Neuronal Synchronisation-Based Colour Image Segmentation

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Abstract

In this paper, segmentation of colour images using a network of neuronal oscillators is presented. It is combined with a self-organising map based colour reduction approach, where both chromatic components and local spatial characteristics are used. The network consists of a grid of neural oscillators which are locally coupled through excitatory connections and globally inhibited using a global inhibitor. Neurons which belong to the same region synchronise together and desynchronise with other neurons representing other different regions or objects. Consequently, objects represented by similar pixel features emerge one by one as the neural network activity evolves. The segmentation process is achieved through neuronal temporal correlation as opposed to classical methods based on edge detection and/or region growing. Neuron models are simulated using both forward Euler and Runge-Kutta 4th order methods for small size images. However, due to the large number of computations involved in solving the system of ordinary differential equations underlying the neuron model, an algorithmic approach based on the principle dynamics of neuron activity is used for large images. Numerical simulations were carried out using Matlab© R13 and results of segmented sample images are presented.

Keywords : neuron oscillators, temporal correlation, synchronisation, desynchronisation, colour image segmentation, self-organising maps, colour reduction.

1. Introduction

Image segmentation is a crucial problem in machine vision, as there is no generic method that can be applied to all types of images and each chosen method is rather problem specific. The segmentation process consists of partitioning an image into its homogenous regions. It has an important role in image understanding and object recognition process. Although the human visual system performs image segmentation with apparent ease, it remains a difficult task for computer vision. Research in machine vision has produced several techniques, usually based on pixel classification [1][3][4], edge detection [1][3], or region growing [1][3]. However, the work presented in this paper is biologically inspired, and based on neuronal temporal correlation. A recent hypothesis in neuroscience is that segmentation of different objects in a visual scene is based on the temporal correlation of neural activity [5][6][7]. Accordingly, a population of neurons which fire in synchrony, or in a highly correlated way, would signal attributes of the same object. Also, neurons with asynchronous activity would participate in the formation of different objects [8]. In this paper, a locally excitatory globally inhibitory oscillator network (LEGION) as defined in [9][10] is employed. It is first applied to gray scale images and to colour images using the HSV colour space transformation, and a Kohonen self-organising map based colour reduction method, where both pixel chromatic components and local spatial characteristics are used.

2. Neuron dynamics

The LEGION network consists of a grid of neural oscillators locally connected with positive weights and a global neuron negatively connected to all neurons in the grid. Each neuron is assigned a characteristic of the image pixel value, see Fig.1.

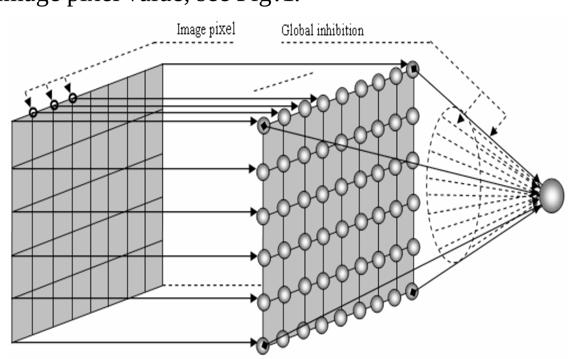

Fig. 1: Legion network architecture and input image

The segmentation of existing objects (groups of pixels that are spatially connected and share similar characteristics) consists of synchronous activity of neurons which are mapped to the same object.

The building block of the network architecture is the oscillator neuron whose dynamics are governed by the following equations [10]:

$$\begin{cases} \dot{x}_i = 3x_i - x_i^3 + 2 - y_i + I_i H(p_i - q) + S_i + r \\ \dot{y}_i = e(g(1 + tanh(x_i / b)) - y_i) \end{cases} \quad (1)$$

where x_i is an excitatory unit, y_i is an inhibitory unit, and H is a heaviside function. I_i and S_i represent external input (eg. pixel values) and coupling from other neighbouring oscillators, respectively (see Fig 2. for an example of two coupled oscillators). p_i is the lateral potential and q is a threshold.

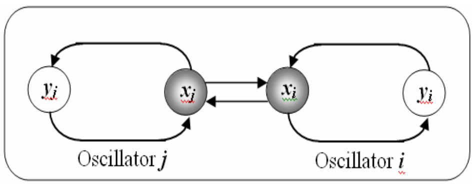

Fig.2. Example of two coupled oscillators x_i and x_j.

ρ is a Gaussian noise added to the total oscillator input in order to test its robustness to noise, and also to participate in the desynchronisation process. ε is a small positive number. The amount $I = I_i H(p_i - q) + S_i + \rho$ represents the total stimulation of an oscillator x_i. The x-nullcline is a cubic while the y-nullcline is a sigmoidal function whose steepness is controlled by the parameter β. If I>0, the curves intersect along the middle branch of the cubic and the system of equations in (1) possess a periodic solution (limit cycle), represented by a line which is marked with small arrows in Fig.3.

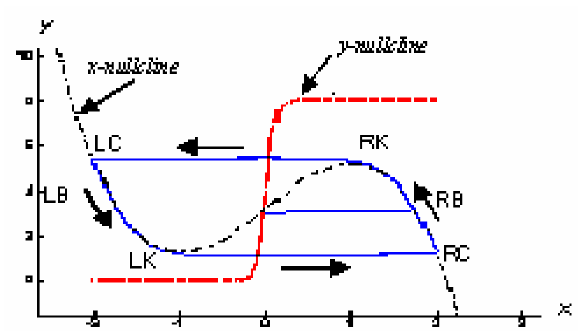

Fig.3: Oscillator x- and y-nullclines with solutions of system in (1) represented in phase plane.

The trajectory of the oscillator moves along the limit cycle line, from left branch (LB, called silent phase) to right branch (RB or active phase). The jumping occurs at both knees (LK or RK). The parameter ε induces different time scales for x and y dynamics, while the parameter γ controls the ratio of the times that the solutions spend on both phases; see oscillator dynamics for two different values of γ (while I is chosen as constant) in Fig.4. Note that when γ=40, the activity of the oscillator is close to firing spikes.

If I<0, the oscillator has a fixed point and no oscillation is produced.

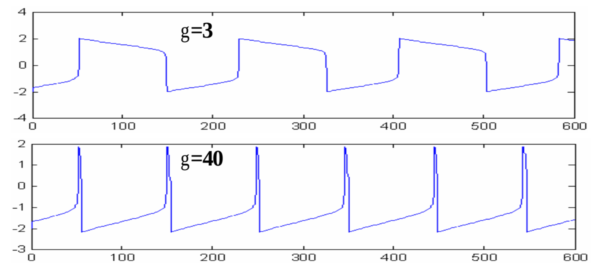

Fig.4: Oscillator activity for different values of γ.

Oscillators defined in (1) are organised in a two dimensional grid where different neighbourhoods can be used (in Fig.1 a neuron is connected to its next four neighbours). The size of the grid is equal to the size of the input image (one neuron for each pixel) and each neuron is connected to a global inhibitor. The coupling from other neighbouring neurons is represented by S_i and defined by:

$$S_i = \sum_{k \in Ni} W_{ik} H(x_k - q_x) - W_z z \quad (2)$$

where W_{ik} are synaptic dynamic weights connecting neuron k and i, and N_i represents the neighbourhood of neuron i. Due to these excitatory connections the activity of a neuron is propagated to its neighbours, and then spread to all oscillators in the same group representing one object. Note that an oscillator can receive its neighbour input only if the latter is above a certain threshold q_x. W_z is the coupling strength with the global inhibitor whose activity is represented by z. Its dynamics are given by $\dot{z} = f(s - z)$, where σ=1 if $x_i > q_{xz}$ for at least one oscillator, and σ=0 otherwise. q_{xz} is a threshold which is chosen so that only an oscillator jumping to the active phase could trigger the global inhibitor. When an oscillator is triggered, z →1, and the parameter φ determines the rate at which the inhibitor reacts to the stimulation from an active oscillator.

The global inhibitor, which receives excitatory input from all the neurons and sends back inhibitory outputs to all neurons, leads to desynchronisation of other oscillators which does not belong to the object being detected. It cannot affect synchronised oscillators as the sum of the inputs from synchronised neighbours is greater than W_z.

In (1), the function p, called lateral potential, determines whether or not an oscillator is a leader, and also has a role in removing noise from the input image

It is given by he following equation :

$$\dot{p}_i = l\,(1-p_{i_i})H(\sum_{k\in Ni} T_{ik}H(x_k-q_x)-q_p)-m\;p_i$$

where $\lambda>0$, T_{ik} is the permanent weights (reflecting wired connections) connecting oscillator i and k. if the weighted sum of active neighbours exceeds a certain threshold q_p, then p_i approaches one, otherwise it relaxes to zero on a time scale determined by μ. Thus, only oscillators which are surrounded by a large number of active oscillators can maintain their p_i high. These oscillators are called *leaders*, and more formally, an oscillator is defined as a leader if $p_i>q_p$ and it is stimulated.

3. Numerical simulations

A network of 10 by 10 neural oscillators based on the models described above was numerically simulated using Matlab© R13. The differential equations were integrated using the Runge-Kutta 4th order method for better accuracy. However the forward Euler method was also used and the same results were obtained. Therefore, as the Runge-Kutta method needs more computations than its counterpart forward Euler, the latter is preferable since it requires a smaller number of integrations. However the Runge-Kutta method offers better accuracy. A 10 by 10 sample synthetic gray scale image is fed to the network, see Fig.5.

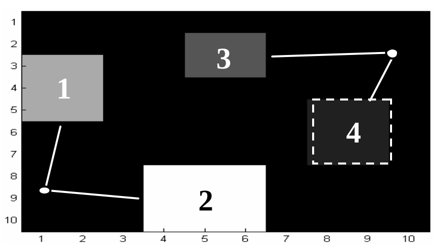

Fig.5: A 10x10 synthetic gray scale image, object number 4 highlighted with dashed line to be contrasted from the black background

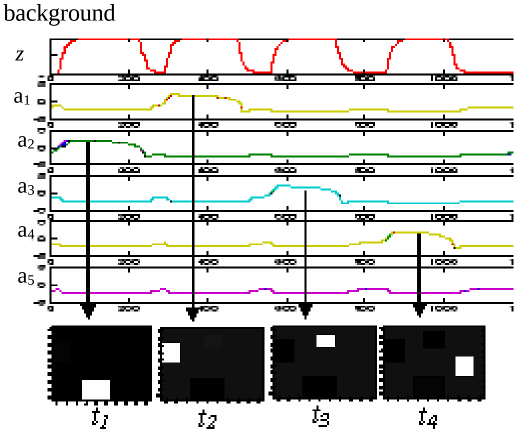

Fig.6: Activity (x) evolution of oscillators for each group of neurons belonging to the same object (a_1, a_2, a_3, a_4, a_5).

It consists of four separate shapes with different gray scale each on a black background. Each pixel value is used as external input to the corresponding neuron in the network. The network outputs are shown in Fig.6 where the neurons outputs which correspond to each object are shown together (superimposed). The graph in Fig.6 shows that neurons of the same object are active in synchrony and desynchronised with other neurons belonging to other different objects.

In Fig.6, a_5 is the activity of the neurons belonging to the background, z is the activity of the global inhibitor ($z\in[0,1]$), and waveforms a1,a2,a3,a4 correspond to neurons activities belonging to blocks 1,2,3,4 respectively.

For larger images, the activity of the neuron oscillators is calculated using an algorithmic approach instead of solving the set of ordinary differential equations (ODE) described previously. This approach is based on analysis of neurons trajectories on both cubic branches and at jumping points (LK, RK) between left and right branches (LB, RB) [10]. The use of algorithmic approach considerably reduces the computation time induced by integration of the set of ODEs. Only the x value of oscillator i is used in this algorithm.

1. Initialisation

- set z(0)=0 and calculate the connecting weights $W_{ij}=I_m/(1+|I_i-I_k|)$; where I_m is the maximum gray scale value, I_i, I_k is pixel value corresponding to neuron i and k.
- find leaders: $p_i = H(\sum_{k\in Ni} W_{ik} - q_p)$

and randomly start oscillators on the left branch.

2. Selection

- Find the closest leader *j* to left knee (LK).
- Jump the found leader to right branch (RB), the other oscillators move towards LK

$x_j(t+1)$=RK; z(t+1)=1 *{jump up};*

$x_k(t+1)=x_k(t)+(LK-x_j(t))$; for $k \neq j$

3. Jumping

Iterate until stop

If *$x_i(t)$=RK and z(t)>z(t-1)*

$x_i(t+1)=x_i(t)$; *{stay on the RB}*

elseif *$x_i(t)$=RK* and *z(t)<=z(t-1)*

$x_i(t+1)$=LC; z(t+1)= z(t)-1; *{jump down}*

if z(t+1)=0 go to ***Selection.***

else

{calculate input to neuron}

$Si(t+1)=sum(w_{ik}.H(x_k(t)-LK)) - WzH(z(t)-q_z)$;

If Si(t+1)>0

$x_j(t+1)$=RK; z(t+1)=z(t)+1 *{jump up};*

else

$x_j(t+1)=x_j(t)$; *{stay on LB}*

The algorithm above is demonstrated on a 110 by 90 pixels image, which contains five chess pieces. A network of 110 by 90 oscillators is formed, and each neuron is stimulated with its corresponding pixel value. Each neuron has eight neighbouring neurons, and the connecting weights are formed based on the image pixel values. Therefore, oscillators with similar pixel values have large weights while the ones belonging to different regions have weaker connections. This will ensure the leaders will propagate their activity to the oscillators in the same group representing an object. As the network activity evolves, the different objects (chess pieces) emerge one by one, in addition to the image background; see Fig.7 for images of segmented objects.

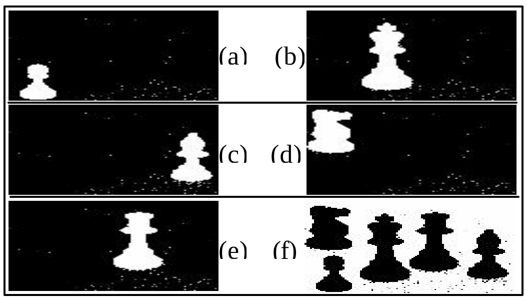

Fig.7: Segmented objects from 110x90 image containing five chess pieces. (a) to (e): are segmented objects. (f) represent image background.

4. Colour image segmentation

The network of oscillators is applied to colour images where the HSV (hue, saturation, value) colour space is used and a color quantization method is employed. It exploits the colours of the pixels as well as their spatial characteristics such as how the colour of each pixel is related to the colours of the neighbouring pixels. The final reduced set of colours is automatically selected using a Kohonen self-organising map (SOM), which is an unsupervised neural network [11]. It is based on a competitive learning and is a topology preserving map which can be adjusted to represent the probability distribution of the inputs [12]. Specifically, the HSV components (chromatic components h, s and v) of each pixel are considered with additional spatial features (the mean and standard deviation are used here but there is no restriction on the type of possible spatial features that could be used) that are extracted from neighbouring pixels. The SOM is trained according to Kohonen's competitive learning rule [11]. After training, the original image is transformed into a new one with a limited number of colours and spatial characteristics similar to those defined by the adopted features.

The colour quantisation method which has been developed is described as follows:

1. The RGB colour space $[0, 255]^3$ is mapped into the HSV colour space $[0, 1]^3$ where the input image is then represented. The RGB to HSV transform is performed using the Matlab function *rgb2hsv* routine.

2. A one dimensional Kohonen SOM is designed, where the inputs represent the Hue (*h*), Saturation (*s*) and Value (*v*) components, complemented with local spatial characteristics, namely the mean and the standard deviation of the pixels values within a window centred at the pixel being considered. These spatial are computed for each chromatic component, which make the number of inputs amount to nine features (3 for *h,s,v* and 6 for spatial features). See Fig.8 for an illustration.

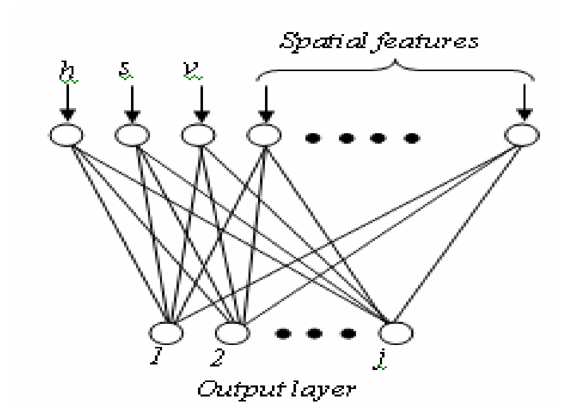

Fig.8. Self-organizing network map used for colour reduction and image transformation. The chromatic components and spatial features are used as inputs. The number of output neurons *j* represents the final number of reduced colours, which are represented in the weights of the output neurons.

For each chromatic component, pixel local spatial characteristics are computed as follows:

Mean values

$$M_{ch}(i,j) = \frac{1}{M} \sum_{(k,l) \in Nij} Im_{ch}(i,j)$$

where ch represent the chromatic component being considered $ch \in \{h,s,v\}$, i,j are the pixel coordinates for which the spatial feature is being calculated, Nij is the neighbourhood of the pixel (i,j), and M is the total number of pixels within a chosen window (usually an odd number is considered) in the input image *Im*. For example, taking a 3 by 3 neighbourhood about pixel (i,j) yields:

$$M_{ch}(i,j) = \frac{1}{9} \sum_{k=i-1}^{i+1} \sum_{l=j-1}^{j+1} Im_{ch}(k,l)$$

Standard deviation values

Likewise, the standard deviation is computed for each chromatic component using the following formula:

$$M_{ch}(i,j)=\sqrt{\frac{1}{M}\sum_{(k,l)\in Nij}(Im_{ch}(i,j)-M_{ch}(i,j))^2}$$

In this paper, a window of size 3x3 is considered and the image is padded with zeros before the spatial characteristics are computed.

3. The network is trained using the Kohonen competitive learning rule where training samples are randomly selected from the input image.

After training, the new reduced set of colours is represented by the final output neurons weights and the input image is transformed into a new one, with reduced colour number, using the SOM final weights. The resulting image, with reduced set of colours each of which represented by one dimensional feature, is eventually fed to the network of oscillators for object segmentation. All the simulations have been implemented using Matlab R13. A network of 9 inputs and 6 outputs is used for colour reduction; therefore the input image is transformed into a new image which consists of a set of six colours. The proposed method is demonstrated on a sample colour image, of size 130x80 pixels, and the segmentation results are shown in Fig.9.

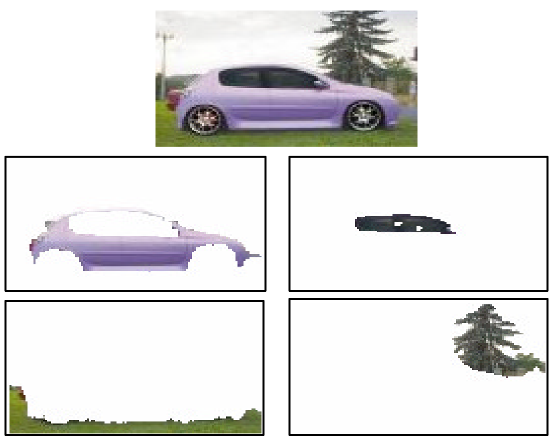

Fig.9. Segmentation of a sample colour image (130 by 80 pixels) into different regions.

5. Conclusions

A neuronal based colour image segmentation approach is presented in this paper. A network of locally excitatory globally inhibitory neural oscillators is studied and further extended to segmentation of colour images, where HSV colour space is employed and a colour reduction method is developed. The process of image colour reduction is based on a one dimensional Kohonen self-organizing map, where the inputs consist of the chromatic components of each pixel and its local spatial features computed for each colour component. The pixel values of the new transformed image with reduced set of colours are used to stimulate a 2D array of oscillator neurons. As the activity of each neuron evolves, neurons which belong to the same object (defined as a coherent region) become coactive in synchrony, and at the same time desynchronise with other neurons representing different objects. The segmentation process is based on the neuroscience principle of temporal correlation as a means of objects perception and binding.

Future work is to consider texture image segmentation and possible pre-processing stages required for applying the network described above, such as statistical pixel characteristics/features extraction.

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6. References

[1] N.R. Pal and S.K. Pal, "A review on image segmentation techniques", Pattern Recognition, vol. 26, pp. 1277-1294, 1993

[2] John C. Russ, The Image Processing Handbook, RC Press, 1999.

[3] Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing, 2001

[4] R.O. Duda, P.E. Hart Pattern Classification and Scene Analysis, 2001.

[5] C. von der Malsburg and W. Schneider.A neural cocktail-party processor. Biological Cybernetics, 54:29-40, 1986

[6] C. von der Malsburg and J. Buhmann. Sensory segmentation with coupled neural oscillators. Biological Cybernetics, 67:233-242, 1992

[7] Singer, W. and Gray, C.M. Visual feature integration and the temporal correlation hypothesis, Annu. Rev. Neurosci.18 pp 555-586, 1995.

[8] Mauro Ursino, Giuseppe-Emiliano La Cara, Modeling segmentation of a visual scene via neural oscillators: fragmentation, discovery of details and attention, Network: Comput. Neural Syst. 15 69-89, 2004.

[9] Wang, D, & Terman, D. Locally excitatory globally inhibitory oscillator networks. IEEE Transactions on Neural Networks, 6, 283- 286, 1995.

[10] Wang, D, & Terman, D. (1995). Image segmentation based on oscillatory correlation, neural computation, vol 9, pp: 805-836, 1997.

[11] Haykin, S., Neural networks : a comprehensive foundation. - New York : Macmillan, Oxford, Maxwell Macmillan International, 1994

[12] Kohonen, Teuvo. - Self-organizing maps- 2nd edition, New York : Springer, 1997