Oscillatory neural network for adaptive dynamical image processing

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Abstract

We develop a biologically motivated oscillatory network model and related dynamical synchronization-based method of image segmentation. The first version of successive segmentation algorithm was based on coupling adaptation in the oscillatory network. New model developments, presented in the paper, include: 1) a modified version of single oscillator dynamics; 2) new network connectivity rule. These modifcations permit to significantly improve the oscillatory method capabilities, providing image processing with significantly larger pixel array sizes and ensuring higher segmentation accuracy. In addition the improved network model allows to perform selective image segmentation tasks (extraction of prescribed subset of image fragments). New method capabilities have been demonstrated in computer experiments.

1. Introduction

We present further development of a neuromorphic dynamical method of synchronization-based gray level image segmentation, provided by oscillatory neural network. Although a great variety of traditional methods of image processing has been developed in the field of computer vision, there is a significant interest in neuromorphic methods, based on imitation of neurobiological processes in the brain neuronal structures. Since synchronized oscillations of neural activity of 40-60 Hz frequency were experimentally discovered in the brain visual cortex (VC) in 1988-1989 (and confirmed in later experiments) the attention to oscillatory aspects of visual information processing was reinforced. A series of oscillatory network models for image processing, demonstrating synchronization capabilities, has been created. Two of them are most closely related to our model. The first one, developed by D.Wang with coauthors [1-4], delivers effective oscillatory method of brightness and texture image segmentation, that is capable to process real multipixel images. The dynamical method demonstrates real advantages compared with modern computational methods of image segmentation. The second biologically motivated oscillatory neural network model was developed by Z.Li [5-8] for contour integration tasks and texture image segmentation. Relation of our model to those by D.Wang and Z.Li was discussed in detail in [15].

Our network, providing dynamical method of image processing, was obtained by reduction from more general oscillatory neural network model that can be viewed as an oscillatory model of the brain visual cortex. Namely, the starting model simulates self-organized collective behavior of orientation selective cells of the primary visual cortex at low (preattentive) level of visual information processing. Active network unit is neural oscillator, formed by a pair of interconnected cortical neurons. It is a limit cycle oscillator with dynamics, controlled by image characteristics. Network oscillators are located at the nodes of 3D spatial lattice. Spatial network architecture imitates the columnar structure of VC: one oscillator column corresponds to each image pixel. Network connectivity rule defines self-organized nonlocal dynamical coupling of network oscillators, nonlinearly dependent on oscillator states. The hypothesis on existence of synchronization-based dynamical binding in VC during visual information processing [9-11] has been just reflected in the construction of network connectivity rule. The reduced 2D oscillatory network, providing a workable segmentation method, was obtained as a limited case of initial 3D model, [12-16].

A number of advantages is inherent to dynamical methods of image segmentation. These are: parallel distributed way of information processing, "automatic" performance, noise reduction, possibility of extention to analog methods with real-time performance. Natural and easy way of introduction of filtering, resulting in capability of selective image segmentation, can be considered as additional advantage of our dynamic method.

It is also noteworthy that our method have something in common with computational approach based on normalized graph cuts [17]. The segmentation method, developed in [17], is based on processing of graph, related to image pixel array. The information on spatial and brightness proximity of image pixels is used to specify the graph edge weights. Image segmentation is then reduced to recurrent procedure of graph cuts into two subgraphs, using information on internal connectivity of subgrapghs and their mutual connectivity. Connectivity rule in our network model shows a resemblance with graph connectivity principle used in [17].

2. The oscillatory network model for image segmentation: main model characteristics

Oscillators of the reduced network located at the nodes of 2D spatial square lattice being in one-to-one correspondence with pixel array of segmented image. Image segmentation is carried out by the oscillatory network via successive synchronization of network assemblies (clusters), corresponding to image fragments of various brightness levels. If an image to be segmented is defined by $M \times N$-matrix $[I_{jm}]$ of pixel brightness, the network state is defined by $M \times N$- matrix $\hat{u} = [u_{jm}]$ of complex-valued variables, defining states of all network oscillators. System of ODE, governing oscillatory network dynamics, can be written as

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

Here functions $f(u_{jm}; I_{jm})$ define internal dynamics of isolated network oscillators whereas the second terms define oscillator coupling. Single network oscillator is a limit cycle oscillator, the limit cycle size (oscillation amplitude) being dependent on pixel brightness I of corresponding pixel. In the first model version the parametric dependence of oscillator dynamics on I has been chosen in the form [15]:

$$f(u, I) = (\rho_0^2 + i\omega - |u - c|^2)(u - c) + g(I), \qquad (2)$$

where

$$g(I) = 1 - H(I - h_0), \;\; H(x) = 1/(1 + e^{-2\nu x}), \;\; \nu \gg 1, \qquad (3)$$

being a continuous step-function dependent on threshold h_0. This provided in the following dynamical behavior of isolated oscillator: a) at $I \le h_0$ oscillator is in "passive" state (quicly damping oscillations); b) at $I > h_0$ oscillator is in "active" state (stable oscillations of amplitude $\rho(I)$, $\rho(I) \le \rho_0$, $\rho(I)$ being monotonically increasing function of I).

The values $W_{jj'mm'}$, defining coupling strength of network oscillators *(j,m)* and *(j'm'),* were designed in the form nonlinear functions dependent on oscillation amplitudes of oscillator pair and spatial distance between oscillators in the network. Namely, $W_{jj'mm'}$ are defined in the form:

$$W_{jj'mm'} = P_{jj'mm'}(\rho, \rho') \cdot D_{jj'mm'}(|r - r'|). \qquad (4)$$

The cofactors $P_{jj'mm'}$, providing the dependence of network connectivity on oscillation amplitudes, are specified as

$$P_{jj'mm'}(\rho, \rho') = w_0 \cdot H(\rho_{jm}\rho_{j'm'} - h), \qquad (5)$$

where $H(x)$ is a continuous function of the same type as that one in eq. (3), and w_0 is a constant, defining total strength of network interaction. The cofactors $D_{jj'mm'}(|r - r'|)$, providing dependence of network coupling on oscillator spatial locations, can be specified by any function $|r_{jm} - r_{j'm'}|$, vanishing at some finite distance. For instance, it is convenient to choose D in the form $D_{jj'mm'} = 1 - H(|r_{jm} - r_{j'm'}| - r_*)$, where r_* is a prescribed radius of spatial interaction. As a result, accordingly to connectivity rule (4), any network oscillators are 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.

Oscillatory network performance consists of two steps: 1) preliminary network tuning by an image to be segmented; 2) multi-step process of successive image segmentation. Network tuning consists in parametric tuning of network oscillator dynamics. After tuning one of two possible dynamical regimes is prescribed to each network oscillator: either auto-oscillation regime with amplitude value $\rho(I)$ or relaxation into stable equilibrium state. The stage of successive segmentation consists of L steps, L being the number of fragments of segmented image). It requires L procedures of network relaxation into synchronization state under different configurations of network connections. Special simple method of interaction adaptation (gradual increasing of total network interaction), combined with "switching off" of synchronized clusters from network interaction just provides successive image segmentation: exactly one synchronized cluster, corresponding to l-th image fragment, arises at l-th step of segmentation stage. Eventually all the network is turned out to be decomposed into the set of internally synchronized but mutually desynchronized clusters, corresponding to complete set of image fragments. Synchronized clusters oscillate with slightly different frequencies, and so all the image fragments are clearly distinguishable. As a result, oscillatory network delivers very informative visualization of segmentation result: a number of different "versions" of processed image can be extracted from the whole set of synchronized network states(see Fig. 1). It is especially helpful in the case of ambiguous image fragment existence (for instance, contours of low contrast).

3. Modified model version

3.1. Modified single oscillator dynamics

Function *g(I),* contained in eq. (2), can be viewed as controlling function, providing the following behavior of attractors of dynamical system of single oscillator: a) at $I > h_0$ the dynamical system possesses a stable limit cycle of radius $\rho(I)$, where $\rho(I)$ is monotonically increasing function of I ($0 \le \rho \le \rho_0$): b) at $I \le h_0$ bifurcation of the limit cycle into stable focus occurs. Although function *g(I),* defined by (3), ensures qualitatively correct response of oscillator dynamics to pixel brightness variations, it does not allow to flexibly regulate the oscillator response (because in the first model version $\rho(I)$ is some fixed monotonic function). So the problem was to design new control of oscillator dynamics by *I*, satisfying the following requirements: 1) dependence of limit cycle size on *I* would be defined by arbitrary monotonic function $\rho(I)$; 2) bifurcation of limit cycle into stable focus would occur at some given threshold value $I = h$. The solution to the problem has been obtained in variables $r = |u|$, $\theta = \arg(u)$. (Then the problem has been reduced to analysis of fixed points of the equation for r-variable). The final dynamical system, delivering the solution in variables (r, θ), can be written as

$$dr/dt = r(\rho^2 - r^2) + g(I), \quad d\theta/dt = \omega, \tag{6}$$

where

$$g(I) = -\beta[1 - T(I-h)], \; T(x) = 0.5(th(\sigma x) + |th(\sigma x)|). \tag{7}$$

Parameter ρ in eq. (6) is just the limit cycle radius. Now it figures as a free parameter and so can be specified by any monotonically increasing function ρ. Constant β in eq. (7) is an explicitly calculated one ($\beta = \beta(\rho)$) and σ is a constant, satisfying the condition $\sigma \gg 1$. Thus, now we have the following behavior of stable limit cycle of system (6): a) stable limit cycle is the circle of arbitrarily prescribed radius $\rho(I)$ at $I > h_*$; b) at $I = h_*$, $h_* \approx h$. the limit cycle bifurcates into a stable focus. Returning to variable $u = r \cdot \exp(i\theta)$, we obtain the required new version of oscillator dynamical system:

$$\begin{aligned} du/dt = (\rho^2 + i\omega) - |u - \rho(1+i)|^2)(u - \rho(1+i) \\ - g(I)[u - \rho(1+i)]/|u - \rho(1+i)|, \end{aligned} \tag{8}$$

where function *g(I)* is defined by formula (7).

The limit cycle collection at different I (at $\rho(I) = \alpha I$) is shown in Fig. 2.

3.2. Modified connectivity rule and new method of successive image segmentation

New version of network connectivity was designed, being guided by the requirements: 1) it should provide oscillator coupling in accurate relation to brightness scale, defining image pixel decomposition; 2) it should be recurrently defined at the stage of successive segmentation. More sensitive dependence of connectivity rule on oscillation amplitudes is necessary to provide accurate fragment detection in the case of small fragment brightness difference. This condition can be formulated as requirements to new cofactor $P(\rho,\rho')$, defined by eq. (4). Let the scale $\{I^{(l)}\}$ of brightness levels be given. It is required to design the cofactor $P(\rho,\rho')$, providing the following features of network connectivity rule: a) oscillator with amplitude $\rho(I)$, where I satisfies the conditions $I \in \{I^{(l)}\},\ I \geq h_*,\ h_*$ being a current threshold, would be coupled with all the oscillators which amplitudes $\rho(I')$ satisfy the same conditions $I' \in \{I^{(l)}\},\ I' \geq h_*$; b) the oscillator would not be coupled with those oscillators, which amplitudes are defined by sub-threshold values I'' $(I'' \in \{I^{(l)}\},\ I'' < h_*)$. A version of connectivity rule, defined at each current step of successive segmentation procedure has been designed. Let the scale $\{I^{(l)}\},\ I^{(1)} > I^{(2)} > ... > I^{(L)}$, be given. At the first step we put:

1) $I = I^{(1)},\quad h_* = I^{(2)},\quad h_{**} = [I^{(2)}/I^{(1)}]I^{(2)}$;

2) $P^*_{(1)} = (\rho,\rho') = T(\sigma x)$, where

$x = \rho\rho' - h_{**},\ T(x) = 0.5(th(x) + |th(x)|),\ \sigma \gg 1.$

As one can verify, $P^*_{(1)}(\rho,\rho')$ does not vanish ($P^*_{(1)} \approx 1$) only for oscillators, satisfying the conditions $I \in [I^{(2)}, I^{(1)}]$ and $I' \in [I^{(2)}, I^{(1)}]$. So, at first step of segmentation only oscillators, corresponding to the first, most bright image fragment, will be coupled and synchronized. For going over to the next step it is necessary to operate with two oscillatory network states – current and stored ones. After synchronization the first cluster is memorized in stored state and "switched off" in current state (via putting $\rho = 0$ for all oscillators of the cluster). In this way the first cluster will be further uncoupled with the rest network. Then the second step of segmentation stage can be carried out via shifting down over the brightness scale and calculating $P^*_{(2)}(\rho,\rho')$. It will provide synchronization of new network cluster, exactly corresponding to the second image fragment. Further the procedure should be repeated $L-1$ times, where L is the number of brightness level in the scale $\{I^{(l)}\}$.

New version of network connectivity rule independently on new version of single oscillator dynamics is expected to provide much higher segmentation accuracy for images with weak brightness gradient. However, as preliminary computer experiments show, the improvement of network performance due to new version (8) of oscillator dynamics is so noticeable, that possibly more simple version of network connectivity rule will turn out to be acceptable.

4. Selective image segmentation.

Oscillatory network model with new version of single oscillator dynamics admits selective image segmentation. For the purpose one should introduce new function $\tilde{\rho}(I)$ in eq. (8), putting

$$\tilde{\rho} = \rho(I)F(I) \qquad (9)$$

where *F(I)* is a "filtering" function. If it is necessary to select only image fragments of brightness levels $I \in [I^*, I^*]$, we choose *F(I)* to be equal 1 inside interval $[I^*, I^{**}]$ and vanishing outside the interval. For example,

$$F^{(1)}(I) = 0.5 \cdot \{th[\gamma(I - I^*)] - th[\gamma(I - I^{**})]\},\ \ \gamma \gg 1. \qquad (10)$$

Indeed, in the case of dynamics (8) only oscillators, corresponding to fragments with $I \in [I^*, I^*]$, will be "active". The rest oscillators, possessing zero oscillation amplitudes, will drop out of network interaction.

For selection of arbitrary collection of image fragments of brightness levels $I^{(l_1)}, ...\ I^{(l_m)}$ it is sufficient to use "filtering" function in the form

$$F^{(2)}(I) = \sum_{k=1}^{m} \Gamma(\gamma\,|I - I^{(l_k)}|),\ \ \Gamma(x) = 2\exp(-\gamma x)/(1 + \exp(-2\gamma x)),$$
$$\gamma \gg 1. \qquad (11)$$

Obviously, the introduction of function $F^{(2)}$ corresponds to selective brightness filtering.

An example of selective image segmentation is demonstrated in Fig. 3. Segmented synthetic image is shown on the left. Extraction of two image segments of least brightness via filtering function $F^{(1)}(I)$ is demonstrated in the upper row, where three image versions are presented. Similarly, extraction of two most bright image segments is shown in lower row.

5. Conclusion

Biologically motivated oscillatory network, based on preliminary oscillatory model of the brain visual

cortex, is under development. The network is characterized by tunable oscillator dynamics and dynamical controllable coupling. It provides synchronization based dynamical image processing (adaptive image segmentation), demonstrating a number of advantages. Presented new model developments enlarged its capabilities, admitting:
1) processing of images with much greater size of pixel array; 2) improved accuracy of segmentation;
3) selective image segmentation.

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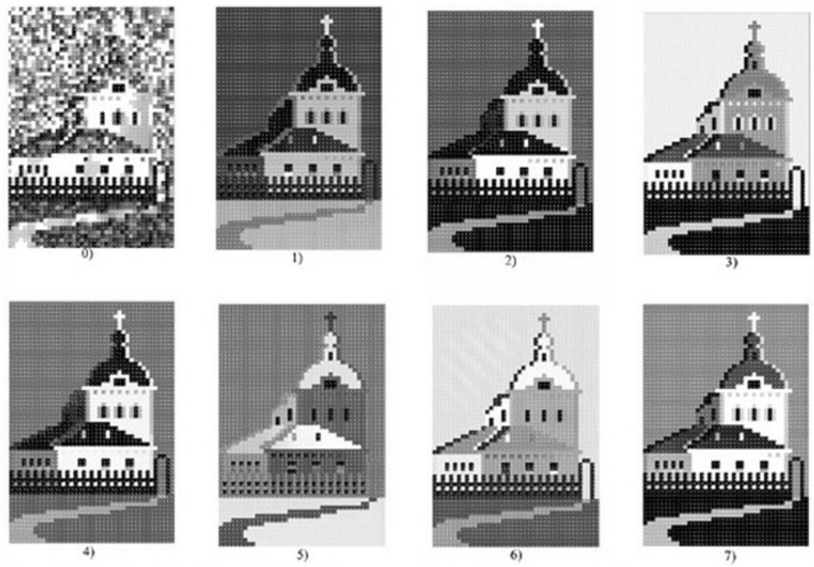

Fig. 1. Versions of segmented image, processed via the first method of sequential segmentation.

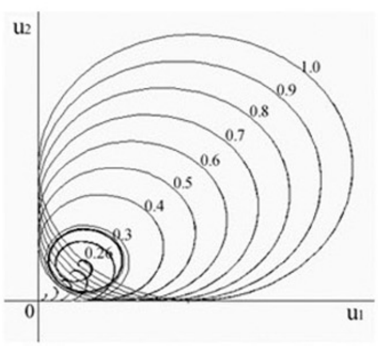

Fig. 2. Dependence of limit cycle size on pixel brightness I
for new version of single oscillator dynamics.

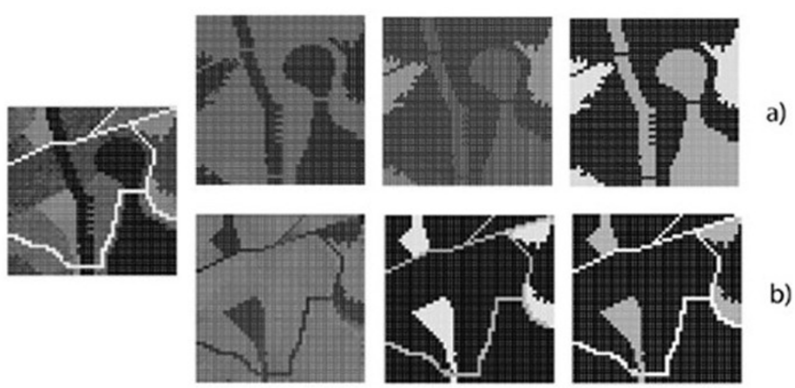

Fig. 3. Selective segmentation carried out via new version of oscillatory network model:
a) two less bright fragments of segmented image (left) are extracted;
b) two most bright image fragments are extracted.