Adaptive Image Processing via Synchronization in Self-Organizing Oscillatory Network

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Abstract. We develop a biologically inspired method of image processing based on synchronization-based performance of oscillatory network with controllable self-organized coupling. The oscillatory network, obtained from previously designed biologically motivated oscillatory neural network model of the brain visual cortex, provides automatic, adaptive and active image segmentation. Being tuned by an image to be processed, the network dynamics realizes network decomposition into the set of synchronized ensembles of oscillators, corresponding to image decomposition into the required set of image fragments. Current network model version provides: a) full segmentation of real grey-level and colored mages; b) selective image segmentation (extraction of subset of image fragments with brightness values contained inside arbitrary given brightness interval).

Key-Words: Image processing, biologically inspired methods, networks of coupled oscillators, synchronization.

1 Introduction

Currently there is a significant interest in neuromorphic methods of image processing, based on imitation of neurobiological processes in the brain neuronal structures, despite a great variety of traditional methods developed in the field of computer vision. Such advantages as self-organized automatic performance, capability of adaptive and active processing are usually inherent to biologically inspired methods. Specifically, interest in oscillatory methods of image processing was related to synchronized oscillations of neural activity that were experimentally discovered in the brain visual cortex (VC) in 1988-1989 and were confirmed in later experiments [1-3]. The synchronized oscillations are believed to accompany visual information processing in the brain visual structures. The attention to oscillatory aspects of visual information processing resulted in creation of series of oscillatory network models for image processing, demonstrating synchronization capabilities [4-18]. Oscillatory network models developed by D.Wang and Z.Li [4-12] are most closely related to our model, but nevertheless different. Relation of our model to those by D.Wang and Z.Li was discussed in detail in [16]. Our oscillatory network, providing dynamical method of image processing, was obtained by reduction from previously designed oscillatory network model of the primary visual cortex. The starting model simulated self-organized collective behavior of orientation selective cells of the primary visual cortex at low (pre-attentive) level of visual information processing. Active network unit is neural oscillator, formed by a pair of interconnected cortical neurons. It is a relaxational (limit cycle) oscillator with dynamics, controlled by image characteristics. Spatial architecture of the 3D starting model imitated the columnar structure of VC. Network coupling principle was designed based on known neurobiological data on connections in VC and also on general principles of connection formation in the brain neural structures. The coupling principle of working 2D oscillatory network model causes self-organized emergence of synchronization in the network and realizes the simplest type of dynamical binding (on brightness). Current model version provides a workable dynamical method of image segmentation. It capable to process both grey-level and colored real multi-pixel images. Besides, it admits a natural way for selective image segmentation, that can be regarded as a simple kind of active image processing.

2 Main Characteristics of the Oscillatory Network

The 2D oscillatory network is designed for brightness image segmentation tasks. We mean image segmentation as image decomposition into a set of image fragments – sub-regions of image pixel massive with constant level of brightness. Oscillators of the network are located at the nodes of two-dimensional square lattice being in one-to-one correspondence with pixel array of segmented image. 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 $[I_{jm}]$ of pixel brightness values, 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

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

Here functions $f(u_{jm}; I_{jm})$ define internal dynamics of isolated network oscillators whereas the second term defines contribution into dynamics via oscillator coupling. Single network oscillator is limit cycle oscillator defined by a pair of real-valued variables

(u_1, u_2). Dynamical system, governing single oscillator dynamics, can be written in the form of ODE for complex-valued variable $u = u_1 + iu_2$:

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

where

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

$$\rho = \rho(I); \quad T(\rho) = 0.5[|th(\sigma(\rho - h_*))| - th(\sigma(\rho - h_*))]. \tag{4}$$

The limit cycle of dynamical system (2)-(4) is the circle of radius ρ, circle center being located at the point with coordinates $u_{10} = u_{20} = \rho$ in phase plane (u_1, u_2). Dynamical system (2)-(4) contains the following parameters: the parameter ρ, defining limit cycle radius (free parameter which can be specified by arbitrary monotone continuous function of brightness, $\rho = \rho(I)$); ω is the frequency of free oscillations, h_* is the parameter, defining brightness threshold value, below which Hopf bifurcation of converting the limit cycle into stable focus occurs, α is the parameter, defining quickness of oscillation damping after limit cycle converting into focus, σ is a constant ($\sigma \gg 1$). Oscillator "response" to pixel brightness variation at $\rho(I) = \alpha I$ is depicted in Fig. 1, where time behaviors $u_1(t)$ and $u_2(t)$ and the corresponding phase trajectory of oscillator dynamical system are shown.

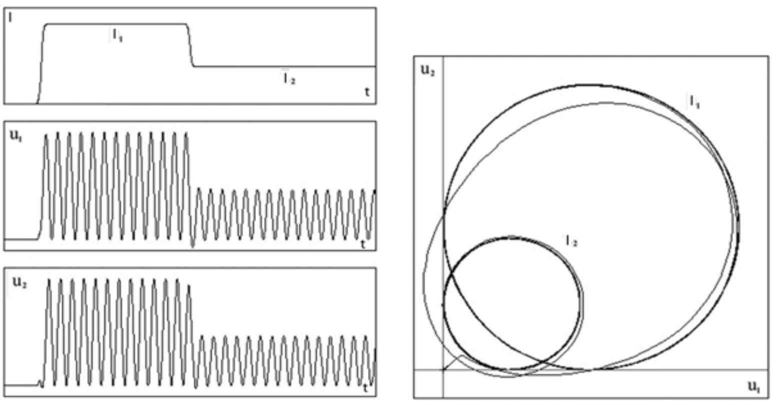


Fig. 1. Oscillator dynamics response to pixel brightness variation

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

$$W_{jj'mm'} = P_{jj'mm'}(\rho,\rho')\cdot D_{jj'mm'}(|r-r'|). \tag{5}$$

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

$$P_{jj'mm'}(\rho,\rho') = w_0 \cdot H(\rho_{jm}\rho_{j'm'} - h), \tag{6}$$

where $H(x)$ is a continuous step-function and w_0 is a constant, defining total strength of network interaction. The cofactors $D_{jj'mm'}(|r-r'|)$, providing coupling spatial restriction, can be specified by any function, vanishing at some 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 Grey-level image segmentation

The oscillatory network performance consists of two steps: 1) preliminary tuning of oscillator dynamics by pixel brightness values of an image to be segmented (after the tuning operation own limit cycle size has been specified for each network oscillator); 2) network relaxation into the state of cluster synchronization, that is, to the state, at which oscillatory network is decomposed into the set of internally synchronized, but mutually desynchronized oscillator ensembles (clusters), each ensemble being correspondent to appropriate image fragment.

The gradual type of oscillator response on pixel brightness, guaranteed by oscillator dynamics (2-4), plays a crucial role for providing high segmentation accuracy. An improved coupling rule has been also used besides the initial biologically motivated coupling rule (5) to raise segmentation accuracy. It is based on prescribing to each oscillator of some “mask”, restricting its coupling “response”. The modified coupling rule is defined by modified cofactor $\tilde{P}$ in (5), namely

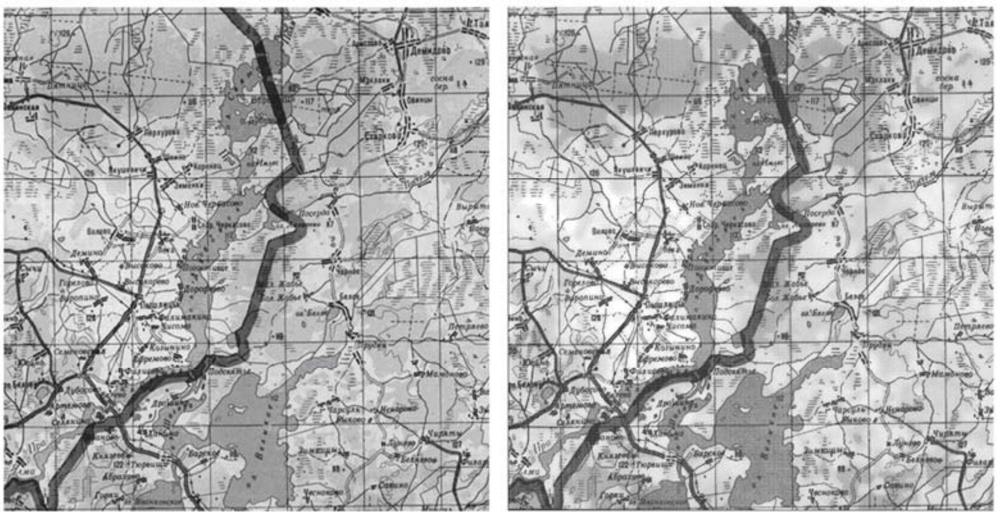
$$\tilde{P}_{jj'mm'}(\rho,\Delta;\rho',\Delta')=T(\rho,\Delta)T(\rho',\Delta')P_{jj'mm'}(\rho;\rho'), \tag{7}$$

where

$$T(\rho,\Delta)=0.5[th(\sigma(\rho+\Delta))-th(\sigma(\rho-\Delta))]. \tag{8}$$

Here $T(\rho,\Delta)$ defines a “mask”, restricting the size Δ of oscillator interaction vicinity. Accordingly to coupling rule (5) with $P=\tilde{P}$ any pair of network oscillators is coupled only in the case, if mask supports $[-\Delta,\Delta]$ and $[-\Delta',\Delta']$ of both the oscillators are intersected.

A flexible code ONN was created for computer experiments. An adaptive 5th-order Cash-Karp Runge-Kutta scheme has been incorporated for the ODE system integration. A series of computer experiments on real image segmentation have been performed. The example of map fragment segmentation at $\rho(I)=\alpha I$ and coupling rule (5) is presented in Fig. 2, where a) is original image and b) is segmentation result.



a) b)

Fig. 2. Map fragment segmentation (492×475 pixels).

3.2 Colored image segmentation

New ONN code version has been created for colored mage segmentation. At the first step the pixel array of an original colored image is decomposed into three sub-arrays, corresponding to red, blue and green components of pixel colors. Further these three sub-arrays are processed by the usual ONN code independently. Visualization of segmentation result is performed via conjunction of all three sub-arrays into single array. The example of colored image segmentation is presented in Fig. 3. (where a) is the original image, b) is the final segmentation result).

a) b)

Fig. 4. Colored image segmentation (524×374 pixels).

4 Selective Image Segmentation

The most useful operation that can be easily carried out via the oscillatory network model is selective image segmentation. Selective segmentation can be viewed as simplest type of active image processing and consists in extraction of desirable subset of image fragments which brightness values contained inside some given interval. As it is intuitively clear, the selective segmentation can be often more informative compared to usual complete segmentation of the same image. Oscillator dynamics (2)-(4) provides very natural way of selective segmentation realization. It is sufficient to introduce new function

$\tilde{\rho}(I)$ instead of $\rho(I)$ in eq. (3), putting $\tilde{\rho} = \rho(I)F(I)$, where *F(I)* is a "filtering" 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. For example, one can use

$$F^{(1)}(I) = 0.5 \cdot \{th[\gamma(I - I^*)] - th[\gamma(I - I^{**})]\}, \quad \gamma \gg 1. \tag{9}$$

In the case only the oscillators, corresponding to image fragments with brightness values $I \in [I^*, I^{**}]$, will be "active" whereas the rest oscillators will drop out of network interaction because of zero oscillation amplitudes. Similarly selection of arbitrary collection of image fragments of given brightness levels is possible. Fig. 4 demonstrates informative character of selective segmentation. Here one can compare complete

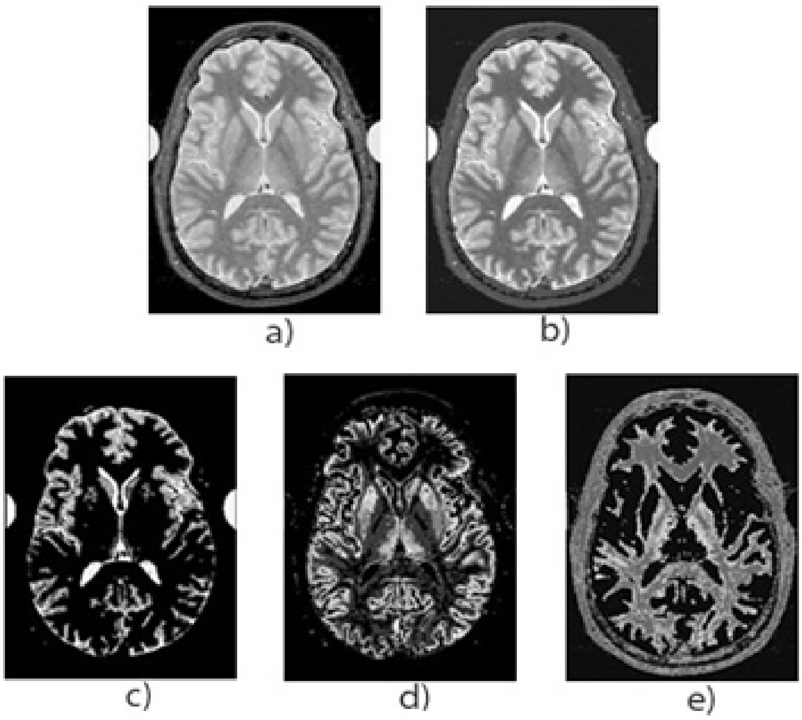


Fig. 5. Selective image segmentation.
a) – original image; b) – complete image segmentation; c) – extraction of several the most bright image fragments; d) – extraction of a set of fragments of middle brightness; e) – extraction of several the least bright fragments.

segmentation (picture b)) of the image (human brain section) with three different cases of selective segmentation (pictures c), d) and e). In each case of selective segmentation only several image fragments with brightness values inside a narrow interval have been selected.

Conclusion

Synchronization-based approach of image processing via tunable oscillatory network with self-organized coupling is presented. The following advantages are inherent to the approach:

a) parallel and automatic character of processing;

b) adaptive type of processing (as far as both background level and noise reduction can be easily controlled);

c) active image processing (due to capability of selective segmentation).

The designed oscillatory network is actually closely related to multi-agent systems – distributed networks of active processing units with complicated controllable internal dynamics and reorganizable structure of cooperative connections.

References:

1. Kreiter AK, Singer W (1996) On the role of neural synchrony in primate visual cortex. In: Aertsen A, Braitenberg V (eds) Brain Theory, pp 201-226.
2. Gray CM (1999) The temporal correlation hypothesis is still alive and well. Neuron, 24: 31-47.
3. Singer W (1999) Neuronal synchrony: a versatile code for definition of relations? Neuron 24: 49-65.
4. Wang DL, Terman D (1995) Emergent synchrony in locally coupled neural oscillators. IEEE Trans. NN 6: 283-286.
5. Wang DL, Terman D (1997) Image segmentation based on oscillatory correlations Neur. Comp. 9: 805-836.
6. Chen K, Wang D, Liu X (2000) Weight adaptation and oscillatory correlation for image segmentation. IEEE Trans. on NN 11:1106 -1126.
7. Cesmeli E, Wang DL (2001) Texture segmentation using Gaussian-Markov random fields and neural oscillator networks. IEEE Trans. NN 12: 394-409.
8. Wang D (2005) The time dimension for scene analysis. IEEE Trans on NN.
9. Li Z (1998) A neural model of contour integration in the primary visual cortex. Neur.Comp. 10: 903-940.
10. Li Z (1999) Visual segmentation by contextual influences via intra-cortical interactions in the primary visual cortex. Network 10: 187-212.

11. Li Z (2000) Pre-attentive segmentation in the primary visual cortex. Spatial Vision 13: 25-50.
12. Li Z (2001) Computational design and nonlinear dynamics of a recurrent network model of the primary visual cortex. Neural Comp. 13/8: 1749-1780.
13. Kazanovich Y, Borisuyk R (2002) Object selection by an oscllatory neural network. Biosystems. 67: 103-111.
14. Kuzmina MG, Manykin EA, Surina II (2000) Spatially distributed ocillatory networks related to modeling of the brain visual cortex. Proc. of NOLTA'2000, Dresden, Germany, 1, pp 335-338.
15. Kuzmina MG, Manykin EA, Surina II (2001) Tunable oscillatory network for visual image segmentation. Proc. of ICANN'2001, Vienna, Austria. Lecture Notes in Comp. Sci. 2130 pp 1013-1019.
16. Kuzmina MG, Manykin EA, Surina II (2004) Oscillatory network with self-organized dynamical connections for synchronization-based visual image segmentation. BioSystems 76: 43-53.
17. Kuzmina MG, Manykin EA, Surina II (2004) Biologically motivated oscillatory network model for dynamical image segmentation. Biologically Inspired Cognitive Systems (BICS'04), Stirling, Scotland , Aug. 29 - Sept. 1.
18. Grichuk ES, Kuzmina MG, Manykin EA (2006) Oscillatory network for synchronization-based adaptive image segmentation. IEEE World Congress on Computational Intelligence (WCCI 2006), July 16-21 2006, Vancouver, BC, Canada; WCCI 2006 CD, IEEE Catalog Number: 06CH37726D, ISSN: 0-7803-9489-5.