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BIOLOGICALLY MOTIVATED OSCILLATORY NETWORK MODEL FOR DYNAMICAL IMAGE SEGMENTATION

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ABSTRACT

We continue to develop the 2D oscillatory network model with self-organized dynamical coupling and synchronization-based performance for image segmentation tasks. The model has been extracted via proper reduction from 3D oscillatory network, previously designed by the authors as oscillatory model of the brain visual cortex (VC). Known neurobiological data on VC structure and functioning were reflected in design of the 3D network architecture and single oscillator dynamics, and the idea of dynamical binding was attracted in construction of network connectivity rule. Under supplemented coupling adaptation method the 2D network is capable to provide accurate segmentation of gray-level brightness images and to perform some texture segmentation tasks. Besides, the network demonstrates capabilities of smooth contour integration.

New advanced versions of internal oscillator dynamics and network connectivity rule have been designed and introduced into the 2D model at current study. The modified network characteristics encompass promising possibilities of more efficient network performance, providing higher accuracy of brightness image segmentation.

Keywords: neural oscillators, oscillatory networks, synchronization, image processing, dynamical binding, self-organization.

INTRODUCTION

Synchronization of neural activity is exploited in a variety of brain structures, and hypotheses on its functional significance in brain information processing were induced since 70th. After experimental discovery of synchronous oscillations in VC of cat and monkey [1,2] the attention to oscillatory aspects of visual information processing was reinforced. A series of network models with various types of oscillators as processing units were designed since 90th [6-11]. Elaboration of oscillatory network models and related neuromorphic dynamical algorithms of visual processing is actively continued nowadays [3,4; 12-23].

Two oscillatory network models developed with a view to image segmentation are closely related to ours. The first one was developed in a series of deep and detailed papers by Z.Li [15-18]. It was designed as a biologically motivated network model of the primary visual cortex. Active network unit is neural oscillator formed by a pair of interconnected cortical neurons — an excitatory pyramidal cell and inhibitory interneuron. The oscillator model reflects orientation-selective response of simple cells of VC. Besides, 3D oscillatory network of columnar architecture was first designed in [15]. Excitatory and inhibitory connections for network oscillators were constructed based on experimental neurobiological data on horizontal intra-cortical connections in VC. The model was tested in problems on pre-attentive image processing, including contour integration and texture segmentation tasks. It demonstrated good synchronization-based performance.

The second remarkable oscillatory network model for visual image segmentation is oscillatory network LEGION, designed first in 1995 [10-14]. The model cannot be viewed as directly related to modelling of the brain visual processing. But nevertheless its the most perfect model version [13] delivers highly effective dynamical image segmentation algorithm based on synchronization in oscillatory network. Active network unit is a relaxational 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 and global inhibitory connections a kind of dynamical coupling has been designed in the network. Besides, a dynamical coupling adaptation algorithm was developed. It allowed to essentially improve the network performance efficiency. As a result the model version [13] demonstrates capability of accurate segmentation of real grey-level images containing more than 400 000 pixels. The comparisons of the oscillatory algorithm with several modern traditional algorithms showed real advantages of the dynamical algorithm.

Our 3D oscillatory network model of VC concerns visual image processing typical to low level vision, that includes only bottom-up processes (with no feedback loop). Namely, it simulates a single step of bottom-up processing: given retinal image induces synchronization-based network model performance, realizing image segmentation. At present stage only the performance of orientation-selective (simple) cell subset of VC has been taken into account in the model. Network processing units are relaxational (limit cycle) oscillators. Simple cell receptive field orientations (RF) figure in the model as internal parameters of network oscillators. Besides, single oscillator dynamics parametrically depends on two more parameters. These are visual image characteristics — local brightness and elementary bar orientation. Imitating VC simple cell response, the oscillator can demonstrate stimulus-dependent dynamical behavior — either activity state (stable oscillations of noticeable amplitude) or silence (quickly damping oscillations). The designed network connectivity rule induces self-organized finite-range dynamical coupling, nonlinearly dependent both on oscillator activities and on RF orientations. The idea of dynamical binding on brightness and RF proximity is reflected in connectivity rule construction. Being tuned by some retinal visual image, the oscillatory network relaxes into a stable state of clusterized synchronization, corresponding to the visual image. The clusters are internally synchronized, but mutually desynchronized network assemblies, encoded by image fragments. Simplified 2D version of the designed 3D oscillatory network model was extracted and tested in image segmentation problems. It demonstrated good performance in a variety of brightness and texture image segmentation tasks. Computer experiments on image segmentation confirmed the intuitively clear fact on significant influence of both internal oscillator dynamics and network connectivity rule upon network performance accuracy. So, our further step to model development, undertaken in present study, concerns the design of advanced network model characteristics.

BRIEF DESCRIPTION OF 3D OSCILLATORY NETWORK MODEL

The 3D oscillatory network (the source model) can be viewed as a biologically motivated oscillatory model of VC. Namely, the network performance imitates self-organized collective behavior of orientation-selective cells of the primary visual cortex in preattentive stage of image processing. Spatial architecture of 3D network simulates columnar structure of VC. The oscillators of the 3D network are located at the nodes of 3D spatial lattice containing $M \times N$ columns of K oscillators each ($M \cdot N \cdot K$ is the total number of oscillators). The columns are orthogonal to VC surface plane. The column bases are located at the nodes of 2D square lattice $G_{M\times N}$, identical to retina lattice, so that there is one-to-one correspondence between $G_{M\times N}$ and retina lattice. As a result just one oscillator column of the network corresponds to each retina lattice node. We introduce further a set of internal network parameters — receptive field orientations $\mathbf{n}^k_{jm}$. Unit vectors $\mathbf{n}^k_{jm}$ are defined at each 3D lattice node and are located in the plane orthogonal to column direction. In accordance with neurobiological data [5], orientations of $\mathbf{n}^k_{jm}$ are deterministically uniformly distributed over each column (similarly to spiral stairs with constant step). It is supposed that an image to be processed is specified by some pixel decomposition. For each pixel we define two pixel characteristics — brightness I and elementary bar orientation $\mathbf{s}$. So the $N \times N$ matrix $[(I_{jm}, \mathbf{s}_{jm})]$, $\quad j, m = 1, \ldots, N$ figures as the set of image characteristics. Thus, 3D array $\{I_{jm}, \mathbf{s}_{jm}; \mathbf{n}^k_{jm}\}$ represents the whole set of 3D network parameters.

Biologically motivated model of neural oscillator, formed by a pair of interconnected cortical neurons, was designed by Z.Li in 1998 [15]. Based on preliminary study of oscillator model by Z.Li, we designed neural oscillator with qualitatively similar internal dynamics and proper response to image characteristics $(I, \mathbf{s})$. It is a relaxational, or limit cycle oscillator with dynamics, parametrically dependent on $(I, \mathbf{s}; \mathbf{n})$. The oscillator demonstrates either activity state (stable oscillations) or "silence" (quickly damping oscillations). The activity state occurs at combination of the following two conditions: a) pixel brightness I is noticeable (exceeds some threshold value h_0); b) image bar orientation $\mathbf{s}$ is sufficiently close to receptive field orientation $\mathbf{n}$. Otherwise, the oscillator is in a "silence" state [22, 23].

The 3D network state is defined by $(N \times N \times K)$-array of oscillator states $[u_{jm}^k]$. Network dynamics is governed by the system of ODE for complex-valued variables u_{jm}^k:

$$\dot{u}_{jm}^k = f(u_{jm}^k, \mu_{jm}^k) + S_{jm}^k;$$

$$1 \leq j \leq M, \quad 1 \leq m \leq N, \quad 1 \leq k \leq K. \qquad (1)$$

Here functions $f(u_{jm}^k, \mu_{jm}^k)$ define internal dynamics of oscillators (parameter μ_{jm}^k is actually nonlinear function on network parameters: $\mu_{jm}^k = g(I_{jm}, \mathbf{s}_{jm}; \mathbf{n}_{jm}^k))$, and the terms S_{jm}^k specify network coupling:

$$S_{jm}^k = \sum_{j',m',k'} W_{jj'mm'}^{kk'} \cdot (u_{j'm'}^{k'} - u_{jm}^k). \qquad (2)$$

The elements of coupling matrix W (network connectivity rule), defining oscillator coupling strength, are constructed in the form of product of three nonlinear functions, dependent on oscillator activities, RF orientations and spatial distance between oscillators:

$$W_{jj'mm'}^{kk'} = P_{jj'mm'}^{kk'}(\rho, \rho') Q_{jj'mm'}^{kk'}(\mathbf{n}, \mathbf{n}') D_{jj'mm'}^{kk'}(|\mathbf{r} - \mathbf{r}'|), \qquad (3)$$

The dependence of $P_{jj'mm'}^{kk'}$ on oscillator activities ρ and ρ' is constructed in such a way that P is negligible if at least one of two interacting oscillators is in the state of low activity. The dependence of $Q_{jj'mm'}^{kk'}$ on $\mathbf{n}$ and $\mathbf{n}'$ guarantees nonzero Q only in the case of sufficiently close $\mathbf{n}$ and $\mathbf{n}'$. At last, $D_{jj'mm'}^{kk'}$ is introduced to cut off the coupling at some prescribed spatial distance. As a result, in accordance with the constructed network connectivity rule, any pair of oscillators is proved to be dynamically connected if: a) both oscillators are active, b) they possess close RF orientations and c) they separated by a distance not exceeding the prescribed radius of spatial interaction.

2D REDUCED OSCILLATORY NETWORK

The 2D reduced network has been extracted as a limit version of the 3D columnar oscillatory network. It is located in 2D lattice, identical to retina lattice, and can be considered as the network of idealized oscillator-columns. Each oscillator of the reduced network correponds to suitable image pixel. The network state is defined by $N \times N$ matrix $\hat{u} = [u_{jm}]$, and network dynamical equations, similar to (1), can be written as

$$\dot{u}_{jm} = f(u_{jm}; \nu_{jm}) + \sum_{j',m'=1}^{N} W_{jmj'm'} \cdot (u_{j'm'} - u_{jm}), \qquad (4)$$

where

$$W_{jj'mm'} = P_{jj'mm'}(\rho, \rho') Q_{jj'mm'}(\mathbf{s}, \mathbf{s}') D_{jj'mm'}(|\mathbf{r} - \mathbf{r}'|). \qquad (5)$$

Single oscillator dynamics is now specified by functions $f(u_{jm}; \nu_{jm})$, parametrically dependent solely on pixel brightness (via parameters $\nu_{jm} = G(I_{jm})$). The cofactors $P_{jj'mm'}$ and $D_{jj'mm'}$ in eq.(5) 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 network is capable both to provide segmentation of pure brightness images and to perform some texture segmentation tasks (the last capability is just provided by presence of $Q_{jj'mm'}(\mathbf{s}, \mathbf{s}')$ in 2D network connectivity rule (5)). To guarantee high accuracy of network performance in brightness image segmentation tasks the additional procedure of network coupling adjustment was utilized [22, 23]. It allowed to realize synchronization control, providing sequential synchronization of network clusters, corresponding to image fragments of different brightness level. Shortly speaking, the synchronization control is achieved via gradual increasing of total network coupling strength, starting from very weak one, at which the network is completely desynchronized. Under gradual coupling strengthening the clusters become synchronized one after another, starting from the cluster, corresponding to the most bright image fragment. At final stage the network is completely synchronized and decomposed into the set of internally synchronized, but mutually desynchronized clusters, corresponding to all image fragments. In addition, the clusters oscillate with slightly different frequencies and so are clearly distinguishable.

The reduced network was tested in a series of brightness image segmentation tasks, that confirmed its good performance. The significant advantage of dynamical segmentation method is that oscillatory segmentation proved to be very informative: as far as any segmented image is decomposed into its set of fragments, oscillating with slightly different frequences, it can be observed in a number of different current versions. It is especially helpful for visualization of weakly contrasting fragments. One can see the examples of these image versions, arising at final stage of complete network synchronization, in Fig. 1.

The example of texture image segmentation is demonstrated in Fig.2. The image contains a fragment in the form of a contour of complicated form, that is selected from background only via monodirected texture (it is very poorly noticeable in the left square of Fig.2). Two different image versions, figuring at network synchronization stage, are shown in the other two squares.

The example of contour integration, performed by the network, is demonstrated in Fig.3. The image contains two closed contours, which brightness coincides with that one of background (left square of Fig.3). The contours are selected via texture in the form of oriented bars of varied orientations (the bars approximate local tangent direction at contour points). The network performance provides clear segmentation of the double contour.

MODIFIED 2D NETWORK MODEL

The current series of computer experiments on image segmentation carried out demonstrated good network performance. At the same time the segmentation results prompted some natural ways of network performance improvement. Two significant modifications of 2D network dynamics are currently under investigation. These are: a) single oscillator dynamics modification; b) modification of cofactor P in network connectivity rule (5). The modified network dynamical system can be written in the form:

$$\dot{u}_{jm} = \tilde{f}(u_{jm};\rho_{jm}) + \sum_{j',m'=1}^{N} \tilde{W}_{jmj'm'} \cdot (u_{j'm'} - u_{jm}), \quad (6)$$

where

$$\tilde{W}_{jj'mm'} = \tilde{P}_{jj'mm'}(\rho,\rho') Q_{jj'mm'}(\mathbf{s},\mathbf{s}') D_{jj'mm'}(|\mathbf{r}-\mathbf{r}'|). \quad (7)$$

The modified dynamical system, governing single oscillator dynamics, can be written as:

$$\dot{u} = \tilde{f}(u;\rho,I) = \tilde{f}(u;g(I),I),$$

$$\tilde{f}(u;\rho,I) = [\rho^2 + i\omega - |u-\rho(1+i)|^2] \cdot (u - \rho(1+i)) + \mathcal{F}(I;h_0,h_1), \quad \rho = g(I), \quad (8)$$

where

$$\mathcal{F}(I;h_0,h_1) = a(1 - T(\alpha(I-h_0))) \cdot (1 - T(\sigma(I-h_1)));$$

$$T(x) = 0.5 \cdot (thx + |thx|), \quad 0 < \alpha < 1, \sigma \gg 1, h_1 > h_0.$$

New oscillator dynamics demonstrates the former bifurcation (converting of limit cycle into stable focus), when brightness I approaches the threshold value h_0. At the same time new dynamics is "more sensitive" to I variation, because in parametrical region $I \gg h_0$ the limit cycle radius ρ can be specified by any explicit monotonic function $g(I)$).

The modified factor $\tilde{P}$ in new network connectivity rule is defined by different nonlinear threshold-dependent function. Instead of former coupling strength adaptation process, some multi-step process of image segmentation will be realized. The number of steps is defined by the choice of discrete scale $\mathcal{I} = \{I^{(l)}\}, \quad (I^{(1)} > I^{(2)} > \ldots > I^{(L)})$ of brightness levels, associated with image pixel decomposition. At s-th step the function $\tilde{P}^s$ depends on current threshold value h_s:

$$\tilde{P}^s(\rho,\rho') = w_0 \mathcal{H}(\nu(I-h_s) T(\sigma(\rho\rho' - h_s)),$$

$$h_s = (I^{(L-1-s)})^2 / I^{(L-s)}, \quad s = 0, \ldots L-2, \quad (9)$$

where

$$\mathcal{H}(x) = 1/(1+e^{-2x}); \quad T(x) = 0.5 \cdot (thx + |thx|).$$

The new connectivity rule is expected to guarantee a higher segmentation accuracy due to the following $\tilde{P}$ feature: it provides dynamical coupling of two network oscillators under the condition, that their activity difference $\rho - \rho'$ belongs to given finite interval. New series of experiments on image segmentation is started.

SUMMARY

Oscillatory network model with self-organized dynamical coupling and synchronization-based performance has been designed, providing neuromorphic image segmentation method. The network was extracted via proper reduction from more general 3D network model, previously designed as a biologically motivated oscillatory model of VC. Computer experiments demonstrate accurate syncronization-based network performance in brightness and texture image segmentation tasks and also network capability of smooth contour integration.

Some directions of further model extension can be pointed out. These are: 1) design and testing of new oscillator dynamics and network connectivity rules; 2) model extension to on-line segmentation of moving images; 3) extension to color image segmentation; 4) development of active vision approaches. New versions of internal oscillator dynamics and network connectivity rule are just proposed in present paper. They encompass promising possibilities of network performance improvement, what will provide higher image segmentation accuracy.

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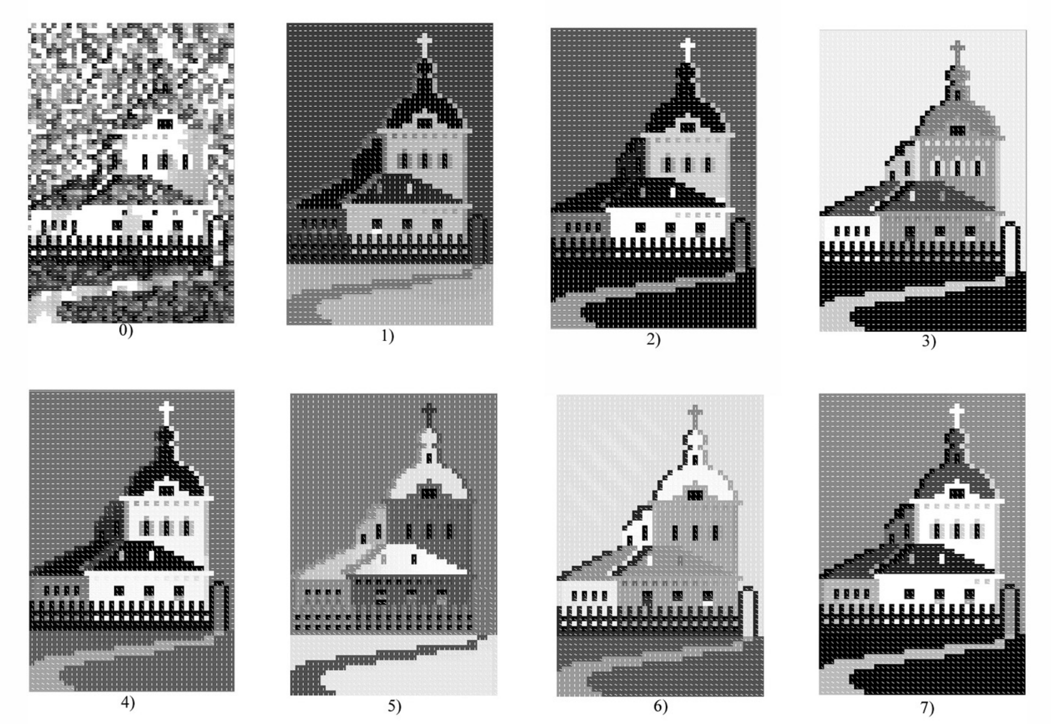

Fig. 1. A series of instantaneous versions of segmented image in the case of complete oscillatory network synchronization.

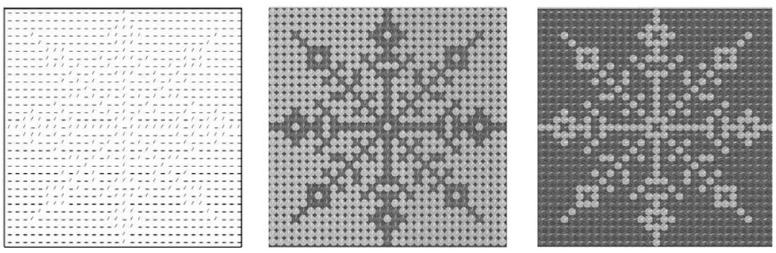

Fig. 2 Segmentation of complicated contour selected solely by monodirected texture.

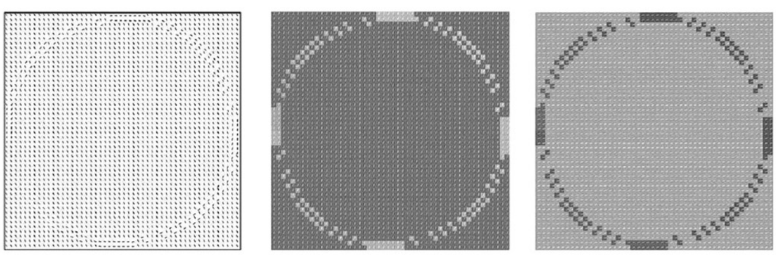

Fig. 3 Segmentation of double closed contour selected solely by texture of continuously varied direction ("contour integration").