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SYNCHRONISATION-BASED COMPUTATIONAL MODEL OF ATTENTION-GUIDED OBJECT SELECTION AND NOVELTY DETECTION

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ABSTRACT

We develop a new biologically inspired 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 simulations of the model are illustrasted for visual stimuli representing printed words.

INTRODUCTION

A traditional approach to visual pattern recognition is based on the assumption that objects are presented one at a time, but in reality biological systems must be able to deal with visual scenes that contain several objects simultaneously. Experimental studies show that a number of cognitive functions are in action when analyzing complex scenes. Firstly, the whole information should be collected in the pools belonging to different objects and the background. This separate representation must be preserved in the further process of feature extraction and transformation, which ensures a proper conjunction (binding) of features at the level of object recognition and memorization. Secondly, attention is necessary to decrease the amount of information that is processed in detail and to improve the binding of features. Thirdly, pattern recognition and memorization should be combined with novelty detection to ignore familiar or unimportant objects.

Until now most papers on neural networks have been focused on modeling a particular cognitive function. Models of feature extraction and binding have been developed in [8, 22, 26]. Models of attention are represented by both traditional connectionist networks [7, 10, 21] and oscillatory networks [5, 12, 13, 16]. Models of memorization and novelty detection can be found in [4, 18, 25]. These models paved the way to combining in one system a set of cognitive functions covering the whole range of visual image processing.

Below we describe a large-scale model that includes the main stages of information processing in the visual pathway: (1) segregation of information from different objects according to their spatial connectivity; (2) consecutive selection of objects into the attention focus; (3) extraction of features and their transformation to the form invariant to object location and scale; (4) representation of objects in the working memory and novelty detection.

Presuming that the brain does not invent a special procedure for each cognitive function but adapts similar mechanisms for a particular type of processing, it has been a challenge to develop a model that would rely on a small set of general principles. As such principles we use oscillations, synchronization, and resonance. The choice of an oscillatory neural network for the development of the model is conditioned by 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., [2, 15]) and that oscillatory principles provide efficient means for many types of information processing [3].

NOMENCLATURE

The Model

The model is designed as a hierarchy of interactive modules. Each module consists of oscillators with synchronizing or desynchronizing connections. 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 [4, 13]. The values of these variables change in time according to prescribed rules of interaction.

The flow of information between the modules of the network is presented in Figure 1. The components of the network are called Object Selection Module (OSM), Local Feature Module (LFM), Invariant Feature Module (IFM), and Novelty Detection Module (NDM). The oscillators comprising these modules 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 OSM. The top-down interaction is reduced to the one from the NDM to the OSM (its role is explained in Section 2.1). More sophisticated top-down interaction is postponed for future versions of the model.

In biological terms the model is interpreted in the following way. It is assumed that oscillators in OSM, LFM, and IFM represent cortical columns in the areas of the visual pathway. The OSM is located in the primary visual cortex (striate cortex), LFM can be attributed to different regions of the cortex (striate, extrastriate and higher) depending on the type and complexity of the features, IFM represents feature detectors of the temporal area invariant to geometrical transformations (IT and higher associative areas). The CO plays the role of a central executive of the attention system [1, 6]. To simplify the model, we consider only the interaction between the CO and OSM and ignore the influence of the CO on other modules. The NDM is associated with the hippocampus [14]. The groups of NDOs represent hippocampal segments.

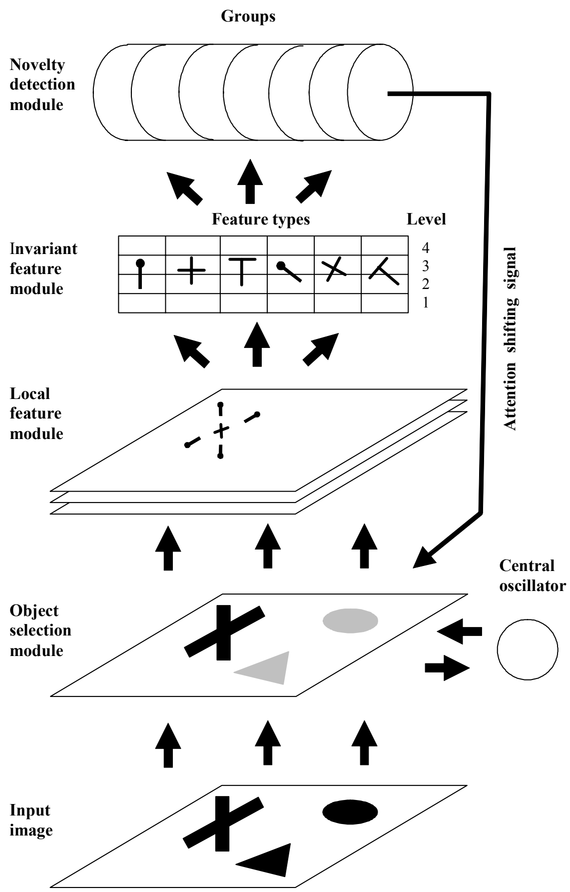

Figure 1. The architecture of the network. The input image contains three objects. In the OSM an object in the focus of attention is painted in black, other activated regions are painted in gray. In the LFM and IFM, there are five features of the object in the attention focus: four endpoints of different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

Object Selection Module

The OSM is responsible for grouping the information from the external input into separate clusters according to spatial connectivity of objects. The OSM has the same 2D grid-like structure as the visual field with one-to-one correspondence between the pixels of the image and the elements of the module. An OSO with coordinates *(x, y)* is activated by the input signal from the pixel *(x, y)*. The grouping of pixels into object representation is realized through synchronizing local connections between OSOs.

The OSM is also used to organize consecutive selection of objects into the focus of attention. This is achieved through the interaction with the CO (see [13] for details). The interaction is organized in such a way that at any moment the CO works coherently with an assembly *A* of OSOs that represent a single object. Due to the resonance with the CO, the amplitude of oscillations in *A* is made high while the activity of other OSOs is inhibited to a low level. Being in the resonant state is interpreted as the fact that *A* is included in the focus of attention.

The resonant state in *A* is interrupted by the top-down signal from the NDM that is generated when 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. This signal blocks the assembly of OSOs so that it is unable to interact with the CO until the whole image is analyzed. This gives the CO an opportunity to change the attention focus by synchronizing its activity with another assembly of OSOs, etc. The order in which objects are included in the focus of attention is determined by their saliency. The objects of greater size and contrast have an advantage in being attended first.

Local Feature Module

The LFM is responsible for transforming the information about an object from representation by pixels to representation by local features. The oscillators in the LFM are arranged into a 3D structure with different types of feature detectors occupying different layers (planes). An LFO is active if a corresponding local feature is present in the object that is currently in the attention focus. The assembly *A* is used as a common source of synchronization for active LFOs. The gating of signals outside the attention focus is determined by the amplitudes of the signals coming from the OSM. This gating prevents erroneous conjunction of features of different objects during memorization.

Invariant Feature Module

The IFM is used for representing an attended object by a set of features that are invariant to object transformations such as translation, scale, etc. The module is arranged as a set of K columns of oscillators, where K is the number of types of feature detectors in the LFM. An IFO at the level i in the column k is active if a local feature of the kth type is present i times in the attended region of the input image. Thus at most one IFO can be active in a column at any moment. Such a coding automatically makes the activity in the IFM invariant to translation. Invariance to scaling can be achieved if the set of features extracted from an object is independent of the scale. We will give an example of such features in Section 3.

The assembly of synchronous LFOs plays the role of a common source of synchronization for all active oscillators in the IFM. In this way the synchronization that has appeared in the OSM is spread to higher modules generating a representation of an object in the form of coherent oscillations.

Novelty Detection Module

The NDM is responsible for memorization of objects in the working memory and making decisions about novelty of objects. The discrimination between novel and familiar objects is made in terms of duration of oscillatory activity in the NDM in response to external stimulation by a visual object. Following the experimental evidence on the theta activity in the hippocampus during orienting response [19, 23], the NDM generates a long (tonic) response when an object is new and a short (phasic(response when an object is familiar. The memorization of an object in the NDM is achieved under fixed connection strengths by a proper modification of internal parameters of NDOs. The details of this modification can be found in [4].

The NDM 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 IFM to the NDM 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.

A basic principle of NDM 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 IFM arrive in-phase. For a given set of active oscillators in the IFM, due to random delays in connections, the resonant activity in the NDM 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 NDM is low. Thus each object is represented in the NDM by a sparse assembly of oscillators that is specifically related to the object in the attention focus.

The activity in the NDM is organized so that under the influence of the coherent input from the IFM the number of resonant NDOs gradually increases until it reaches a certain threshold H, that is until the assembly of resonant oscillators in the NDM becomes sufficiently large. At that moment the NDM generates the top-down signal to the OSM that leads to the shift of the attention focus to another object. The important parameter is the period of time Δt from the moment when attention is focused on a given object and until the assembly of at least H resonant oscillators in the NDM is formed. By a proper modification of parameters of NDOs during memorization, it is possible to accelerate their capability to generate the resonant activity, therefore Δt can be made much smaller for familiar objects than for novel objects [4].

A Simulation Example

We illustrate the principles of network performance using a simple black and white image representing the characters of the word "HELLO". The image is exposed at the input for 35 time units and is processed sequentially object by object with memorization and novelty detection of all 5 objects. In this example the order in which objects are selected is conditioned by their size.

Since the object L occurs two times in the image, it should be detected as familiar at the second appearance in the attention focus. Other objects occur in the image only once, therefore they will be detected as new.

Fig. 2 shows the types of features used to represent the image HELLO in the LFM. For example, the object H is represented by six active LFOs - four endpoints (two top and two bottom) and two T-shape crossing (left and right). In the IFM this character is represented by four active IFOs – top endpoint (level 2), bottom endpoint (level 2), left T-shape crossing (level 1), and right T-shape crossing (level 1).

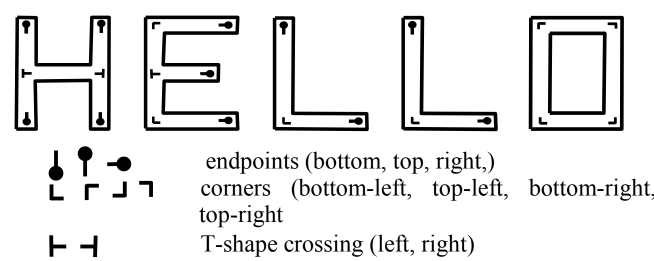

Figure 2. The features used for coding the shape of objects in the image.

Figure 3 shows the dynamics of the amplitudes in the OSM. By this figure one can see the periods when different objects are attended which is reflected in high amplitudes of oscillations of the OSOs corresponding to these objects while the amplitude of other OSOs is low. The period of time Δt when an object is attended varies between 4.1 and 5.0 for a new object, For a familiar object (the first appearance of L in HELLO) the value of Δt is 1.6 which is about 3 times shorter.

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 system architecture and functionality reflect (in a very simplified form) 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

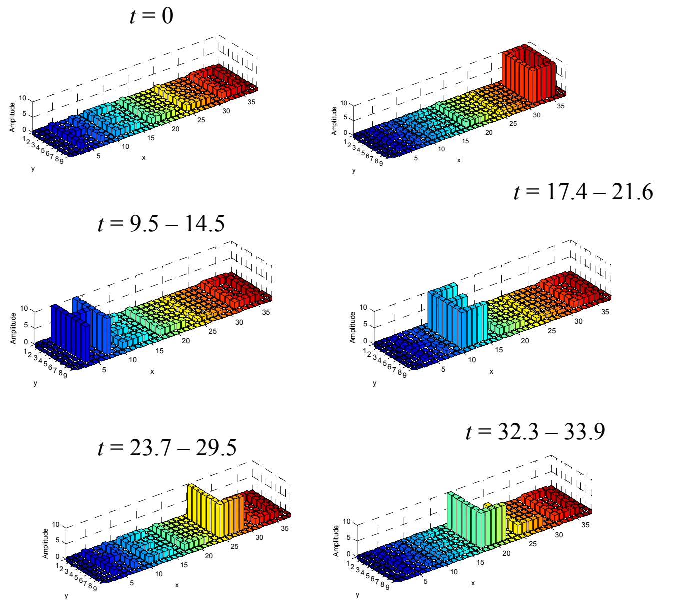

Figure 3. Dynamics of the amplitudes in the OSM. The numbers above the graphs show the period of time when attention is focused on a given character.

novelty detection in terms of the duration (tonic or phasic) of the oscillatory response at the output module (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 [4, 13], now we provide a framework where both models can be properly adjusted to each other.

The principles of information processing used in our system have already appeared in other 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 [3] for a review), reformulating them in terms of oscillators with the explicitly defined phase. The peculiarity of our model is that we use the characteristics of individual pixels as primary features. The advantage of this approach is that it can be applied to any type of images and not only to contour objects.

The idea of the resonant interaction is very attractive and finds support in experimental and modeling studies [9, 11]. Our approach differs from the one developed in these works because we explicitly postulate the type of dynamics of the oscillator amplitude depending on the synchronization with other oscillators.

The adaptation of natural frequencies of oscillators has been used before as a mechanism of learning and memorization [4, 17, 20]. Here it provides 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 [24, 26], where the role of a central element in the network LEGION is played by a global inhibitory neuron, and [5], 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.

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