has been inspired by some fascinating experimental evidence about the orienting reflex and theta activity in the septo-hippocampal region (Sokolov 1975, Vinogradova 1995). The presentation of a new stimulus elicits high and stable theta-rhythmic activity of the hippocampus. This activity continues with a slow decrease long after the stimulus is switched off. This is the so-called tonic reaction of the hippocampus. On the other hand, when this stimulus becomes familiar after a sufficient number of presentations, the theta-activity response of the hippocampus to the stimulus is brief and vanishes swiftly after the stimulus is switched off. This is the so-called phasic response of the hippocampus. The phasic response demonstrates habituation in the theta-activity of the hippocampus. It may be presumed that the theta-activity is necessary for information processing and memory storage and it can be used as an efficient mechanism for selecting what should be processed and stored.

There are two ways by which the information about a stimulus reaches the hippocampus. The main information channel, which delivers the stimulus information to the hippocampus, goes first to the neocortex, where certain features of the stimulus are extracted and combined, then to the entorhinal cortex, and thence to the hippocampus. The spatial distribution of inputs from the entorhinal cortex to the hippocampus causes different time delays, which result in-phase lags that may be as high as one half of the period of the theta rhythm (Miller 1991). The other channel, which goes via the reticular formation, the medial septum and eventually to the hippocampus, reflects the significance (in some context) of the signal. Experimental data suggest that the signals in both inputs to the hippocampus contain theta rhythm frequencies (Vinogradova 1995, Iijima *et al* 1996, Kirk 1998). The septal signal is responsible for appearance and disappearance of the theta-activity in the hippocampus (Vinogradova 1995), while the signal from the entorhinal cortex seems to control this activity in a more delicate way according to the informational characteristics of the stimulus. There is some experimental evidence for a special type of phase relationship between hippocampal neural activity and the theta wave during spatial information processing in the hippocampus (O'Keefe and Reece 1993).

Trying to reproduce tonic and phasic types of hippocampal dynamics in our model of novelty detection, we do not claim that the suggested mechanisms of novelty detection exactly reflect those used in the septo-hippocampal system. Despite many studies of this system and the availability of a huge amount of experimental evidence, there are still many open questions. For example, in a recent review by Eichenbaum (1999) it is stated that: ‘Recent successes in functional brain imaging have suggested that the hippocampus is part of a novelty-detection network; but consideration of the available evidence and of the cognitive demands of novelty processing suggests that things are not so simple’. Nevertheless, we think that some aspects of our model may be useful in developing a biologically plausible model of novelty detection in the hippocampus.

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Appendix A. Dynamics of the network

The network consists of m groups of oscillators. Each group contains q oscillators. There are all-to-all connections between oscillators of one group while there are no connections between oscillators of different groups. During stimulation each oscillator receives an n-dimensional ($n = 20$) periodic input signal $C = (C_1, \ldots, C_n)$, where $C_i = \sin(2\pi\omega_0 t + \psi_{ij})$ ($i = 1, \ldots, n$, $j = 1, \ldots, m$). The parameters ω_0 and ψ_{ij} represent the frequency of the input signal and phase shifts, respectively. An oscillator is described by three variables: oscillator phase θ_k^j; amplitude a_k^j; and natural frequency ω_k^j ($j = 1, \ldots, m$, $k = 1, \ldots, q$): the dynamics of the network in the active state is determined by the following differential equations:

$$\frac{\mathrm{d}\theta_k^j}{\mathrm{d}t} = 2\pi\omega_k^j + \frac{v}{n}\sum_{i=1}^{n}\sin(2\pi\omega_0 t + \psi_{ij} - \theta_k^j) + \frac{w}{q}\sum_{l=1}^{q} g_1(a_l^j)\sin(\theta_l^j - \theta_k^j), \tag{1}$$

$$\frac{\mathrm{d}a_k^j}{\mathrm{d}t} = -\beta a_k^j + \gamma g_2\left(\frac{1}{n}\sum_{i=1}^{n}\cos_+^2(\omega_0 t + \psi_{ij} - \theta_k^j)\right), \tag{2}$$

$$\frac{\mathrm{d}\omega_k^j}{\mathrm{d}t} = -\alpha\, g_1(a_k^j)\left(\omega_k^j - \frac{\mathrm{d}\theta_k^j}{\mathrm{d}t}\right), \tag{3}$$

where $v, w, \alpha, \beta, \gamma$ are positive parameters;

$$\cos_+(x) = \begin{cases} \cos(x), & \text{if} \quad \cos(x) > 0, \\ 0, & \text{otherwise,} \end{cases}$$

g_1 and g_2 are sigmoid functions of the form

$$g_i(x) = \frac{\exp((x - \xi_i)/\eta_i)}{1 + \exp((x - \xi_i)/\eta_i)}, \qquad (i = 1, 2)$$

with parameters ξ_1, η_1 and ξ_2, η_2, respectively.

Equation (1) represents a traditional description of phase-locking. The second term in the right part of this equation describes the influence of the input signal, the third term describes internal interactions in the group. Due to the multiplier $g_1(a_l^j)$, only oscillators in a resonant state can efficiently influence on the other oscillators of their group.

Table 5. The values of parameters used in computations of network dynamics.

Parameters	Values	Parameters	Values
m	500	w	16
n	20	ξ_1	0.7
q	50	η_1	0.02
α	1	ξ_2	0.86
β	4	η_2	0.02
γ	4	T	3
v	0.5	T_{cr}	1.5

Equation (2) provides different amplitudes for resonance and non-resonance response of an oscillator. Note that the second term in the right part of this equation reaches its maximum value for those oscillators which work approximately in-phase with the input.

Equation (3) provides the frequency learning mechanism. According to this equation, the natural frequency of an oscillator changes in the direction of the current frequency of this oscillator. The parameter α regulates the speed of adaptation of natural frequencies. The value of α provides the rate of adaptation of natural frequencies that is much slower than changes in the current frequency. The multiplier $g_1(a_k^j)$ restricts frequency adaptation to those oscillators that have reached a resonant state.

The parameters in equation (1) are chosen so that the oscillators with natural frequencies near ω_0 will be phase-locked by the input signal at the frequency ω_0. If phase shifts between such an oscillator and the input are near zero, the argument of the function g_2 in equation (2) will be about 1. The parameters ξ_2 and η_2 are chosen so that $g_2(x)$ approaches to 1 for $x \in (\xi_2, 1)$, where ξ_2 is slightly lower than 1; also $g_2(x)$ is rapidly vanishing for $x < \xi_2$. This implies that if an oscillator works nearly in-phase with the input signal, the second term in the right side of (2) will be about γ, hence the amplitude a_k^j will have a stable state at about $R = \gamma/\beta$. In this case we have a resonant state of the oscillator.

For an oscillator that is not capable of running nearly in-phase with the input most of the time, the argument of the function g_2 will be much lower than ξ_2, hence the amplitude of such an oscillator will stabilize near zero, which implies that the oscillator is in a non-resonant state.

The parameter values used in the simulation are presented in table 5. According to these parameters, the maximum amplitude in a resonant state is $R = 1$. An oscillator is defined as being in a resonant state if its amplitude is greater than $0.8R$.

Appendix B. Phase-locking condition

We are going to find conditions when a phase oscillator can be phase-locked by the input which combines the signals of the same frequency but with different phase shifts. This is a generalization of a similar result obtained in Borisyuk and Hoppensteadt (1999) for the input of two signals.

Let us consider an oscillator whose dynamics is determined by the equation

$$\dot{\theta} = \omega + \mu \sum_{i=1}^{n} \sin(\omega_0 t + \psi_i - \theta).$$

This equation can be written in an equivalent form as

$$\dot{\theta} = \omega + \mu \sum_{i=1}^{n} \sin[(\omega_0 t + \tilde{\psi} - \theta) + (\psi_i - \tilde{\psi})] = \omega + \left(\mu \sum_{i=1}^{n} \cos(\psi_i - \tilde{\psi})\right)$$

$$\times \sin(\omega_0 t + \tilde{\psi} - \theta) + \left(\mu \sum_{i=1}^{n} \sin(\psi_i - \tilde{\psi})\right) \cos(\omega_0 t + \tilde{\psi} - \theta).$$

There is a value of $\tilde{\psi}$ for which the second term in the right part of the equation is equal to 0,

$$\sum_{i=1}^{n} \sin(\psi_i - \tilde{\psi}) = \left(\sum_{i=1}^{n} \sin\psi_i\right) \cos\tilde{\psi} - \left(\sum_{i=1}^{n} \cos\psi_i\right) \sin\tilde{\psi} = 0.$$

Hence

$$\tan\tilde{\psi} = \frac{\left(\sum_{i=1}^{n} \sin\psi_i\right)}{\left(\sum_{i=1}^{n} \cos\psi_i\right)}.$$

For this value of $\tilde{\psi}$ the equation for θ takes the form

$$\dot{\theta} = \omega + \left(\mu \sum_{i=1}^{n} \cos(\psi_i - \tilde{\psi})\right) \sin(\omega_0 t + \tilde{\psi} - \theta).$$

Denote

$$Q = \mu \sum_{i=1}^{n} \cos(\psi_i - \tilde{\psi}).$$

The condition for phase-locking is

$$|\omega - \omega_0| \leqslant Q.$$

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