

# SEGMENTATION OF TEXTURED IMAGES USING NETWORK OF SYNCHRONISED OSCILLATORS

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**Abstract:** The temporal correlation based method for image texture 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. Examples of numerical simulation of oscillator network for segmentation of natural textures along with feature selection method is also presented.

## 1. Introduction

Segmentation of image texture is very important but still very difficult task of image analysis and image understanding in machine vision. Visual texture is present in a wide spectrum of different images and plays significant role in image scene analysis.

This paper briefly describes one of the recently emerged segmentation methods, based on temporal correlation. This technique was first applied for texture segmentation in [1]. In this study, more general method for texture feature selection is proposed, along with different formulation of oscillator weights.

The temporal correlation 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 sensed. 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 object pixel intensity. Then a 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 [8,9].

## 2. Model description

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

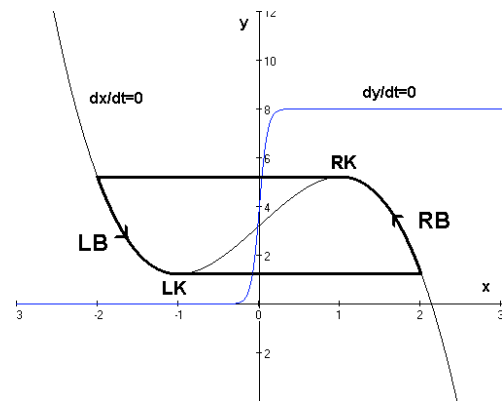


Fig.1. Nullclines of eq. (1)

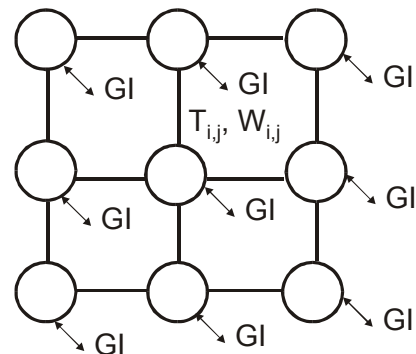


Fig. 2. 3x3 LEGION network

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

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  $\varepsilon, \gamma, \beta$  are parameters. The  $x$ -nullcline is a 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 together to form

a 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):

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

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  $k$ th 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 group  $\theta_x$  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 than 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 than  $W_z$ .

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

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

where  $\lambda$ ,  $\mu$  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  $\theta_p$  then  $p$  approaches to 1 ( $\lambda \gg \mu\epsilon$ ), otherwise it relaxes to 0. If  $p$  is greater than a threshold  $\theta$ , then the oscillator receives stimulation. To obtain this, a large number of its neighbours must exceed  $\theta_x$  at the same 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 becomes 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. Examples of image segmentation based on equations (1)-(3) are presented in [5,6].

### 3. Feature selection

One of the most important problems in segmentation of textured images is feature selection. There is no unique feature set capable to proper classification of large number of different textures. Feature selection should be performed separately for each texture segmentation task. In this study the following texture feature groups were taken into consideration [10]:

- 5 gradient-based features (absolute gradient mean, variance, skewness, kurtosis, and percentage of non-zero gradients),
- 20 run-length matrix-based features (short run emphasis inverse moment, long run emphasis moment, grey level nonuniformity, run length nonuniformity and fraction of image in runs, separately for horizontal, vertical, 45° and 135° directions),
- 220 co-occurrence matrix based features [11 features calculated for matrices constructed for five distances between image pixels ( $d=1, 2, 3, 4$  and 5), and for the four directions as in the case of RL features].
- 5 autoregressive model based features (parameters  $\theta_1, \theta_2, \theta_3, \theta_4$  and  $\sigma$ ),

resulting in 250 features. The next step was feature reduction. It was made based on Fisher coefficient ( $F$ ) value [4]. For each texture in the analysed image 20 non-overlapping squares with size 20×20 were defined. For each square, the whole feature set was calculated. Then, for every feature the  $F$  coefficient was computed and features with highest  $F$  were selected for further processing. These features were fed to the input of a three-layer feedforward artificial neural network (ANN), shown in Fig. 3. This network was used to project the input to a 2-dimensional space, called the nonlinear discriminant analysis (NDA) space [3]. This feature extraction technique provides that NDA features have lower variance comparing to input features and its separation is easier. This is very important for forming oscillator weights based on these features, because the weights reflect similarity of neighbouring image pixels. The output network layer was for texture classification, to compare ANN-based and oscillators network and segmentation methods.

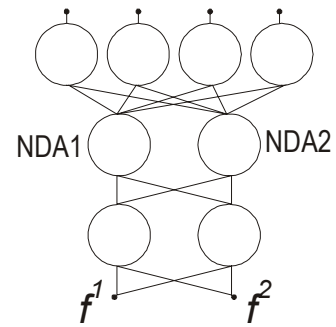


Fig.3. ANN used for feature extraction and texture classification;  $f^1, f^2$  are the input features

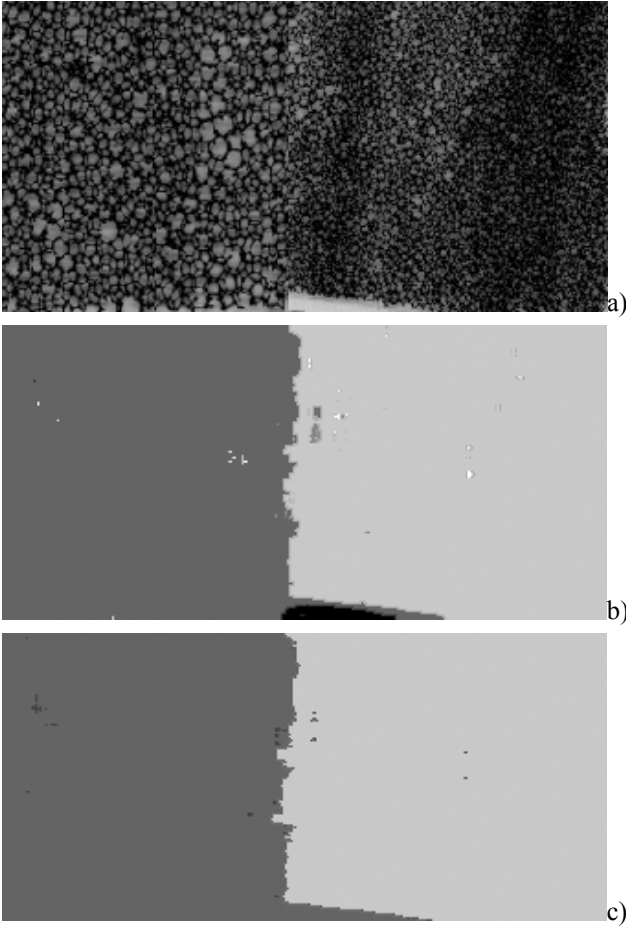


Fig.4. Original image with two foam textures (a), image (a) after segmentation using network of oscillators (b), image (a) after segmentation using ANN (c)

#### 4. Computer simulation

The LEGION network of size  $330 \times 169$  was simulated using oscillator model described by (1). The sample image 8 bit grey level to be analysed is shown in Fig. 4a. It is an optical image of two foams with different porosity used for construction of phantom objects applied in NMR imaging [10]. For this image, two texture features with the highest F coefficient were selected: contrast (calculated based on horizontal co-occurrence matrix with distance equal to 1) and  $\sigma$  (autoregressive model parameter). These two features (without further feature extraction based on ANN network) were used to form weights of LEGION network according the following formula:

$$W_{ij} = \frac{\sqrt{(f_i^1 + f_i^2)(f_{N(i)}^1 + f_{N(i)}^2)}}{\varepsilon + |f_i^1 - f_j^1| + |f_i^2 - f_j^2|} \quad (4)$$

where  $f_i^1, f_i^2, f_j^1, f_j^2$  are two selected features for oscillators  $i$  and  $j$  respectively,  $f_{N(i)}^1, f_{N(i)}^2$  are mean values of  $f^1$  and  $f^2$  calculated for active oscillators in neighbourhood of oscillator  $i$ ,  $\varepsilon$  is a small number.

Equation (4) is a simplified version of weight setting proposed in [1].

Instead of solving the set of nonlinear differential equations (1) and (3) for each network oscillator, so called singular solution method was applied [2]. 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 [2]. The segmentation algorithm based on singular solution method was described in [6]. Segmentation results are shown in Fig. 4b. Segmentation errors are visible on small white areas (where oscillator network could not make a decision) and in two small objects located in left side of second texture foam. For comparison, the segmentation result of the same image using two-layer ANN is presented in Fig. 4c. What is interesting, the ANN [7] classifier was unable to separate an artefact present in left lower part of right-hand second foam texture.

Another 8-bit test image, with size  $256 \times 256$  is shown in Fig. 5a. It contains a mosaic of four textures from Brodatz album. For these textures, the features with the highest F coefficient were  $\theta_2$  and  $\theta_4$ . These features were used as an input to ANN from Fig. 3. The network generated two NDA features, used to formation of oscillator network. In this case, the weights were computed according to equation (5)

$$W_{ij} = \begin{cases} U[\sum_{k=1}^2 f_i^k / (f_j^k + \varepsilon)]^{-1} & \text{if } f_i^k > f_j^k \\ U[\sum_{k=1}^2 f_j^k / (f_i^k + \varepsilon)]^{-1} & \text{if } f_i^k \leq f_j^k \end{cases} \quad (5)$$

where  $U$  is a constant and  $\varepsilon$  is a small constant to avoid division by zero.

Equation (5) is an intuitively derived formula, which provides small weight values when features representing oscillators  $i$  and  $j$  are similar and large weight values when they differ much from each other. This equation provides smoother weight value distribution over similar regions compared to (4). Fig. 5b shows segmentation result. The largest problem was to separate texture 1 and 2. For comparison, Fig. 5c shows segmentation of the same image using ANN. The network had the similar problem with segmentation of textures. Additionally, a spurious texture 3 region appeared between the areas of correctly recognised textures 2 and 4.

#### 5. Discussion

The presented method provides promising segmentation results for sample natural texture images. The computation time, applying the singular solution method is in range of few seconds, using Celeron 400 based PC. The most important problem to solve is an appropriate choice of texture features. The future investigations will comprise searching for more efficient

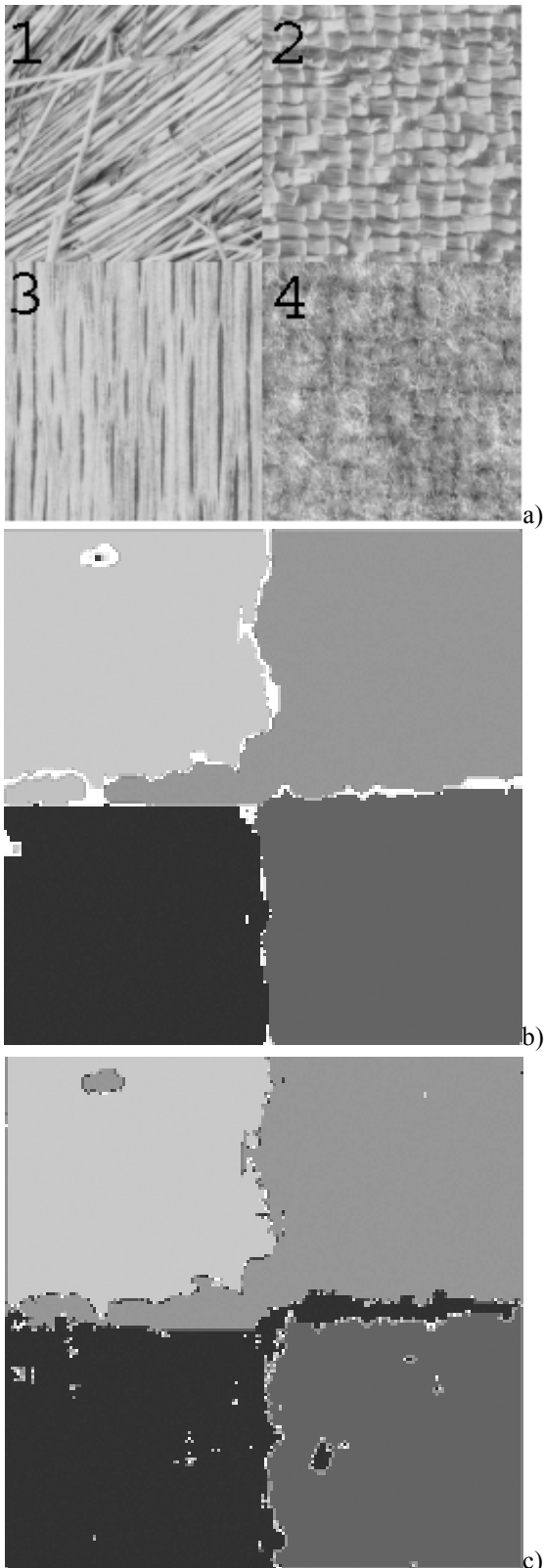


Fig. 5. Mosaic of four Brodatz tetures (a), image from (a) after segmentation using network of oscillators (b), image from (a) after segmentation using ANN (c)

texture features different then used in this study (eg. optimised linear filters). The advantage of presented method is its possibility of parallel implementation in hardware realisation.

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