M. Strzelecki: *Image Texture Segmentation Using Linear Filter Based Features and Network of Synchronised Oscillators*, 12th Portuguese Conference on Pattern Recognition Aveiro, Portugal, June 27th- 28th, 2002, accepted

Image Texture Segmentation Using Linear Filter Based Features and Network of Synchronised Oscillators

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***Abstract* - This paper presents recently emerged temporal correlation based method for image texture segmentation. It uses locally connected network of oscillators, which are able to synchronise while given image object is detected, and desynchronise for other objects. Texture features, necessary for appropriate oscillator weight setting, are obtained using linear filtering technique. The mathematical oscillator model is described. Example of numerical simulation of an oscillator network for segmentation of natural textures is also included and discussed.**

I. INTRODUCTION

The segmentation of an image into a set of different patterns is a very important aspect of visual perception. Especially, texture segmentation is still a difficult task for image analysis and image understanding systems in machine vision. Visual texture is present in a wide range 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 theory. This technique was applied for texture segmentation in [1]. In this study, the different method of texture feature extraction is proposed. It is based on adaptive linear filtering.

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. 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 a group of oscillators, which are oscillating in synchrony, while different oscillator groups, which are desynchronised, represent other objects. Such oscillator groups form a network called LEGION (locally excitatory globally inhibitory oscillators network), proposed in [8,9].

II. MODEL DESCRIPTION

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

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

where x is referred to as an excitatory variable and y is an inhibitory variable. I_T is a total stimulation of an oscillator and ε, γ, β 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 a 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 the whole network. Generally, the total oscillator stimulation I_T is given by equation (2):

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

where I_{in} represents external stimulation to the oscillator (image pixel value). W_{ik} are synaptic weights connecting oscillator k and i. Number of these weights depends on neighbourhood size $N(i)$. In the case considered here $N(i)$

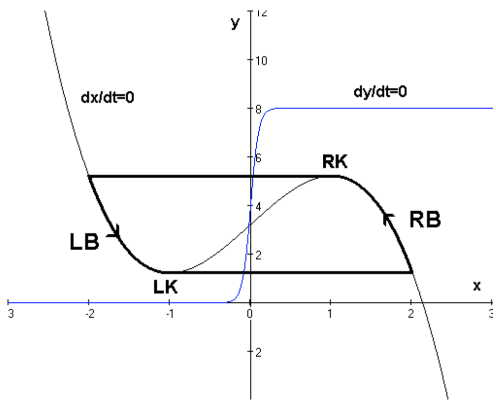


Fig.1. Nullclines of eq. (1)

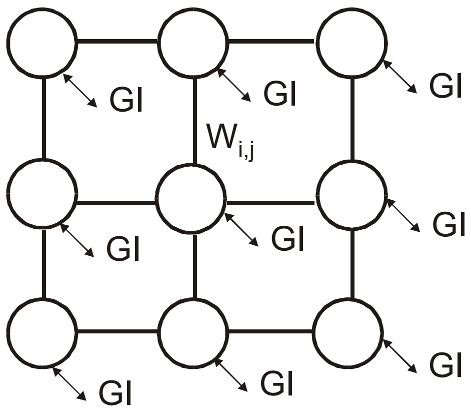


Fig. 2. 3×3 LEGION network

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 represents image object. This provides synchronisation of the whole group. Parameter 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 to one if at least one network oscillator is in active phase (x>0) and is equal to zero otherwise. The role of global inhibitor is to provide desynchronisation of oscillator groups representing different objects from the one, which is being under synchronisation. Global inhibitor does not affect any synchronised oscillator group because in such a group the sum in (2) has greater value then W_z.

Instead of solving the set of nonlinear differential equations (1) 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 [7].

III. Feature selection

One of the most important problems in segmentation of textured images is to find an appropriate set of features providing texture classification. Unfortunately, there is no universal feature set capable to proper classification of large number of textures. Feature selection should be performed independently for each texture segmentation task. A method for feature selection along with some texture segmentation results using oscillator network was presented in [6]. In this study texture features are calculated based on optimised linear filtering. In this method, a linear filter defined by mask $\boldsymbol{h}$ filters each texture in space domain:

$$\boldsymbol{h} = \begin{bmatrix} h_{11} & h_{12} & \dots & h_{1r} \\ h_{21} & h_{22} & & h_{2r} \\ \dots & & & \dots \\ h_{r1} & h_{r2} & \dots & h_{rr} \end{bmatrix}$$

where r is the filter size.

Elements of mask $\boldsymbol{h}$ are optimised in such a way that for analysed textures a Fisher coefficient is maximised [5]. It is a ratio of mean-squared between-class distance D^2 (computed between the filtered image means $\boldsymbol{\mu}_k$, k=1,2,...,K) to the mean-squared within-class distances V_k^2 (computed between the image k and its corresponding image mean $\boldsymbol{\mu}_k$)

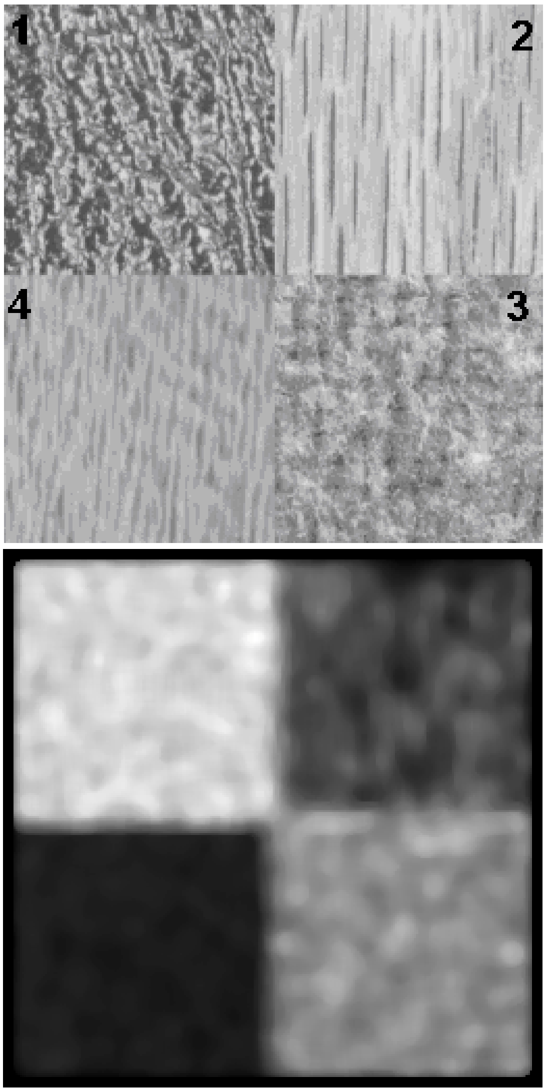
$$F = \frac{D^2}{V^2} = \frac{\frac{1}{K-1}\sum_{k=1}^{K}\sum_{j=1}^{K}\left|\boldsymbol{\mu}_k - \boldsymbol{\mu}_j\right|^2}{\sum_{k=1}^{K} V_k^2} \tag{3}$$

where K is a number of different textured images. In the (3) it is assumed an equal number of samples for each texture. The mean values $\boldsymbol{\mu}_k$ and variances V_k^2 may be directly computed for image texture or may be related to other features defined for filtered texture. In this study, the features are mean values calculated for non-overlapping image regions. The feature vector comprising of these means is calculated for each texture after filtering, and then these vectors are used to evaluate Fisher criterion (3). High value of F means that analysed textures after filtering have significantly different mean values and small variances, which in consequence facilitates their segmentation. Filtered image is then used as a base for oscillator weight setting.

IV. Computer simulation

The LEGION network of size 256×256 was simulated using oscillator model described by (1). The sample 8 bit grey level image to be analysed is shown in Fig. 3. It represents a mosaic of four textures from Brodatz album. This image was filtered using a linear filter mask of size 7×7. After filtering, the mean values calculated in 17×17 non-overlapping squares were used as features. Four feature vectors (one for each texture class) with 49 elements were evaluated and used to compute F coefficient. The filter optimisation was performed using a numerical routine based on direct search Davies-Swann-Campey method [4]. After optimisation the image was filtered using the obtained filter mask. Then for each image point the mean value was calculated for a 17×17 square centred at this point. Finally, the image of mean values was filtered using median filter to further reduce feature variance. This feature image (example shown in Fig. 3b) was used to form oscillator i excitation according the following formula:

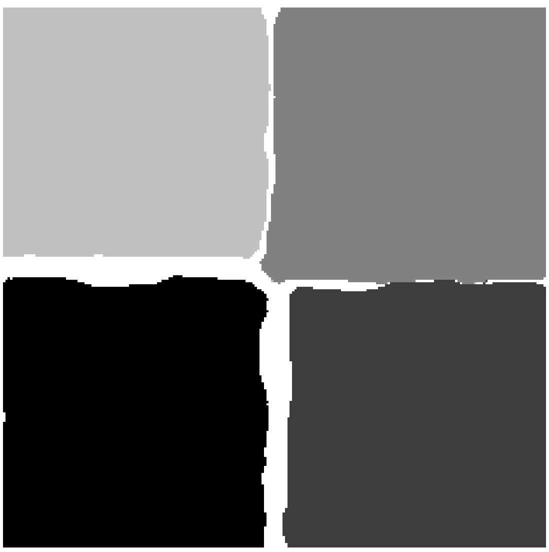
$$I_{Ti} = f_{\mathbf{max}} N_A \sum_{j \in N_i} \frac{1}{\varepsilon + |f_i - f_j|} - W_z z \tag{4}$$



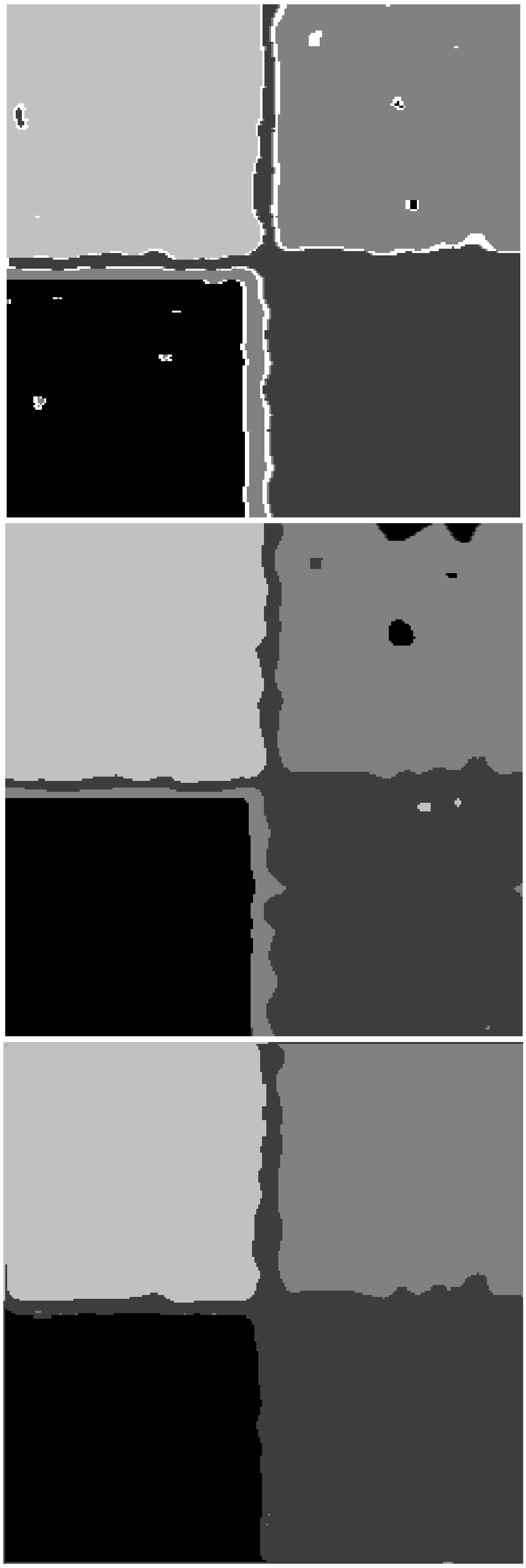
a)

b)

Fig. 3 (a) A mosaic of four Brodatz textures, (b) feature image obtained after filtering of image (a).



a)



b)

c)

d)

Fig. 4 Segmentation results of image from Fig. 3a. (a) Network of oscillators, (b) ANN, (c) thresholding, (d) region-growing method.

where f_i, f_j are two feature image points, further related as features, selected for oscillators i and j respectively, f_{max} is a maximum feature value in the image, N_i is a neighbourhood of oscillator i, N_A is the number of active oscillators in neighbourhood N_i, ε is a small number, W_z and z are defined as in (2). Equation (4) is a simplified version of weight setting proposed in [1].

Segmentation results are shown in Fig. 4a. Segmentation errors are visible between textures, marked in white. In these regions oscillator network was not able to classify analysed image point to any of texture classes.

To compare the oscillator network classifier with other techniques, the image from Fig. 3a was segmented using three different methods. The first one was an artificial neural network classifier trained using the feature image from Fig. 3b. The network contains one input, 2 neurons in hidden layer and four output neurons representing four texture classes. A training set consists of four vectors, calculated for each class. Each vector contains 49 mean values calculated in 17×17 non-overlapping squares for a filtered texture. The training was performed based on backpropagation algorithm [3]. Next, the network was used for image segmentation. For each point of filtered image (except lateral points) the mean value was calculated for a 17×17 square centred at this point. This mean value was fed into network input. In response, the network assigned the corresponding point to one of four classes or to none of them (white areas in Fig. 4b). Segmentation results are presented in Fig. 4b. It can be noticed that some regions for texture 2 and 4 are misclassified. Also, there exist a misclassified area between textures. The second method was a simply thresholding applied to the feature image. Three thresholds were chosen to provide the best segmentation results, shown in Fig 4c. As in the case of ANN classifier, some segmentation errors occur in textures 2, 3 and in regions between textures. The last method was based on region growing. It provides good segmentation results for texture regions (Fig. 4d), however some image area between textures remains misclassified.

V. Discussion

Comparing four segmentation techniques (Fig. 4a-4c), it can be stated that oscillator network provides quite good segmentation results, comparable with region-growing method. The advantage of oscillator network method is a fact, that between analysed textures it generates regions, which are not classified to any texture instead of misclassified ones. The computation time, applying the singular solution method is in the range of few seconds, using P4 based PC. Another advantage of this method is possibility of parallel implementation in hardware realisation. In case of textured images, the most important problem is still an appropriate choice of texture features. The future investigations will comprise improving the optimised filter method.

Acknowledgement

This work was performed within the framework of COST B11 European project: Quantitation of Magnetic Resonance Image Texture

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