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IMAGE SEGMENTATION BASED ON NETWORK OF SYNCHRONISED OSCILLATORS

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Abstract. The temporal correlation based method for image segmentation is presented. It uses locally connected network of oscillators, which are able to synchronise while image object is detected, and desynchronise for other objects. The mathematical oscillator model is described along with an algorithm for image segmentation. Examples of numerical simulation of oscillator network and segmentation results of sample images are also presented.

Keywords: image segmentation, network of oscillators

1. INTRODUCTION

Image segmentation is a process which refers to partitioning an image into a set of coherent regions. This covers also object identification and separation of different objects. Although humans can perform this process effortlessly, the image segmentation remains one of the main hurdles in many image analysis tasks and image understanding algorithms for machine vision.

This paper briefly describes one of the recently emerged segmentation methods, based on temporal correlation. This method was developed by analysing behaviour of human brain. It was stated, that an object is represented by the temporal correlation of the firing activities of the neural cells coding different features of the object. The temporal correlation can be encoded using neural oscillators, where each oscillator encodes a single feature of an object. In the simplest case this feature can be represented by a value of object pixel intensity. In this case given object is represented by group of oscillators, which are oscillating in synchrony, while other objects are represented by different oscillator groups, which are desynchronised. Such oscillator groups form a network called LEGION (locally excitatory globally inhibitory oscillators network), proposed in [3,4].

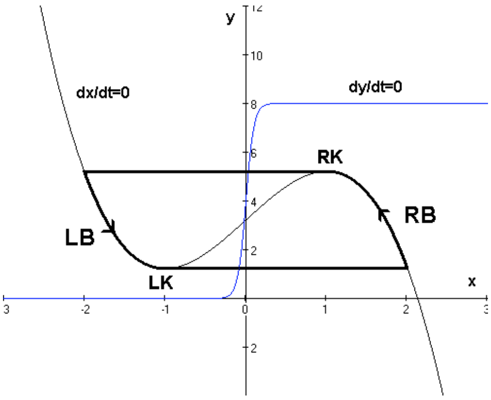


Fig.1. Nullclines of eq. (1)

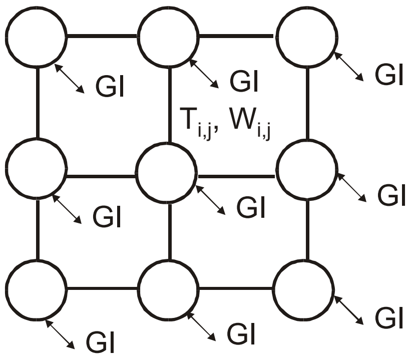


Fig. 2. 3×3 LEGION network

2. MODEL DESCRIPTION

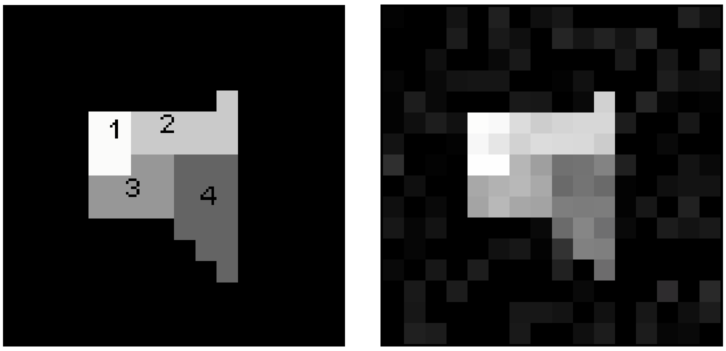
Each oscillator in LEGION network is defined by a set of two differential equations:

$$\frac{dx}{dt} = 3x - x^3 + 2 - y + I_T \qquad \frac{dy}{dt} = \varepsilon[\gamma(1 + \tanh(\frac{x}{\beta})) - y] \tag{1}$$

where x is referred to as an excitatory variable while y is an inhibitory variable. I_T is a total stimulation of an oscillator and ε, γ, β are parameters. The x-nullcline is cubic curve while the y-nullcline is a sigmoid function as shown in Fig.1. If $I_T > 0$, then equation (1) possesses periodic solution, represented by bold line shown in Fig. 1. The operating point moves along this line, from left branch (LB, representing so-called silent phase), then jumping from left knee (LK) to right branch (RB, representing so-called active phase), next reaching right knee (RK) and jumping again to left branch. If $I_T \leq 0$, the oscillator is inactive (produces no oscillations). Oscillators defined by (1) are connected in two-dimensional network, in the simplest case each oscillator is connected only to its four nearest neighbours (Fig. 2) (larger neighbourhood sizes are also possible). Network dimensions are equal to dimensions of analysed image and each oscillator represents single image pixel. Each oscillator in the network is connected with so-called global inhibitor (GI in Fig. 2), which receives information from oscillators and in turn eventually can inhibit whole network. Generally, the total oscillator stimulation I_T is given by equation (2):

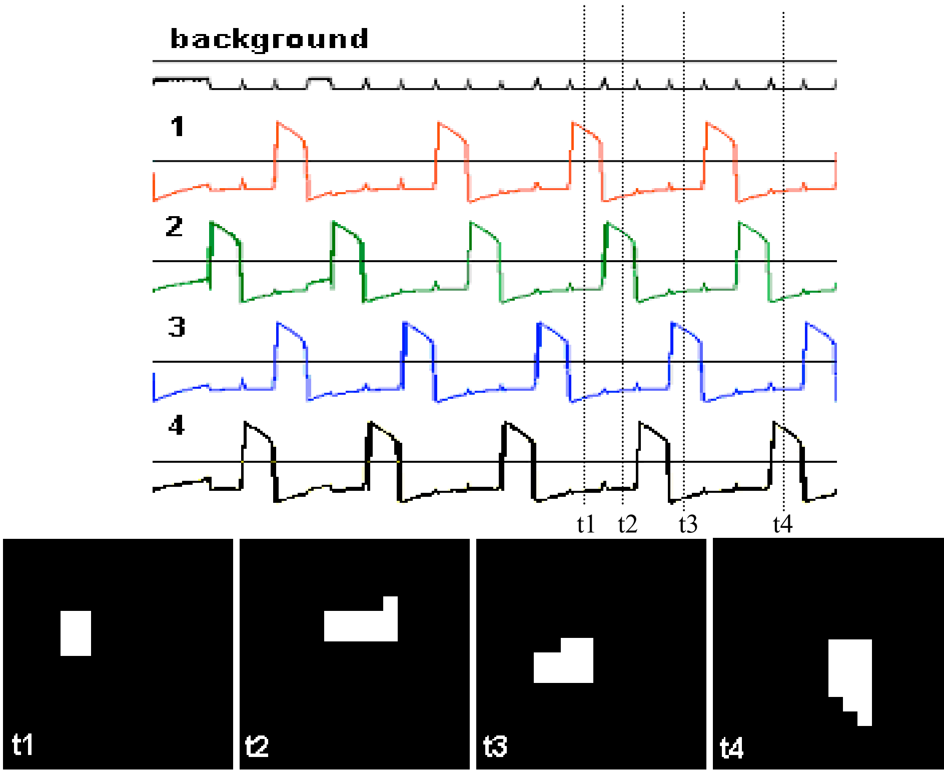
$$I_T = I_{in} H(p - \theta) + \sum_{k \in N(i)} W_{ik} H(x_k - \theta_x) - W_z z \tag{2}$$

where I_{in} represents external stimulation to the oscillator (image pixel value). W_{ik} are synaptic dynamic weights connecting oscillator k and i. Number of these weights depends on neighbourhood size $N(i)$. In the case considered here, $N(i)$ contains eight nearest neighbours of kth oscillator (except for these located on network boundaries). Due to these local excitatory connections an active oscillator spreads its activity over the whole oscillator group, which represent image object. This provides synchronisation of the whole



a) b)

Fig. 3. The sample image with marked 4 objects (a), the same image corrupted with Gaussian noise (b).



a)

b)

Fig. 4. The waveforms of oscillator groups for different objects (a), snapshots taken for times t1, t2, t3 and t4 marked in (a) representing oscillator activities (b).

group θ_x is a threshold, above which oscillator k can be affected by its neighbours. H is a Heaviside function, it is equal to one if its argument is higher then zero and zero otherwise.

W_z is a weight (with negative value) of inhibitor z, which is equal one if at least one network oscillator is in active phase (x>0) and it is equal to zero otherwise. The role of global inhibitor is to provide desynchronization of oscillator groups representing different objects from this one which is actually being under synchronisation. Global inhibitor will not affect any synchronised oscillator group because the sum in (2) has greater value then W_z.

The function p (so called *lateral potential*) is used to remove noise from image. For oscillator i, it is defined as

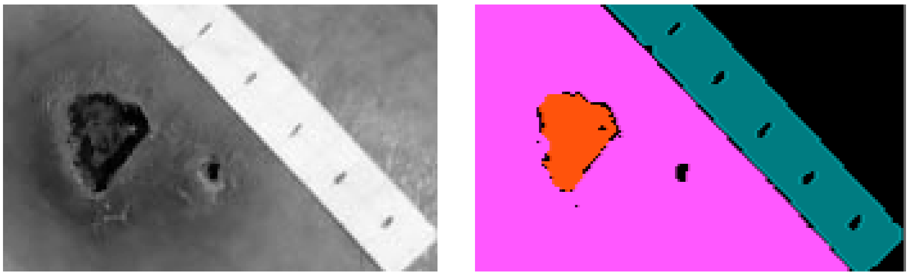
$$\frac{dp}{dt} = \lambda(1-p)H\left[\sum_{k\in N(i)} T_{ik} H(x_k - \theta_x) - \theta_p\right] - \mu\varepsilon p \qquad (3)$$

where λ, μ are parameters and T_{ik} – permanent connection weights from oscillator k to i. If the weighted sum of active neighbours of given oscillator exceeds a threshold θ_p then p approaches to 1 ($\lambda >> \mu\varepsilon$), otherwise it relaxes to 0. If p is greater than a threshold θ, then the oscillator receives stimulation. To obtain this, a large number of its neighbours must exceed θ_x at the some time. Thus only these oscillators which are surrounded by an adequately large number of active oscillators will be able to maintain p high. These oscillators are so called *leaders*. If in a small block no oscillator will become a leader, this block will stop oscillating after a beginning period because the Heaviside function in (2) will become zero and each oscillator in the block become unstimulated.

3. COMPUTER SIMULATION

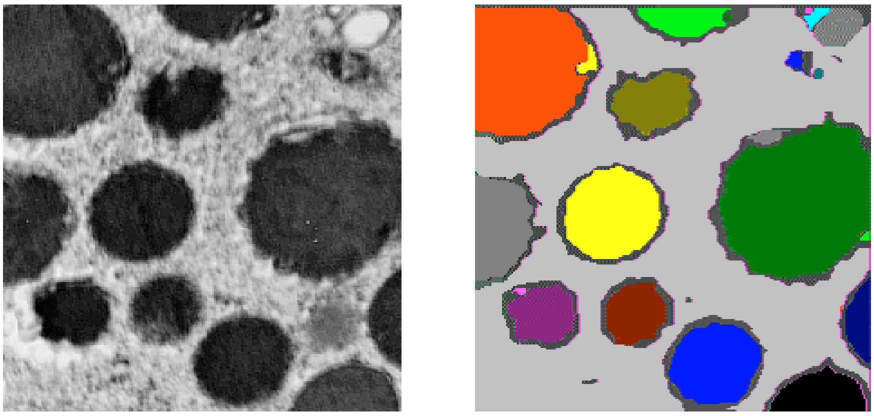
The LEGION network of size 16×16 was simulated using oscillator model described by (1). The sample image 8 bit grey level to be analysed is shown in Fig. 3a. It contains 5 objects corrupted by Gaussian noise, which zero mean value and standard deviation equal to 27 (Fig. 3b). Intensity value of each image pixel was used as an external input to appropriate oscillator in LEGION network. Instead of solving the set of nonlinear differential equations (1) and (3) for each network oscillator, so called singular solution method was applied [1]. It is based on analysis of oscillation behaviour during its periodic movement on trajectory shown in Fig. 1. This provides much faster computation, compared to traditional method based on solving differential equations [1]. The waveforms representing outputs of network oscillators are shown on Fig. 4a. These oscillator are grouped and each group represents different image object. After some time, oscillator groups are oscillating in synchrony, and all other oscillator groups are disabled. This provides a clear segmenting of each image object, as shown in Fig. 4b where each image represents network output for active phases of different oscillator groups. Another example of noisy binary image segmentation by LEGION network was presented in [2].

To further reduce the computation time, the modified version of singular solution algorithm is proposed. In this algorithm, after a group of oscillators is activated, detecting an object, all oscillators are forced to jump from RK to LB and in the next iteration another object is detected. This algorithm can be presented as follows:



a) b)

Fig. 5. Skin abscess image (a), image from (a) after segmentation (b)



a) b)

Fig. 6. Skin cell image (a), image from (a) after segmentation (b)

Step 1.

1.1 Set the weights W_{ij}:

$$W_{ij} = \frac{U_{\max}}{1 + \left|U_i - U_j\right|} \tag{4}$$

where U_i, U_j characterise oscillators i and j. These can be grey levels of image pixels i and j or other features chosen for image description. U_{max} denotes the maximum value among all U_i.

1.2 Find the leaders. As a leader, that oscillator i is considered, for which the following equation is satisfied:

$$\sum_{k \in N(i)} W_{ik} > \theta_p \tag{5}$$

1.3 Randomly start oscillators on Left Branch (LB, see Fig. 1).

Step 2. For each leader calculate the time t_i to Left Knee (LK, see Fig. 1).

Step 3. Find the oscillator m with the shortest time t_m to LK. Move each oscillator toward LK by the time interval t_m. Jump oscillator m to Right Branch.

Step 4. For each oscillator i (except m) do the following:
4.1 Update its nullcline by calculation of its I_T
4.2 If oscillator i is at or beyond its updated knee then i jumps to RB
Repeat Step 4 until no further jumping occurs.

Step 5. Mark all leaders, which jumped to RB. Force all oscillators on RB back to LB

Step 6. Go to Step 2, considering only these leaders, which are not marked.

Algorithm stops when all leaders jumped up. Because groups of leader oscillators represent different image objects, the algorithm ensures that all objects will be detected during segmentation.

4. SEGMENTATION OF SAMPLE REAL IMAGES

The algorithm described in the previous section was used to test sample biomedical images. The image shown in Fig. 5a represents skin abscess located on a forehand along with a length standard used for abscess measurements. This is a 168×104, 8 bit grey level image. The neighbour size *N(i)* was equal to 9. Fig. 5b shows this image after segmentation. In this case, as U_i the grey level value of pixel i was used. Thus the W_{ij} connections have large value for oscillators representing pixels with similar grey levels and small value otherwise. This will ensure that leader oscillators will spread its activity over the whole oscillator group, which represent an image object. Fig. 6a presents image of skin cells. Segmentation results are shown in Fig. 6b. This is a 221×226, 8 bit grey level image. In this case, the grey level characteristics were not enough to provide proper image segmentation. The weights W_{ij} were calculated based on medians computed for each pixel. The U_i was equal to median of pixel i calculated for 5×5 neighbourhood of this pixel. This caused appropriate segmentation of different skin cells and a background.

5. DISCUSSION

The presented method provides reliable segmentation results of sample biomedical images. The computation time, applying an algorithm described in section 3 is in range of few seconds, using Celeron 400 based PC. The future investigations will comprise extension of this method to textured images. Another advantage of this method is possibility of parallel implementation in hardware realisation.

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