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BioSystems 67 (2002) 103–111

Bio Systems

www.elsevier.com/locate/biosystems

Object selection by an oscillatory neural network

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Accepted 22 August 2002

Abstract

We describe a new solution to the problem of consecutive selection of objects in a visual scene by an oscillatory neural network with the global interaction realised through a central executive element (central oscillator). The frequency coding is used to represent greyscale images in the network. The functioning of the network is based on three main principles: (1) the synchronisation of oscillators via phase-locking, (2) adaptation of the natural frequency of the central oscillator, and (3) resonant increase of the amplitudes of the oscillators which work in-phase with the central oscillator. Examples of network simulations are presented to show the reliability of the results of consecutive selection of objects under conditions of constant and varying brightness of the objects.

Keywords: Oscillatory neural network; Synchronisation; Resonance; Object selection

1. Introduction

The principles of neural network design and functioning make them efficient and convenient for parallel computations, but much effort is required when consecutive procedures of information processing should be implemented in a neural network. The experimental evidence shows that there is a combination of parallel and consecutive procedures of information processing in the living systems (Treisman and Gelade, 1980; Mesulam, 1998; see also Koch and Ulman, 1985; Moore and Wolfe, 2001, and further references there). Consecutive selection of objects (CSO) presents an example when both procedures are combined to extract the information corresponding to individual objects from a complex scene.

CSO is a classical task in the theory of neural networks that appears in relation to the problems of unsupervised learning, feature binding, and attention modelling. In application to visual scenes, the task of CSO can be formulated in the following way. Consider a network whose elements receive the signals from the pixels of the input image where several objects are simultaneously presented. The dynamics of the network elicited by this stimulation should be organised so that

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PII: S0303-2647(02)00068-0

(a) the activity of neurons in an assembly representing a single object changes coherently; (b) assemblies of neurons consecutively increase and decrease their activity in such a way that for a given period of time the activity of the assembly corresponding to a selected object is significantly higher than the activity in any other part of the network.

Several approaches to CSO have been suggested recently. The paper (Tsotsos et al., 1995) implements the idea of a top-down hierarchy of winner-take-all processes. Ritz et al. (1994a,b) describe an oscillatory variant of the associative memory with synchronising and desynchronising connections providing cooperation between oscillators coding one object and competition between oscillators coding different objects. Both approaches suffer from the exponential growth of the number of connections in the network with the increase of the size of input information. Wang and Terman (1995, 1997) developed a network (LEGION) of locally interacting Van-der-Pol type oscillators whose activity is globally controlled by an inhibitory neuron. Oscillators representing different objects are consecutively activated during one cycle of oscillations. In this model, the duration of the cycle should increase with the increasing number of presented objects.

We describe a new solution to CSO in an oscillatory neural network with a special architecture of connections, the so-called network with a central oscillator (CO) (Kryukov, 1991; Kazanovich and Borisyuk, 1994, 1999). The number of connections in the network is of the same order as the number of elements. There is no dependence between the frequency of oscillations and the period of the cycle of object selection. Network functioning is based on the principles of phase-locking (Kuramoto and Nishikawa, 1987; Schuster and Wagner, 1990; Golomb et al., 1992; Ermentrout and Kopell, 1994; Hoppensteadt and Izhikevich, 1997; Aoyagi and Kitano, 1998; Neltner and Hansel, 2001; Kazanovich and Borisyuk, 1994, 1999; Borisyuk et al., 2000, 2001), adaptation of the natural frequency of oscillators (Torras, 1986; Hoppensteadt, 1992; Nishii, 1998, 1999; Borisyuk et al., 2001) (in the model this adaptation is applied to the natural frequency of the CO), and the resonance influence of the CO on the assembly of oscillators that work in-phase with the central element (Borisyuk et al., 2001).

We use the synchronisation hypothesis (Singer and Gray, 1995; Gray, 1999; Singer, 1999) for implementation of a "label" that identifies the neural assembly coding a specified object. It is assumed that the task of grouping pixels or features of a locally connected object is solved at the preattention level due to local coupling but attention (and global coupling) is involved when selection of individual objects is required. An object that is included in the attention focus is supposed to be represented by an assembly of POs working in-phase with the CO. The amplitude of oscillations in the assembly is amplified by the attention system while the activity of other oscillators is temporally shut down to a low level.

An approach to attention modelling that is to some extent similar to ours has been suggested by Koch and Ulman (1985) and developed in detail by Niebur and Koch (1996, 1998). An important distinction is that Niebur and Koch rely on a traditional winner-take-all procedure while in our model a phase-locking mechanism is used to organise the cooperation in the assemblies of oscillators and competition between the assemblies. The consequence of this fact is that in our model the amplification of activity in the network is realised through top-down influences of the CO on POs. In the Niebur–Koch model "essentially bottom-up strategies for the rapid selection of the most conspicuous parts of the visual field" are implemented.

2. Model description

The architecture of the network connections is shown in Fig. 1. The network consists of a CO that has feedforward and feedback connections to a set of oscillators located in the vertices of a square grid. We refer to these oscillators as peripheral oscillators (PO). Besides the CO, each PO is coupled with its four nearest neighbours except on the boundaries where no wrapped-around connectivity is applied.

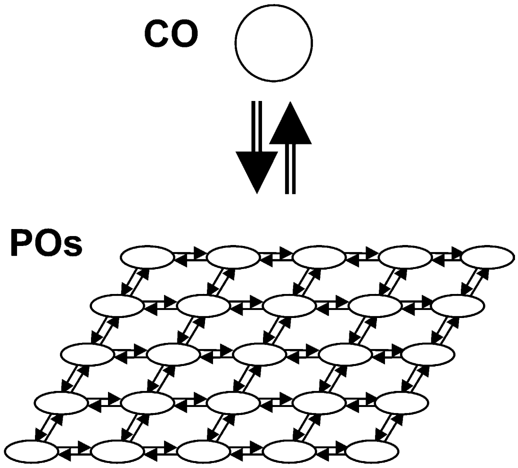

Fig. 1. The architecture of connections in the network.

An oscillator 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 between the oscillators.

The input to the network is an image on the plane grid of the same size as the grid of POs. So there is a one-to-one correspondence between the pixels in the image and the POs. Each PO receives an external input from the corresponding pixel. This signal determines the natural frequency of the PO. It is assumed that the image contains several non-overlapping greyscale objects on the white background of the constant brightness B. The natural frequency of the ith PO is set to be equal to

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

where P_i is the grey level of the ith pixel and λ is a scaling parameter. We call an *assembly* a group of mutually connected oscillators that are stimulated by a single object. We say that an object is coded by the corresponding assembly of POs.

Depending on the input signal and previous dynamics, a PO can be in one of four states: *active, resonant, passive, and silent*. If a PO 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 is not included in the dynamics equations shown below. If a PO is not silent, it consecutively (and probably repeatedly) goes through a cycle of states: active–resonant–passive. Such an oscillator starts working in the active state; then if the amplitude of its oscillations exceeds a certain threshold, it changes its state to the resonant one. After spending long enough time in the resonant state, the oscillator becomes passive. It spends in the passive state a prescribed time and returns to the active state. This completes the first round of state changes and gives a start to the next round, etc. A PO can influence the dynamics of the CO if only the PO is in the active or resonant state. In the passive state the PO temporarily becomes "invisible" for the CO.

The dynamics of the network are described by the following equations:

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

$$\frac{d\theta_i}{dt} = \omega_i - a_0 w_0 h(\theta_0 - \theta_i) + w_1 \sum_{j\in N_i} a_j p(\theta_j - \theta_i) + \rho, \tag{2}$$

$$i = 1, \ldots, n$$

$$\frac{da_i}{dt} = \beta_1(-a_i + \gamma s_i f(\theta_0 - \theta_i))^{+} + \beta_2(-a_i + \gamma s_i f(\theta_0 - \theta_i))^{-}, \tag{3}$$

$$\frac{d\omega_0}{dt} = -\alpha\left(\omega_0 - \frac{d\theta_0}{dt}\right). \tag{4}$$

In these equations, θ_0 is the phase of the CO, θ_i are the phases of POs, $d\theta_0/dt$ and $d\theta_i/dt$ are the current frequencies of oscillators, ω_0 is the natural frequency of the CO, ω_i are the current frequencies of POs, a_0 is the amplitude of oscillations of the CO (a constant), a_i are the amplitudes of oscillations of POs, w, w_0, w_1 are constant positive parameters that control the strength of interaction between oscillators, s_i is the state of a PO ($s_i = 1$ if the oscillator is in the active or resonant state, $s_i = 0$ if the oscillator is in the passive state), n is the number of non-silent oscillators, N_i is the set of non-silent oscillators in the nearest neighbourhood of the oscillator i, ρ is the gaussian noise with the mean 0 and standard deviation σ, functions g, h, p control the interaction between oscillators (these functions are 2π-periodic, odd, unimodal in the interval of periodicity), f is the function that controls the amplitude of oscillations of POs and their transition to the resonant state (f is 2π-periodic, even, positive, unimodal in the interval of periodicity with the maxima in the points $2\pi k$), and α, β_1, β_2, γ are network parameters (positive constants). The values ω_i are determined by the input signal; θ_0, θ_i, ω_0, a_i are internal variables that characterise the state of the system. By definition,

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

Eqs. (1) and (2) 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: a PO with greater amplitude has stronger influence on other oscillators.

The coupling strength between oscillators is constant. The connections from POs to the CO and the local connections between POs are synchronising. The connections from the CO to POs are desynchronising. Due to synchronising connections from POs to the CO, the latter can be phase-locked by an assembly of POs. Due to synchronising connections between POs, the oscillators from an assembly of active POs become phase-locked and work nearly in-phase after they reach the resonant state. Desynchronising connections from the CO to POs are used to brake coherence between different assemblies of POs.

The noise ρ in Eq. (2) is used as an additional source of desynchronisation between the assemblies of POs. It helps to randomise the location in phase-frequency space of different assemblies of POs, thus making them distinguishable for the CO.

We use the following interaction functions in Eqs. (1) and (2):

$$h(\phi) = p(\phi) = \sin\phi,$$

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

Outside the interval $(-\pi, \pi)$ the function $g(\phi)$ is continued as periodic. The important feature of $g(\phi)$ 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 $g(\phi)$ improves the capability of the system to separate assemblies with similar values of the natural frequencies of POs. 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.

According to Eq. (1), a PO influences the dynamics of the CO if only the PO is in the active or resonant state. This provides the CO with the capability to synchronise its activity with different assemblies of POs. Transition of an assembly of POs from the resonant to the passive state temporarily excludes this assembly from the synchronisation with the CO thus freeing the CO for synchronisation with another assembly of active POs.

Eq. (3) describes the dynamics of the amplitude of oscillations of POs. This equation provides the mechanism for the resonant increase of the amplitude of oscillations. The function $f(x)$ has the form

$$f(x) = F((\cos x)^+),, \tag{5}$$

where $F(y)$ is a sigmoid function of the type

$$F(y) = \zeta + \frac{\exp((y - \xi)/\eta)}{1 + \exp((y - \xi)/\eta)}. \tag{6}$$

Parameters ξ and η are chosen so that $F(y)$ approaches its maximal value $1 + \zeta$ when y tends to 1; $F(y)$ quickly decays to ζ if y becomes lower than $1 - \varepsilon$ (ε is one order less than 1). Thus the amplitude of a PO increases to the maximum value $a_{\max} = \gamma(1 + \zeta)$ if the PO works synchronously with the CO; the amplitude takes a low value $a_{\min} = \gamma\zeta$ if the phase of the PO is significantly different from the phase of the CO (ζ is one order less than 1). We say that a PO is in the resonant state if its amplitude exceeds the threshold $R = 0.8a_{\max}$. If a PO becomes passive, the amplitude decays to zero. The parameters β_1 and β_2 ($\beta_1 < \beta_2$) determine the rate of amplitude increase and decay.

The amplitude of the CO is constant. It is used as an independent parameter to get the same type of notation in Eqs. (1) and (2) for both feedforward and feedback connections between the CO and the POs. We always put $a_0 = 1$.

We suppose that the duration of the resonant state for a PO is restricted by the energy resource r that can be supplied to this PO. The parameter r varies in the limits $0 \le r \le r_0$. At the initial moment and after changing the state from passive to active, the energy resource for the PO is renewed, that is r is reset to r_0. If the PO is in the resonant state, r decays according to the equation

$$\frac{\mathrm{d}r}{\mathrm{d}t} = -\mu, \quad (\mu > 0, \ \ r \ge 0)$$

If the PO is in the active state, r slowly regenerates according to the equation

$$\frac{\mathrm{d}r}{\mathrm{d}t} = \nu, \quad (0 < \nu < \mu, \ \ r \le r_0)$$

At the moment when r becomes zero the oscillator switches from the resonant to the passive state. The duration of the passive state for a PO is restricted by the constant T_p. After this time is expired, the PO returns to the active state.

Eq. (4) describes the mechanism of adaptation of the natural frequency of the CO. According to this equation, ω_0 tends to the current frequency of the CO. Such adaptation allows the CO to “search” for an assembly of POs with which the CO is going to synchronise. 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 random fluctuations of this frequency.

The values of the natural frequencies of oscillators belong to an interval of admissible frequency values $(\omega_{\min}, \omega_{\max})$. The initial values of the amplitudes of POs are set to a^0 $(a_{\min} < a^0 < a_{\max})$. The initial values of the phases of all oscillators are set to 0. Starting from these initial conditions, the network obeys Eqs. (1)–(4) with the only exclusion of the moments when a PO switches from the passive to the active state. At this moment the amplitude of the PO is set to a^0 and its phase is set to zero.

In biological terms the model is interpreted in the following way. It is assumed that POs represent cortical columns and are constituted of locally interacting populations of excitatory and inhibitory neurons of the cortex. The CO is represented by the septo-hippocampal system whose final position in the pyramid of cortical convergent zones (Damasio, 1989) and feedforward and feedback connections to the cortex give it a direct or indirect access to cortical structures.

CSO is implemented by the following dynamics of the network. Just after the network is initialised and starts its work, the CO is synchronised by an assembly of POs which has the strongest influence on the CO. The POs 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.

After spending some time in a resonant state, the oscillators switch to the passive state and are forced to decrease their amplitudes to a low level. This state of low-level activity is kept for a long enough time to give the CO an opportunity to synchronise its activity with another assembly of oscillators, etc.

3. Simulation results

The first example is an image that contains four bars of the same length and different width separated by narrow spaces of the white background. We suppose that the pixels of the bars have the same grey level to which the noise is added. Therefore the bars are coded by assemblies of oscillators with the natural frequencies randomly and uniformly distributed in a small interval $(\Omega - \Delta, \ \Omega + \Delta)$. The number of oscillators in the network is 85 from which 70 are non-silent. The result of network functioning is shown in Fig. 2. In Fig. 2A each frame shows the state of the network at discrete moments of time $k = 1, 2, \ldots, 60$. Fig. 2B shows the dynamics of the amplitudes of oscillations over the time period 0–60 for the same example. Fig. 2C shows the dynamics of the synchronisation index of POs defined as

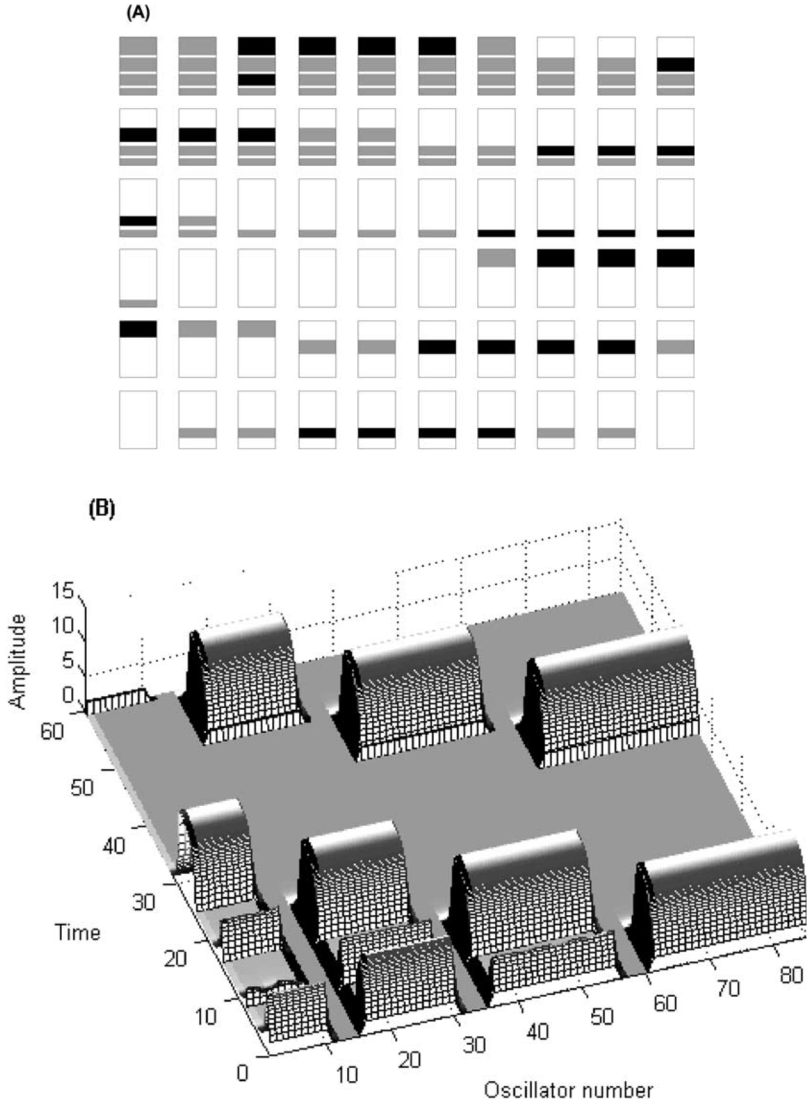

Fig. 2. Dynamics of the network during CSO with constant natural frequencies of POs: The input image of 5*17 pixels contains four bars of the same length (5 pixels) and different width (2, 3, 4, and 5 pixels) separated by narrow spaces (5*1 pixels) of white background. (A) The frames (ordered from left to right and from top to bottom) show the state of the POs at integer moments of time $k = 1, 2, \ldots, 60$. If at the moment k ith PO is in the resonant state ($a_i > 0.8a_{\max}$), the pixel that corresponds to this oscillator in the frame k is black. The pixel is grey if $0.05a_{\max} < a_i \leq 0.8a_{\max}$. The pixel is white if $a_i \leq 0.05a_{\max}$. (B) 3d graphs of the amplitudes of POs as a function of time. The amplitudes vary in the interval (0, 11). The resonance threshold is 8.8. An increase of amplitudes of all non-silent oscillators can be seen during the first 10 time units but only in two assemblies (oscillators 15–30 and 60–85) do the amplitudes exceed the resonance threshold. (C) 3d graphs of the synchronisation index. Dark parts of the graphs correspond to the moments of in-phase activity of a PO and the CO. These moments coincide with the resonant activity of the PO.

$$S_i = \cos(\theta_i - \theta_0).$$

This index takes the largest value (near 1) when the ith PO works synchronously (in-phase) with the CO.

Despite the fact that in our example the assemblies of oscillators (representing different objects) have had identical initial phases and only slightly different natural frequencies, the

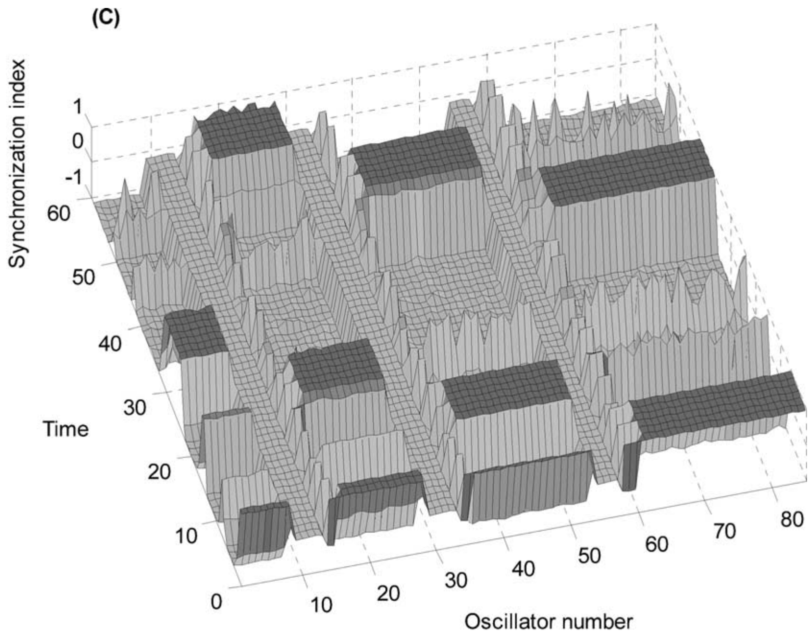

Fig. 2 (*Continued*)

results of CSO are rather good. Only at the moment $k = 3$ (see frame 3 in the first row of frames in Fig. 2A) are the oscillators from two bars simultaneously combined in the resonant state. No error in CSO can be observed in the later dynamics. An interesting fact is that the sequence in which objects are selected correlates with the size of objects. Larger objects have a greater chance to be selected earlier in the round of selection.

The second example is an image that represents four objects of different shape Now we consider the case when the grey level of pixels is not constant but varies as a function of time. This may happen, e.g. due to changes in the brightness of the objects. Thus we put

$$\omega_j^k = \Omega_j^k + V_k(t),$$

where ω_j^k is the natural frequency of the jth oscillator in the assembly of oscillators representing the kth object ($k = 1, 2, 3, 4$), Ω_j^k are random variables uniformly distributed in a small interval $(\Omega - \Delta, \Omega + \Delta)$, and $V_k(t)$ is a function that determines the variation of the natural frequencies. As a particular example we have chosen

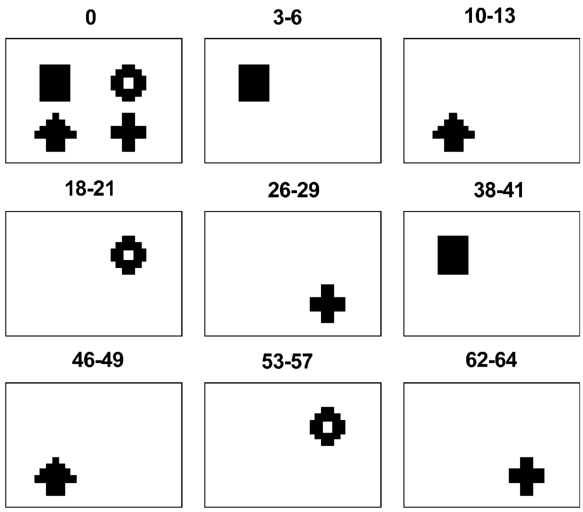

Fig. 3. Dynamics of the network during CSO with varying natural frequencies of POs. Four objects of different shape are presented at the input image of size 30*20 pixels. The first frame shows the initial state of the network. In this frame black and white pixels correspond to non-silent and silent oscillators, respectively. Other frames show the state of the oscillators at integer moments of time $k = 1, 2, \ldots, 64$. Black and white pixels correspond to resonant and non-resonant states of oscillators, respectively. The numbers over the frames show time intervals. The frames without resonant oscillators are omitted.

$V_k(t) = A\ \sin(kt)$.

The first frame in Fig. 3 shows the initial state of the network. In this frame black pixels correspond to the oscillators that receive the non-zero input signal. The frames 2–9 in Fig. 3 show the state of the oscillators for discrete moments of time from 1 to 64. Resonant and non-resonant oscillators are represented by black and white pixels, respectively. Computer simulations show that the network is perfect in accomplishing the CSO task for any type of slowly varying functions $V_k(t)$. The only condition that should be fulfilled for successful CSO is that the natural frequencies of oscillators in an assembly obey the same type of variation.

4. Discussion

As computer simulations show, the model successfully implements CSO, separately synchronising assemblies of oscillators that represent non-overlapping objects. Larger objects have higher priority for earlier selection (example 1). The variation of the natural frequencies of POs that can be associated with the change in the brightness of the object does not impair the results of CSO (example 2). The number of objects that can be consecutively selected is limited only by the constant T_p that controls the duration of the passive state. Depending on this constant, different regimes of CSO can be implemented such as a repetition-free cycle of selection of all objects (if T_p is large enough) or non-deterministic order of selection if T_p is made small or random.

The priority of object selection depends on the size of objects. It is reasonable to assume that new, significant and salient objects elicit the activity of oscillators with the higher amplitude or higher natural frequency. Only slight changes should be introduced in the model to make such objects preferable for earlier selection. Different strategies of selection can be implemented by additional mechanisms of control over the natural frequency of the CO. For example, a set of natural frequencies memorized during learning can be used for the assignment as initial values of the natural frequency of the CO. In this case the procedure of CSO will be biased by preliminary ‘‘expectations’’.

More sophisticated procedures of object selection and segmentation demand preliminary storage of the information about objects in short or long term memory. For example, such storage is necessary if an object similar to the one kept in memory should be selected from a set of different objects or from a complex background. Then the stored information can be used to compare objects in the focus of attention with those kept in memory. In the following papers we are going to present oscillatory principles of information processing for the system that will be able to solve the problems of attention focus formation, novelty detection, memorization, and pattern recognition. The principles of CSO developed here represent an important step in this direction.

Two main ideas are combined in the presented model: the idea of a central executive of the attention system and the idea about the key role of synchronisation in attention focus formation. These ideas seem to be highly promising both for modelling and experimental investigations. The evidence on the synchronous activity between different areas of the neocortex and also between the neocortex and the hippocampus during attention experiments could provide the necessary information to test the validity of the model. First results in this direction are encouraging (Steinmetz et al., 2000) and a lot of work in this field is expected in the near future.

Acknowledgements

This work was supported by EPSRC (grant GR/N63888/01).

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