

# Selective visual attention in a neurocomputational model of phase oscillators

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**Abstract.** In order to understand the dynamic property of covert selective visual attention, which is different from the proposed mechanism of the spotlight metaphor, a two-layered network of phase oscillators was developed. The first layer is related to the hippocampus and controls attention focus formation. The second layer is related to the visual cortex, and each cortical oscillator in it simulates an assembly of cells coding for a particular stimulus in the sense of feature binding. Selective visual attention is interpreted as the result of the emergent synchronization of hippocampus oscillators and a part of cortical oscillators. Numerical experiments are presented to illustrate attention focus formation and attention shifting from one set of stimuli to another. From a neurocomputational point of view, our results demonstrate that attention is an emergent property of the dynamical cell assemblies responding to the whole visual field.

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## 1 Introduction

Selective visual attention is closely related to the problem of how the objects and external knowledge are represented in the brain, and it is highly important for us to understand the mechanism underlying higher cognition and even consciousness. Therefore, selective visual attention has been the focus of a growing amount of research.

Although our knowledge of the specific anatomical areas and the neural mechanism of attention is still incomplete, many previous studies in psychophysics, neurophysiology, and computational modeling have given us an elemental framework for the attention system. For example, in the psychophysics community, the most widely used metaphor for selective visual attention is a spotlight which enhances information within a selected region in the scene and filters out information

outside of it (Crick 1984). According to this metaphor, scenes are searched item by item by a spotlight of attention. Correspondingly, from the neurocomputational point of view, selective visual attention is usually regarded as a means for reducing the amount of incoming visual information to a manageable size so that it can be dealt with by the limited computational resources of the brain (Leow and Miikkulainen 1991; Olshausen et al. 1993; Olshausen and Koch 1995; Niebur and Koch 1996; Larr et al. 1997). On the one hand, the popularity of the spotlight metaphor reflects the idea that selective attention is necessary for the limited computational capacity of visual systems. On the other, some difficulties arise when the existing models are employed to explain the neurophysiological or neurocomputational mechanisms underlying the spotlight metaphor. For instance, how the attention spotlight moves from one location to another within a scene is an unresolved issue (Olshausen and Koch 1995). Another question given in Desimone and Duncan (1995) concerns the role of attention in binding. A common view is that attention helps solve the binding problem by linking together different features at the location of interest (Treisman and Gelade 1980). However, experiment data support the opposite argument: targets may pop up in a visual search display before they are the focus of attention, even when they are defined by the conjunction of elementary attributes (McLeod et al. 1988; Duncan and Humphreys 1989; Wolfe et al. 1989). Desimone and Duncan (1995) reviewed a large number of psychophysical and neurophysiological experiments which have argued this spotlight metaphor, and the data cited cast doubt over many of its postulates.

An alternative to the spotlight metaphor proposed by Desimone and Duncan (1995) is that the control of attention is highly distributed through the cortex, without any explicit saliency map for registering potentially interesting areas of the input (Koch and Ullman 1985). This general model possesses the following main features (Desimone and Duncan 1995). (1) At some points between input and response, objects in the visual input compete for limited processing capacity. (2) The

competition is biased in part by bottom-up neural mechanisms that separate figures from their background (in both space and time) and in part by top-down mechanisms that select objects of relevance to current behavior. (3) Objects act as wholes in neural competition. The construction of object representations from the conjunction of many different features appears, in many cases, to occur in parallel across the visual field before individual objects are selected and, hence, prior to any attentional binding. (4) Though the matter remains controversial, according to their analysis, attention is not a high-speed mental spotlight that scans each item in the visual field. Rather, attention is an emergent property of slow, competitive interactions that work in parallel across the visual field.

The aim of this paper, inspired by Desimone and Duncan (1995), is to develop a model to explore the emergent dynamic property of covert selective visual attention from a neurocomputational point of view. A two-layered network of phase oscillators is used as the selective attention module: the underlying neurophysiological reason to employ phase oscillators will be discussed in Sect. 2. Neurophysiological studies have disclosed a wide variety of brain areas involved in selective visual attention, including the posterior parietal cortex (Posner et al. 1984), the frontal cortex (Heilman and Valenstein 1972), and even the thalamus (Crick 1984; Rafal and Posner 1987). However, our knowledge of the neuroanatomical constraints of attention is still incomplete (Posner and Petersen 1990). Our model is based on the cortico-hippocampal interplay, i.e., the top layer represents the hippocampus and the bottom one corresponds to the visual cortical areas. This neurophysiological constraint derives from the following findings. The entorhinal cortex provides the major visual cortical input to the hippocampus (Iijima et al. 1996), and the information transmitted from the entorhinal cortex can reach the pyramidal cells directly or indirectly by way of the granule cells (Amaral and Witter 1989; Lopes da Silva et al. 1990). In addition, real-time imaging revealed that neural activity is transferred in a frequency-dependent manner from the entorhinal cortex to the hippocampus (Iijima et al. 1996). In that study, the dynamics of neuronal circuits in the entorhinal-hippocampal system was studied in slices by optical imaging with high spatial and temporal resolution. Reverberation of neural activity was detected in the entorhinal cortex and was more prominent when the inhibition due to  $\gamma$ -aminobutyric acid (GABA) was slightly suppressed. Neurons in the superficial layers of the entorhinal cortex, which send their axons to the hippocampus, are under strong local inhibitory control by GABA. Results showed that the decline in GABA inhibition is frequency-dependent. For slices in normal solution, stimulus frequencies of 1 Hz and higher can overcome the local inhibition. For slices bathed in bicuculline which partly suppresses the inhibition by GABA, the reverberating circuit at 0.1 Hz might be sufficient to overcome inhibition, resulting in activation of the perforant pathway.

Furthermore, there are many experiments which confirm that the hippocampus is involved in the for-

mation of attention in classical conditioning (for a review, see Schmajuk and Dicarlo 1992), though its precise role and the mechanism of its interaction with the cortex are still under discussion. Miller (1991) formulated the theory of representation of information in the brain based on corticohippocampal interplay. He assumed that this representation results from synchronization of the oscillatory activity of the hippocampus and some part of the cortex due to a proper choice of time delays in the connections between these structures.

In this model, selective visual attention is interpreted as the result of the synchronous oscillation not only among the cell assemblies in the neuronal pools within the hippocampus but also between the hippocampus and some parts of the visual cortex.

## 2 Selective visual attention model

This model consists of two-layer phase oscillators. The bottom layer involves the visual perception input layer, while each oscillator (denoted as CO in the following text) in it represents the pertaining cells which are 'bound' into one assembly for coding for a particular object. The top layer is related to the hippocampus. As mentioned in Sect. 1, many experimental results confirm that the hippocampus is involved in the formation of attention in classical conditioning (for a review, see Schmajuk and Dicarlo 1992), and the neurophysiological data reviewed in this paper support the following arguments. (1) Hippocampal pyramidal activity in CA3 and CA1 is correlated with the presentation of simple and compound conditioned stimuli. (2) Hippocampal CA1 and CA3 activity increases during acquisition and decreases during extinction of classical conditioning. Thus, the CA1 and CA3 hippocampal regions are thought to be related to the top layer in our model. Each phase oscillator in it simulates a hippocampal pyramidal cell or an assembly of pyramidal cells participating in selective attention, and is denoted as HO. Moreover, in our model, the top layer is assumed to have long-range connections. Coupling among HOs may be achieved by putative interneurons with wide-ranging axon collateral systems which are not simulated in this model (for a review see Buzsáki and Chrobak 1995).

The dynamics of the network is described by:

$$\frac{d\theta_i^h}{dt} = \omega_i^h + u \sum_{j=1}^{N^h} \sin(\theta_j^h - \theta_i^h) + b \sum_{k=1}^{N^c} \sin(\theta_k^c - \theta_i^h) \quad (1)$$

$$\frac{d\theta_k^c}{dt} = \omega_k^c + b \sum_{i=1}^{N^h} \sin(\theta_i^h - \theta_k^c) \quad (2)$$

where  $i = 1, \dots, N^h, k = 1, \dots, N^c$  the superscripts  $h$  and  $c$  denote the oscillators in the hippocampus and the visual cortex, respectively.  $\theta_i^h$  and  $\theta_k^c$  represent the phases of the HOs and COs, and  $\omega_i^h, \omega_k^c$  are natural frequencies of the oscillators separately. The hippocampus layer has long-range (all-to-all) connections. Every HO interacts with other all  $N^h-1$  HOs, and the coupling strength

between any two HOs is the same and denoted as  $u$ . In order to simplify the analysis, connections between COs are ignored. Each CO interacts with all the HOs with the coupling strength  $b$ .

This network is developed on the inspiration of the model suggested by Kryukov (1991) in which a network of phase oscillators was proposed for attention modeling. In that work, the idea that the spetohippocampus region is a central executive of the attention system was proposed. The spetohippocampus region is simulated by a central oscillator, while the peripheral oscillators coupled with this central oscillator represent the cortical columns. The regime of partial synchronization in such an attention network was studied in detail by Kazanovich and Borisyuk (1994). Here partial synchronization means that only some proportion of the peripheral oscillators has current frequencies similar to that of the central oscillator, while current frequencies of other peripheral oscillators are quite different. Instead of only using one central oscillator for the hippocampal model, we employ a large number of oscillators to simulate the hippocampal region in (1) and (2). This is the essential difference between our model and the one considered by Kryukov (1991) and Kazanovich and Borisyuk (1994).

The underlying neurophysiological evidence for employing phase oscillators comes from a large variety of oscillations discovered in neural systems. Stimulus-evoked oscillation of neural activity has been reported in many systems, such as the cerebral cortex of mammals and the brain of insects (Freeman 1978; Eckhorn et al. 1988; Gray and Singer 1989; Gelperin and Tank 1990; Laurent and Davidowitz 1994; Laurent and Naraghi 1994). Also, it is found that under some conditions the oscillations become coherent both in adjacent and distant groups of neurons. The hippocampus exhibits rhythmic oscillatory field potentials at theta (4–12 Hz) and gamma (40–100 Hz) frequencies during its activated, exploration-associated state. More important is the fact that the neocortical projection from the superficial layers of the entorhinal cortex to the dentate, CA3, and CA1 regions also exhibits theta-modulated gamma-oscillations. These oscillations entrain the discharge of layers II-III neurons that innervate the hippocampus (for a review, see Buzsáki and Chrobak 1995).

Following from these neurophysiological experiments, we are prompted to use phase oscillators to describe the elements of both the bottom and top layers. On the other hand, the relationship between the frequency band and selective attention is, at present, very unclear. In relevant experimental results, gamma-rhythm has been shown to be more likely involved in cognition operations than other frequencies band including theta-rhythm (for review, see Ritz and Sejnowski 1997). For example, in the visual cortex, gamma-oscillations can be evoked by visual stimulation. Synchronous oscillatory activity in the gamma-band occurs in both awake and alert states of the brain. Furthermore, it has been suggested that cortical oscillations in the gamma-frequency band might underlie the binding of several features into a single perceptual entity (Milner 1974; Malsburg 1981; Singer and

Gray 1995). From these results, we hypothesize that gamma-oscillations in both the visual cortex and hippocampus are involved in selective visual attention. Thus, only the gamma-rhythm of the CO and HO layers is dealt with in our model, although to date no direct evidence is available to support or refute the role of theta-oscillations in visual attention. Note that the mathematical formulation of the model is invariant with regard to the choice of the specific frequency band of phase oscillators.

Moreover, in this model, feature binding is assumed to be completed before selective visual attention. This assumption is consistent with the conclusion that objects act as wholes in neural competition (Desimone and Duncan 1995). According to current understanding, different features of a particular object are represented by cells which are spatially distributed across multiple visual areas in the brain. Thus, a binding process which helps group feature cells together is crucially required for the neural system. Under the circumstances that each cell may be involved in more than one cell assembly at a given time, the synchronization of neuronal activity is assumed to provide an appropriate label for identifying those cells representing a particular object (Schillen and König 1994). A earlier hypothesis proposed by Milner (1974) and Malsburg and Schneider (1986) suggested that binding is achieved by the synchronous oscillatory activity of cells responding to different properties of the same object. This hypothesis implies that no matter whether these cells are located in the same cortical column (or layer), they can be instantly bound to an assembly when they respond to the features of the same object at a given time. The plausibility of binding by synchrony has been increased by some new findings in recent neuroscience research (for a review, see Treisman 1996). Thus, an assembly which is bound together to represent a particular object is assumed to be simulated by a cortical oscillator CO in our model, and cells belonging to such a CO might be distributed across different cortical columns (or layers).

Since the formation and segregation of these cell assemblies are performed in a stimulus-dependent manner (Gray et al. 1989; Engel et al. 1991a,b), the existence of COs is stimulus-dependent. Dynamic link architecture suggests that rapid synaptic plasticity is the potential mechanism underlying feature binding (Malsburg 1995). Through rapid reversible synaptic plasticity, the synaptic weight  $J_{ij}$  between neurons  $j$  and  $i$  can vary on a fast time scale. If the neurons  $i$  and  $j$  fire synchronously, the dynamic weight  $J_{ij}$  is rapidly increased from a resting value to the maximal value set by the permanent synaptic strength. If both neurons are active but fire asynchronously, the synaptic weight is rapidly decreased to zero. When there is no more activity in one or both of the neurons, the dynamic weight slowly falls back to the resting value, with the time constant of short-memory. According to above theoretical hypothesis (Malsburg 1995), it is reasonable to assume that the interactions within the same assembly CO are stronger than that between any different COs in the sense of feature binding, although cells belonging to each CO

might be distributed across multiple visual areas in the brain. Therefore, in order to simplify the analysis, the connections between COs are neglected in this model.

### 3 Representing attention state by synchronization of HOs

First, we discuss the dynamics in the population of interacting HOs when there are no visual stimuli (i.e.,  $b = 0$ ).

Early in 1967, such all-to-all coupled self-oscillators were considered by Winfree on his attempt to understand physiological clocks in terms of individual cellular oscillators. Without resorting to specialized models but only phenomenologically, Winfree (1967) discovered that such oscillator populations exhibit a phenomenon reminiscent of a phase transition: collective rhythm suddenly emerges in the population when the coupling strength exceeds a critical value. It was realized afterwards that the dynamic behavior in (1) with  $b = 0$  is too complex to be solved mathematically. Therefore, most of the work on these all-to-all coupled oscillators focuses on an easier but more important question: Under what conditions is there a stable solution in which some or all of the oscillators are running with the same frequency (Kuramoto 1975, 1984, Yamaguchi and Shimizu 1984; Ermentrout 1985; Daido 1986, 1987; Sakaguchi and Kuramoto 1986)? For the systems having the form  $d\phi_i/dt = w_i + v \sum_{j=1}^N \sin(\phi_j - \phi_i)$  ( $i = 1, \dots, N$ ), the condition was obtained by Ermentrout (1985). It is stated as follows. Let  $w_i$  be randomly distributed in the interval  $(\bar{w} - \beta, \bar{w} + \beta)$  with mean  $\bar{w}$  and density  $f(w - \bar{w})$ . If  $f(w - \bar{w})$  is symmetric and nonincreasing, phaselocking occurs if and only if

$$\frac{\beta}{vN} \leq \gamma(f) \quad (3)$$

where the function  $\gamma(f)$  is of the form  $\gamma(f) = 2 \int_0^1 \sqrt{1 - u^2} f(u) du$ , and  $u$  is related to  $w$  through the change of variables  $u = (w - \bar{w})/\beta$ . Under the change of variables  $w \rightarrow u$ , there is  $-1 \leq u \leq 1$ . According to (3), for a given all-to-all coupled system, the synchronization condition is influenced by the number of oscillators, the coupling strength, and the ‘variance’ of the native frequency of oscillators. Function  $\gamma(f)$  gives a threshold range in which these factors are taken into account,  $\gamma(f)$  is dependent on the density function of the random native frequency  $w$  through the way of  $f(u)$ . For the uniform density function  $f(w - \bar{w})$ , it is easy to judge that  $f(u) = 1/2$ . Substituting  $f(u) = 1/2$  into  $\gamma(f) = 2 \int_0^1 \sqrt{1 - u^2} f(u) du$ , we can obtain  $\gamma(f) = \pi/4$ . Similar to most other work, this condition is derived in the situation  $N \rightarrow \infty$ ; whether it still works when  $N$  is finite remains to be answered. Considering that the number of neurons in the brain is much smaller than that in the systems which statistical physics can handle and larger than that deterministic theories can be applied to, we investigate in this section the conditions of global synchronization for the systems consisting of a finite number of oscillators by employing computer simula-

tion. Our computer experiments are limited to the scope of  $N \leq 500$ .

Two possible states exist for the HOs layer when there are no visual stimuli. One is global synchronization in the sense that all the HOs run at the same frequency (denoted as  $\Omega$ ), while their phases are different from each other, but the phase difference between any two HOs is locked in a constant. The other is global desynchronization, which means that all the HOs cannot reach a common frequency. Occasionally, another situation happens, in which only some of the HOs are synchronous. In order to simplify the analysis, we classify such a partial synchronization in the hippocampus as the second kind, i.e., global desynchronization. While global synchronization occurs in (1) with  $b = 0$ ,  $d\theta_i^h/dt = \Omega$  ( $i = 1, \dots, N^h$ ) is satisfied. Adding the same sides of (1) separately, it is easy to derive:

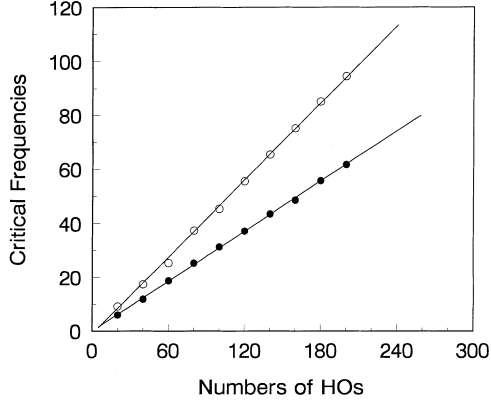
$$\Omega = \frac{1}{N^h} \sum_{i=1}^{N^h} \omega_i^h \quad (4)$$

Take  $b = 0$ . The initial phases of HOs were chosen randomly according to a uniform distribution in the range  $[0, 2\pi]$ . The natural frequencies  $\omega_i^h$  ( $i = 1, \dots, N^h$ ) of the HOs range randomly within  $(\omega_0^h - \alpha, \omega_0^h + \alpha)$  with a uniform density, where  $\alpha$  represents the maximum deviation of the frequencies of HOs from a given constant  $\omega_0^h$ . In the limit  $N \rightarrow \infty$ , there is  $\Omega = \omega_0^h$ . Observe the dynamic behavior in the HOs layer while setting  $\alpha$ ,  $N^h$ , and  $u$  fixed and slowly changing  $\omega_0^h$  from one value to another. No qualitative effects on the synchronization of HOs are found; the only result is that the synchronization frequency  $\Omega$  has been changed by way of (4). Hence, we only discuss the effect of parameters  $\alpha$ ,  $N^h$  and  $u$  on the dynamics of system (1) with  $b = 0$ .

When  $u$  is given, computational simulation experiments show that the dynamics of the HOs layer strongly depends on  $\alpha$  and  $N^h$ . For a fixed  $N^h$ , there exists a critical value  $\alpha^{(s)}$ . If  $\alpha \leq \alpha^{(s)}$  is satisfied, global synchronization happens in the HOs layer, otherwise HOs do not work at a common frequency. This means that a network with smaller deviations of initial frequencies from each other more easily reaches synchronization than one with larger deviations. On the other hand, for a given  $\alpha$ , the more HOs the network contains, the more easily it achieves synchronization. There also exists a critical value  $N^{h(s)}$  for which if  $N^h \geq N^{h(s)}$ , global synchronization happens in the HOs layer, otherwise HOs do not work at a common frequency. Moreover, a linear relation between  $\alpha^{(s)}$  and  $N^h$  can be summarized from our simulation experiments. In a good approximation, this relation can be described as:

$$\alpha^{(s)} = A + BN^h \quad (5)$$

While  $u$  is alerted, it is worth noting an interesting phenomenon. The coupling strength  $u$  determines the slope  $B$  of the line  $\alpha^{(s)} = A + BN^h$ , and furthermore, the quantitative law as  $B = (3/4)u$  is confirmed by a large number of numerical experiments in the scope of  $N^h \leq 500$ . Two examples with  $u = 0.4$  and  $u = 0.6$  are shown in Fig. 1: For parameter value  $u = 0.4$ , there is



**Fig. 1.** Linear functional relation between the critical frequency deviation  $\alpha^{(s)}$  and the number  $N^h$  of hippocampus oscillators (HOs) in the network without stimuli input. Open circles (solid circles) represent the exact simulation results with  $u = 0.6$  ( $u = 0.4$ )

$A = 0.71$ ,  $B = 0.31$ , and for  $u = 0.6$ , there is  $A = -1.06$ ,  $B = 0.48$ . Numerical results reveal that the value of  $BN^h$  in (5) is definitely larger than the value of  $A$ , especially for relatively greater  $N^h$ . Thus,  $A$  can be neglected in a good approximation in (5), and we have  $B = \alpha^{(s)}/N^h$ . Considering  $B = \alpha^{(s)}/N^h$ , above law  $B = (3/4)u$  can be expressed as  $\alpha^{(s)}/uN^h = 3/4$ . This means that the threshold for global synchronization in HOs layer is  $\alpha/uN^h \leq (\alpha^{(s)}/uN^h = 3/4)$ , and if  $\alpha/uN^h > 3/4$ , it will be impossible to phaselock for HOs. Our computational experiments show that not only qualitatively but also quantitatively the threshold accords with the analytical result (3) in a good approximation, i.e., both the finite-size or infinite-size systems of phase oscillators described by (1) with  $b = 0$  have the same critical condition for global synchronization.

These results suggest that the extent of synchronization can be used to qualitatively measure the attention state of this attention network from a neurocomputational point of view. For instance, the line  $\alpha^{(s)} = A + BN^h$  divides the  $\alpha$ - $N^h$  plane into two regions. Parameters ( $N^h$ ,  $\alpha$ ) below that line are related to the preparing states for attention, while other parameters above that line correspond to the states incapable of attention. It will be shown in the following sections that the network with parameters ( $N^h$ ,  $\alpha$ ) which are above but near the line  $\alpha^{(s)} = A + BN^h$  also has an effective attention.

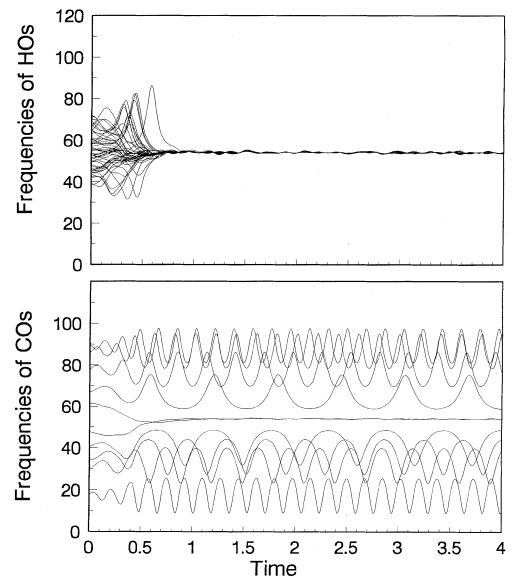
#### 4 Selective attention

In this section, we will illustrate through several computer simulation experiments how selection attention is realized in the network of phase oscillators.

After preprocessing including feature binding, the entire information of a stimulus corresponding to an object in the visual field is represented by  $(\omega^c, b)$ . A larger coupling coefficient  $b$  is assumed to correspond to the object having a stronger competitive advantage, and  $\omega^c$  is assumed to represent this object's relevance to current behavior, which can be seen clearly from the given numerical experiments. Take  $N^h = 50$ ,  $\omega_0^h = 55.0$ ,

and  $u = 0.4$ , we can estimate  $\Omega = 54.0$  from (4) and  $\alpha^{(s)} = 16.2$  from (5). In order to show that networks with a parameter  $\alpha$  slightly larger than  $\alpha^{(s)}$  still possess an effective attention capacity, here we set  $\alpha = 17.0$ . Now there are  $N^c = 10$  different stimuli, and their initial frequencies are in the range  $\omega^c = \{17.2, 31.5, 35.6, 40.0, 48.2, 60.6, 67.2, 78.0, 86.8, 89.3\}$ . To examine what stimuli are the targets of selective attention, we first set  $b = 0.2$ , implying that the coupling strength between every CO and the HOs layer is equal. The results are displayed in Fig. 2, in which two stimuli  $\omega^c = 48.2$  and  $\omega^c = 60.6$  are focussed on, other stimuli remaining outside the focus of attention. During the entire selective attention process, the average frequency of global synchronization between the HOs layer and two target stimuli equals  $\Omega$  in a good approximation. It can be seen that the network has the tendency to select stimuli whose frequencies are near to  $\Omega$ . Apparently,  $\Omega$  is relevant to every HO and is stored in parallel in the HOs layer, and thus we can think that  $\Omega$  has the meaning of working memory, and that the information of current behavior is stored in  $\Omega$  as a part content of working memory. This is consistent with the finding that the hippocampus could provide a useful working memory (Olton 1983).

It is interesting to make an estimation of the range of CO natural frequencies for those cortical oscillators, which work synchronously with the HOs. Suppose the  $k$ th CO is synchronized by the HOs layer after a transient process, we can substitute the frequency  $d\theta_k^c/dt$  in (2) by  $\Omega$  and obtain the expression  $\Omega - \omega_k^c = b \sum_{i=1}^{N^h} \sin(\theta_i^h - \theta_k^c)$ . Apparently, the necessary condition for the  $k$ th CO to run synchronously with HOs is  $|\Omega - \omega_k^c| < bN^h$ . This condition can be tested by the example shown in Fig. 2. Thus, knowing the initial natural frequencies  $\omega_k^c$ , we can roughly predict or estimate those visual stimuli to be targetted. This estimation  $|\Omega - \omega_k^c| < bN^h$



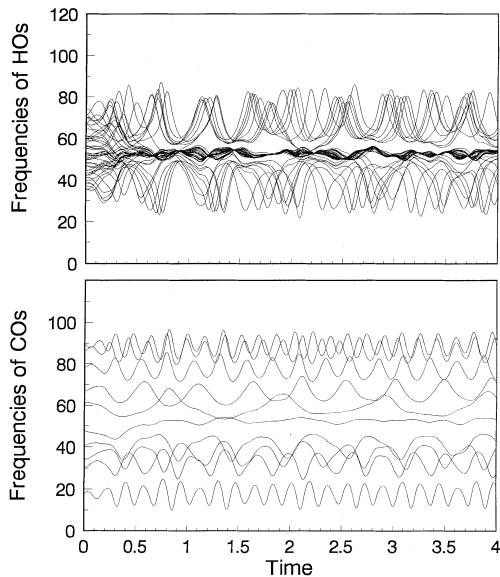
**Fig. 2.** Selective attention in the network with  $\alpha = 17.0$ . The other parameters are given in the text. The evolution of every HO's frequency  $d\theta_i^h/dt$  ( $i = 1, \dots, N^h$ ) is shown at the top of the figure, and that of every CO's frequency  $d\theta_k^c/dt$  ( $k = 1, \dots, N^c$ ) at the bottom

is consistent with the results of Kazanovich and Borisyuk (1994). In their work, a similar estimation is used to distinguish the peripheral oscillators which can be synchronized by the central oscillator.

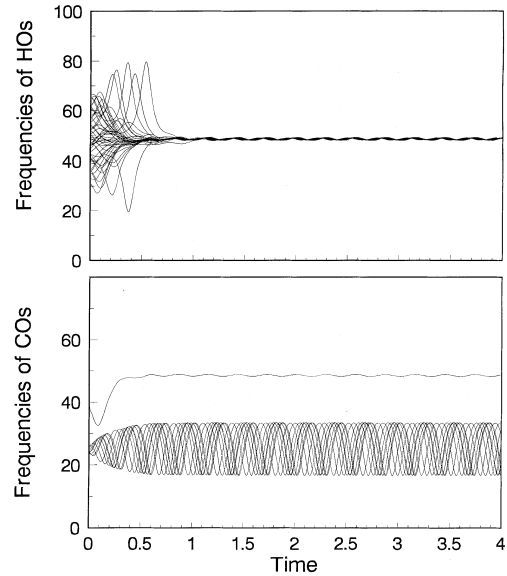
Changing the state of the attention network by increasing the value of parameter  $\alpha$  from 17.0 in Fig. 2 to 21.0 in Fig. 3, it can be observed immediately that no object enters the focus of attention. A large scale of desynchronization occurred in the HOs. This example demonstrates that overly large frequency deviations of HOs from the constant  $\omega_0^h$  do not ensure that the attention system has the capacity to perform visual selective attention.

One factor influencing selectivity is the bottom-up mechanism, i.e., the visual stimuli have a considerable effect on the targets of visual attention. It is very easy, for example, to find a unique target in an array of homogeneous nontargets, perhaps reflecting an enduring competitive bias towards local inhomogeneities. Such a psychophysical experiment is simulated in Fig. 4, in which the inhomogeneous stimulus is  $(\omega^c, b) = (40.0, 0.5)$ , and the other nine oscillators representing homogeneous stimuli have the same parameters as  $(\omega^c, b) = (25.0, 0.2)$ .

When there is only one stimulus in the visual field, a very interesting phenomenon can be observed in this system for some proper parameters. The only stimulus targetted at the beginning is no longer at the focus of attention after a period of time. For instance, if the network has the parameters  $N^h = 50$ ,  $\omega_0^h = 40.0$ ,  $u = 0.4$ ,  $\alpha = 16.0$ ,  $N^c = 1$ ,  $\omega^c = 35.0$ ,  $0.54 \leq b \leq 0.61$ , and the initial phases  $\theta_i^h$  of HOs were chosen randomly according to a uniform distribution in the range  $[-4.0, +4.0]$ , the single stimulus object is focussed on by HOs at once. But when  $t \geq 4.0$ , this object is not the target of the attention system any longer; an example with  $b = 0.60$  is displayed in Fig. 5. The numerical result simulates the situation in

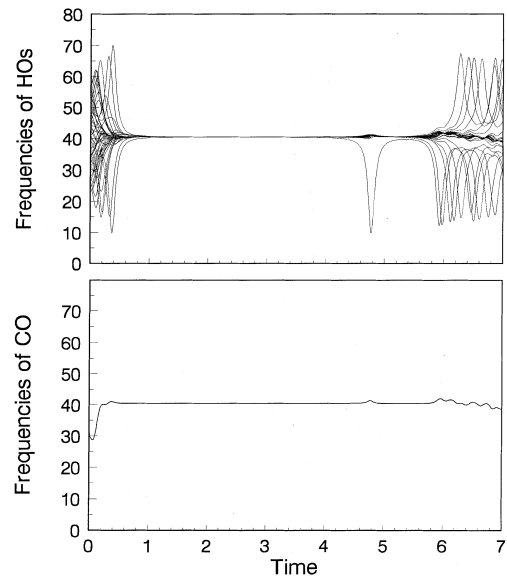


**Fig. 3.** Selective attention in the network with  $\alpha = 21.0$ . The other parameters are the same as in Fig. 2

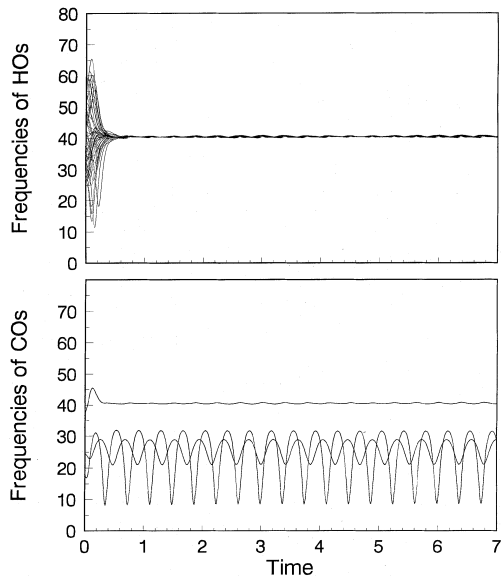


**Fig. 4.** Selective attention to a unique target  $(\omega^c, b) = (40.0, 0.5)$  which is presented together with nine other homogeneous nontargets  $(\omega^c, b) = (25.0, 0.2)$ . The parameters in the network are the same as in Fig. 2 except  $\omega_0^h = 50.0$

which the neural system is too tired of the single dull stimulus to preserve attention for a long time. On the other hand, from a large number of numerical experiments we find that this distraction of attention can be inhibited by employing another two stimuli. As shown in Fig. 6, the stimulus  $(\omega^c, b) = (35.0, 0.60)$  can remain in the focus of attention forever after two stimulus inputs  $(\omega^c, b) = (25.0, 0.10)$  and  $(\omega^c, b) = (20.0, 0.30)$  are presented together from the beginning. The underlying dynamic mechanism for such a phenomenon is not clear and needs further investigation.



**Fig. 5.** The single targetted stimulus moves outside the focus of attention after a period of time. The relevant parameters are given in the text



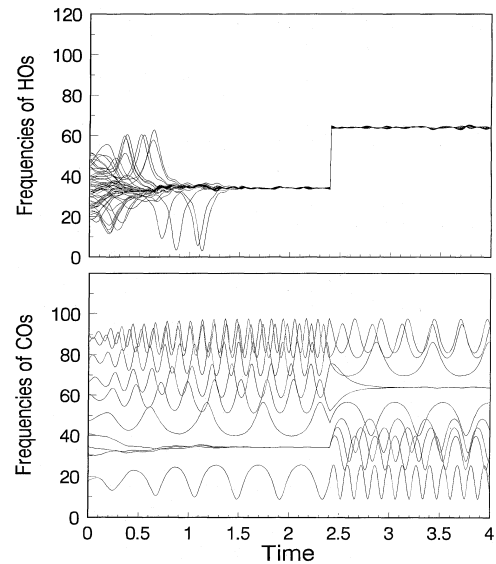
**Fig. 6.** Keeping the stimulus in Fig. 5 in the focus of attention by adding two stimuli described by  $(\omega^c, b) = (25.0, 0.10)$  and  $(\omega^c, b) = (20.0, 0.30)$

### 5 Attention shifting from a set of stimuli to another one

The basic feature of the selective visual attention system is to shift the focus of attention from one object to another. In this network, attention shifting is realized in such a way that the HOs run synchronously with some COs at first and then with other COs. This shifting may be caused by top-down or bottom-up mechanisms, and in most cases, the true explanation is probably a cooperation of these two mechanisms.

For this network (1) and (2), one of the most remarkable advantages lies in the quick attention shifting among different stimuli. Choose the parameters  $N^h = 50$ ,  $\omega_0^h = 35.0$ ,  $u = 0.4$ ,  $N^c = 10$ ,  $b = 0.2$ ,  $\alpha = \alpha^{(s)} + 0.8 = 17.0$ . According to (4), the average natural frequency of HOs is  $\Omega = 34.0$ . Assume that in the visual field there are ten stimulus inputs in total, after pre-processing these inputs have the frequencies:  $\omega^c = \{17.2, 31.5, 35.6, 40.0, 48.2, 59.6, 67.2, 78.0, 86.8, 89.3\}$ , respectively. After a transient process, the network selects three stimuli with  $\omega^c = \{31.5, 35.6, 40.0\}$ . As mentioned in Sect. 4, the average frequency  $\Omega$  (or  $\omega_0^h$ ) is assumed to represent the information of current behavior which is stored as a part of the working memory. This implies that different current behavior corresponds to different values of  $\omega_0^h$ . When  $t \geq 2.4$ , suppose that the current behavior is changed, and the value of  $\omega_0^h$  is changed to 65.0 under the control of the control structures of the attention system. Repeating the above simulation, it is found that attention shifts to another two stimuli with  $\omega^c = \{59.6, 67.2\}$  immediately. The entire attention shifting process is shown in Fig. 7.

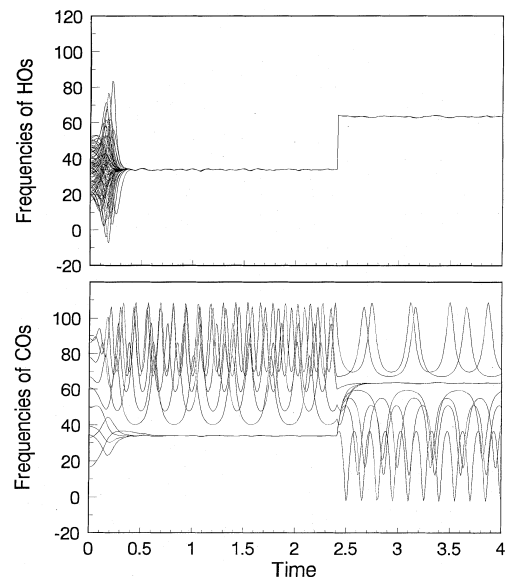
To compare the attention capacity among different systems, we give another example in which all the parameters are the same as in Fig. 7 except  $N^h = 100$ . As shown in Fig. 8, five stimuli with  $\omega^c = \{17.2, 31.5, 35.6,$



**Fig. 7.** Attention shifting after the attentional state of the network is changed from  $\omega_0^h = 35.0$  to  $\omega_0^h = 65.0$ . The network contains  $N^h = 50$  HOs and  $\alpha = 17.0$ . The other parameters are given in the text

$40.0, 48.2\}$  are the targets of attention at the beginning ( $t < 2.4$ ), and the network instantly shifts attention to another four stimuli with  $\omega^c = \{48.2, 59.6, 67.2, 78.0\}$  after the attentional state of the network is changed from  $\omega_0^h = 35.0$  to  $\omega_0^h = 65.0$ . Apparently, when the number of HOs is increased, the network can focus on more stimuli than before. It can be concluded that the attention system containing larger HOs has a stronger attention capacity.

The above two examples are mediated by the top-down mechanism, but this network can also accomplish shifting attention mediated by a bottom-up mechanism.



**Fig. 8.** Attention shifting after the attentional state of the network is changed from  $\omega_0^h = 35.0$  to  $\omega_0^h = 35.0$ . The network contains  $N^h = 100$  HOs. The other parameters are the same as in Fig. 7

This has been tested in numerical examples which are not given in this paper.

It is interesting to compare the above results with those on spontaneous attention switching reported in Borisyuk and Borisyuk (1997). The common character for their work and ours is the employment of phase oscillators in attention models. Both models view the selective attention as the result of the synchronization between some oscillators in the bottom layer representing the input stimuli and the top layer representing the hippocampus. Another similarity between the two models lies in the attention shifting pattern: the top layer runs synchronously with some oscillators in the bottom (input) layer at first, and then with other oscillators in the bottom layer. On the other hand, there are several differences between our results and theirs. In their work, attention shifting is induced through increasing the coupling strength between the central oscillator and stimuli outside the ‘focus of attention’. The more the average frequency value of the central oscillator is attracted by a stimulus which is outside the ‘focus of attention’, the nearer the network comes to the point of attention switching. In our method, the direct reason for attention shifting is to change the parameter  $\omega_0^h$ , which is related to the information of current behavior in the brain. The closer the frequency of a cortical oscillator is to the new  $\omega_0^h$ , the easier it is for it to become the target of attention shifting. It can be seen that our results simulated the top-down mechanism, while their work concentrated on the attention shifting caused by the bottom-up mechanism. In addition, when attention shifting occurs in Borisyuk and Borisyuk (1997), the average frequency of the central oscillator is always drawn to the average frequency of the targetted group of cortical oscillators. The situation is otherwise in our results, i.e., the frequencies of the targetted COs are bound to the synchronization frequency of the HOs. The reason for this difference probably lies in the models themselves. The top layer includes only one central oscillator in Borisyuk and Borisyuk (1997), while in our model it consists of a large number of oscillators. In particular, interactions within the HOs layer are stronger than those between HOs and COs. The last important difference is the existence of spontaneous switching of the attention focus in their model. This interesting mode can be used to explain the phenomenon of attention shifting between two sets of input stimuli having equal competitive advantages. In our results, such a mode of spontaneous switching of attention focus has not been found yet.

## 6 Discussion

We have proposed a neural network model for covert selective visual attention. From a neurocomputational point of view, it illustrates that the attention mechanism suggested by Desimone and Duncan (1995) is possible, although this mechanism is totally different from the spotlight metaphor. In order to stress the characteristics of this model, it is worth comparing it with the other

computational models which are usually employed to explain the selective attention mechanism of the spotlight metaphor. First, in other models, a topographic saliency map is usually necessary for registering potentially interesting areas of input. Through one or more of such maps that do not code for particular features, but rather for how different or how salient a particular stimulus is relative to its neighborhood, a winner-take-all mechanism selects the currently most interesting feature in the map and directs attention to its location through a gating mechanism. Apparently, these models employ a serial process that analyzes each object one at a time. In our model, it need not employ such a saliency map. No matter whether a region within a scene is ‘conspicuous’ or ‘salient’, the information in this region has an equal opportunity to enter the attention system. The competition is performed among all the objects in the visual field in a parallel manner. The more relevant to the current behavior an object is, the stronger competitive advantage it has. The final targets are the objects which can be synchronized by the hippocampus. It can be seen that in our model, the control of attention is not limited to certain cortical oscillators coding for some particular objects in the visual field, whereas it takes effect across the whole COs layer. From a neurocomputational point of view, our results demonstrate that attention is an emergent property of the dynamic cell assemblies responding to the entire visual field.

Second, in this model, selective visual attention results from a natural evolution of a nonlinear system equation, and no external perturbation is necessary in this process. This means that selective attention is the emergent dynamic property of this two-layered network containing a large number of elements. However, in order to obtain a proper attention network, a particular weight for a training network or a particular local winner-take-all rule for the gating mechanism is usually imposed in other networks.

Finally, compared with the fixed structures in many attention systems, in this model the top layer can be adjusted quickly according to the current behavior and external stimuli. For example, the coupling strength  $u$  may vary on a fast time scale (small fractions of a second) through the rapidly reversible synaptic plasticity of dynamic link architecture proposed by Malsburg (1981, 1995). Also, the number of HOs taking part in selective attention can be functionally changed according to the dynamical cell assembly hypothesis (Fujii et al. 1996). In a sense, this reflects the idea that vision is an active process. Therefore, we conjecture that the hippocampus need not always keep the attention state, but only when attention is necessary. It is proposed that a desired cell assembly having appropriate parameters  $u$  and  $N^h$  will be organized and picked up from the large neuronal pool in the hippocampus whenever attention is needed. For the neural system, such a pattern may be an optimum working method.

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