Oscillatory Network with Self-Organized Dynamical Connections for Synchronization-Based Image Segmentation

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Abstract.

An oscillatory network of columnar architecture located in 3D spatial lattice was recently designed by the authors as oscillatory model of the brain visual cortex. Single network oscillator is a relaxational neural oscillator with internal dynamics tunable by visual image characteristics — local brightness and elementary bar orientation. It is able to demonstrate either activity state (stable undamped oscillations) or "silence" (quickly damped oscillations). Self-organized nonlocal dynamical connections of oscillators depend on oscillator activity levels and orientations of cortical receptive fields. Network performance consists in transfer into a state of clusterized synchronization. At current stage grey-level image segmentation tasks are carried out by 2D oscillatory network, obtained as a limit version of the source model. Due to supplemented network coupling strength control the 2D reduced network provides synchronization-based image segmentation. New results on segmentation of brightness and texture images presented in the paper demonstrate accurate network performance and informative visualization of segmentation results, inherent in the model.

Keywords: neural oscillators, oscillatory networks, synchronization, self-organizing systems, distributed visual image processing.

1. Introduction

As well known, synchronization of neural activity was found in various brain structures such as olfactory bulb and cortex, visual cortex, hippocampus, neocortex, thalamo-cortical system, and hypotheses on its functional significance in brain information processing were induced since 80th. (Freeman, 1978; Malsburg, 1981). Experimental discovery of synchronous oscillations in the brain visual cortex (VC) in 1988-1989 (Eckhorn et al., 1988; Gray and Singer, 1989) reinforced the attention to oscillatory aspects of visual

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information processing. Numerious network models with various types of oscillators as processing units and synchronization-based performance were designed since 90th in attempt to elucidate synchronization abilities in visual processing (Schuster and Wagner, 1990; König and Schillen, 1991; Sompolinsky et al., 1991; Gerstner et al., 1993; Malsburg and Buchmann, 1994; Wang and Terman, 1995). The discussions on a role of dynamical binding in visual processing and elaboration of oscillatory network models and related neuromorphic dynamical algorithms for visual processing are actively continued nowadays (Kreiter and Singer, 1996; Gray, 1999; Li, 1998-2001; Wang et al., 1999 -2001; Kuzmina et al., 1999-2001). We mention further only those models where relaxational oscillators with two degrees of freedom, imitating real neural oscillators, were used as network processing units. First of all it is worth mentioning a series of deep and detailed papers by Z.Li (Li, 1998-2001), where a biologically motivated network model of the primary visual cortex was designed and developed. Active network unit is neural oscillator formed by a pair of interconnected cortical neurons — an excitatory pyramidal cell and inhibitory interneuron. Similar model of neural oscillator was previously proposed by W.Freeman (Freeman, 1978), when prominent the 40-60 Hz synchronous oscillations had been reported in the rat and rabbit olfactory bulb and cortex. Following W.Freeman, Z.Li and J.Hopfield suggested oscillator model, closely imitating real cortical neural oscillator, and used it in modelling of olfactory brain system, where oscillations and synchronization play a key role in odor recognition task (Li and Hopfield, 1989). Cortical oscillator model proposed further in (Li, 1998), reflects orientation-selective response of simple cells of VC. Besides, 3D oscillatory network of columnar architecture was first designed in (Li, 1998). Excitatory and inhibitory connections for network oscillators were constructed based on experimental neurobiological data on horisontal intra-cortical connections in VC. The model was tested in problems of pre-attentive image processing, including contour integration and texture segmentation tasks. It demonstrated successful synchronization-based performance.

The second remarkable oscillatory network model for visual image segmentation is oscillatory network LEGION, designed first in 1995 (Wang and Terman, 1995; Wang and Terman, 1997; Wang, 1999; Chen, Wang and Liu, 2000; Cesmeli and Wang, 2001). The model cannot be viewed as directly related to modelling of the brain visual processing. But nevertheless its most perfect version (Chen, Wang and Liu, 2000) delivers highly effective dynamical image segmentation algorithm based on synchronization in oscillatory network. Active network unit is a relaxational (limit-cycle) oscillator with internal dynamics dependent on image pixel brightness. Network oscillators are located in 2D spatial lattice being in one-to-one correspondence with image pixels. In addition to stationary local excitatory connections and global inhibitor a dynamical coupling has been designed in the network. Besides, an algorithm of dynamical coupling adaptation was developed, what allowed to essentially improve the network performance efficiency. As a result the model version (Chen, Wang and Liu, 2000) provides successful segmentation of real grey-level images containing more than 400 000 pixels. The comparisons of the oscillatory algorithm with several modern effective traditional algorithms demonstrated real advantages of the dynamical algorithm.

Our oscillatory model of VC (Kuzmina, Manykin, Surina, 2001) was in fact inspired by the model (Li, 1998). However, our intention was to model just dynamical type of image processing typical to low level (pre-attentive) vision, that includes only bottom-up processes (with no feedback loop). So our network model performance simulates a single step of bottom-up VC performance in the task of image reconstruction (without recognition). The model can be considered as a coupled system of 2D lattice ("retina"), where pixel image representation is defined, and oscillatory network of columnar architecture, located in associated 3D spatial lattice. There is one-to-one correspondence between image pixels and oscillator columns: one oscillator column corresponds to single pixel. Network processing unit is a limit-cycle oscillator. Designing its internal dynamics we took into account and preserved the main features of dynamics of cortical neural oscillator used in (Li, 1998). As a result the dependence of single oscillator dynamics on two image characteristics — pixel brightness and elementary bar orientation — is essentially exploited in our model performance. Besides, following (Li, 1998), we also preserved the columnar architecture of oscillatory network. But there is an essential distinction between our model and that one by Z.Li. First of all it concerns the level of modelling. Our model is entirely formulated in terms of oscillatory system and oscillator interaction. Self-organized oscillator coupling has been constructed, and the idea of dynamical binding on proximity of oscillator activity levels and their receptive field orientations has been reflected in the form of network connectivity rule. The oscillatory network performance consists in relaxation into a stable stationary state. In the case of our model it is a state of clusterized synchronization. Internally synchronized network assemblies (clusters) correspond to fragments of processed image. The simplified 2D limit version of oscillatory network has been extracted from the initial 3D model. As it turned out, the reduced 2D network is capable to provide a synchronization-based brightness image segmentation via supplemented network interaction strength control. Besides, the reduced network is capable to texture image segmentation in the case of textures, representable by collections of oriented bars.

2. 3D Oscillatory Network Model of VC

Before description of the 3D network architecture and explanation the method of image segmentation that it provides we would like to remind the traditional statement of image segmentation problem. Let $I(x,y)$ be continuous brightness function of an ideal image, defined in a rectangular domain $V=[0,L_1]\times[0,L_2]$ in the plane. Segmentation problem includes: 1) discretization, that consists in pixel decomposition of V (pixels V_{jm} being squares of side h so that $M\cdot h=L_1$, $N\cdot h=L_2$)), specification of square lattice $G_{M\times N}$ with the nodes (x_j,y_m) at pixel centers and calculation of matrix $[I_{jm}]=[I(x_j,y_m)]$ of brightness values at the lattice nodes; 2) "quantization", that is realized with the help of some discrete scale $\mathcal{I}=\{I^{(l)}\}$, $(I^{(1)}>I^{(2)}>\ldots>I^{(L)})$ of brightness levels: elements of matrix $[I_{jm}]$ are approximated by the values from $\mathcal{I}$. As a result we get $M\times N$ matrix $[I^d_{jm}]$ which elements receive discrete values from $\mathcal{I}$. Now image fragments can be defined as subdomains $V^{(l)}=\{x,y \mid I^d(x,y)=I^{(l)}\}$. Thus, image segmentation problem consists in the decomposition of the domain V, in which brightness function $I(x,y)$ is defined, into a set of subdomains — image fraqments : $V=\bigcup_l V^{(l)}$.

Now we are going over to the model explanation. More short and formal model description is given in (Kuzmina, Manykin, Surina, 2001).

2.1 Spatial Architecture of the Network

We suppose that pixel representation of an image to be segmented is given in a lattice $\tilde{G}_{M\times N}$. The 3D oscillatory network is located in 3D spatial lattice consistent with $\tilde{G}_{M\times N}$. The network contains of $M\cdot N$ oscillator columns of K oscillators each so that $M\cdot N\cdot K$ is the total number of oscillators. The bases of the columns are located at the nodes of 2D lattice $G_{M\times N}$ similar to $\tilde{G}_{M\times N}$, whereas oscillators of each column are located at the nodes of 1D lattice L^K oriented normally with respect to the plane of $G_{M\times N}$. Thus, the oscillators of the whole network are located at the nodes of 3D lattice $G_{M\times N}\times L^K$. Therefore, any oscillator column corresponds to proper image pixel (see Fig. 1). We prescribe further to each network oscillator an internal parameter — the receptive field (RF) orientation, specified by two-dimensional unit vector $\mathbf{n}^k_{jm}$, $\mathbf{n}^k_{jm}=(\cos\psi^k_{jm},\sin\psi^k_{jm})$, located in the plane orthogonal to column direction. Based on neurobiological data (Hubel, 1988), vectors $\mathbf{n}^k_{jm}$ are assumed uniformly distributed over each column: $\psi^k_{jm}=\psi^0_{jm}+k\cdot\pi/K,\quad k=1,\ldots,K.$

The next step consists in inclusion into consideration of the additional set of image characteristics — the set of unit vectors $\{\mathbf{s}_{jm}\}$, defining elementary image bar orientations at the nodes of $\tilde{G}$. Vectors $\{\mathbf{s}_{jm}\}$ can be naturally related to brightness nonhomogeneity inside pixels. Namely, they are obviously orthogonal to the direction of brightness gradient at pixel centers, and so obtaining of $\{\mathbf{s}_{jm}\}$ can be reduced to the problem of brightness gradient estimation. We suppose that the set $\{\mathbf{s}_{jm}\}$ has been extracted via proper preprocessing, and the $M\times N$ matrix of pairs $\mathcal{M}=[(I_{jm},\mathbf{s}_{jm})],\quad j=1,\ldots,M;\quad m=1,\ldots,N,$ is defined. The matrix $\mathcal{M}$ figures in the model as the set of tuning parameters for internal dynamics of network oscillators.

2.2 Single Network Oscillator

Network processing element is a neural oscillator. Instead of biologically motivated model of cortical oscillator designed in (Li, 1998) we used in our model a version of familiar Ginzburg-Landau limit-cycle oscillator with properly modified dynamics. The reason was that Ginzburg-Landau oscillatory systems are widely used for modelling of various types of collective behavior and phase transitions inherent in macroscopic physical systems and so are studied very well. The authors of the paper also dealt with Ginzburg-landau oscillators previously. Internal dynamics of our neural oscillator has been designed based on preliminary mathematical study of main features of oscillator dynamics (Li, 1998).

If one defines oscillator state by a pair of real-valued variables (u_1,u_2), the system of two coupled ODE, governing oscillator dynamics, can be written in the form of single equation for complex-valued variable $u=u_1+i\cdot u_2$:

$$\dot{u}=f(u,\mu),$$
$$f(u,\mu)=(\rho_0^2+i\omega-|u-c|^2)(u-c)+\mu,\quad \mu=g(I,\mathbf{s};\mathbf{n})=p(I)+q(\mathbf{s},\mathbf{n}). \tag{1}$$

Here ρ_0, c, ω are constants, defining the parameters of limit cycle of system (1) at $\mu = 0$: the cycle is the circle of radius ρ_0, its center is located in the plane (u_1, u_2) at the point $u_0 = (c_1, c_2)$, $\quad c = c_1 + ic_2$, $\quad \omega$ being cycle frequency. At $\mu > 0$ the size and location of the limit cycle are controlled by $(I, \mathbf{s})$ via properly selected functions p and q:

$$p(I) = 1 - \mathcal{H}(I - h_0), \quad \mathcal{H}(x) = 1/(1 + e^{-2\nu x}), \tag{2}$$

$$q(\mathbf{s}, \mathbf{n}) \equiv q(|\beta - \psi|) = 1 - \Gamma(|\beta - \psi|), \quad \Gamma(|\phi|) = 2e^{-\sigma|\phi|}/(1 + e^{-2\sigma|\phi|}). \tag{3}$$

Here $\mathcal{H}(x)$ is a sigmoidal function depending on threshold h_0; $\quad \Gamma(|\phi|)$ is a symmetrical peak-shaped function, nonzero only at small vicinity of $\phi = 0$ (delta-like function); $\quad \phi = \beta - \psi$ is the angle between elementary bar orientation $\quad \mathbf{s} = (\cos\beta, \sin\beta)$, and RF orientation $\mathbf{n} = (\cos\psi, \sin\psi)$.

The parameter $\mu = g(I, \mathbf{s}; \mathbf{n})$ is a bifurcation parameter of dynamical system (1). The limit cycle radius $\rho(\mu)$ (oscillation amplitude), maximal at $\mu = 0$ $(\rho(0) = \rho_0)$, monotonically decreases at μ increasing and then bifurcates into stable focus at some $\mu = \mu_*$, $\quad \mu_* \in (0, 1)$. Due to the designed dependence μ on $(I, \mathbf{s})$ the cycle size is sufficiently great if two following conditions are satisfied simultaneously:

a) I essentially exceeds the threshold value h_0;

b) the angle between $\mathbf{s}$ and $\mathbf{n}$ is sufficiently small.

Otherwise, either the cycle size is very small, or it degenerates into stable focus (quickly damping oscillations). The bifurcational character of single oscillator dynamics is essentially exploited in image processing realized by oscillatory network.

The response of network oscillator to variation of pixel brightness is shown in Fig. 2. As one can see, the oscillator demonstrates almost momentary response to sudden decreasing of pixel brightness via oscillation amplitude reduction.

2.3 Self-organized Dynamical Connections

Let the state of the 3D network be defined by $(M \times N \times K)$-array of oscillator states $[u^k_{jm}]$. Then dynamical system governing the network dynamics can be written as:

$$\dot{u}^k_{jm} = f(u^k_{jm}, \mu^k_{jm}) + S^k_{jm}; \quad j = 1, \ldots, M, \quad m = 1, \ldots, N, \quad k = 1, \ldots, K. \tag{4}$$

Here $f(u^k_{jm}, \mu^k_{jm})$ is defined accordingly (1), and $\mu^k_{jm} = p(I_{jm}) + q(\mathbf{s}_{jm}, \mathbf{n}^k_{jm})$.
The term S^k_{jm} specifying interaction between oscillators is chosen as:

$$S^k_{jm} = \sum_{j',m',k'} W^{kk'}_{jj'mm'}(u^k_{jm}, u^{k'}_{j'm'})(u^{k'}_{j'm'} - u^k_{jm}). \tag{5}$$

Here the values $W^{kk'}_{jj'mm'}$, defining the connection of network oscillators (j, m, k) and $(j,' m', k')$, are nonlinear functions of their states: $\quad W^{kk'}_{jj'mm'} = W^{kk'}_{jj'mm'}(u^k_{jm}, u^{k'}_{j'm'})$. Obviously, the form of the dependence of connection strength of network oscillator pair on their states (network connectivity rule) influence crucially both on network dynamics and on its performance. We have constructed functions $W^{kk'}_{jj'mm'}(u^k_{jm}, u^{k'}_{j'm'})$ based on results of our previous mathematical study of synchronization in oscillatory networks governed by dynamical equations (4), (5) in more simple special case at $c = 0, \mu^k_{jm} = 0, W^{kk'}_{jj'mm'} = const$ (Kuzmina, Manykin and Surina, 1995; 1996; 1997).

The following form for elements of matrix of connections W has been chosen:

$$W^{kk'}_{jj'mm'}(u, u') = P^{kk'}_{jj'mm'}(\rho, \rho')Q^{kk'}_{jj'mm'}(\mathbf{n}, \mathbf{n}')D^{kk'}_{jj'mm'}(|\mathbf{r} - \mathbf{r}'|), \tag{6}$$

where ρ and ρ' are limit cycle radii for oscillators defined by indices (j, m, k) and (j', m', k'), $\mathbf{n}$ and $\mathbf{n}'$ are RF orientations for these oscillators, $\mathbf{r}$ and $\mathbf{r}'$ are radius-vectors defining their spatial locations in the network.

The cofactors $P^{kk'}_{jj'mm'}$, providing connectivity rule dependence on oscillator activities, are chosen in the form:

$$P^{kk'}_{jj'mm'} = w_0 \cdot \mathcal{H}(\rho^k_{jm}\rho^{k'}_{j'm'} - h), \tag{7}$$

where $\mathcal{H}(x)$ is a sigmoidal function depending on threshold h, w_0 is a constant, defining total strength of network interaction. As it is clear from (7), the connection (6) is negligible if at least one of interacting oscillators is in the state of low activity. The cofactors $Q^{kk'}_{jj'mm'}$, providing the connection dependence on RF orientations, are defined in terms of delta-type function Γ dependent on orientation difference of $\mathbf{n}$ and $\mathbf{n}'$:

$$Q^{kk'}_{jj'mm'} = \Gamma(|\psi^k_{jm} - \psi^{k'}_{j'm'}|). \tag{8}$$

So Q is nonzero only if $\mathbf{n}$ and $\mathbf{n}'$ orientations are sufficiently close. At last, the cofactors $D^{kk'}_{jj'mm'}$ permit to control spatial radius of oscillator interaction. Surely, only spatially finite-range types of connections can exist in VC. Therefore, the cofactors $D^{kk'}_{jj'mm'}$ can be defined by any function vanishing at some finite distance. For example (Kuzmina et al., 2001), D can be chosen in the form $D^{kk'}_{jj'mm'} = 1 - \mathcal{H}(|\mathbf{r}^k_{jm} - \mathbf{r}^{k'}_{j'm'}| - r_*)$, where r_* is a given radius of spatial intraction.

Thus, accordingly to connectivity rule (6), any two network oscillators are proved to be sufficiently strongly dynamically connected if they both are active, possess close RF orientations and are located at the distance not exceeding the prescribed radius of spatial interaction.

3. 2D Reduced Oscillatory Network

The 3D oscillatory network can be naturally reduced to its limit version — 2D network which oscillators are located in the nodes of lattice $G_{N\times N}$ and can be interpreted as idealized oscillator-columns. The reduced network can be obtained in the following way. Let us fix parameters (I, β), $I \geq h$ of some pixel of sufficient brightness and consider the response of oscillator column, corresponding to the pixel. Obviously, only several neighboring oscillators in the column will be active — those that possess RF orientations close to β. Let the number of oscillators in the column is gradually increasing and the width of function Γ at the same time is respectively reduced. Then the number of active oscillators of the column will be gradually decreased, and in the limit of infinitely long column and infinitely narrow Γ we would get the single active oscillator in each column, namely that one which RF orientation coincides with β. So the response of the idealized column (infinitely long one with infinitely narrow function Γ) is reduced to the response of single oscillator in the column. Its dynamics is governed by eq. (1) with function $G(I) \equiv g(I, \mathbf{s}; \mathbf{s}) = 1 - \mathcal{H}(I - h_0)$. The 2D reduced network of these oscillator-columns is located in $G_{M\times N}$ lattice, which is in one-to-one correspondence with retina lattice $\tilde{G}_{M\times N}$, that is, one oscillator corresponds to one image pixel. The network state is defined by $M \times N$ matrix $\hat{u} = [u_{jm}]$, and network dynamical equations are:

$$\dot{u}_{jm} = (\rho_0^2 + i\omega_{jm} - |u_{jm} - c|^2)(u_{jm} - c) + G(I_{jm}) = \sum_{j',m'=1}^{N} W_{jmj'm'}(u_{j'm'} - u_{jm}), \quad (9)$$

where

$$W_{jj'mm'} = P_{jj'mm'}(\rho, \rho')Q_{jj'mm'}(\mathbf{s}, \mathbf{s}')D_{jj'mm'}(|\mathbf{r} - \mathbf{r}'|), \quad (10)$$

The cofactors $P_{jj'mm'}$ and $D_{jj'mm'}$ in eq. (10) are calculated in the same manner as in the case of 3D network, but the cofactor Q is now depends on image bar orientations. As it turned out, the presence of cofactor $Q(\mathbf{s}, \mathbf{s}')$ in network connections provides the network capability to perform some texture segmentation tasks.

4. Brightness Image Segmentation via Controlled Synchronization in the Reduced Network

As one could naturally expect, the reduced network is capable to provide segmentation of pure brightness images for which information on elementary bar orientations is absent. For brightness images we can simply suppose that bar orientations are the same for all the pixels and put $\beta_{jm} = const$. Then the dependence on bar orientations disappears, because $Q = 1$ in eq. (10). Due to one-to-one correspondence between image pixels and oscillators of the 2D network at the initial network state the distribution of oscillator activities exactly corresponds to pixel brightness distribution. But association of pixels into a whole image fragment is achieved via synchronization of oscillators with close activities. For high performance in brightness image segmentation task (accurate detection of image fragment boundaries) we included an additional procedure of synchronization control. It is a simple algorithm of gradual increasing of total network coupling strength that permits to realize successive selection of synchronized assemblies (clusters), corresponding to image fragments of different brightness levels.

For the purpose a matrix $\mathcal{N} = [\gamma_{jm}]$ of additional control parameters has been introduced, and we put first $\gamma_{jm} \equiv 0$. A modified matrix $\tilde{W}$ of network connections, depending on $\{\gamma_{jm}\}$, has been further introduced instead of W: $\tilde{W}_{jj'mm'} = W_{jj'mm'}\Gamma(|\gamma_{jm} - \gamma_{j'm'}|)$.

At the beginning of interaction strength control stage we specify initial interaction so weak that the network is completely desynchronized. We realize it by a choice of sufficiently high initial threshold value h in cofactor P (see eq. (7)). Further we gradually increase $\tilde{W}$ via decreasing h up to the moment of synchronization of the first network cluster. It happens at some $h = h_1$. The first cluster, formed by oscillators of maximal activity, corresponds to image fragment of maximal brightness. Under further decreasing h inside some interval (h_2, h_1), $h_2 < h_1$, the first cluster remains to be the single synchronized cluster of the network. This fact is a consequence of monotonic dependence of oscillator limit cycle size on brightness I. Being convinced that the single cluster is synchronized whereas the rest network is desynchronized, we separate the first cluster via excluding it from interaction with all the rest network oscillators. It is achieved by means of the matrix $\mathcal{N}$ modification: we prescribe some nonzero value $\gamma = \gamma_1$ to those components of $\mathcal{N}$ that correspond to spatial locations of oscillators, belonging to the synchronized cluster. After that the above process of interaction strengthening can be continued until the second cluster will be synchronized and excluded from mutual interaction, and so on. Finally all the clusters will be sequentially synchronized and separated. Thus, the network will be decomposed into a set of internally synchronized, but mutually desynchronized clusters, corresponding to image fragments of different brightness levels. Moreover, in final state the desynchronized clustes oscillate with slightly different frequencies what just provides additional tool for analysis of segmentation result.

The described procedure of interaction control has been fulfilled so far manually in current version of computer code. However, its automatic performance can be realized and is in progress. One of the ways consists in that appropriate dynamical equations for time evolution of both network interaction strength w_0 and controlling parameters γ_{jm} could be joined to dynamical system (9), governing 2D network dynamics. A version of the equations can be schematically written in the form:

$$\dot{w}_0 = \mathcal{F}_1(\lambda t), \quad \dot{\gamma}_{jm} = \mathcal{F}_2(||\dot{u}_{jm}| - < |\dot{u}| > |), \tag{11}$$

where $\mathcal{F}_1$ is a slowly varied function of time ($\lambda \ll 1$), $\mathcal{F}_2$ is a sharply varied function in the vicinity of zero, $|\dot{u}| \equiv (\dot{u}_1^2 + \dot{u}_2^2)^{1/2}$, $< \dot{u} >$ is a mean value (over the network) of instantaneous oscillator frequency, $< \dot{u} > \equiv (MN)^{-1} \sum_{jm} \dot{u}_{jm}$. Under w_0 slow growing the fast variables γ_{jm} are changed in a jump-like manner at the moments of successive cluster synchronization, what just results in automatic synchronized cluster exclusion from network interaction.

In a series of computer experiments on synthetic brightness image segmentation good network performance has been demonstrated. The visualization of segmentation process has been realized in the following manner. The network state is depicted in computer screen in the form of pixel array (one pixel — one oscillator), what exactly reproduces pixel representation of the image. The brightness $\hat{I}_{jk}(t)$ of each pixel in the array is directly related to state variable $u_{jk}(t)$ of corresponding oscillator: $\hat{I}_{jk}(t) = |u_{jk}|(t)$, $|u| \equiv (u_1^2 + u_2^2)^{1/2}$. Besides, the phases $\theta_{jk}(t) = arg(u_{jk})(t)$ of current oscillator states are depicted by time-dependent vectors of proper length, localized inside pixels. As a result one can see in the screen the whole set of network states, arising in the process of network dynamics, and select any desirable subset to analyze. It should be noted, that oscillatory character of segmentation results proves to be very informative. First of all, as far as synchronized clusters, corresponding to image fragments of different brightness levels, oscillate with slightly different frequences, all the fragments are clearly distinguishable.

Besides, the whole set of network states, obtained in the process of image segmentation, is available. A large number of different "versions" of segmented image is contained in this set, what is quite helpful in the situations when some ambiguous image fragments exist (for instance, contours of low contrast).

The example of processing of the synthetic image containing 2460 pixels is presented in Fig. 3. A noisy image version was given as the initial network state, the noise being imposed via network oscillator frequency dispersion. Three stages of network performance during interaction strengthening procedure are shown: a) initial state of total desynchronization; b) the state of partial synchronization (several clusters are already synchronized and excluded from network interaction whereas the rest part of the network is desynchronized); c) the state of complete clusterized synchronization. In each case an example of instantaneous network state (left) and time dependence curves $r_{jk}(t) = |u_{jk}|(t)$ and $\theta_{jk}(t) = arg(u_{jk})(t)$ for all network oscillators (right) are shown.

It is remarkable that there is an evidence on sequential type of image segmentation performed by the visual cortex. Namely, image fragments of different brightness are processed not simultaneously. Instead there is some time delay in fragment reproduction: the most bright fragments are reproduced faster than the less bright ones (Wörgötter, 2001). Probably it is achieved via additional image processing fulfilled in high cortical areas.

5. Texture Image Segmentation

The processing of texture visual images is usually regarded as special class of problems in the field of traditional computer vision algorithms. In particular, there exist special methods of texture representation and synthesizing. There are also catalogues of artificial textures. In the frames of our approach we are able to include into consideration only the simplest texture types, representable as collections of oriented bars.

The 2D reduced network is capable to process texture images because of the dependence on bar orientations preserved in its connectivity rule (10). In the case of texture images one has to deal with brightness-texture image fragments instead of pure brightness ones. In the first series of computer experiments on texture image segmentation we processed images with monodirected textures and concentrated attention on texture images with homogeneous mean brightness. In the task the network performance is based on desynchronization of clusters corresponding to different texture fragments. Unlike the case of pure brightness image segmentation, network coupling control is unnecessary here.

Two examples of the texture image segmentation are shown in Fig. 4, 5. Here texture structures of processed images are presented in the left squares in the form of oscillator phase distribution at initial network state. Two instantaneous states of synchronized network, in which the segmentation is clearly observed, are shown in the middle and right squares. Desynchronized clusters, corresponding to different texture fragments, are in different phases of oscillation and therefore are accurately segmented. In Fig. 5 the segmentation of texture-marked contour of complicated form ("fractal"-like) is shown. In the case it is necessary to choose a sufficiently great radius of spatial coupling.

A kind of contour integration task, fulfilled by the oscillatory network, is demonstrated in Fig. 6. The image contains two closed contours marked solely be texture, defined by oriented bars of continuously varied direction (approximating local contour tangent). As one can see, the network provides accurate segmentation of the double contour via its desynchronization with respect to background.

6. Comparisons with Another Oscillatory Models

There are two oscillatory network models for image segmentation that are closely related to ours. The first one is the model by Z.Li, developed in the series of papers (1998-2001). The following distinctions of our model from the model by Z.Li should be marked:

1) two features of single oscillator dynamics — its bifurcational character and the monotonic dependence of oscillation amplitude on pixel brightness — have been actively exploited in our network model performance;

2) self-organized dynamical connections are designed in our model; they automatically emerge after tuning of single oscillator dynamics by image characteristics $(I_{jm}, \mathbf{s}_{jm})$ (in contrast, stationary excitatory and inhibitory connections, designed in the model by Li, cannot be considered as self-organized ones);

3) the reduced network, extracted from our source network model of VC and supplemented by the method of interaction strength control is capable for brightness image segmentation (whereas image processing tasks related only to contour and texture segmentation can be solved via the model by Li).

As compared with another oscillatory network model — the model by D.Wang et al, (1995-2001) — our model require considerable improvement before being tested in real image segmentation problems. First of all, essential enlargement of admissible image lattice size is necessary. However, we could mention some advantages of our model with respect to the model by Wang. These are:

1) there exist only dynamical connections in our model (stationary connections are absent as unnecessary);

2) the connectivity rule, constructed in our model, leads to automatic formation of self-organized network coupling and flexibly controlled synchronization (in contrast, special calculations are necessary in the model by D.Wang et al. to reveal for each network oscillator the set of oscillators, interacting with the selected one);

3) our method of interaction strength control is definitely more simple as compared to algorithm of interaction adaptation developed in the last version of the model (Chen, Wang and Liu, 2000).

7. Summary. Discussion. Further Perspectives

An oscillatory network model of VC of columnar architecture has been designed by the authors. Internal dynamics of single network oscillator is tunable by image pixel characteristics — brightness and elementary bar orientation. The designed network connectivity rule implies the emergence of nonlocal self-organized dynamical connections dependent on oscillator activities and receptive field orientations. Accurate brightness and texture image segmentations are provided by the 2D reduced oscillatory network by means of simple method of network interaction adjustment.

Two basic cofactors P and Q, contained in network connectivity rule (6), are responsible for different aspects of image segmentation task. The construction of cofactor Q reflects neurobiologically evident fact of preferable connectivity of VC neurons with close RF orientations. The network capability of texture detection and contour integration is just the consequence of presence of cofactor Q in network connectivity rule. A general idea on extraction of "coherent" objects in visual scenes via dynamical binding, expressed by variouos well known VC researches, is reflected in the construction of cofactor P, responsible for the network capability of brightness image segmentation. The example of function P construction, given in our model, seems rather natural from neurophysiological viewpoint. Namely, the connections defined accordingly the connectivity rule (7), could be regarded as a spatial version of nonlinear Hebbian connections.

One could hardly expect to answer (in the frames of a single model) the question whether or not the model captures the way the visual cortex works. A diversity of investigations, including experiments, is necessary to elucidate the problem of whether or not dynamical binding is exploited in VC. A version (biologically reasonable, as it seems) of dynamical connectivity, suggested in our model, "force" dynamical binding to "work". Maybe just this fact could be regarded as a small contribution into insight how the brain visual system could in principle work.

We also would like to note that in addition to technical aspects of model improvement (enlargement of pixel field size of processed image, automatization of the stage of network interaction control) the following directions of further model extension are possible: 1) design and testing of diffenent kinds of dynamical connectivity rules; 2) extension to on-line segmentation of moving images; 3) extension to color image segmentation; 4) development of active vision approaches.

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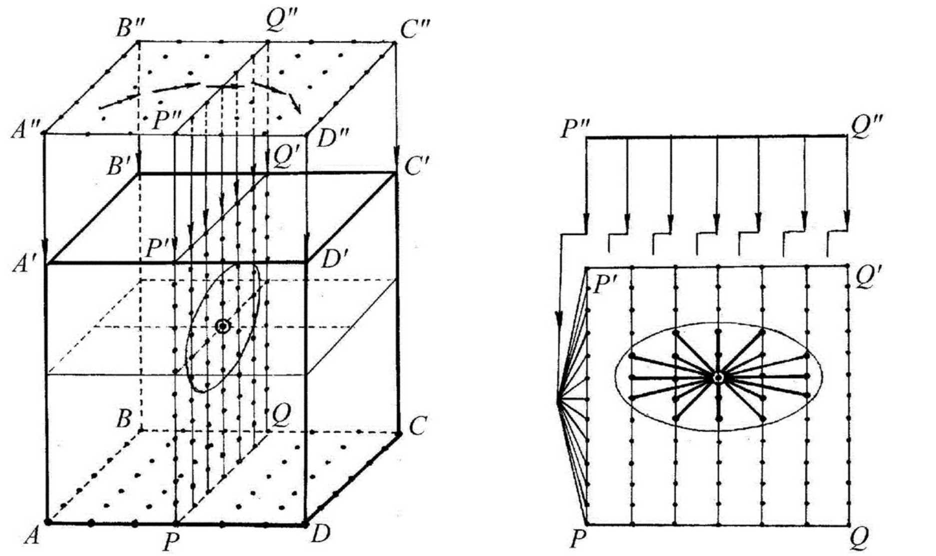
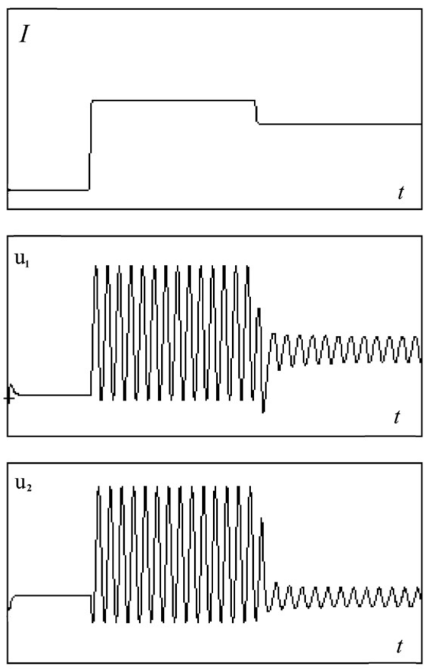


Fig. 1. The scheme of relation between image lattice and 3D network architecture. Discretized image is located in 2D lattice inside the rectangle A"B"C"D" ("retina"). Network oscillators are located in 3D lattice inside the parallelepiped ABCDA'B'C'D', oscillator columns being oriented along the parallelepiped height. It is shown in the section PP'Q'Q depicted also separately on the right. Pixel characteristics (I, s), defined at each node in A"B"C"D", are the same for all oscillators of corresponding column. Dynamical connections that are nonzero inside bounded spatial vicinity, are depicted for distinguished oscillator.



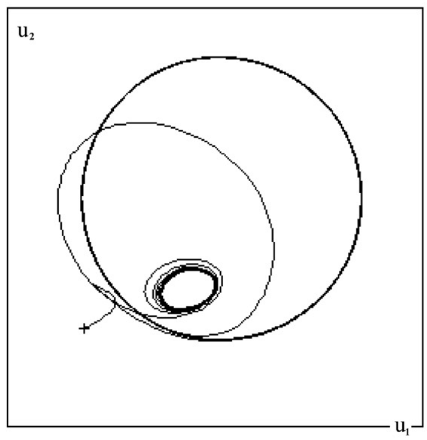


Fig. 2. The " response" of single network oscillator to time variation of pixel brightness: time-dependencies of both state variables (left) and the trajectory of dynamical system (right).

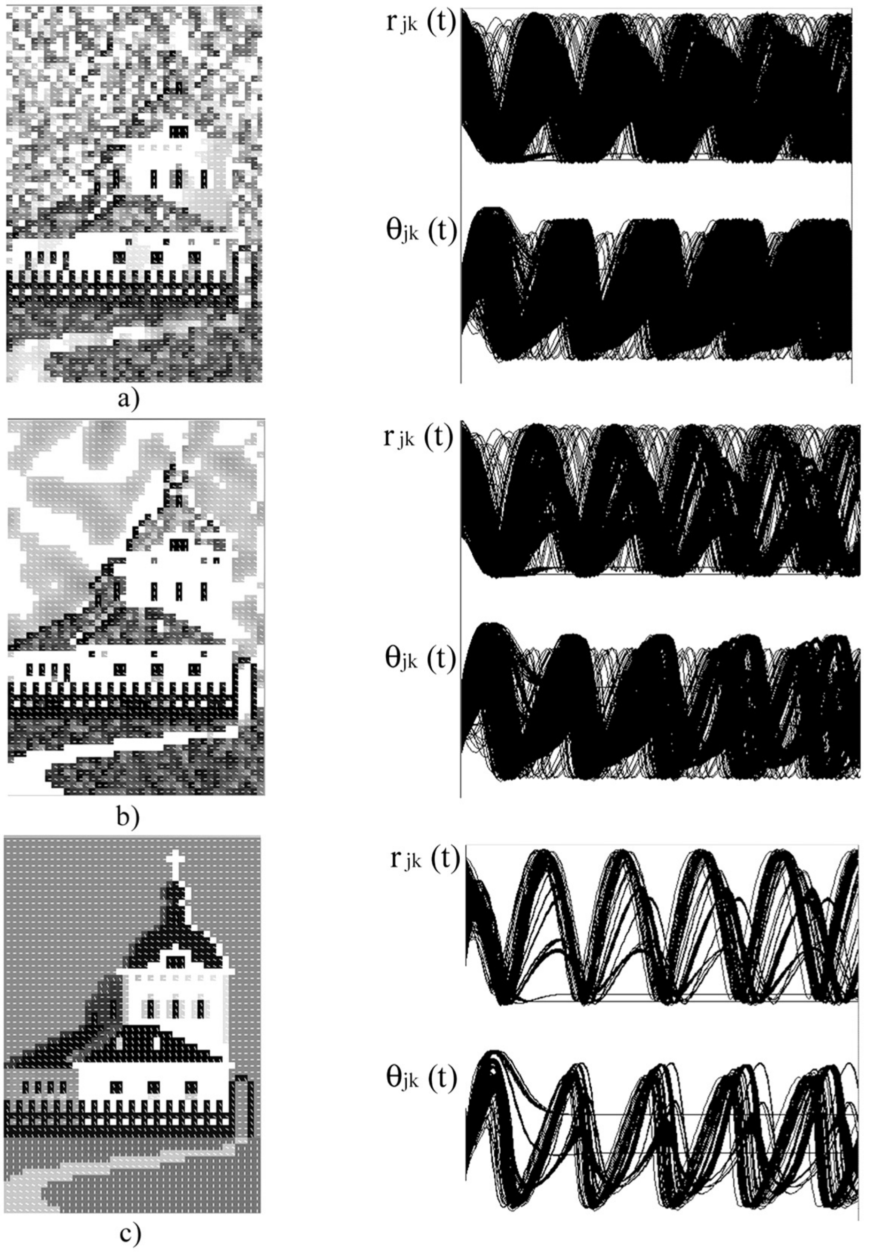


Fig. 3. Three main types of network dynamical behavior that occur in the process of interaction strengthening: a) total desynchronization (h=1.25); b) partial synchronization (h=0.5); c) almost complete synchronization (h=0.01). One of instantaneous network states, mapping current result of image segmentation (left), and time-dependence curves of all oscillator variables (right) are shown.

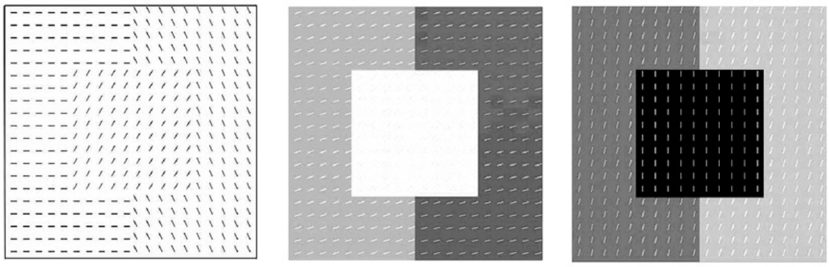


Fig. 4. Segmentation of the image consisting of three fragments of the same brightness but different monodirected texture.

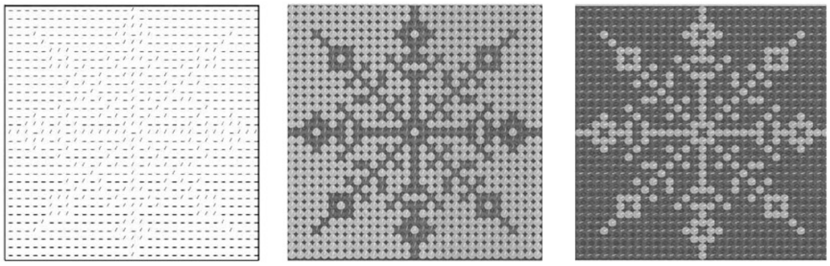


Fig. 5. Segmentation of complicated contour selected solely by monodirected texture.

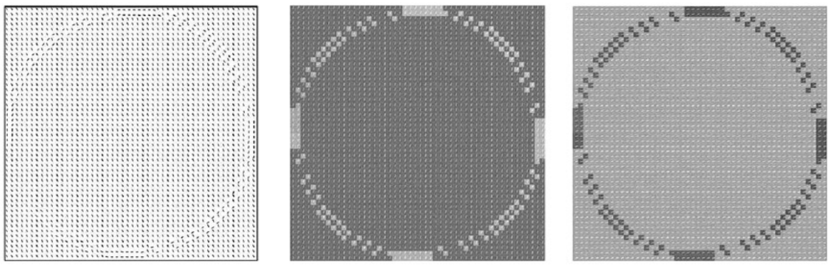


Fig. 6. Segmentation of double closed contour selected solely by texture of continuously varied direction ("contour integration").