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Object Selection in Visual Scene via Oscillatory Network with Controllable Coupling and Self-Organized Performance

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Abstract—An oscillatory network model with controllable coupling and self-organized synchronization-based performance was developed for image processing. The model demonstrates the following capabilities: (a) brightness segmentation of real grey-level images; (b) colored image segmentation; (c) selective image segmentation—extraction of the subset of image fragments with brightness values contained in an arbitrary given interval. An additional capability—successive selection of spatially separated fragments of a visual scene—has been achieved via further model extension. The fragment selection (under minor natural restrictions on mutual fragment locations) is based on in-phase internal synchronization of oscillator ensembles, corresponding to all the fragments, and distinct phase shifts between different ensembles.

Keywords: oscillatory networks, synchronization, image processing, visual scene analysis.

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1. INTRODUCTION

A series of oscillatory network models for image processing based on principle of dynamical binding via synchronization [1–13] was developed. The models and related dynamical approaches to image processing represent a special interest despite a great variety of traditional methods created in the field of computer vision. Our model was obtained from preliminary designed biologically motivated oscillatory network model that simulated self-organized collective behavior of orientation selective cells of the primary visual cortex at low level of visual information processing [11]. The final network model version [13–15] provides a neuromorphic synchronization-based dynamical method for solving of different image processing tasks.

The interest in neuromorphic models, imitating various aspects of functioning of brain neural structures, is induced by the desire to create computational models, which performance would possess some of impressive features inherent to the brain functioning, such as: (a) parallel and distributed type of information processing; (b) capability of adaptation, control and learning; (c) reliability; (d) capability to operate with incomplete and noisy information; (e) "automatic" style of performance. The appeal to oscillatory approaches to visual image processing is related to the fact that synchronized oscillations of neural activity accompany visual information processing in the brain visual structures. Synchronization and resonance are also used in many other brain neural structures: olfactory and auditory systems, thalamo-cortical system, hippocampus, neocortex. So, a number of oscillatory neural network models, exploiting a principle of dynamical binding via synchronization, have been designed. Besides the models [1–13] developed for image processing, oscillatory network model for processing of mixed sound fluxes [16] and biologically motivated oscillatory network model for odor recognition [17] were designed. As it further turned out, the oscillatory dynamical methods of image processing can demonstrate some advantages in comparison with traditional computational methods, mainly due to their distributed and automatic style of performance.

In the last decade new powerful and flexible computational approaches based on MAS (multi-agent systems) models were successfully developed in addition to usual neural network algorithms. Each MAS model can be considered as a collective of interacting autonomous processors (agents), that work cooperatively to solve a mutual problem. Single agent can represent a complicated dynamical system capable to change its internal dynamics and to plan cooperation strategy with the other agents of the collective. Cooperative solution (achieved via coordinated behavior of the whole system) has been realized by means of operating with several independent criterions, such as effective resource utilization, a restriction on time, reliability conditions, and a possibility of unforeseen situations. Error correction becomes an integral characteristic of the system and is carried out via coordination between control of single agent behavior and the whole system control. Both collectives of autonomous robots working in coordination and smart adaptive self-organizing parallel computational algorithms can be created as examples of MAS models. Our oscillatory network model just has some resemblance to MAS models. Namely, in our case the MAS agents are network oscillators located in a lattice. Their internal dynamics is modified in accordance with the problem that has to be solved (concrete image processing task). Agent interactions, being dependent on agent internal dynamics, are also modified according to the coupling principle, related to the problem.

The current model version [13–15] provides a workable dynamical synchronization-based method of brightness image segmentation, demonstrating accurate processing of real grey-level and colored images. It also admits a natural and simple way of selective image segmentation (selection of image fragment set with brightness values belonging to a given narrow interval). Besides, recent model extension [15] provides the solution to a simple problem of visual scene analysis—successive extraction of all spatially separated patches of a visual scene under the condition that the patches are image fragments of almost equal, weakly inhomogeneous brightness.

2. OSCILLATORY NETWORK MODEL

At first we shortly describe the main features of oscillatory network model for brightness image segmentation. Brightness segmentation is implied as image decomposition into a set of brightness fragments—sub-regions of image pixel array with constant values of brightness. Oscillators of the network are located at the nodes of two-dimensional square lattice that is in one-to-one correspondence with pixel array of image to be segmented. Image segmentation is carried out by the oscillatory network via synchronization of network assemblies, corresponding to image fragments of various brightness levels. If an image to be segmented is defined by $M \times N$-matrix $[I_{jk}]$ of pixel brightness values, the network state is defined by $M \times N$-matrix $[u_{jk}]$ of complex-valued variables, defining states of all network oscillators. System of ODE, governing oscillatory network dynamics, can be written as

$$du_{jm}/dt = f(u_{jm};I_{jm}) + \sum_{j',m'}^{M,N} W_{jj'mm'} \cdot (u_{j'm'} - u_{jm}), \quad j = 1, \ldots, M; \quad m = 1, \ldots, N. \tag{1}$$

Here functions $f(u_{jm}; I_{jm})$ define internal dynamics of isolated network oscillators whereas the second term defines the contribution into network dynamics via oscillator coupling. Single network oscillator is a limit cycle oscillator, defined by a pair of real-valued variables (u_1, u_2). Two-dimensional dynamical system, governing single oscillator dynamics, can be written in the form of single ODE for complex-valued variable $u = u_1 + iu_2$:

$$du/dt = f(u, I), \tag{2}$$

$$f(u, I) = (\rho^2 + i\omega - |u - \rho(1+i)|^2)[u - \rho(1+i)] - \alpha H(\rho)[u - \rho(1+i)], \tag{3}$$

where $H(\rho)$ is a continuous step function. The limit cycle radius ρ of dynamical system (2)–(3) is a free parameter of the system that can be specified by an arbitrary monotone continuous function of brightness, $\rho = \rho(I)$. Stable limit cycle exists at $I \geq h_*$, whereas at $I < h_*$ the cycle bifurcates into stable focus (the threshold h_* figures as an internal parameter of the dynamical system). Oscillator "response" to pixel brightness variation at $\rho(I) = \alpha I$ is depicted in Fig. 1, where the curves of temporal behavior of oscillator state components $u_1(t)$ and $u_2(t)$ are shown (left) and the corresponding phase space trajectory of the dynamical system is presented (right).

As one can see from Fig. 1, network oscillator provides quick response to pixel brightness variation via immediate change of oscillation amplitude.

The values $W_{jj'mm'}$, defining coupling strength of network oscillators (j, m) and (j', m'), are designed in the form of a product of two nonlinear functions depending on oscillation amplitudes (limit cycle radii) of an oscillator pair and spatial distance between the oscillators in the network:

$$W_{jj'mm'} = P(\rho_{jm}, \rho_{j'm'}) \cdot D(|r_{jm} - r_{j'm'}|). \tag{4}$$

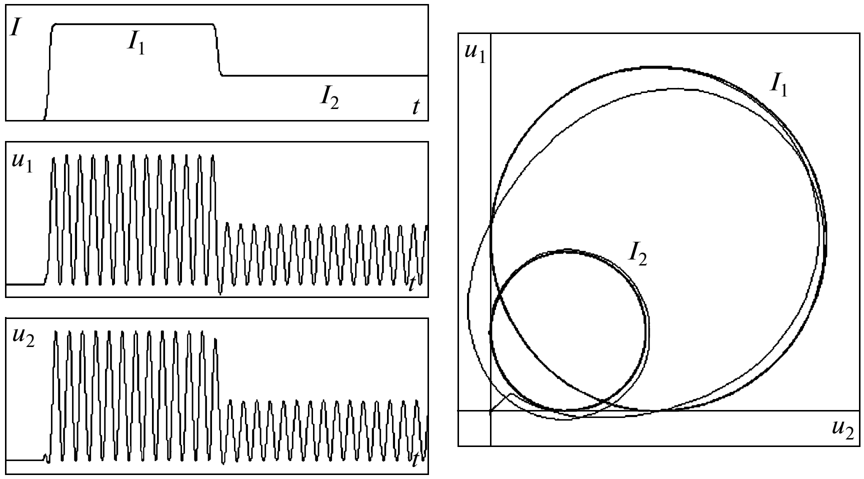


Fig. 1. Oscillator dynamics "response" to pixel brightness variation.

The cofactors P, providing the dependence of network coupling on oscillation amplitudes, are specified as

$$P(\rho_{jm}, \rho_{j'm'}) = w_0 \cdot H(\rho_{jm}\rho_{j'm'} - h), \tag{5}$$

where $H(x)$ is a continuous step-function, w_0 is a constant, defining total strength of network interaction, and h is some threshold value. The cofactors D, providing spatial coupling restriction, can be specified by any function, vanishing at given finite distance. As a result any pair of network oscillators is proved to be coupled if they both possess sufficiently great oscillation amplitudes and are separated by a distance not exceeding the prescribed radius of spatial interaction. Otherwise the connection is absent.

3. NETWORK SEGMENTATION CAPABILITIES

3.1. Gray-Level Image Segmentation

Brightness image segmentation is realized by the oscillatory network via two steps: (1) preliminary tuning of oscillator dynamics by pixel brightness values (after the tuning operation definite limit cycle size has been specified for each network oscillator); (2) network relaxation into the state of cluster synchronization (at which oscillatory network will be decomposed into the set of internally synchronized but mutually desynchronized oscillator ensembles (clusters), so that each ensemble corresponds to a fragment of appropriate brightness. The gradual type of oscillator response to pixel brightness (via function $\rho(I)$) plays a crucial role, providing high segmentation quality. Also the more flexible version of coupling principle has been used besides the coupling rule (4) to further raise segmentation accuracy. It is based on prescribing some "mask" to each oscillator, restricting its coupling "response". The modified coupling rule is defined by modified cofactor $\tilde{P}$ in (4):

$$\tilde{P}(\rho, \Delta; \rho', \Delta') = H(\rho - \rho' + \Delta') \cdot H(\rho' - \rho + \Delta). \tag{6}$$

According to the coupling rule (4) with $P = \tilde{P}$ any pair of network oscillators is coupled only in the case, if the segments $[\rho - \Delta, \rho + \Delta]$ and $[\rho' - \Delta', \rho' + \Delta']$, defined for both the oscillators, are intersected. The parameters Δ and Δ' can be dependent on ρ and ρ' correspondingly.

The result of image segmentation is provided by the network in the oscillatory form so that the ensemble of oscillators corresponding to each image brightness fragment demonstrates internally synchronized dynamics, being at the same time desynchronized with the oscillations of all other ensembles corresponding to another brightness fragments. To select correct stable version of reconstructed image from its oscillatory version, provided by the network, simple methods of post-processing can be used. The example of segmented gray-level image, obtained via the simplest post-processing method, based on selection of the maximal values of $\mathrm{Re}(u_{jm})$, is presented in Fig. 2.

(a) (b)

Fig. 2. Grey-level image segmentation (609 × 422 pixels). (a) original image; (b) segmentation result.

(a) (b)

Fig. 3. Colored image segmentation (524 × 374 pixels). (a) original image; (b) segmentation result.

3.2. Colored Image Segmentation

Colored image segmentation has been realized via pixel array decomposition into three sub-arrays, corresponding to red, blue and green components of pixel colors (RGB). These three sub-arrays are processed by the oscillatory network independently. Final visualization of segmentation result after completion of network performance is realized via reverse joining up of three sub-arrays into single array. The example of colored image segmentation is presented in Fig. 3.

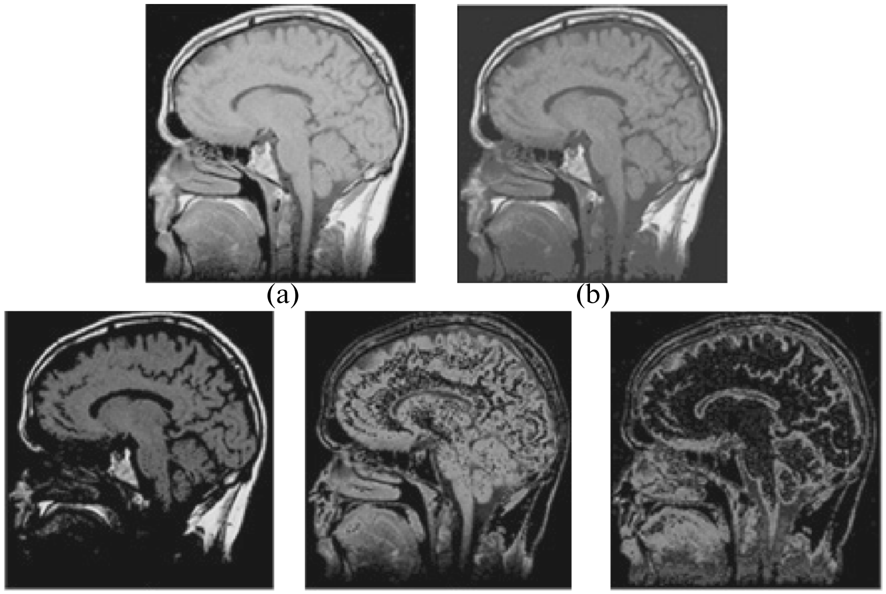
Another way of colored image segmentation is possible as well. Let us use vector parameter $\mathbf{I} = (I_R, I_G, I_B) = (I_1, I_2, I_3)$ with components equal to red, green and blue pixel brightness components, and represent scalar pixel brightness I in the form

$$I = \sum_{k = R, G, B} c_k I_k, \quad c_k > 0, \quad \sum_{k = R, G, B} c_k = 1.$$

Then the coupling principle (4) with $P = P_{\text{col}}$,

$$P_{col} = \prod_{k = R, G, B} H(2\Delta - |I_k - I'_k|),$$

can be used for segmentation of colored images (Δ is a constant parameter).



(a) (b)

(c) (d) (e)

Fig. 4. Selective image segmentation. (a) original image; (b) complete brightness segmentation; (c) several of the most bright image fragments; (d) a set of fragments of middle brightness; (e) several of the least bright fragments.

3.3. Selective Image Segmentation

Selective segmentation can be viewed as a simple type of active image processing. It consists in the extraction of desirable subset of image fragments with brightness values contained in some given interval. As it is intuitively clear, the selective segmentation can often be more informative compared to usual complete segmentation. Oscillator dynamics (2)–(3) provides a natural way of selective segmentation realization. It is sufficient to introduce a new function $\tilde{\rho}(I)$ instead of $\rho(I)$ in Eq. (3), putting $\tilde{\rho} = \rho(I)F(I)$, where $F(I)$ is a "filter" function. If one desires to select only image fragments of brightness values $I \in [I^*, I^{**}]$, we choose $F(I)$ to be equal 1 inside the interval $[I^*, I^{**}]$ and vanishing outside the interval. In the case only the oscillators, corresponding to image fragments with brightness values $I \in [I^*, I^{**}]$, will possess nonzero oscillation amplitudes, whereas the rest of the oscillators will drop out of network interaction because of vanishing limit cycle sizes. The examples of selective segmentation are given in Fig. 4.

4. A PROBLEM OF FRAGMENT SELECTION IN VISUAL SCENE

The problem of object selection in a visual scene belongs to the class of high level image processing tasks and demands additional methods of image analysis in dependence on the problem statement. For instance, in the problem of texture patch selection it is necessary to use collections of filters and spectral histograms [18]. At the first step we restricted ourselves to a simple problem of visual scene analysis which does not require additional computational tools. It is the problem of successive fragment selection from some finite set of spatially separated image patches of almost equal, weakly inhomogeneous brightness. The condition of brightness homogeneity of the patches should be stressed, because in the case of different patch brightness they could be easily separated by the network without any additional efforts. In the case of homogeneous patch brightness the problem can be solved in the frames of our oscillatory network approach by proper model extension. Namely, we introduce two identical independent (mutually uncoupled) oscillatory sub-networks, corresponding to segmented image, denoted as x-layer and y-layer. The initial phase distributions for oscillators of sub-networks of the x-layer and the y-layer are defined as

$$\varphi_{jk}^{(x)}(0) = 2\pi j/M, \quad \varphi_{jk}^{(y)}(0) = 2\pi k/N, \quad j = 1, \dots M, \quad k = 1, \dots N, \tag{7}$$

where M is image width and N is its height. As one can see from (7), the initial phases of network oscillators of x-layer are chosen to be proportional to x-coordinates of image pixels, whereas the initial phases of network oscillators of y-layer are proportional to y-coordinates of image pixels. As a result after relaxation of both sub-networks into synchronization state, one will obtain the following relations for phase shifts:

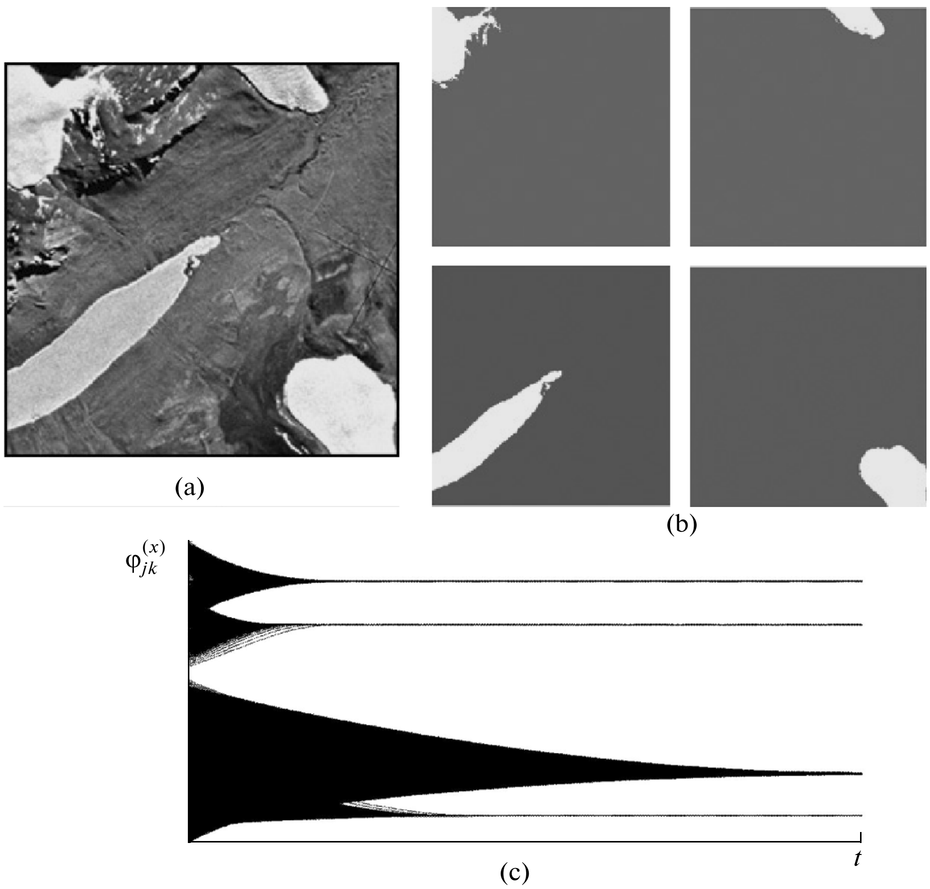


Fig. 5. (a), (b). Selection of spatially separated fragments of visual scene: (a) original image; (b) successive selection each of four fragments. (c) Dependencies $\varphi_{jk}^{(x)}(t) = \arg(u_{jk}(t)) - \omega t$, corresponding to patch selection, shown in Fig. 5a, 5b.

(1) in the x-layer the phase shift between two in-phase synchronized oscillator ensembles, corresponding two different image fragments, is proportional to the difference of x-coordinates of fragment "centers of region"; (2) in the y-layer the phase shift between the same two oscillator ensembles is proportional to the difference of y-coordinates of the fragment "centers of region". So, finite phase shifts arise between all oscillatory ensembles, corresponding to spatially separated fragments. Therefore, all the spatially separated fragments (despite equal brightness) can be clearly distinguished and successively selected. As it is clear, the difficulties in fragment separation can arise, for instance, in the situations when a fragment is contained inside another one, which form is topologically similar to a ring or to a spiral, that is, when the coordinates of "region centers" coincide for two different spatially separated fragments. The example of solvable problem of fragment separation is presented in Fig. 5. A fragment of the Earth surface obtained via satellite observation is presented in Fig. 5a. The scene contains four spatially separated patches of almost equal brightness.

The two-network approach allows to successively select the fragments. Temporal behavior of network oscillator phases for oscillators of the x-layer is shown in Fig. 5c. Similar type of temporal behavior of oscillator phases occurs for oscillators of the y-layer.

5. CONCLUSIONS

Oscillatory network approach to image processing has been developed based on synchronization-based performance of oscillatory network with image encoded oscillator dynamics and controllable network coupling. The approach provides:

(a) self-organized dynamical brightness segmentation of real grey-level images;

(b) colored image segmentation;

(c) selective image segmentation;

(d) successive selection of spatially separated fragments of a visual scene via simple model extension—introduction of two independent identical oscillatory networks instead of single one.

The successive selection of spatially separated image fragments of almost equal brightness is admissible under proper natural restrictions on fragment set. The selection is performed solely in the frames of oscillatory network approach, without incorporation of additional computationally expensive non-oscillatory methods of image analysis (of filtration type). It is realized via in-phase internal synchronization of proper network ensembles and creation of distinct phase shifts between the ensembles.

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