

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.

1. Introduction

Current opinion about information processing in the brain presumes that biological memory systems constantly make decisions concerning the storage of incoming information. 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 to avoid storage of redundant information and to concentrate 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 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.

Recently, Borisjuk 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 generalised in two respects. First, we consider multidimensional input signals (the dimension is more than 2) 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 transformation of time-frequency code at the input of the network into 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 memorising 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 memorisation through adaptation of natural frequencies of oscillators. We suppose that the input signal synchronises 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 has 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 $0.5 * N^2$.

Another component of our model is 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 of 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 ART-networks to distinguish between the objects belonging to a learned category and the objects belonging to previously unseen category (Carpenter and Grossberg, 1987a, 1987b; 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 oscillators interaction 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 synchronisation 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 generalisation 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 synchronisation 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 the synchronisation 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 1997; Hoppensteadt and Izhikevich, 1997; Wu and Guo, 1999).

2. Model description

The model for novelty detection is a network of oscillators with a loop of inhibitory feedback control (Fig. 1). The oscillators are combined into groups $G_j (j = 1, \dots, m)$ 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 $C = (C_1, \dots, C_n)$ with the components $C_i = \sin(\omega_0 t + \psi_{ij})$ ($i = 1, \dots, n, j = 1, \dots, m$). 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 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 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 at the beginning of a new stimulation (no memory decay). These modified natural frequencies are the only information stored by the network about 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. This type of activity appears during both memorization and recall. We call it a sparse representation (coding) of stimuli in 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 memorised 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 memorised in different locations of the network.

Memory storage is conditioned by specially organised dynamics of oscillators and 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 is controlled by a phase-locking procedure (1). Phase-locking is used to synchronise some oscillators with the input signals. Analytical description of conditions for phase locking in the case of a multidimensional 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)). In particular, this implies that this oscillator is synchronised 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 synchronisation, 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 organised 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 it has been introduced in (Kazanovich and Borisyuk, 1999). During partial synchronisation, the current frequencies of oscillators have a tendency to synchronise with the frequency of the central element or at least to approach it. 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 is the natural frequency of an oscillator 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 recruited to synchronisation and resonance by oscillators that are already resonant. Second, due to principle 2 the synchronisation results in these oscillators "learning" the new frequency. Thus their natural frequencies are gradually tuned to the frequency ω_0 .

After several oscillators in a group reach a resonant state, they combine their efforts to recruit other oscillators of the group to synchronisation 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 r) 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) for all the time 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, $T_H = T$ if the threshold has not been reached during current stimulation). We say that a network is in the *active* state during 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 is governed by equations (1-3). We say that a network is in the *passive* state during 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 oscillators are zero and the natural frequencies of oscillators are unchanged.

During memorisation 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 as a new one if $T_H > T_{cr}$ and $T_{cr} < T$, where T_{cr} is a given threshold (critical time). If $T_H \leq T_{cr}$, a stimulus is considered as familiar. In network simulations we put $T_{cr} = T/2$.

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

3. The simulation

As we stated in the previous section, each stimulus is coded by both a frequency and a set of phase shifts. To make 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 make simulation in a large network with many groups of oscillators and show how different stimuli are coded in different locations of the network depending on 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 5 times at the moments sT ($s = 0, 1, \dots, 4$) (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 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 $T_{cr} = 1.5$. Other parameter values are presented in Table 5 of Appendix A.

The parameters of the network have been chosen in such a way that 5 presentations of a stimulus are sufficient to memorise this stimulus. More precisely, for each stimulus the

network reacts on its first P presentations ($1 \leq P < 5$) as to a new stimulus and the network reacts on the presentations $P + 1, \dots, 5$ as to a familiar stimulus. Usually, the number of groups with resonant oscillators involved in coding each stimulus in simulation experiments has been about 10 – 20, which is more than one order lower than the number of groups m . This insured sparse coding of stimuli in the network.

The results of simulations are presented in Figs.2-4. Fig.2 shows an example of evolution of natural frequencies of oscillators in two groups during 5 presentations of the same stimulus. Fig.2a shows a group, where resonance activity appeared in response to the given stimulus. Fig.2b shows a group where no resonance activity takes place in response to the given stimulus. The adaptation of natural frequencies is induced in the case of Fig.2a only. The values of natural frequencies in Fig.2b do not change. In Fig.2a the adaptation of 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 obtained approximately the same natural frequencies.

Fig.3 shows the evolution of amplitudes in the same groups. Those oscillators in Fig.3a that have been synchronised with the input signal sharply increase their activity, while oscillators in Fig.3b work with a relatively low level of activity which does not reach the resonance level. In Fig.3b, relatively small increase of amplitudes can be seen for oscillators whose natural frequencies are near $\omega_0 = 7$. These oscillators are synchronised 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 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 Fig.3a, the size of the population of 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 .

Fig.4 presents the graphics of the number of resonant oscillators in the network for 4 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 memorisation 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 memorisation is the same for each group where resonance oscillations appear. To ensure the appearance of the 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 gives the possibility to memorise several frequencies since each stimulus of a given frequency is memorised by its own ensemble of oscillators. The frequency codes ω_0 of four stimuli are 5,6,7, and 8, respectively. Other parameter values are presented in Table 5 of Appendix A.

The results of simulation are presented in Figs 5-6. Fig.5 shows an example of evolution of natural frequencies of oscillators during stimuli presentations (each stimulus is repeated 5 times). Fig.5a corresponds to the first stimulus with the frequency code $\omega_0 = 5$. It can be seen that presentation of this stimulus results in 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 the frequencies approximately equal to 5 is formed. This population codes the stimulus in the network memory.

In a similar way, Figs.5b-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 frequency codes of these stimuli are far away from each other.

Fig.6 shows the evolution of the amplitudes of 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. In line with the expectation, for each stimulus resonant increase of amplitudes and adaptation of 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 synchronisation of 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 memorisation in frequency domain is possible if only the difference between input signal frequencies is sufficient to make the coding populations of oscillators non-overlapping. Due to restricted range of frequencies, a limited (and relatively small) number of different stimuli can be coded in frequency domain. Yet, combination of both space and frequency codes described in Section 3 makes the memory capacity potentially unlimited when the number of groups in the network increases.

4. Estimation of memory reliability

The memory of a neural network can be associated with two parameters describing its quality: memory capacity and memory reliability. By the latter we mean the average number of errors made when trying to memorise different sets of input patterns. In what follows, we are going to suggest some estimates of memory reliability, basing on Monte-Carlo simulations. We suppose that input patterns are random. For a fixed size r of a set of stimuli and a number m of the groups in the network, we would like to compute the average number of errors that appear during novelty detection. Our simulations are limited to the case of stimuli with a fixed frequency (considered in Subsection 3.1) and therefore this study should be considered as a first step in more detailed investigations of memory characteristics.

For simulations, we have used a network with parameters defined in Subsection 3.1. The only difference with respect to this subsection is that a set of $r = 20$ different stimuli has been presented to the network during each test and 10 such tests have been made with different sets of stimuli. The full number of errors obtained in these tests was 18, that is in 18 cases a new input pattern was mistakenly detected as familiar at the first presentation of a stimulus. On average, this gives 9% of errors. About 6% of these errors have been made during detection of the last ten of 20 input stimuli. This is reasonable, because the probability of an error increases with network memory filling.

Let us consider the source of errors in more detail. Note that the number of oscillators tuned with the frequency ω_0 of the input signal monotonically increases during learning. In a 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. In an intermediate case, an error may appear if a new stimulus evokes resonant oscillations in the groups already associated with previously learned stimuli. Then if the number of tuned oscillators in these groups exceeds the threshold H , the error in detection will appear.

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. Denote by u the number of balls in a trial that fall into occupied boxes. If u is greater than a given constant p , we say that an error in balls distribution appeared during the trial. Denote by E_r the average number of errors that appear in a sequence of r trials. Below we present some results on estimation of E_r for different values of m , s , r , and p by Monte-Carlo simulation. Averaging has been made via 1000 sequences of trials for each value E_r .

The correspondence between the formulated model and the problem of estimation of memory reliability is evident. The groups in the network are associated with the boxes in the model. Learning a stimulus is associated with a trial (distribution of s balls among m boxes). If a group j of oscillators participates in coding the stimulus by tuning the frequencies of 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 balls distribution 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 learning a stimulus after 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 is the coincidence of input phase shifts at this group. Due to such simplifications, estimation of E_r cannot be considered as a rigorous approximation of memory reliability. Yet, such estimation puts 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 memory can be of any use.

The values presented in Tables 1-4 show normalised values $e_r = E_r / r$. The tables correspond to 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 $r = 0.05m$. In other words, the number of memorised stimuli is 3% or 5% of the whole number of groups, respectively. Tables 1 and 3 correspond to $p = 0$. Tables 2 and 4 correspond to $p = \lfloor s/2 \rfloor$. In the first case, no overlap is permitted between the groups coding different stimuli. In the second case, half of the groups coding a stimulus may overlap with the groups coding previous stimuli.

In terms of network memory reliability, the tables illustrate two trivial and two non-trivial facts: First, for a fixed number of groups the larger is the set of learnt stimuli the greater is the number of errors during novelty detection. This is the consequence of memory filling. Second, permitting an overlap between the groups coding different stimuli decreases the number of errors.

The other two facts are not so evident. Looking at the columns of the tables, one can notice that for higher values of m the values of e_r show the tendency to increase to an

asymptotic level. This can be interpreted as asymptotically linear increase of memory capacity when n increases. Looking at the rows, one can notice that the values of e_r in tables 2 and 4 do not show the tendency to increase monotonically like in tables 1 and 3. This means that in the case of permitted overlap there is an optimal value of s (greater than 1) that gives the minimal number 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 in stimulus coding.

5. Discussion

We have developed an oscillatory network for novelty detection basing on the following ideas that evolve from our previous results:

- 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 synchronisation as an important type of dynamics for tuning neural oscillators (Kazanovich and Borisyuk, 1994, 1999);
- frequency adaptation as a mechanism for memory storage;
- resonance as a recognition principle to detect items retained in the network memory.

By simulation experiments we have shown that the model can store the information about incoming stimuli and respond to new and familiar stimuli by different types of dynamical behaviour.

The storage of information is done in the space-frequency domain. This can be considered as a generalisation of the results obtained in the paper (Torrás, 1986), where the

author presented the storage of information about two stimuli in frequency domain. The ideas of this storage are similar to those described here in Section 3.2. The main difference is that C. Torras constructs the network from biologically plausible neurons while we use a network of phase oscillators. Such choice of a unit makes the dynamics of the network more evident and controllable. But the main advantage of our approach is in 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 made potentially unlimited, while C. Torras was able to demonstrate the storage of two stimuli only.

Until now we described the model of novelty detection in an abstract form without relating it to definite brain structures. This has been done purposefully because our main objective is to suggest some general oscillatory mechanisms of memory storage and novelty detection. Still, we should admit that our model was inspired by evidence of novelty detection in the hippocampus and we consider this structure as a most suitable candidate for the application of the model. Therefore, it would be interesting to compare anatomical and neurophysiological data on the role of the septo-hippocampal system in novelty detection with the results of our modelling.

The analysis of brain regions that are involved in reaction to novelty shows that the presentation of new stimuli induce higher activity in some neocortical structures (specific for the given type of stimulation), in the limbic system (including the hippocampal formation and parahippocampal gyrus) and the thalamus (Tulving et al., 1994). It is hypothesised that the hippocampus plays a co-ordinating role in forming the flow of information in the brain (Damasio, 1989) and is used as temporal information storage for the time interval between information coding and permanent storage in the neocortex (Squire, 1992).

It is known that the hippocampus has special types of activity in the range of the theta-rhythm (4-9 Hz) that are closely related to novelty detection (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.

Physiological and anatomical experiments indicate the complex three-dimensional structure of the hippocampus (Isaacson 1982; Amaral and Witter, 1989; 1995). One can visualise the hippocampus as being a 3-dimensional structure having a long septotemporal axis and a transverse plane that is orthogonal to the long axis. Each two-dimensional slice in the transverse plane contains three main regions: the dentate gyrus, the CA₁ field, and the CA₃ field. The connections between hippocampal neurons are as extensive and highly organised in the septo-temporal axis of the hippocampus as in the transverse plane (Amaral and Witter, 1989).

There are two ways by which information about a stimulus reaches the hippocampus. The main information channel goes via the neocortex, where certain features of the stimulus are extracted and combined, then it comes to the entorhinal cortex, and thence to the hippocampus. The spatial distribution of inputs from the entorhinal cortex to the hippocampus cause time delays, which result in phase lags which may be as high as one half of period of the theta-rhythm (Miller, 1991). Miller's theory of cortico-hippocampal interplay postulates that the memory is formed by appropriate resonant loops between the entorhinal cortex and the hippocampus, each with specific propagation time.

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. Physiological 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 informational characteristics of the stimulus.

There evidently is a correspondence between the septo-cortico-hippocampal system and the components of the model described above. The network represents the hippocampal model, a group of oscillators is supposed to describe the activity of hippocampal slice. The input C relates to the signal from the entorhinal cortex modulated by the theta-rhythm. The inhibitory signal that stops the activity in the network in the case of a familiar stimulus is supposed to be generated in the second channel and supplied to the hippocampus from the medial septum. We do not model in detail how the resonant activity in the hippocampus can be detected by brain circuits and transformed into such inhibitory signal. In principle, there are several possibilities that might be used to implement the inhibitory loop. First, the inhibitory connection from the hippocampus to the medial septum can be used to control and inhibit the theta activity in the medial septum (Denham and Borisyuk, 2000). There is also a loop from the hippocampus to the raphe nucleus and reticular formation that can be used for the same purpose. Finally, there is a complex loop of hippocampus interaction with the cortex whose functioning is essentially determined by long-term memory traces. Consideration of these complex mechanisms of novelty detection is certainly beyond the scope of our modelling.

In the model, we ignore the backward loop from the hippocampus to the cortex. This loop is known to be used for hippocampal control of information processing in the cortex and for long-term memory storage. On the contrary, the memory in the hippocampus that we

model is of a temporary type (working memory). In terms of the model, we assume that oscillator tuning is not kept forever. Without constant repetition of the same stimulus the oscillators that code this stimulus gradually "recall" their original natural frequencies. Thus, the memory about this particular stimulus is freed for the storage of other stimuli.

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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 $C = (C_1, \dots, C_n)$, where $C_i = \sin(\omega_0 t + \psi_{ij})$ ($i = 1, \dots, n, j = 1, \dots, m$). 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 ($j = 1, \dots, m, k = 1, \dots, q$): The dynamics of the network in the active state is determined by the following differential equations:

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

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

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

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

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

g_1 and g_2 are sigmoid functions of the form

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

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

Equation (1) represents a traditional description of phase synchronisation. 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 $g_1(a_i^j)$, only oscillators in a resonant state can efficiently influence on the other oscillators of their group.

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 synchronise their current frequencies at 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 parameter 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 from the first layer, 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 to run 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 stabilise near zero, which implies that the oscillator is in a non-resonant state.

Parameter values used in the simulation are presented in Table 1. 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. Synchronisation condition

We are going to find conditions when a phase oscillator can be synchronised by the input which combines the signals of the same frequency but with different phase shifts. This is a generalisation of a similar result obtained in (Borisjuk and Hoppensteadt,) 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

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

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

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 synchronisation is

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

Under synchronisation, the phase shift ψ of θ relative to $\tilde{\psi}$ will satisfy the equality

$$|\omega - \omega_0| \leq Q \sin(\tilde{\psi} - \psi)$$

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Table 1. Normalised number of errors e_r in novelty detection; $r = 0.03m, p = 0$.

m	s							
	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

Table 2. Normalised number of errors e_r in novelty detection; $r = 0.03m, p = \lfloor s/2 \rfloor$.

m	s							
	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. Normalised number of errors e_r in novelty detection; $r = 0.05m, p = 0$.

m	s							
	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. Normalised number of errors e_r in novelty detection; $r = 0.05m, p = \lfloor s/2 \rfloor$.

m	S							
	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

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

FIGURE CAPTIONS

Fig. 1. Network architecture. The oscillators are combined into groups G_j ($j = 1, \dots, m$) with all-to-all connections between oscillators in the groups. There are no connections between oscillators of different groups. Each oscillator receives a multidimensional input signal C . The inhibitory backward loop stops the activity in the network after the number of resonant oscillators exceeds a threshold level.

Fig. 2. Evolution of natural frequencies of 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 5 times at the moments 0, 3, 6, 9, and 12. The frequency code of the stimulus is $\omega_0 = 7$.

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

Fig. 4. Graphics of the number of resonant oscillators in the network under stimulation by four stimuli. Each stimulus has been repeated 5 times. The moments when stimulations begin are shown by arrows. 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.

Fig. 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 5 times at the moments 0, 3, 6, 9, and 12. Note that each stimulus induces the evolution of natural frequencies in its own population of oscillators, leaving the natural frequencies of other oscillators unchanged.

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