Oscillatory network for synchronization-based adaptive image segmentation

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Abstract— **Oscillatory network model with controllable oscillator dynamics and self-organized dynamical coupling has been created for synchronization-based image processing. The model was previously obtained via reduction from a biologically motivated oscillatory model of the primary visual cortex. The reduced network model performance consists in network relaxation into the state of synchronization. The set of internally synchronized but mutually desynchronized network ensembles (clusters), arising at final synchronization state, corresponds to full set of image fragments. New model developments, presented in the paper, include: a) the advanced version of single oscillator dynamics, admitting introduction of arbitrary continuous dependence of oscillator limit cycle size on pixel brightness; b) new principle of network coupling, permitting to increase image segmentation accuracy and to control network noise reduction. In addition new capability of selective image segmentation (extraction of image fragment subset of a priori prescribed brightness levels) is inherent to current model version .**

I. INTRODUCTION

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 range 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 [1]-[11], [15]-[20]. Two of them are most closely related to our model. The first one, developed by D. Wang with coauthors [1]-[5], delivers effective oscillatory method of brightness and texture image segmentation, that is capable to process real multi-pixel images and demonstrates some advantages compared to modern computational methods of image segmentation. The second biologically motivated oscillatory neural network model was developed by Z .Li [6]-[9] 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 [18]. 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 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 limit cycle oscillator with dynamics, controlled by image characteristics. The first version of single oscillator dynamics (see [15]-[19]) was constructed in relation to biologically motivated neural oscillator model, designed in [6]. Network oscillators of the source model were located at the nodes of 3D spatial lattice. Spatial network architecture imitated the columnar structure of primary visual cortex, one oscillator column being corresponded to each image pixel. Network connectivity rule specified self-organized nonlocal dynamical coupling of oscillators in the 3D network. The known neurobiological data on connections in VC (in particular, connection dependence on orientations of cortical receptive fields) were reflected in the connectivity rule construction. The hypothesis on existence of synchronization-based dynamical binding in the brain visual cortex during visual information processing [12]-[14] was also taken into account. As it turned out, the simplified 2D oscillatory network model, extracted as limiting case of the initial 3D source model, provides a workable dynamical image segmentation method [15]-[18]. The presented paper contains new steps of further model development. Computer results, confirming the improvement of performance of new model version, are presented. Noticeable increasing of segmentation quality has been achieved mainly due to new version of single oscillator dynamics.

To conclude the introduction it is worth to stress general advantages inherent to dynamical network methods of image processing. These are: parallel distributed way of information processing, "automatic" performance,

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noise reduction. In particular, an easy way of introduction of a simple type of filtration can be also regarded as additional advantage of the developed image segmentation method .

II. CURRENT MODEL VERSION

Oscillators of the network are 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 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 term defines contribution into dynamics via oscillator coupling. Single network oscillator is limit cycle oscillator, being defined by a pair of real-valued variable (u_1, u_2). Oscillator dynamical system can be written in the form of single ODE for complex-valued variable $u = u_1 + iu_2$:

$$du / dt = f(u, I), \qquad (1)$$

where

$$f(u, I) = (\rho^2 + i\omega) - |u - \rho(1+i)|^2)(u - \rho(1+i)$$
$$- \alpha \cdot T(\rho)[u - \rho(1+i)]; \qquad \rho = \rho(I); \; (2)$$

$$T(\rho) = 0.5[| th(\sigma(\rho - h_*)) | - th(\sigma(\rho - h_*))]. \qquad (3)$$

The limit cycle for dynamical system (1)-(3) 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). The following parameters are contained in (2),(3): 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 ($\sigma \gg 1$). A family of limit cycles and focuses at some collection of brightness values is shown in Fig. 1.

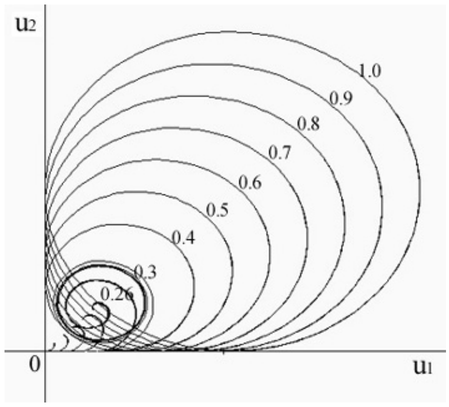

Fig. 1. The collection of limit cycles and focuses at different values of brightness *I*.

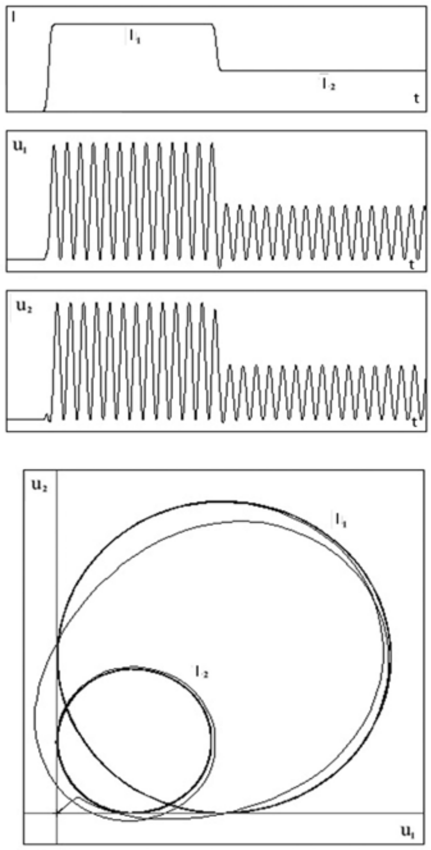

Fig. 2. Oscillator dynamics “response” to pixel brightness variation.

Oscillator "response" to pixel brightness variation at $\rho(I) = \alpha I$ is depicted in Fig. 2, where the curves of time dependence $u_1(t)$ and $u_2(t)$ and the corresponding phase trajectory are presented.

In the first model version the values $W_{jm\,j'm'}$, defining coupling strength of network oscillators *(j,m)* and *(j'm'),* were designed in the form nonlinear functions dependent on oscillation amplitudes (limit cycle radii) of oscillator pair and spatial distance between oscillators in the network. Namely, $W_{jm\,j'm'}$ are defined in the form:

$$W_{jm\,j'm'} = P_{jm\,j'm'}(\rho,\rho')\cdot D_{jm\,j'm'}(|\,r-r'\,|). \tag{4}$$

The cofactors $P_{jm\,j'm'}$, providing the dependence of network connectivity on oscillation amplitudes, were specified as

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

where $H(x)$ is a continuous step-function ,

$$H(x) = 1/(1+e^{-2\nu x}), \quad \nu \gg 1, \tag{6}$$

and w_0 is a constant, defining total strength of network interaction. The cofactors $D_{jm\,j'm'}(|\,r-r'\,|)$, providing dependence of network coupling on oscillator spatial locations, can be specified by any function of $|\,r_{jm}-r_{j'm'}\,|$, vanishing at some finite distance. For instance, it is convenient to choose D in the form $D_{jm\,j'm'} = 1 - H(|\,r_{jm}-r_{j'm'}\,| - r_*)$, where r_* is a chosen radius of spatial interaction. 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.

III. MODEL SEGMENTATION CAPABILITIES

A. Sequential brightness 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 to each network oscillator); 2) network relaxation into the state of cluster synchronization, corresponding to image decomposition into the whole set of its fragments.

In the first version of our model (see [17], [18]), a modified version of single oscillator dynamics was used instead of (2)-(3). It was characterized by the fixed monotone function $\rho(I)$ of ρ dependence on pixel brightness *I,* that was not sufficiently sensitive to provide high segmentation accuracy at network coupling accordingly to connectivity rule (4). To increase segmentation accuracy special method of network interaction adjustment has been introduced. It permitted to realize the procedure of sequential image segmentation via gradual increasing of total network interaction, combined with "switching off" of synchronized clusters from common network interaction. The sequential segmentation consists of *L* steps*,* (*L* being the number of image fragments), and requires *L* procedures of network relaxation into different synchronization states. During the procedure exactly one synchronized cluster arises at *l*-th step of segmentation. 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 fragments are clearly distinguishable. Surely, the sequential segmentation delivers additional tools for segmentation result analysis.

B. Texture image segmentation

In the framework of our model texture images with simplest texture types, represented with collections of oriented bars, can be processed. Texture image segmentation is realized via introduction of the additional cofactor in the connectivity rule (4):

$$\tilde{W}_{jmj'm'} = P_{jmj'm'}(\rho,\rho')\cdot Q_{jmj'm'}(\beta,\beta')\cdot D_{jmj'm'}(|\,r-r'\,|), \tag{4*}$$

where angle β defines orientation of elementary bar, prescribed to each pixel. As it turned out, the oscillatory network with connectivity rule (4^*) is capable to provide texture image segmentation even in the case when all the texture segments are of the same brightness level. In particular, the network is capable to provide solving of some contour integration tasks (see [18]).

C. Segmentation of real brightness images

Two model developments are proved to be crucial for significant improvement of segmentation capabilities. These are: 1) enlargement of admissible image pixel array size and 2) design of new version (2)-(3) of single oscillator dynamics. New code ONN was created for computer experiments. An adaptive 5th-order Cash-Karp Runge-Kutta scheme has been incorporated for the ODE system integration. The maximum size of processed image is now limited only by the computation time. For example, it takes about 10 minutes for processing of an image with pixel array size about 250000 pixels on an Intel Pentium 4 3GHz processor. Optimization of the program code and utilization of faster ODE integration algorithm are expected to provide acceleration of processing procedure.

A series of computer experiments on real image segmentation have demonstrated a key role of new dynamics, that is characterized by analogy type of oscillator response to pixel brightness. An example of segmentation of real gray-level photograph is shown in Fig. 3. Here the segmented image is depicted in the picture 3a. Segmentation results obtained via network model with previous version of oscillator dynamics (picture 3b) and with new version (picture 3c) are presented. A noticeable improvement of segmentation quality is just the consequence of monotonic continuous dependence of oscillator limit cycle size on pixel brightness. A number of various natural types of monotonic functions $\rho(I)$ is now included into current segmentation code ONN.

The example of map fragment segmentation (of 492×475 pixels) is presented in Fig. 4. The segmentation has been carried out at $\rho(I)=\alpha I$ and network connectivity rule (4)-(6).

D. Selective image segmentation

Current network model version with oscillator dynamics (2)-(3) provides also selective image segmentation. Namely, one should introduce new function $\tilde{\rho}(I)$ instead of $\rho(I)$ in (2), putting

$$\tilde{\rho} = \rho(I)F(I) \qquad (7)$$

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 the interval $[I^*, I^{**}]$ and vanishing outside the interval. For example, one can use

$$F^{(1)}(I) = 0.5\cdot\{th[\gamma(I-I^*)] - th[\gamma(I-I^{**})]\},\quad \gamma \gg 1. \qquad (8)$$

Indeed, in the case only the oscillators, corresponding to image fragments with brightness values $I \in [I^*, I^*]$, will be "active". The rest oscillators will drop out of network interaction because of zero oscillation amplitudes.

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

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

Obviously, the introduction of function $F^{(2)}$ corresponds to selective brightness filtering. An example of selective image segmentation (where two most bright image fragments and two least bright ones were selected) was given in [20].

a

b

c

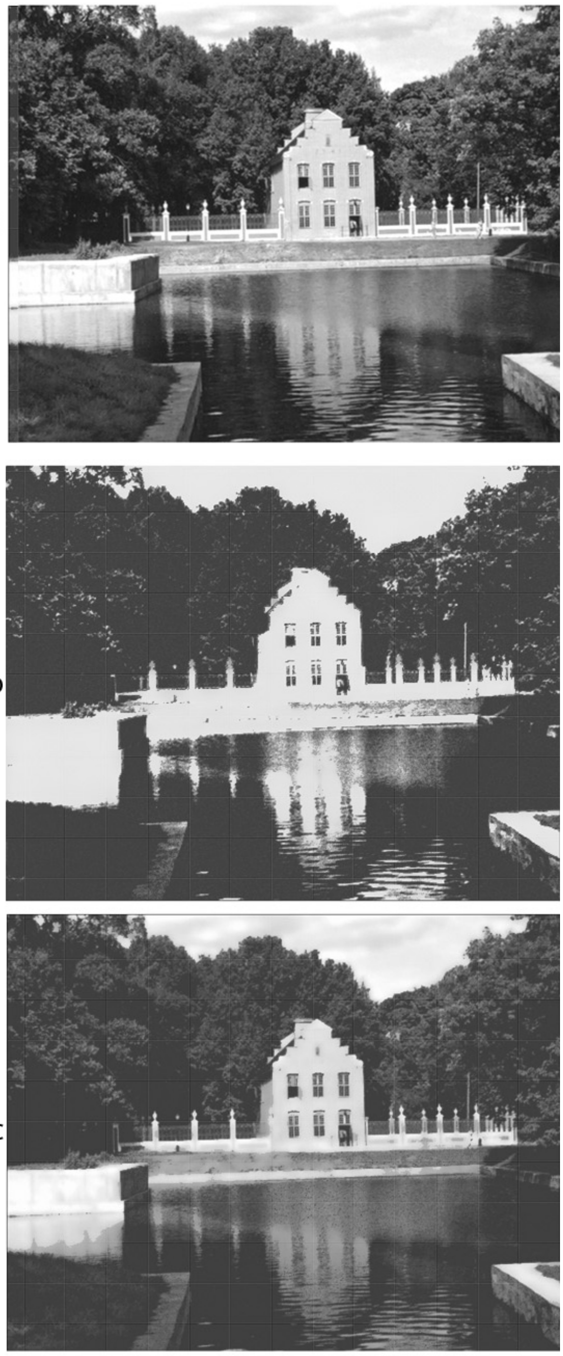

Fig. 3. Segmentation of gray-level photograph (657×432 pixels).

IV. NEW VERSION OF CONNECTIVITY RULE

In a number of situations the biologically motivated network connectivity rule (4) does not provide sufficient segmentation accuracy. It was just the reason for introduction a method of sequential brightness image segmentation. Although the method applied in [16]-[20] guaranteed an acceptable segmentation accuracy, it was computationally expensive. So, new connectivity rule versions are needed to be developed. One of the versions, that is expected both to guarantee high segmentation accuracy (without utilizing the procedure of sequential segmentation) and to provide flexible control of noise reduction, is currently under testing. The rule, based on prescribing to each oscillator of some "mask", restricting its coupling "response", can be defined by adding a proper cofactor to $P_{jm\,j'm'}$ in rule (4), namely, one should define

$$\tilde{P}_{jmj'm'}(\rho,\Delta;\ \rho',\Delta') = T(\rho,\Delta)T(\rho',\Delta')P_{jmj'm'}(\rho,\Delta;\ \rho',\Delta'), \quad (9)$$

where

$$T(\rho,\Delta) = 0.5\cdot[th(\sigma(\rho-\Delta)) - th(\sigma(\rho+\Delta))]. \quad (10)$$

Here $T(\rho,\Delta)$ defines a "mask" for the oscillator with limit cycle radius ρ, the parameter Δ specifies the size of interaction vicinity for the oscillator and constant σ defines the form of "mask" $T(\rho,\Delta)$: at $\sigma \gg 1$ the mask is of approximately rectangular form.

Accordingly to new connectivity rule (4) with $P=\tilde{P}$ any pair of network oscillators is turned out to be coupled, if mask supports $[-\Delta,\Delta]$ and $[-\Delta',\Delta']$ of both the oscillators are intersected. Otherwise the oscillator pair does not interact. The advanced feature of new connectivity rule is that highly "active" oscillators (with large ρ values) do not now influence on spatially neighboring weakly active ones. So, such type of coupling permits to prevent a "parasitic" smoothing of image fragment boundaries in the situations with contrasting neighboring image fragments.

As computer experiments show, the new connectivity rule provides good segmentation accuracy for images of "sharp contrast" (with a dense net of thin contours and sufficiently low noise level, like maps). On the contrary, for soft contrasting images (for instance, portraits) the old connectivity rule (4)-(6) leads to good segmentation quality.

V. SUMMARY

Oscillatory network model for dynamical synchronization-based image segmentation is presented. The following features are inherent to current improved model version:

a) advanced version of single oscillator dynamics, that permits to specify the dependence of limit cycle radius ρ on pixel brightness I by an arbitrarily chosen monotone continuous function $\rho(I)$;

b) new version of network connectivity rule, providing "selectivity'' of oscillator coupling (that is, coupling only the oscillator pairs with intersecting mask supports $[-\Delta,\Delta]$ and $[-\Delta',\Delta']$, where Δ and Δ' are predefined small values, are coupled).

The new model version demonstrates improved segmentation capabilities, providing good segmentation accuracy for real images of different types. The additional capability of selective image segmentation could be considered as a contribution into tools of active visual scene analysis.

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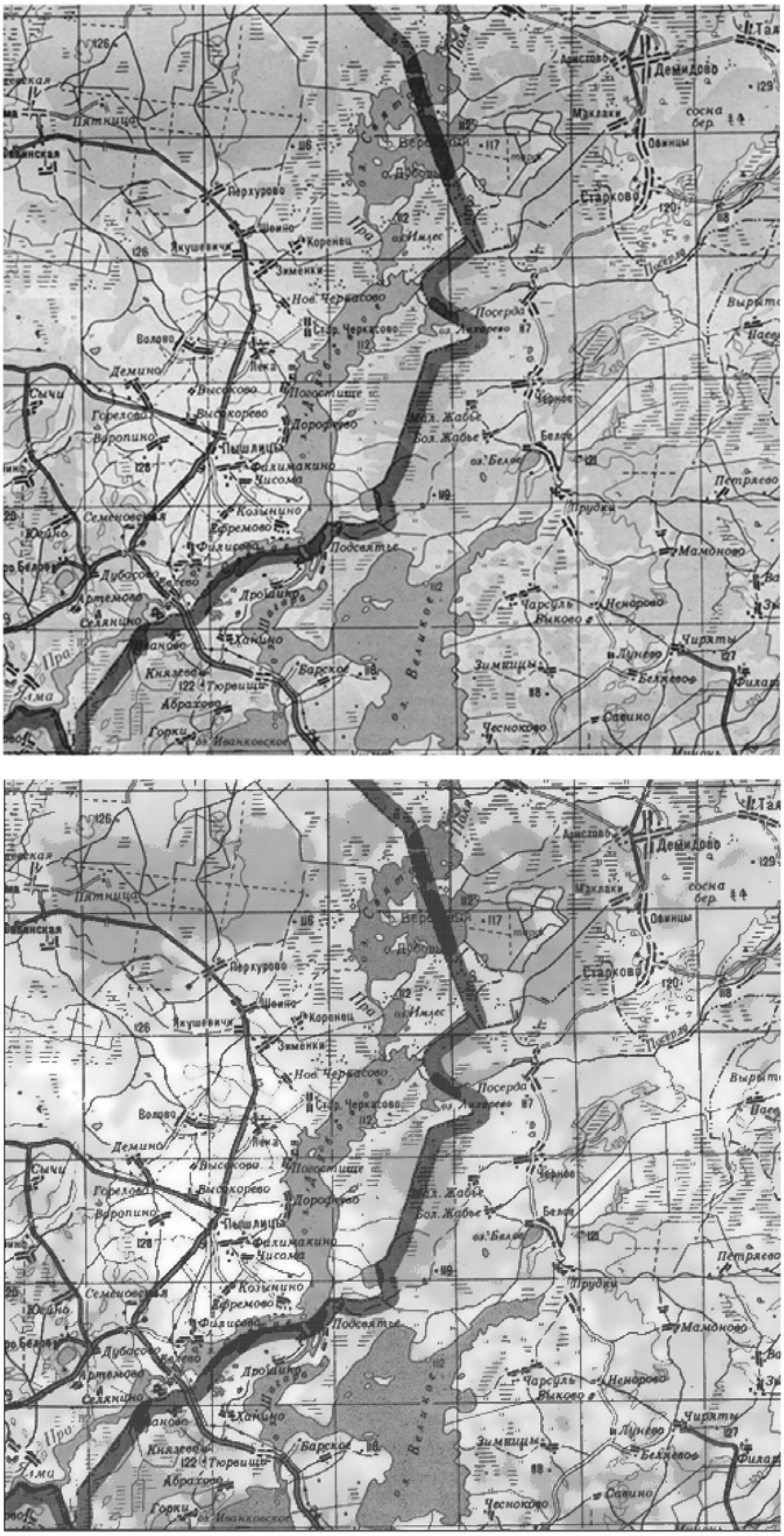

Fig. 4. The example of map fragment segmentation (492×475 pixels).