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Oscillatory Model of Attention-Guided Object Selection and Novelty Detection

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Abstract - We develop a new oscillatory model that combines consecutive selection of objects and discrimination between new and familiar objects. The model works with visual information and fulfils the following operations: (1) separation of different objects according to their spatial connectivity; (2) consecutive selection of objects located in the visual field into the attention focus; (3) extraction of features, (4) representation of objects in the working memory; and (5) novelty detection of objects. The functioning of the model is based on two main principles: the synchronization of oscillators via phase-locking and resonant increase of the amplitudes of oscillators if they work in-phase with other oscillators. The results of computer simulation of the model are described for visual stimuli representing printed words.

Keywords – Oscillatory neural networks, Synchronization, Resonance, Selective attention, Novelty detection.

1. INTRODUCTION

Traditional approach to visual pattern recognition is based on the assumption that objects are presented one at a time (Ripley, 1996), but in reality biological systems must be able to deal with visual scenes that contain several objects simultaneously. Many years of experimental studies show that a number of cognitive functions should be combined when consecutive selection of objects in a complex scene is made. Firstly, binding and attention are necessary to properly collect the features of a currently selected object and to separate that object from other elements of the scene (Treisman & Gelade, 1980; Treisman, 1998; Luck & Beach, 1998; Wolfe & Cave, 1999). Secondly, novelty detection and memory are needed to avoid the waste of time on processing familiar objects (Vinogradova, 2001). Though selective attention and memory have been largely investigated in isolation but recent progress in neuroimaging technique significantly increased available experimental data on the relation between selective attention and memory tasks (Schneider, 1999; Awh et al., 2000; Awh & Jonides, 2001).

Until now most papers on neural networks have been focused on modeling a particular cognitive function. Models of feature binding have been developed in (Schillen & König. 1994; Grossberg & Grunewald, 1997; Wang & Terman, 1995, 1997; Verschure & König, 1999, Hummel, 2001). Models of attention are represented by both traditional connectionist networks (Tsotsos et al., 1995, Niebur & Koch, 1998; Moser & Silton, 1998; Grossberg & Raizada, 2000) and oscillatory networks (Niebur & Koch, 1994; Kazanovich & Borisyuk, 1994, 1999, 2002; Wang, 1999; Corchs & Deco, 2001). Novelty detection has been formulated as a statistical problem in (Parra et al., 1996). Borisyuk et al. (2001) developed an oscillatory neural network of novelty detection in the hippocampus. These efforts paved the way to models that would combine in one system a set of cognitive functions covering the whole range of image processing, including memorization, and recognition. One of the first attempts in this direction is the paper of Wang & Liu (2002), where an oscillatory model integrating image segmentation with associative memory is presented.

In this paper we describe a large-scale model that solves the problem of consecutive selection of objects by combining feature binding, object oriented attention, and novelty detection. Since we believe that the brain does not invent a special mechanism of processing for each cognitive function but adapts similar mechanisms for a particular type of processing, it has been a challenge for us to develop the model basing on a small set of general principles.

The model is designed as a hierarchy of interactive modules which are associated with different stages of visual information processing. Each module consists of interactive oscillators with synchronising and desynchronising interactions. An oscillator used as an element of the network is described by three variables: the oscillation phase, the oscillation amplitude, and the natural frequency of the oscillator. The values of these variables change in time according to prescribed rules of interaction. Such an oscillator can be considered as a generalization of a phase oscillator (Kazanovich & Borisyuk, 1999).

The model works with images represented by several isolated grey-scale objects. The processing of images includes the following operations:

1. Segregation of information from different objects according to their spatial connectivity.
2. Consecutive selection of objects located in the visual field into the attention focus.

3. Extraction of features describing object shape and invariant to object location and scale.
4. Representation of objects in the working memory.
5. Novelty detection of objects (differential response of the output layer to new or familiar objects).

The functioning of the system is based on the principles of synchronisation (phase-locking) and resonant increase of activity. By the resonance we mean a sharp increase of the amplitude of oscillations when some input signals permanently arrive at an oscillator in phase with its own oscillations. In particular, this implies that this oscillator is synchronized with the input and operates at the same frequency.

Attention is realised in the system in the form of synchronisation of the Central Oscillator (CO) with an assembly of oscillators representing an object in the image. Those oscillators that work synchronously with the CO are supposed to be included in the attention focus (Kryukov, 1991). Due to the resonance with the CO, the amplitudes of oscillators in the attention focus drastically increase while the amplitudes of other oscillators are shut down to a low level (Kazanovich & Borisyuk, 2002). This demonstrates the regime of partial synchronisation which appears as a stimulus driven response of a neural sub-population (Kazanovich & Borisyuk, 1999). The presence of the CO in the system design is important because it allows one to organise the global interaction without connections of "all-to-all" type, thus avoiding an exponential explosion of the number of lateral connection.

The fact that at each moment of time the activity of an assembly of oscillators corresponding to a selected object is significantly higher than the activity in other regions of the network allows the system to separate objects at the decision making level. According to the assumptions of the model, only the activity in the focus of attention is taken into account during novelty detection. Since attention is automatically directed to one object at a time, this allows the memorization of this object in the working memory without erroneous conjunction of features of different objects.

The same principles of synchronization and resonance of neural activity are also used for novelty detection implementation. It is based on sparse spatial representation of objects by groups of resonant synchronous oscillators in the memorizing module and adaptation of the value of a parameter that controls the resonant dynamics of the oscillator's amplitude. This results in different reaction times after the presentation of new and familiar stimuli in agreement with what has been found in the experiments on the orienting response (Sokolov, 1975; Vinogradova, 1995): tonic (long) response to a new stimulus and phasic (short) reaction to a familiar object.

Our choice of the oscillatory neural network for the development of the model is based on the fact that animals and humans display a wide spectrum of rhythmic activity patterns in many areas and structures of the brain (see, e.g., Gray, 1994, Basar, 1998). Discovery of the phenomenon of synchronous oscillations in the cerebral cortex (Eckhorn et al., 1988; Gray et al., 1989; Singer & Gray, 1995, Gray, 1999; Singer, 1999) is considered as supporting the idea that these oscillations may offer a "label" that identifies the neural assembly, coding a specified object. It might be a solution to the binding problem formulated by von der Malsburg (1981, 1995).

Recent investigations reveal that synchronous oscillations of neural activity can be a correlate of stimulus selection by attention (Steinmetz et al., 2000, Fries et al., 2001, Fries et al., 2002, Niebur et al. 2002; Niebur, 2002). In particular, Steinmetz et al. studied synchronous firing of neuron pairs in the secondary somatosensory cortex of macaque monkeys during two selective attention tasks (one task is simple and other is difficult). It was shown that 80% of the neuronal pairs fired synchronously during performing a difficult task, and 35% of these pairs decreased their degree of synchrony when the monkey switched from difficult to an easy task. Thus, the change in degree of synchrony can be considered as a correlate of switching the attention focus from one task to another. In the paper (Fries et al. 2001) multi-unit and LFP recordings from the monkey extrastriate area V4 show high frequency (>35 Hz) increasing and low (<17 Hz) frequency decreasing when the monkey attended to the stimulus within the receptive field of the neuron. A simple model in support of the fact that attention can improve the synchrony of neural oscillations has been suggested in (Borisyuk, 1994).

In our model, the CO plays the role of the central executive as it is suggested by Cowan (1988). In psychological literature the central executive is considered as a system which is responsible for attentional control of the working memory (Baddeley, 1996, 2002, 2003; Shallice, 2002). For a long time the functions of the central executive have been attributed mostly to a local region in the prefrontal cortex (D'Espasito et al., 1991; Loose et al., 2003) but later studies have shown that the central executive may be represented by a distributed network that includes lateral, orbitofrontal, and medial prefrontal cortices linked with motor control structures (Barbas, 2000). Recent neuroimaging data show that "different executive functions do not only recruit various frontal areas, but also depend upon posterior (mainly parietal) regions" (Collett & Van der Linden, 2002). The paper (Daffner et al., 2003) shows the relative contribution of the frontal and posterior parietal regions to the differential processing of novel and target stimuli under conditions in which subjects actively directed attention to novel stimuli. The prefrontal cortex may serve as the central node in determining the allocation of attentional resources to novel events, whereas the posterior lobe may provide the neural substrate for the dynamic process of updating one's internal model of the environment to take into account a novel event. We think that in addition to neocortical areas the hippocampus should play an important role in implementing central executive functions. This is conditioned by its final position in the pyramid of cortical convergent zones and participation in controlling the processing of information in most parts of the neocortex (Damasio, 1989).

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. Many studies show that the hippocampus significantly contributes to novelty detection (Knight, 1996; Knight & Nakada, 1998; Jessen et al., 2002). A well-known manifestation of novelty detection is the change in oscillatory activity during the orienting response (Sokolov, 1975; Vinogradova, 1995). In these experiments the animals detected novelty by comparing input stimuli with what had been previously stored in their working memory after repeated presentations of different stimuli. It has been shown that in the hippocampus the long (tonic) theta activity that appears after presentation of a new or significant stimulus is gradually changed to a short (phasic) reaction during repeated presentations of the same stimulus. The tonic reaction is immediately restored when a stimulus with different characteristics is presented.

In what follows we show that the ideas of synchronous oscillations and the central executive represent a powerful instrument in designing neural networks that can perform complex information processing in agreement with known neurobiological and psychological results on the functioning of visual systems.

2. THE MODEL: GENERAL DESCRIPTION

The model consists of four layers of oscillators with feedforward connections between the layers. The flow of information between the modules of the network is presented in Fig. 1. The layers of the network are called Object Selection Layer (OSL), Local Feature Layer (LFL), Invariant Feature Layer (IFL), and Novelty Detection Layer (NDL). The oscillators comprising these layers are denoted as OSO, LFO, IFO, and NDO, respectively. There is also an additional Central Oscillator (CO) with global feedforward and feedback connections to the OSL.

In biological terms the model is interpreted in the following way. It is assumed that oscillators in the OSL, LFL, and IFL represent cortical columns in the areas of the visual pathway. The OSOs are located in the primary visual cortex (striate cortex), LFOs can be attributed to different regions of the cortex (striate, extrastriate and higher) depending on the type and complexity of the features, IFOs represent feature detectors of the temporal area invariant to geometrical transformations (IT and higher associative areas). To simplify the model, we consider only the interaction between the CO and OSL and ignore the influence of the CO on other layers. The NDL is associated with the hippocampus. The groups of NDOs represent hippocampal segments. For simplicity, we restrict the interaction in the hippocampus by connections in the segments and ignore long-range coupling. We think that the main role of long-range coupling in the hippocampus is related to memorization of the sequences of events (Borisyuk & Hoppensteadt, 1998), but here we consider static images only.

The components of the model are similar to those generally used in pattern recognition systems. The main difference is that the problem of novelty detection is simpler than the problems of learning (supervised or unsupervised), therefore it can be solved without backward connections from higher to lower levels of the network. The advantage of our system is that there is no necessity in separate presentation of objects at the input. The automatic selection of objects from a composite visual scene and their sequential presentation to the novelty detection system are essential attributes of network functionality.

2.1. Object Selection Layer

The OSL is responsible for grouping the information from the external input into separate clusters according to spatial connectivity of input objects. This layer is also used to organize a consecutive selection of different objects into the focus of attention. The OSL has the same 2D grid-like structure as the visual field with one-to-one correspondence between the pixels of the visual field and the elements of the layer. An OSO with the coordinates *(x, y)* responds to the input signal from the pixel *(x, y)* of the visual field. The grouping of pixels into object representation is realized through synchronizing local connections between OSOs. In computations we use 4 nearest connections coming to each node except the nodes at the boundary where the number of connections may be equal to 3 or 2.

The focus of attention is formed in the OSL due to the interaction of this layer with the CO. Each OSO sends to the CO a synchronizing signal and receives back a desynchronizing signal. The interaction is organized in such a way that at any moment the CO works synchronously (in-phase) with an assembly of OSOs that represent a single object. Due to the resonance with the CO, the amplitude of oscillations in this assembly is made high while the activity of other OSOs is inhibited to a low level.

Synchronizing connections are used for phase-locking of the CO by an assembly of OSOs. Desynchronizing connections from the CO to the OSL are used to desynchronize different assemblies of OSOs to prevent simultaneous synchronization with the CO of several assemblies of OSOs.

Depending on the input signal and previous dynamics, an OSO can be in one of four states: *active, resonant, passive, and silent*. If an OSO receives zero input signal (corresponding to the signal from the background), it is in the silent state. In this state the oscillator does not participate in the network dynamics and it is not included in dynamics equations. If an OSO is not silent, it consecutively (and probably repeatedly) passes through a cycle of states: active – resonant – passive. An OSO starts working in the active state; then if the amplitude of its oscillations exceeds a certain threshold T it changes its state to the resonant one. Being in the resonant state is interpreted as the fact that this oscillator is included in the focus of attention. Resonant oscillators increase their influence on the CO and prevent the focus of attention from unwanted switching during memorization and novelty detection of the object.

The time which an assembly of OSOs spends in the resonant state is determined by the NDL. The resonant state continues until an object in the attention focus is detected as a new one and memorized in the working memory or when the familiarity of the object is detected.

After the resonant state the assembly of OSOs switches to the passive state and is forced to be in this state a prescribed time. It is presumed that in the passive state an OSO does not interact with the CO and is blocked for a prescribed time from being again included in the attention focus. In other words, the assembly of OSOs in the passive state temporarily becomes “invisible” for the CO. This gives the CO an opportunity to change the attention focus by synchronizing its activity with another assembly of OSOs, etc. The introduction of the passive state reflects the experimental evidence that attention is biased against returning to previously attended locations (Klein, 1988; Takeda & Yagi, 2000).

When the time for the passive state is expired, the OSO returns to the active state. This completes the first round of state changes and gives a start to the next round, etc. In this particular realization of the model, the order in which different objects of the image are included in the attention focus is random with the advantage provided to lager objects since their influence on the CO is made greater.

2.2. Local Feature Layer

The LFL is responsible for transforming the information about an object from representation by pixels to representation by local features. These features give a concise and specific description of visual information that depends on local geometrical characteristics of objects in the visual field.

Let $F_1,...F_K$ be a set of local features that can be detected in each point of the image. We say that a feature F_k is present at the location *(x, y)* if the values of the intensities in the local neighborhood of *(x, y)* satisfy the conditions of F_k. The oscillators in the LFL are arranged into a 3D structure with different types of feature detectors occupying different levels (planes). Each position *(x, y)* of the LFL is occupied by a column of LFOs of height *K*. We do not model the formation of features in detail. It is simply postulated that an LFO in a column at the level *k* is active if the feature F_k is present in the image at the attended location *(x, y)*.

Since in the LFL the signals outside the focus of attention are ignored, this prevents erroneous conjunction of features of different objects during memorization. This principle is based on the experimental evidence that the activity of neurons and neural assemblies that are not included in the attention focus is lower than those in the attention focus (Moran & Desimone, 1985; Chelazzi, 1995; Treue & Maunsell, 1996; Kastner et al. 1998). We suppose that the information outside the focus of attention has no access to novelty detection level of information processing, so to simplify the model we make early gaiting of unattended information. This does not imply that this information can be used in other (e.g., unconscious) cognitive processes.

The oscillators in a column of the LFL receive a synchronizing connection from the OSO with the same coordinate *(x, y)*. There are no connections between LFOs. A synchronous assembly in the OSL that forms the attention focus is used as a source of synchronization for the oscillators in the LFL. The interaction between the OSL and LFL is strong enough to make the activity of LFOs coherent. Therefore the principle of binding-by-synchronization is valid for the LFL too.

2.3. Invariant Feature Layer

The IFL is used for representing an attended object by a set of features that are invariant to translation and scale. The layer is arranged as a set of *K* columns of oscillators (*K* is the number of different features that can be detected in the LFL) of height *H*. An IFO at the level *h* in the column *k* is active if the feature F_k is present h times in the attended region of the input image. Thus only one IFO can be active in a column. Such a coding automatically makes the activity in the IFL invariant to translation. Invariance to scaling demands some restriction on the detectors of local features in the LFL: the set of features extracted from an object should be independent of the scale. We will give an example of such features in Section 3.3.

The oscillators in the column k of the IFL receive strong synchronizing connections from all oscillators of the level k in the LFL. There are no connections between the IFOs. Such connections allow an IFO to register the number of arriving input signals from the LFL and to properly control its activation. In addition, the assembly of synchronous LFOs plays the role of a common source of synchronization for all active oscillators in the IFL.

2.4. Novelty Detection Layer

The NDL is responsible for memorization of objects in the working memory and making decisions about novelty of objects. Since the same features can appear in representations of different objects, another transformation of information is necessary to improve the separation of representations of objects. This is implemented in the NDL, where each object is represented by a sparse assembly of oscillators that is specifically related to the object in the attention focus.

The NDL is an elongated structure divided into independent (disconnected) groups of oscillators located in the planes orthogonal to the long horizontal axis. There are all-to-all synchronizing connections between NDOs in each group. Connections from the IFL to the NDL are of all-to-all type with random delays. These delays mimic phase lags in transmission of the signals from the neocortex to the hippocampus that can be as high as one half of the period of the theta rhythm (Miller, 1991).

A basic principle of NDL functioning is that an NDO reaches and keeps a high level of activity (resonant amplitude) if the signals that are supplied to this oscillator from the IFL arrive in-phase. For a given set of active oscillators in the IFL, due to random delays in connections, the resonant activity in the NDL takes place 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 NDL is low. The important feature of this sparse coding is that if the number of groups in the NDL is large relative to the number of memorized objects, then different objects (even those that have some common features and are labeled by the same or similar frequency) will activate different (though possibly slightly overlapping) regions in the NDL.

At any moment, a NDO can be in one of two states, active or resonant. As in the case of the OSL, we say that a NDO is in the resonant state if its amplitude exceeds the threshold T_1, otherwise the NDO is in the active state. NDOs start their work from the active state with amplitudes lower than T_1. Then, depending on the input signals the NDO may switch to the resonant state and later return to the active state after novelty detection of an object is over.

Denote by $R(t)$ the number of resonant oscillators in the NDL at time t. Let t_0 be the moment when all features of some object are included in the attention focus and the memorization of this object in the NDL begins. The dynamics of the NDL are organized so that starting from the moment t_0 the value of $R(t)$ gradually increases (not always monotonically) due to phase-locking influence of the input from the IFL. For a chosen threshold H (H is much smaller than the number of oscillators in the NDL) we introduce the first moment t_1 when $R(t_1) > H$; t_1 is considered as the end of novelty detection of the object that is currently included in the focus of attention.

The important parameter used for discrimination between novel and familiar objects is $\Delta t = t_1 - t_0$. This is the time needed by the NDL to reach a high enough level of summed resonant activity. Following the experimental evidence on tonic and phasic responses of the hippocampus, we adjust model parameters to make the value of Δt much higher for a new object than for a familiar one. This is achieved by a proper modification of the value of the parameter that controls the speed with which the amplitude of an NDO increases to the resonant state. This speed is made higher for those NDOs that have been in the resonant state at the moment when novelty of an object has been detected. If the same object later enters the focus of attention, this promptly elicits the resonant activity in the NDOs that have been used to memorize this object. This fact is interpreted by the system as a presentation of a familiar object

3. THE MODEL: MATHEMATICAL FORMULATION

3.1. Input

The input to the system is an image on the plane grid of the same size as the OSL. It is assumed that the image contains several isolated greyscale objects on a white background of constant brightness *B*. An object is represented by a connected set of pixels. Each OSO receives an external input from the corresponding pixel of the input image. This signal determines the natural frequency of the OSO. The natural frequency of the *i*th OSO is set to be equal to

$$\omega_i = \lambda(B - I_i), \ (0 \le I_i \le B),$$

where I_i is the grey level of the *i*th pixel and λ is a scaling parameter. It is assumed that all values of ω_i belong to the range $(\omega_{\min}, \omega_{\max})$ of admissible values of natural frequencies.

3.2. Object segmentation and selection

The OSL is formed by oscillators located in the elementary cells of a square two-dimensional grid. Each OSO is coupled with its nearest neighbors at the left, right, top, and bottom. No rap-around connectivity is assumed.

The dynamics in the OSL are described by the following equations:

$$\frac{d\theta_i}{dt} = 2\pi\omega_i - a_0 w_0 \sin(\theta_0 - \theta_i) + w_1 \sum_{j \in N_i} a_j \sin(\theta_j - \theta_i) + Z, \qquad i = 1, \ldots, n \tag{1}$$

$$\frac{da_i}{dt} = b(-a_i + \gamma f(\theta_0 - \theta_i))^+ + c(-a_i + \gamma f(\theta_0 - \theta_i))^- . \tag{2}$$

In these equations, θ_0 is the phase of the CO, θ_i are the phases of OSOs, $\frac{d\theta_i}{dt}$ are the current frequencies of OSOs, ω_i are the natural frequencies of OSOs determined by the input signal, a_0 is the amplitude of oscillations of the CO (a constant), a_i are the amplitudes of oscillations of OSOs, w_0 and w_1 are constant positive parameters (w_0 controls the strength of the influence of the CO on OSOs, w_1 controls the strength of interaction between OSOs), n is the number of non-silent oscillators, N_i is the set of non-silent oscillators in the nearest neighborhood of the oscillator i, Z is the gaussian noise with the mean 0 and standard deviation σ, f is a function that controls the amplitude of oscillations of OSOs and their transition to the resonant state (f is 2π -

periodic, even, positive, and unimodal in the interval of periodicity with the maxima in the points $2\pi k$), b, c, γ are parameters (positive constants). By definition,

$$(x)^{+}=\begin{cases}x & if\ x \geq 0 \\ 0 & if\ x<0\end{cases},\ (x)^{-}=\begin{cases}x & if\ x \leq 0 \\ 0 & if\ x>0\end{cases}.$$

The influence of the OSL on the CO is described by the equations

$$\frac{d\theta_0}{dt}=2\pi\omega_0+\frac{w}{n}\sum_{i=1}^{n}s_i a_i g(\theta_i-\theta_0), \tag{3}$$

$$\frac{d\omega_0}{dt}=\alpha\frac{w}{n}\sum_{i=1}^{n}s_i a_i g(\theta_i-\theta_0)=-\alpha(2\pi\omega_0-\frac{d\theta_0}{dt}), \tag{4}$$

where (in addition to notation presented above) ω_0 is the natural frequency of the CO, *w* is a constant positive parameter that controls the strength of the influence of OSOs on the CO*,* *g* is a function to implement phase-locking of the CO by OSOs (*g* is 2π -periodic, odd, and unimodal in the interval of periodicity), s_i is a binary variable that depends on the state of a OSO ($s_i=1$ if the oscillator is in the active or resonant state, $s_i=0$ if the oscillator is in the passive state), α is a positive parameter.

Equations (1) and (3) are traditional equations of phase-locking. Note that the interaction between oscillators depends not only on the coupling strength but also on the amplitude of oscillations: an oscillator with greater amplitude has stronger influence on other oscillators.

The coupling strength between oscillators is constant. The connections from OSOs to the CO and the local connections between OSOs are synchronizing. Due to synchronizing connections from OSOs to the CO, the latter can be phase-locked by an assembly of OSOs. Due to synchronizing connections between OSOs, the oscillators from an assembly of active OSOs become phase-locked and work nearly in-phase after they reach the resonant state. The connections from the CO to OSOs are desynchronizing. Their aim is to break the coherence between different assemblies of OSOs.

The noise Z in (1) is used as an additional source of desynchronization between the assemblies of OSOs. It helps to randomize the location in phase-frequency space of different assemblies of OSOs, thus making them distinguishable for the CO.

We use the following interaction functions in (3) (Fig. 2):

$$g(x) = \begin{cases} 10x \quad for\ 0 \le x < 0.1, \\ -4x + 1.4 \quad for\ 0.1 \le x < 0.2, \\ -0.1x + 0.62 \quad for\ 0.2 \le x \le \pi, \\ -g(-x) \quad for\ -\pi < x < 0. \end{cases}$$

Outside the interval $(-\pi, \pi)$ the function $g(x)$ is continued as periodic. An important feature of $g(x)$ is that its extrema are located near the points $2\pi k$. As can be shown by theoretical analysis and computer simulation, such a choice of $g(x)$ improves the capability of the system to separate assemblies with similar values of the natural frequencies of OSOs. Any function of a similar form would be suitable but a piece-wise linear function gives a simple and easily computed approximation of the form required.

Equation (2) describes the dynamics of the amplitude of oscillations of OSOs. This equation provides a mechanism for the resonant increase of the amplitude of oscillations. The function $f(x)$ has the form

$$f(x) = S((\cos x)^{+}, \xi, \eta, \rho), \tag{5}$$

where $S(y, \xi, \eta, \zeta)$ is a sigmoid function of the type

$$S(y, \xi, \eta, \rho) = \rho + \frac{\exp((y - \xi)/\eta)}{1 + \exp((y - \xi)/\eta)} \tag{6}$$

with the parameters ξ, η, ρ. The values of ξ and η are chosen so that $S(y, \xi, \eta, \rho)$ approaches to its maximal value $1+\rho$ when y tends to 1, $S(y, \xi, \eta, \rho)$ quickly decays to ρ if y becomes lower than $1-\varepsilon$ (ε is one order less than 1). Thus the amplitude of an OSO increases to the maximum value $a_{\max} = \gamma(1+\rho)$ if the OSO works synchronously with the CO, the amplitude takes a low value $a_{\min} = \gamma\rho$ if the phase of the OSO is significantly different from the phase of the CO (ρ is one order less than 1). We say that an OSO is in the resonant state if its amplitude exceeds the threshold $T = 0.75 a_{\max}$. The parameters b and c determine the rate of amplitude increase and decay.

The amplitude a_0 of the CO is constant. It is used as an independent parameter to get the same type of notation in (1) and (3) for both feedforward and feedback connections between the CO and the OSOs. We always put $a_0 = 1$.

Equation (4) describes the mechanism of adaptation of the natural frequency of the CO. According to this equation, $2\pi\omega_0$ tends to the current frequency of the CO. Such adaptation allows the CO to "search" for an assembly of OSOs which is an appropriate candidate for synchronization. The parameter α determines the rate of adaptation. The value of α is chosen low enough for ω_0 to follow the main trend of the current frequency of the CO but not fast, random fluctuations of this frequency.

The initial value of the natural frequency of the CO is set to some value in the range of the natural frequencies of network oscillators. The initial phase of the CO is 0. The initial values of the amplitudes of OSOs are set to a^0 $(a^0 < T)$, the initial phases of all OSOs are set to 0. Starting from these initial conditions, the network obeys equations (1)-(4) with the only exclusion of the moment when an OSO switches from the resonant to the passive state. At this moment the amplitude of oscillations of this OSO is set to a^0 and the phase is reset to zero.

We suppose that the duration of the passive state for an OSO is restricted by a constant *D*. After this time is expired, the OSO returns to the active state. We choose the value of *D* large enough for the system to have sufficient time to select sequentially all objects in the visual scene.

The process of object selection is implemented by the following dynamics of the network. Just after the network is initialized and starts running, the CO is synchronized by an assembly of OSOs. The OSOs that work synchronously with the CO significantly increase the amplitude of their oscillations (switching to the state of resonance). The activity of other oscillators is temporarily inhibited to a low level. This prevents the focus of attention from switching during memorization and novelty detection.

3.3. Feature representation

We consider simple geometrical features that are determined by the distribution of black and white pixels in the neighborhood of the pixel *(x, y)* of the input image. For example, feature F_1 can represent two line segments with a definite orientation crossing at the point *(x, y)*, feature F_2 can represent a line segment with a definite orientation that has its free end at the point *(x, y)*, etc. Such an approach to feature representation of shape is similar to the one used by Moser and Silton (1998). In our simulations the full list of features includes corners (bottom-left, top-left, bottom-right, top-right), endpoints (bottom, right, top, left), and T-shape crossing (left, bottom, top, right) with line-components parallel to coordinate axes. This short list has been chosen for illustrative purposes only with the aim to simplify computations and cannot be considered as complete even for the description of black and white images. In principle, any procedure of feature extraction and any set of local features can be adapted for our coding scheme. The only restriction that may be reasonable to impose on the features is their invariance to scale. Since the type of line crossing does not depend on scale, the features that we use satisfy to this condition. The next version of the model will include a module of feature representation with an automatic process of feature extraction.

All oscillators in the LFL with particular coordinates *(x, y)* receive connections from the oscillator with the same coordinates in the OSL. If a LFO is active, its dynamics are determined by the equation

$$\frac{d\phi_i^k}{dt} = 2\pi\omega_i^k + a_i v \sin(\theta_i - \phi_i^k),$$

where ϕ_i^k is the phase of the LFO in the plane k with the coordinates *(x, y)*, ω_i^k is the natural frequency of this oscillator (ω_i^k are randomly and uniformly distributed in the interval $(\omega_{\min}, \omega_{\max})$), θ_i is the phase of the signal arriving from the OSO with the coordinates *(x, y)*, a_i is the amplitude of oscillations of this signal, v is a positive coupling parameter.

The value of *v* is chosen large enough for a LFO to run nearly in-phase with the signal arriving from the corresponding OSO. Since there are no internal connections in the LFL, the oscillators in this layer simply copy the dynamics of the oscillators from the OSL. Therefore the whole assembly of active LFOs works in-phase. The amplitude of oscillations of all active LFOs is supposed to be constant and equal to a.

The oscillators from the layer k of the LFL send their connections to all oscillators in the kth column of the IFL (the oscillators in the kth column are numbered by the index h). The dynamics of an active IFL corresponding to the feature F_k that is present in the focus of attention h times are governed by the equation

$$\frac{d\chi_k^h}{dt} = 2\pi\omega_k^h + a\kappa\sum_i \sin(\phi_i^k - \chi_k^h),$$

where χ_k^h is the phase of the IFO, ω_k^h is the natural frequency of this oscillator (ω_k^h are randomly and uniformly distributed in the interval $(\omega_{\min}, \omega_{\max})$), ϕ_i^k are the phases of the signals coming from the oscillators at the level k of the LFL, a is the amplitude of oscillations in the LFL, κ is a positive coupling parameter. The summation is done over all active oscillators at the level k of the LFL. The value of κ is chosen large enough for the IFO to run nearly in-phase with the signals arriving from the LFL. Therefore the whole assembly of active IFOs works in-phase. The amplitude of oscillations of all active IFOs is supposed to be constant and equal to A.

3.4. Memorization and novelty detection

The NDL is formed by oscillators collected into groups $G_j\,(j = 1,...m)$ 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.

The input to the NDL is formed by the signals from the IFL. Remind that only those IFOs are supposed to be active that belong to the objects included in the attention focus. We assume that there is an all-to-all architecture of feedforward synchronizing connections from the oscillators of the IFL to the oscillators of the

NDL. Each connection is characterized by the phase delay with which the signal is delivered from one layer to another. The values of the delay for different connections are randomly chosen from an interval $(d_{\min}, d_{\max})$ of admissible values for delays. The same value is given to all delays in connections from an IFO to a group of NDOs.

Let P be the set of active IFOs, $p = |P|$ is the number of oscillators in P. The dynamics of a NDO with the number r $(r = 1, \ldots, q)$ in the group s $(s = 1, \ldots, m)$ are described by the following equations:

$$\frac{d\psi_r^s}{dt} = 2\pi\Omega_r^s + \frac{AV}{p}\sum_{k\in P}\sin(\chi_k + d_{ks} - \psi_r^s) + \frac{W}{q}\sum_{l=1}^{q} A_l^s \sin(\psi_l^s - \psi_r^s), \quad (7)$$

$$\frac{dA_r^s}{dt} = B_r^s(-A_r^s + \Gamma F(U_r^s, p))^+ + C(-A_r^s + \Gamma F(U_{kr}^s, p))^-, \quad (8)$$

where U_r^s denotes

$$U_r^s = \frac{1}{p}\sum_{k\in P}[\cos^+(\chi_k + d_{ks} - \psi_r^s)]^2 .$$

In these equations, ψ_r^s are the phases of NDOs, Ω_r^s are the natural frequencies of NDOs, A_r^s are the amplitudes of oscillations of NDOs, χ_k are the phases of IFOs (we omit upper index h since only one oscillator can be active in the kth column of the IFL), A is the amplitude of oscillations of IFOs, d_{ks} are phase delays during transmission of the signals from an IFO to NDOs of the group G_s, V is the strength of synchronizing influence of IFOs on NDOs, W is the coupling strength of internal interaction in the groups of the NDL, $F(x, p)$ is a sigmoid function (see below) of x, B_r^s, C, Γ, W are positive parameters (C, Γ, W are constants, the value of B_r^s can be modified during memorization). The values Ω_r^s are constants. For each group, the values of $\Omega_1^s,\ldots\Omega_q^s$ are homogenously (with a fixed step) distributed in the interval of admissible frequency values $(\omega_{\min},\omega_{\max})$.

Equation (7) implements phase-locking of NDOs by the signal coming from active oscillators of the IFL. The second term in the right hand side of this equation describes the influence of the input signal from the IFL. The third term describes internal interaction in the group to which the NDO belongs. The interaction in the group depends not only on the coupling strength but also on the amplitude of oscillations: an oscillator with greater amplitude has stronger influence on other oscillators.

Equation (8) controls the dynamics of the amplitudes of oscillations. The function $F(x,p)$ is similar to the function $f(x)$ in (5). It is determined by the formula

$$F(x,p)=S(x,\xi_1(p),\eta_1,\rho_1), \tag{9}$$

where the function S is defined by (6). Due to (8-9), a NDO reaches and keeps a high amplitude of oscillations if

(1) the natural frequency of the NDO is similar to the frequency of the signals coming from the IFL;

(2) the components of the signal supplied by the IFL arrive to the NDO nearly in-phase, which is the case if the values of d_{ks} are approximately the same for the given group G_s.

We say that an NDO is in the resonant state if its amplitude exceeds the threshold $T_1=0.75A_{\max}=0.75\Gamma(1+\rho_1)$. The random choice of the values of d_{ks} implies that as soon as the attention focus is formed this results in resonant oscillatory activity at a small number of randomly chosen locations (groups) of the NDL, where an appropriate coincidence of input signal phases takes place. The activity in other groups is low. We call it a sparse representation (coding) of an object in the NDL activity.

How sparse is the representation of an object in the NDL depends on the value of the parameter $\xi_1(p)$. The higher is this parameter, the lower is the number of NDOs with the high amplitude of oscillations coding a given object in the NDL. The probability of coincidence of phase delays at the input of an NDO depends on the dimension p of the input from the IFL: for smaller values of p the probability of coincidence is higher. This is the reason, why ξ_1 is made dependent on p. We make $\xi_1(p)$ a decreasing function of p, choosing the values of $\xi_1(p)$ so that the number of oscillators coding an object in the NDL were more or less independent of the value of p.

Let us describe the dynamics in the NDL that appear according to equations (7-8). At the initial moment $t = 0$ the phases of NDOs are 0. The initial values of the amplitudes are set to A^0 $(A^0 < T_1)$. Consider first the dynamics that take place before any working memory is formed. Suppose that an object under attention is represented in the OSL by an assembly of oscillators working synchronously at the frequency ω. The signal of this frequency will phase-lock those oscillators of the NDL whose natural frequencies are in some range $(\omega - \delta, \omega + \delta)$. The width of the range is determined by the coupling strengths V.

Further dynamics in the groups depend on the values of phase delays d_{ks}. If for a given group G_s the components of the input from the IFL arrive to G_s without being tuned in phase, the oscillators of the group will not be able to cross the threshold for the resonant activity. The amplitude of their oscillations will remain low.

On the contrary, if the components of the input arrive more or less in phase, this results in a sharp increase of the amplitude of those oscillators in the group that have been phase-locked by this signal. Due to the interaction of oscillators in the group, oscillators in the resonant state have strong synchronizing influence on other oscillators of the group. Therefore new oscillators in the group will be recruited to synchronization and resonant activity. This process continues until the whole number of resonant oscillators in the NDL exceeds a threshold H.

At this moment memorization of the object takes place. To simplify the model, memory formation is implemented as an instantaneous event for which a single presentation of an object in the attention focus is sufficient. That is an object is considered as familiar if it has appeared in the attention focus before (at least once). Memorization is realized by increasing the values of some parameters B_r^s. At the initial moment, when the network just starts its work, we put $B_r^s = B_0$. Let B_1 be a value that is several times greater than B_0. The learning rule is formulated as follows: if the oscillator r of the group s is in the resonant state, then $B_r^s = B_1$.

The values of the parameters B_r^s are crucial in determining the time that is needed by the NDL to reach the threshold H. The greater are these values, the faster is the rate with which synchronization and resonance can appear in the NDL in response to the signal from the IFL. As we show by computer simulations, the time spent before reaching the threshold H is decreased several times for familiar objects in comparison to novel objects.

After memorization is over, the resonant oscillators of the OSL are set in the passive state. The resonant oscillators of the NDL are set in the active state with the amplitudes equal to A^o (the same amplitude as in the initial state). The phases of NDOs are kept unchanged.

4. SIMULATION

We illustrate the principles of network performance using a simple example with two input images presented one after another. Both images contain five objects representing the characters of the word "HELLO" and of the word "WORLD", respectively. These are black and white images with the same level of intensity of all black pixels. Therefore the natural frequencies of all active OSOs are the same in this case. This situation is most difficult for processing by the model since the model should be able to separate the objects that are coded by the same frequency and to store these objects in different areas of the memory. We use the theta rhythm as a working range for the model. To follow the experimental evidence on the behavior of the theta rhythm during orienting response, the natural frequencies of active oscillators in the OSL have been set to 5. In fact the choice of the frequency range has no influence on the capabilities of the model.

Each image is exposed at the input for 35 time units, so the whole time of processing of two images is 70. Each image is processed sequentially object by object with memorization and novelty detection of all objects. The order in which objects of an image are selected and memorized is random.

Since the objects L and O occur several times in the images (three and two, respectively), they will be detected as familiar at the second and third appearance in the attention focus. Other objects occur in the images only once, therefore they will be detected as new. To distinguish the two occurrences of the letter L in the word HELLO, we denote them as L1 and L2.

Fig. 3 shows the types of features used to represent the images HELLO and WORLD in the LFL. Each feature label shows the location (on the *(x, y)* plane) of the column of the LFL where there is an active oscillator representing this feature. For example, the object L is represented by three active LFOs - two endpoints (top and right) and one corner (bottom-left). Since the whole number of different features used in the simulation is 12 (see the first paragraph in Section 3.3), both the height of a column in the LFL and the number of columns in the IFL is 12.

The height of a column in the IFL is 3, because this is the maximal number of occurrences of the same feature in an object (for example, we have three right endpoints in the object E and tree top endpoints in the object W). The objects are represented in the IFL by a different number of active oscillators that varies between 2 (the object W) and 7 (the object R).

For simulation we use the NDL with 2000 groups and 10 oscillators in each group. The natural frequencies of NDOs are distributed in the range (4.5, 5.5). We put the threshold H for the number of resonant oscillators in the NDL needed for novelty detection equal to $H = 30$, therefore the number of groups with resonant oscillators is not more than 30. In fact it is lower than 30, because the number of resonant oscillators in a group (if there are any) varied between 1 and 4.

The dynamics of the amplitudes in the OSL are shown in Fig. 4. It reflects the moments when different objects are included in the attention focus. At these moments the OSOs representing an object in the attention focus are in the resonant state. The amplitudes of oscillations of other OSOs are low.

The periods of time when objects are included in the attention focus are shown in Table 1. For each object the moment of attention focusing is determined as the time when all OSOs at the points of location of object features enter the resonant state. The final time of attention focusing is determined by the moment when novelty detection is finished by the NDL.

Fig. 5 shows sparse coding of objects of the images HELLO and WORLD. The height of each bar shows the number of resonant oscillators (between 1 and 4) in the corresponding group. It is worth to note that repeated processing of the same object by the NDL results in similar (but not necessarily identical) sets of resonant NDOs due to constant changes in the NDL that are conditioned by its dynamics and memory formation.

The dynamics in the NDL are illustrated by the graphs of $R(t)$ for the objects constituting the images HELLO and WORLD. These graphs are shown in Fig. 6. The initial positions t_0 of the graphs $R(t)$ corresponding to different objects are shifted to the position $t = 0$ to allow a convenient comparison of times needed to reach the threshold *H*. This figure and the last column in Table 1 show that for a new object the value of Δt varies between 4.1 and 6.0, while for familiar objects the value of Δt is much shorter, between 1.4 and 1.8. This confirms that the time for the detection of familiar objects is radically reduced relative to the time for novel objects.

The parameters for simulation are given in Table 2. The values of most of the parameters are not critical. They can be varied freely if the qualitative conditions mentioned in the text are satisfied. Rigid constrains should be only imposed on the parameters ξ, η in the OSL and $\xi_1(p), \eta_1$ in the NDL since they control the resonance depending on the coincidence between the phases of oscillations. This control should be sensitive even to a slight change in phase difference.

5. DISCUSSION

We have demonstrated that general principles of information processing in oscillatory neural networks can be successfully applied to the solution of complex cognitive tasks that combine several interrelated cognitive components such as feature binding, attention and novelty detection. The main principles that have been used in our modeling: frequency synchronization, phase-locking interaction of oscillators, resonance response, adaptation of the natural frequency, and memorization by the adaptation of oscillator parameters under fixed values of connection strengths. The system architecture and functionality reflect (in a very simplified form) the evidence about the main stages of visual information processing, starting from the primary visual cortex and finishing at the hippocampus. By computer simulations we have shown that the system is capable to fulfill consecutive selection of objects in the image and their novelty detection in terms of the duration (tonic or phasic) of the oscillatory response of the final layer (the hippocampus).

The main new aspects of the model are the implementation of selective attention and novelty detection. Separately these cognitive functions have already been modeled in our previous works (Kazanovich & Borisyuk, 2002; Borisyuk et al. 2001), now we provide a framework where both models can be properly adjusted to each other. Feature extraction (both local features and invariant features) has been modeled here in a very simplistic way with illustrative purposes only. This restricts capabilities of the model to processing simple graphical objects that can be properly described by a short list of geometrical features. Much more efficient and biologically plausible principles of invariant feature computation have been developed in the last years (Mel, 1997; Stringer & Rolls, 2000; Amit & Mascaro, 2003). There are no serious obstacles for their introduction in the model but this would make it much more complicated.

The principles of information processing used in our system have already appeared in other oscillatory neural network models. Our achievements are mostly related to their proper combination and adaptation to the task considered. As far as modeling the binding problem, we follow the already known ideas (see Borisyuk et al., (2003) for a review), reformulating them in terms of oscillators with the explicitly defined phase. Phase-locking of oscillations is a traditional approach to the solution of the binding problem. In particular, the temporal correlation hypothesis (Singer & Gray, 1995, Singer, 1999) states that this could be the way to avoid combinatorial explosion of combinations of features that describe objects in the visual field. There are three approaches to modeling the binding of features. Some authors use a general oscillatory scheme without exact specification of the type of features used for binding (Grossberg & Sommers, 1994; Grossberg & Grunewald, 1997). This allows one to study temporal conditions that can lead to the binding under different types of stimulation. Others prefer to closely follow the experimental evidence using straight segments of the contour as primary features of an object (Sporns et al., 1991). The third approach relies on the characteristics of individual pixels as primary features (Schillen and König, 1994; Ritz et al., 1994; Wang & Terman, 1995, 1997; Wang, 1999). The advantage of the latter approach is that it can be applied to any type of images and not only to contour objects. We follow the third approach assuming that such features as straight segments are obtained as combinations of the characteristics of individual pixels. In fact our model is invariant to what kind of features compose the first layer. The only condition for the proper functioning of this layer is spatial proximity of oscillators that detect these features so that the binding of objects could be done by local connections between these oscillators.

The idea of the resonant interaction is very attractive and finds support in experimental and modeling studies (Hoppensteadt, 1992; Hutcheon et al., 1996a,b; Hutcheon & Yarom, 2000; Izhikevich, 2001). In particular, its efficiency has been demonstrated in the adaptive resonance theory (ART) (Grossberg, 1999). Our approach differs from the one developed in ART since we explicitly use oscillators to obtain their synchronization and resonance. This allowed us to design the working memory without modification of connection strengths which makes this memory different from what is generic in connectionist learning models. We think that it may shed a new light on the controversial role of LTP in the formation of memory traces (Latash, 1997), showing that may be the LTP is not an indispensable mechanism of formation of memory traces.

The adaptation of natural frequencies of oscillators has been used before as a mechanism of learning and memorization (Torras, 1986; Hoppensteadt, 1992; Nishii, 1998, 1999; Borisyuk et al., 2001). We have shown that such adaptation can provide an efficient mechanism of implementing a winner-take-all procedure when different assemblies of oscillators compete for the synchronization with the central oscillator.

Oscillatory models of attention with the central element have been developed in the papers (Wang & Terman, 1995, 1997; Wang 1999), where the role of a central element in the network LEGION is played by a global inhibitory neuron, and (Corchs & Deco, 2001), where the central element is represented by a population of integrate-and-fire neurons. The function of the central element in these works is similar to the one considered here, that is to synchronize some assemblies of oscillators and to desynchronize others.

The principle of memorization by sparse coding and adaptation of internal parameters of network elements was formulated in our paper (Borisyuk et al., 2001). In that paper the adapted parameter was the natural frequency of an oscillator in a novelty detection network. Unfortunately this approach demands time consuming computations, therefore here it was changed to the adaptation of the parameter that controls the speed of transition to the resonance in the NDL. In fact, both methods give similar results. Note that the memory in the NDL is of a special type suitable for novelty detection only. The memory does not include the information about an object that would be needed for its recognition or comparison with other objects. The model memorizes only the fact of novelty or familiarity of an object and this significantly simplifies the memory network architecture, where only feedforward connections are used.

We consider a very simplified version of novelty detection that uses short term working memory of the hippocampus only. In fact the process of novelty detection is much more complicated. It may include long term memory and recruit not only the hippocampus but also many other brain structures. Dias and Honey (2002) have shown by studying the orienting response that the medial prefrontal cortex of the rat's brain contributes to novelty detection. Fischer et al. (2003) studied the habituation during repeated exposure of fearful and neutral faces and found that habituation takes place in the amygdale, hippocampus and the temporal cortex. In addition, it was shown that brain regions involved in novelty detection habituate at similar rates regardless of whether the face in the focus of attention displays an aversive emotional expression or not. Daffner et al. (1998) demonstrated that the amplitude of the novelty P3 response in frontal regions strongly predicts the duration of viewing of novel stimuli and suggested that the P3 might reflect the activity of a neural system that serves to link attentional recourses to novel events. Also, it was shown that frontal lobe injury reduces the amplitude of the novelty P3 response (Herrmann & Knight, 2001). The paper (Daffner et al., 2000) studies P3 event-related potential response to novel stimuli under attentional conditions in normal subjects and patients with frontal lobe damage. The results of the study suggest that frontal lobe damage leads to diminish visual attention to novel events through disruption of neural processes underlying the novelty P3 response. These processes appear to regulate the allocation of attentional resources and early exploratory behavior, and they are not limited to immediate orienting responses. Damage to the frontal lobes may prevent the generation of a signal, which indicates that a novel event in the environment requires additional attention due to its potential behavioral significance. These results show that much more efforts are needed to develop a model of novelty detection that would comply with experimental evidence.

The model is very flexible, so that many improvements and generalizations can be easily introduced in it. Firstly, colored images with overlapping objects on a non-homogenous background can be considered. In this case a more sophisticated coding of the input signal and a more complex scheme of interaction between the elements in the OSL are needed (see, e.g., Schillen, & König, 1994) to solve the problem of object/background separation. Another approach to processing occluding objects is suggested in (Wang and Liu, 2002). The paper presents an integrated approach to scene analysis by combining primitive segmentation with segmentation based on using associative memory where all single objects in a scene are stored. The results of primitive segmentation (based on the T-junction algorithm) are delivered to the modules of associative memory. Recall of an appropriate memorised pattern helps to improve the segmentation of the scene. Whatever the method of feature binding, as soon as it is properly implemented in the form of synchronous oscillations of a neural assembly, the attention system with the central element will work in the same way as it has been described above without any additional complications.

One of the problems in attention modeling is how to combine both bottom-up and top-down processing in the functioning of the attention system. For example in saliency based approach (Koch & Ullman, 1985; Niebur & Koch, 1998; Itti & Koch, 2000) essentially bottom-up strategies are used for the rapid selection of the most conspicuous parts of the visual field. On the contrary Corchs and Deco (2001) apply a top-down search of an object that is described by a given set of features. In their model bottom-up connections are absent. In our model, feedforward and feedback interaction between the CO and the OSL would allow the integration of both approaches. The saliency based not only on the size of an object but also on its brightness/contrast or the concept of a spotlight of attention could be reformulated in terms of an increasing influence on the CO of some oscillators in the OSL. In particular, a strategy of object selection not in a random order but from left to right and from top to bottom (as in scanning devices) can be realized. In the model we restricted attention operation to the first layer, the OSL. In fact attention should operate at all the levels where more and more complex features are computed. This would make our model much more powerful. For example, introducing connections between the LFL and the CO we can bias the choice of an object in the attention focus by increasing the interaction between the CO and the elements in the LFL coding particular features. The choice of particular features can be made in the same way as it is done by Corchs and Deco (2001) through top-down connections from the memory module to the LFL. Using this idea one can overcome the problem of binding disconnected objects with common features (for examples, to obtain a single pattern from a set of points moving in the same direction with a given speed).

Another problem is the noise. It can result in the appearance of spurious objects and in breaking the original relations in connectedness. To some extent this problem can be solved by filtering small or too narrow object. This can be achieved in the OSL by inhibiting the activity of those oscillators that receive too few input signals from their neighbors in the layer. But a general solution to this problem inevitably demands a pattern recognition module that could make a decision whether an object is distorted by noise or just shows the natural variability. This is a separate problem that cannot be considered here in more detail.

Finally, we would like to note that gradual forgetting of the memorized patterns can be introduced in the NDL that will free memory for new objects instead of those that have not appeared in the images for a long time.

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FIGURE LEGENDS

Figure 1. The architecture of the network. The input image contains three objects. In the OSL an object in the focus of attention is painted in black, other activated regions are painted in gray. In the LFL and IFL, there are five features of the object in the attention focus: four endpoints of different orientation and a crossing of two lines. In the LFL the features are attached to special locations where they are found, in the IFL the features are registered independently of their location in the image. The NDL is divided into the groups located along the horizontal axis.

Figure 2. The graph of the function g(x).

Figure 3. The features used for coding the images HELLO and WORLD in the LFL.

Figure 4. Dynamics of the amplitudes in the OSL: Initial presentation of the words HELLO and WORLD are at the moments 0 and 35, respectively.

Figure 5. Sparse coding of objects in the NDL. Vertical bars show the groups with resonant activity. The height of a bar is proportional to the number of resonant oscillators in the group. Note the coincidence of those groups with resonant oscillators that correspond to identical letters in the words HELLO and WORLD.

Figure 6. The graphs of the number of resonant oscillators in the NDL as a function of time since the moment when attention is focused on a given object. Thick curves show the graphs corresponding to the objects detected as familiar. Thin curves show

the graphs corresponding to the objects detected as novel. The horizontal dashed line shows the level of the threshold H.

Table 1. Periods of attention focusing on different objects. The third and fourth columns show the moments when the object is included in the attention focus and excluded from it.

Image	Object	Beginning	End	Duration
HELLO	O	3.1	7.2	4.1
	H	9.5	14.5	4.2
	E	17.4	21.6	5.0
	L2	23.7	29.5	5.0
	L1	32.3	33.9	1.6
WORLD	W	38	44.6	6
	O	46.1	51.1	1.4
	D	49.4	57.9	5.1
	R	56.6	61.5	4.7
	L	64.3	66.1	1.8

Table 2. The values of parameters used in simulation.

Parameter	Value	Parameter	Value	Parameter	Value
$\omega_0(0)$	5	T	0.76	W	2
$\theta_0(0)$	0	$\phi_i^k(0)$	0	B_0	0.3
$\theta_i(0)$	0	$\chi_k^h(0)$	0	B_1	1.5
$a_i(0) = a^0$	2	$\omega_{\min}$	4.5	C	2
ω_i	5	$\omega_{\max}$	5.5	Γ	
w_0	-2	ν	15	$\xi_1(2)$	0.97
w_1	15	κ	15	$\xi_1(3)$	0.96
w	25	a	1	$\xi_1(4)$	0.94
σ	1	A	1	$\xi_1(5)$	0.93
b	1	$\psi_r^s(0)$	0	$\xi_1(6)$	0.92
c	2	$A_r^s(0) = A^0$	0.5	$\xi_1(7)$	0.91
γ	10	q	10	η_1	0.015
ξ	0.9	m	2000	ρ_1	0
η	0.15	$d_{\min}$	$-\pi/4$	H	30
ρ	0.1	$d_{\max}$	$\pi/4$	T_1	7.5
α	2	V	1	D	30

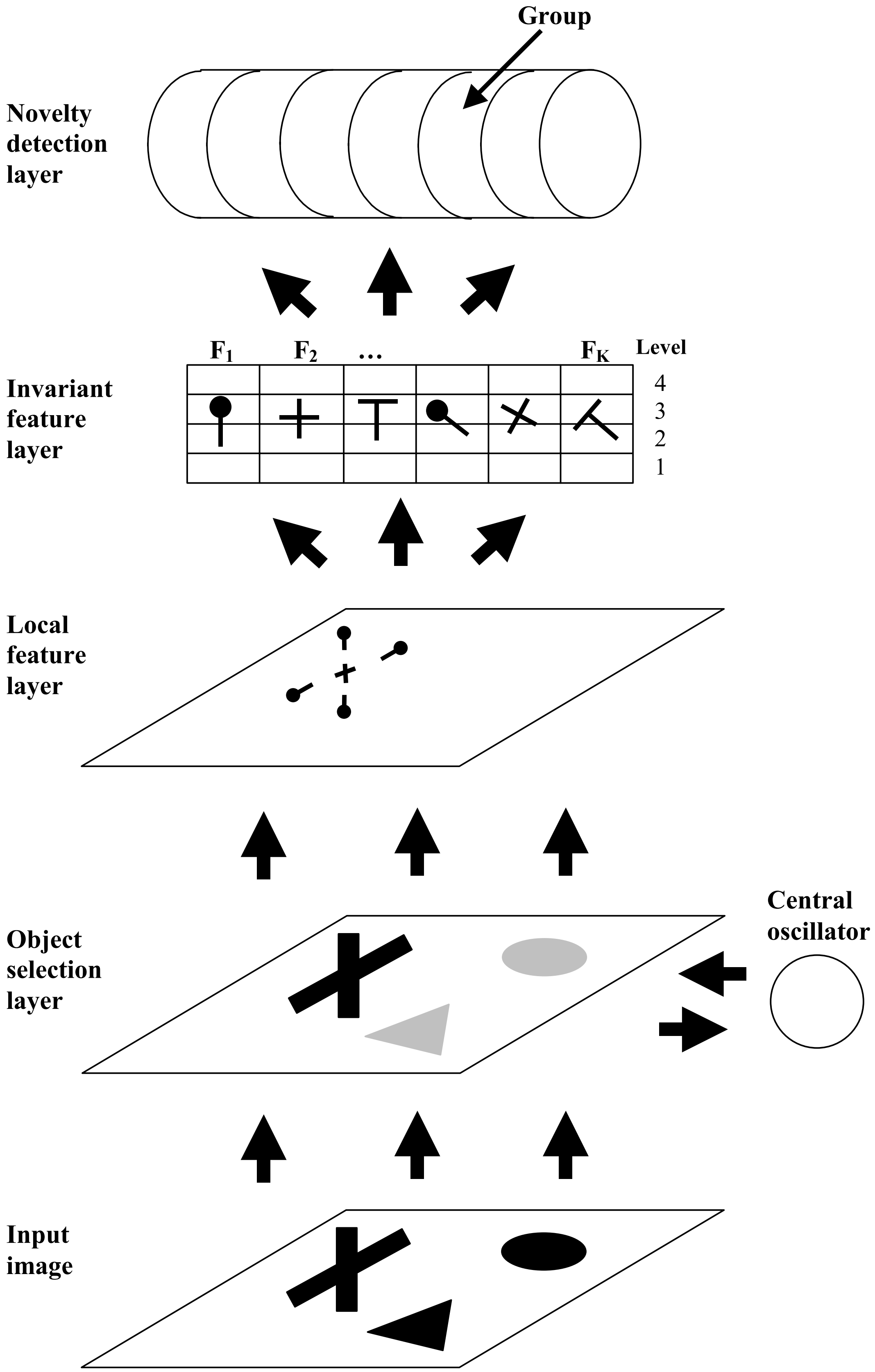

Group
Novelty detection layer
Invariant feature layer
F1
F2
…
FK
Level
4
3
2
1
Local feature layer
Object selection layer
Central oscillator
Input image

Fig. 1

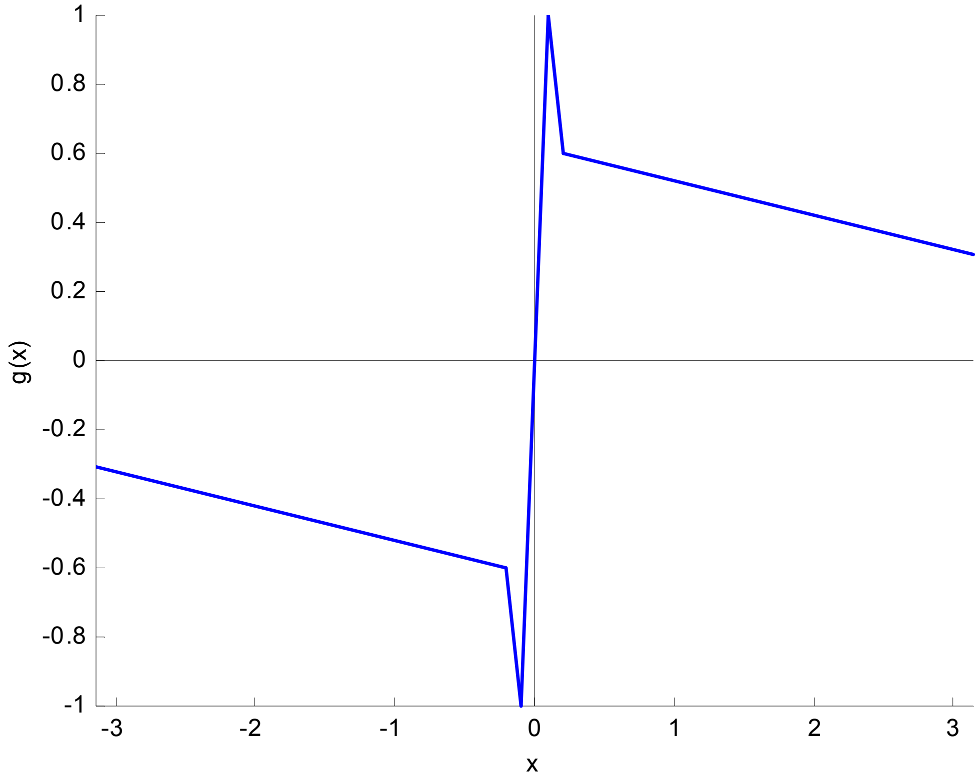
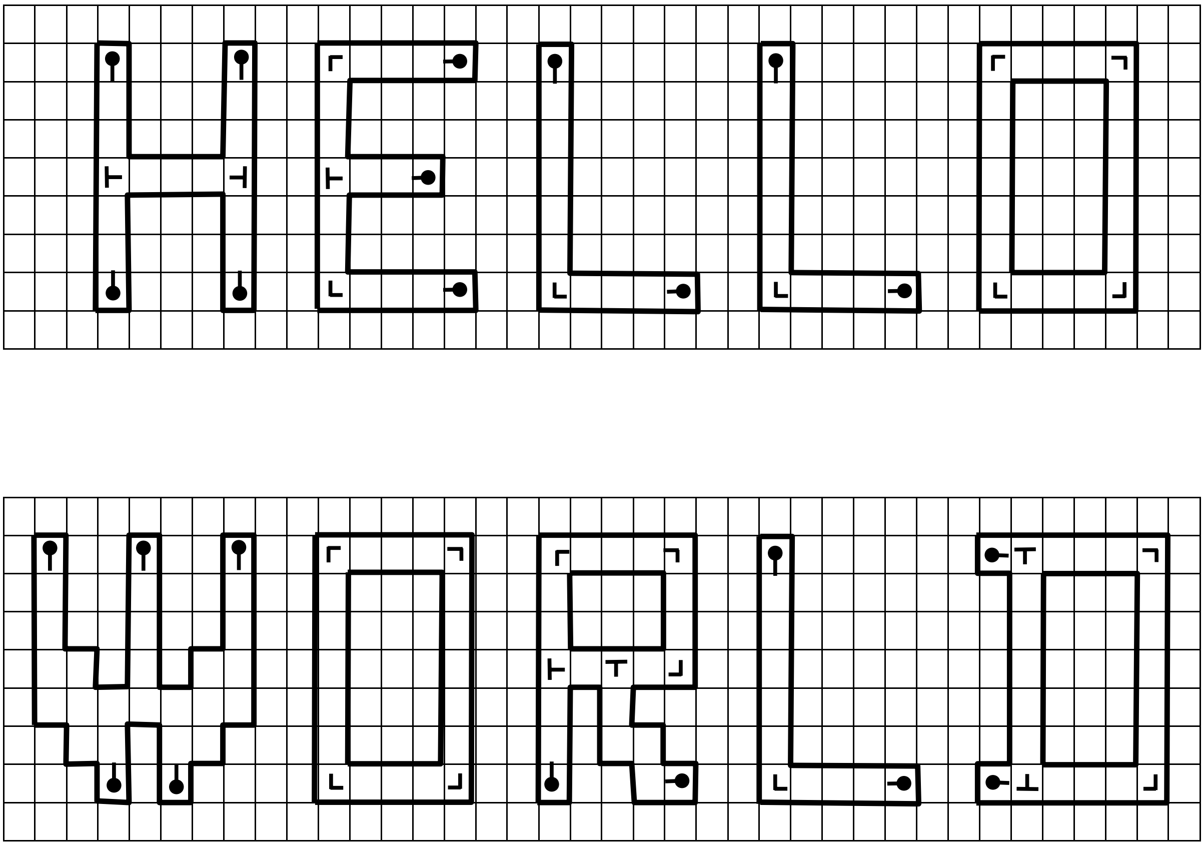


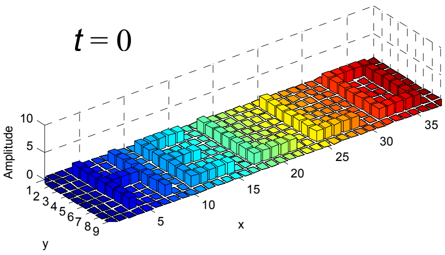
Fig. 2



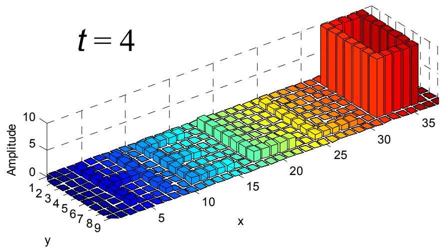
endpoints (bottom, right, top, left)
corners (bottom-left, top-left, bottom-right, top-right
T-shape crossing (left, bottom, top, right)

Fig. 3

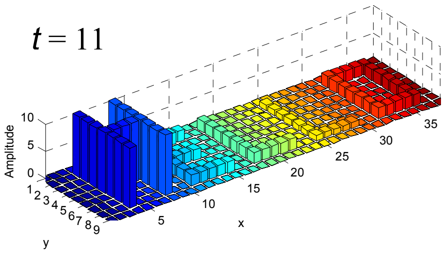
$t = 0$



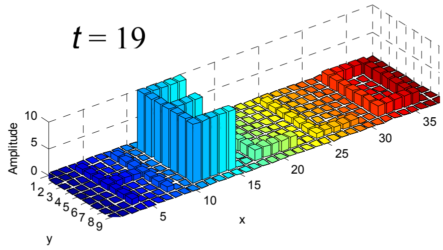
$t = 4$



$t = 11$



$t = 19$



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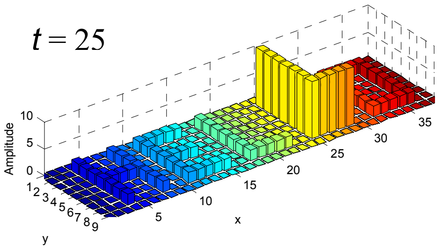
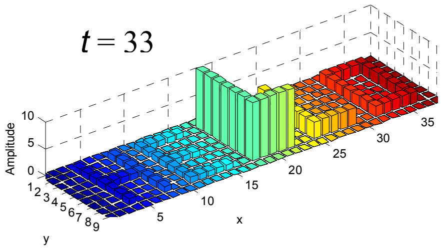


$t = 33$



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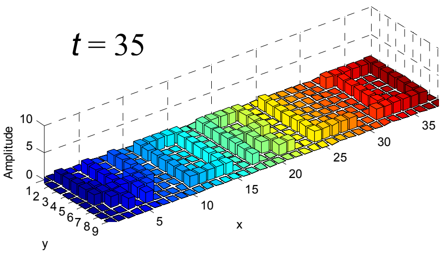

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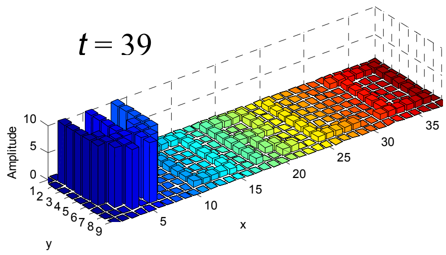

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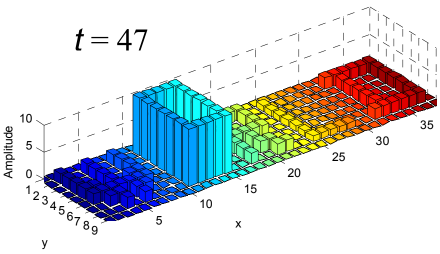

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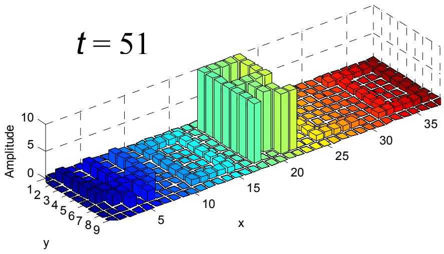
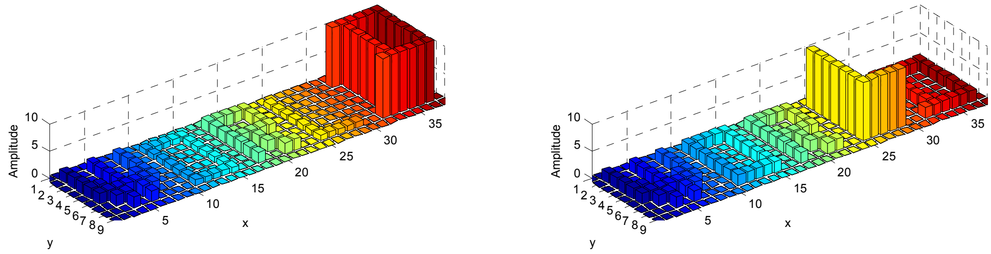


$t = 58$

$t = 65$


Amplitude
10
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0
1 2 3 4 5 6 7 8 9
y
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15
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25
30
35
x
Amplitude
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1 2 3 4 5 6 7 8 9
y
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10
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20
25
30
35
x

Fig4

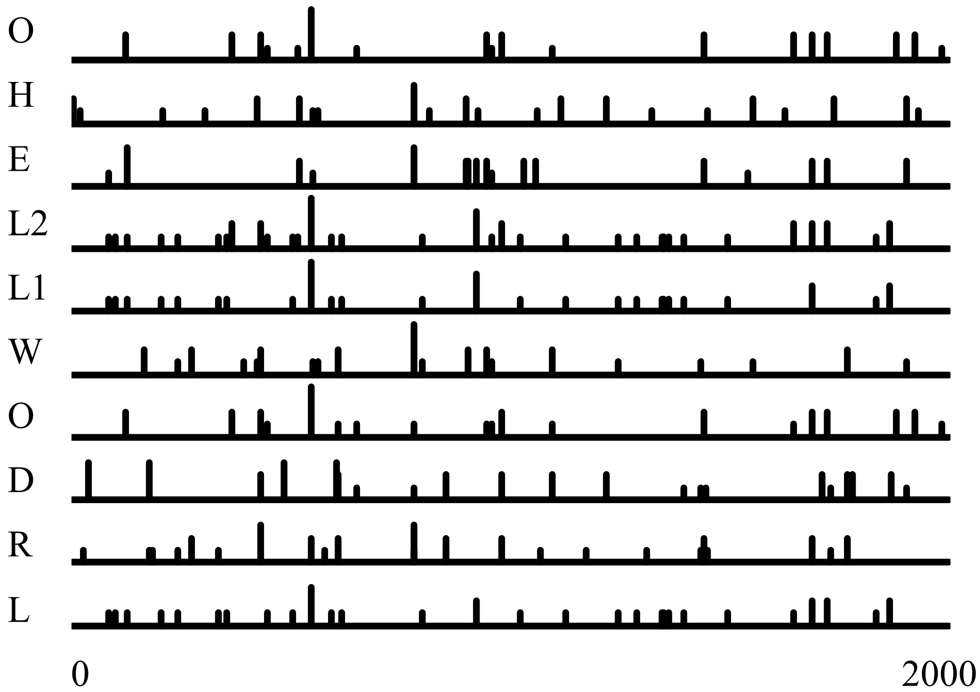
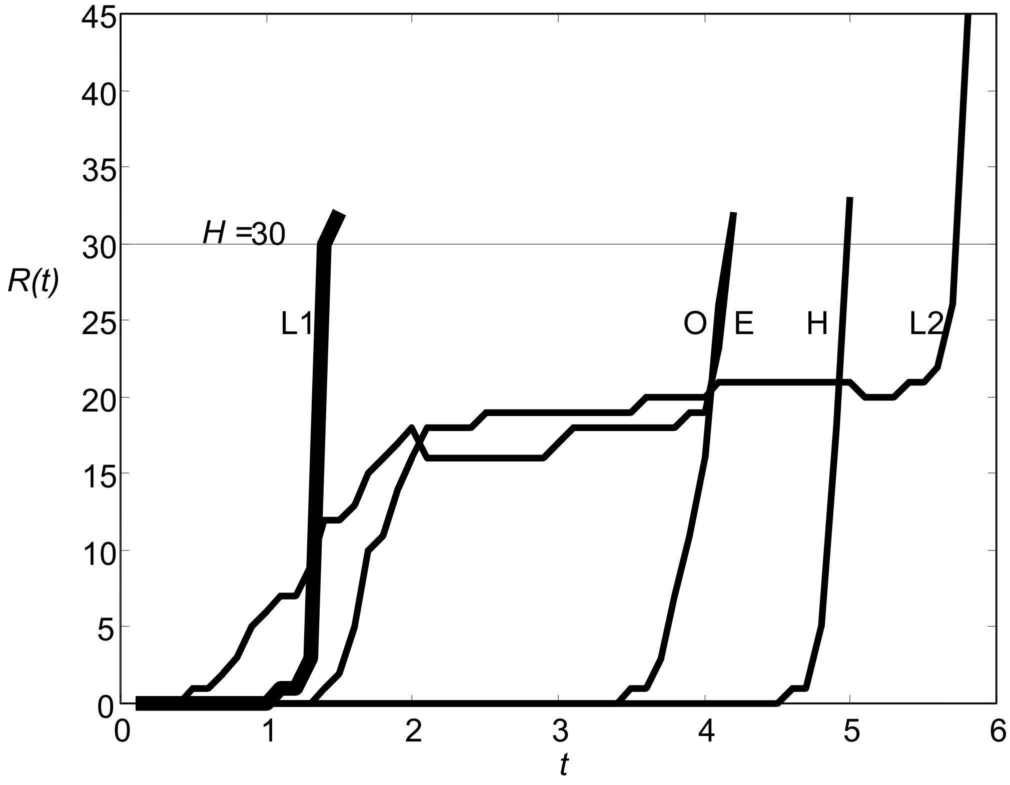


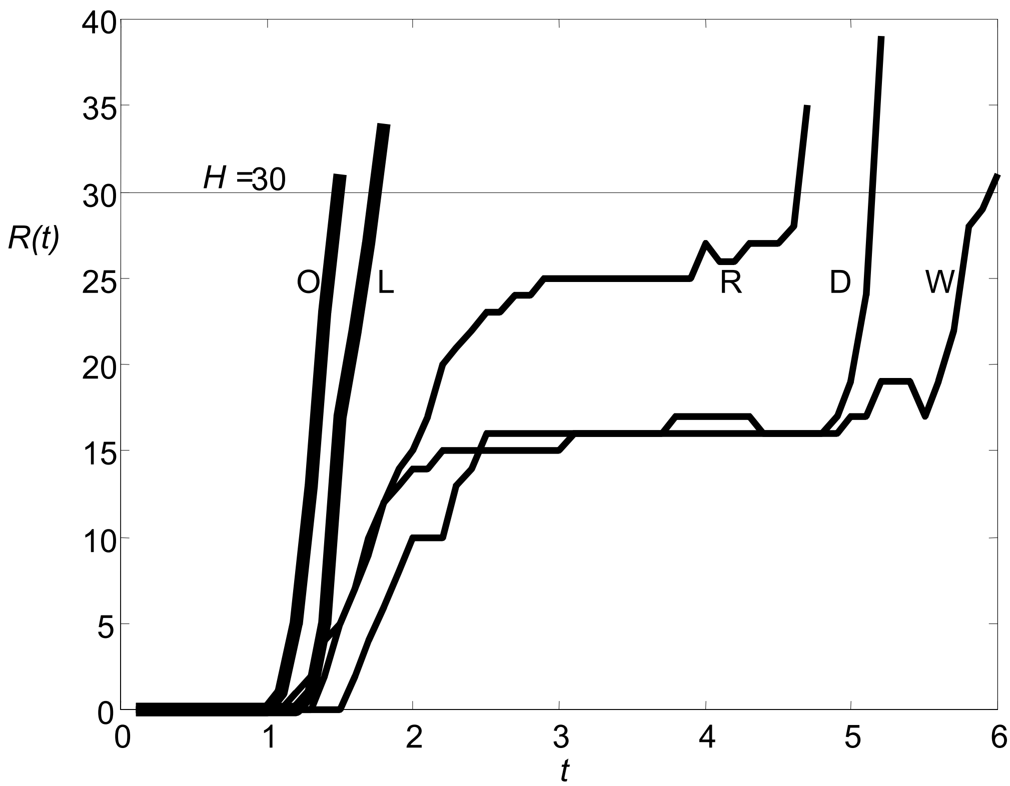
Fig. 5

(a)



45
40
35
30
25
20
15
10
5
0
R(t)
H =30
L1
O
E
H
L2
0
1
2
3
4
5
6
t

(b)



40
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R(t)
H =30
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4
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t

Fig. 6