Proceedings of International Joint Conference on Neural Networks, Atlanta, Georgia, USA, June 14-19, 2009

Chaotic Phase Synchronization for Visual Selection

Fabricio A. Breve, Liang Zhao, Marcos G. Quiles, and Elbert E. N. Macau

Abstract—**Chaotic phase synchronization among coupled oscillators is a phenomenon of interest in many physical and engineering systems. It has also been observed in biological systems, where groups of different functional units interact with each other in order to produce coherent behaviors in higher levels. While biological systems have facility to capture salient object(s) in a given scene, visual selection is still a challenging task to artificial visual systems. In this paper, a visual selection mechanism based on chaotic phase synchronization is proposed. Oscillators representing the salient object in a given scene are phase synchronized, while no synchronization is observed for background objects. In this way, the salient object is highlighted. Due to the modeling by phase synchronization instead of complete synchronization, the proposed model is robust, biologically inspired and good simulation results were achieved.**

I. Introduction

SYNCHRONIZATION is a common phenomenon observed in science, engineering and social life. It is characterized by a tendency of two or more systems to operate in synchrony. It has been observed in systems as diverse as clocks, singing crickets, cardiac pacemakers, firing neurons and applauding audiences [1]. There are different phenomena that are referred to as "synchronization" in chaotic systems, like *complete synchronization* and *phase synchronization*. Complete synchronization is defined as the complete coincidence of the trajectories of the coupled individual chaotic systems in the phase space. Mathematically, given state variable vectors $\mathbf{x}$ and $\mathbf{y}$ representing two dynamical systems, they are said to be completely synchronized if $|\mathbf{x} - \mathbf{y}| \to 0$ as $t \to \infty$. On the other hand, phase synchronization takes place in cases involving almost identical dynamical systems and it means that the phase difference between the systems is kept bounced over the time, while their amplitudes remain chaotic and may be uncorrelated [1], [2].

Evidence from physiological experiments has been accumulating with strong indication on the existence of synchronous rhythmic activities also in different areas of the brain of human beings, cats and monkeys [3], [4], [5], [6], [7], [8], [9]. It has been suggested that this neuronal oscillation and synchronization have a role in feature binding and scene segmentation problems. Von der Malsburg [10] proposed a theory, called *temporal correlation*, where objects are represented by the temporal correlation of the firing activities of spatially distributed neurons coding different object features. In practice, a special form of temporal correlation, called *oscillatory correlation*, has been successfully applied to several computational problems [11], [12], [13], [14]. The oscillatory correlations can be described by the following rule: oscillators which represent different features of the same object are synchronized, while oscillators coding different objects are desynchronized [14]. The model was also extended to utilize the properties of chaos and chaotic synchronization in order to achieve unlimited capacity of segmentation [15], [16], [17].

The role of synchronization in brain functions has received additional support from neurobiological findings [18]. For example, it has been shown that visual attention is strongly linked with synchronization, in which the coherence among neurons responding to the same stimulus is increased [5], [8], [19], [20]. Visual attention is the capacity developed by living systems to select just relevant environmental information to feed their sensory systems. It reduces the combinatorial explosion resulting from the analysis of all incoming visual information [21], [22] and identifies the region of the visual input that will reach awareness level (focus of attention) while irrelevant information is suppressed [23], [24]. Here, we consider pixel contrast as visual attention clue, i.e., the object with the higher contrast in the scene is considered as the most salient object.

Owning to the relation between synchronization and visual attention, some visual attention models have been proposed where the complete synchronization among oscillators are used to represent objects [25], [26], [27], [28]. However, the synchronization phenomena observed in real experiments rarely represent a complete synchronization and other forms of synchronization should be considered. Particularly, phase synchronization is a model of reciprocal interaction, which is believed to be the key mechanism for neural integration in brain. Direct evidence supporting phase synchrony as a basic mechanism for brain integration has recently been provided by extensive studies of visual binding [29].

In this paper we propose a chaotic oscillatory correlation network for object selection. In contrast to other oscillation-based object selection models (see [25], [26]), our model is the first to use chaotic phase synchronization. It is based on a network of coupled chaotic Rössler oscillators [2], which is used to create a selection mechanism where one of several objects is segmented and highlighted (receives the focus of attention). As the system runs, the group of neurons representing the salient object of a visual input is locked in phase, which means each oscillator still produces a unique chaotic trajectory, but with their phases bounded. At the same time, the groups of neurons representing other objects in the scene remain with their phases uncorrelated. The phase

Fabricio Breve, Liang Zhao and Marcos Quiles are with the Department of Computer Science, Institute of Mathematics and Computer Science, University of São Paulo, São Carlos-SP, Brazil (email: {fabricio, zhao, quiles}@icmc.usp.br). Elbert Macau is with the National Institute for Space Research, São José dos Campos-SP, Brazil (email: elbert@lac.inpe.br)

This work was supported by the State of São Paulo Research Foundation (FAPESP) and the Brazilian National Council of Technological and Scientific Development (CNPq)

978-1-4244-3553-1/09/$25.00 ©2009 IEEE

synchronization mechanism is more robust than the traditional complete synchronization and it can be achieved with a much smaller coupling strength, thus avoiding convergence to infinity when stronger coupling strength is applied.

This paper is organized as follows. In section 2, the chaotic phase synchronization is presented. In section 3 the proposed model is described. In Section 4, the results obtained through simulation of the proposed model applied to synthetic and real images are showed. Finally, in Section 5, conclusions are drawn.

II. Chaotic Phase Synchronization

Two oscillators are called phase synchronized if their phase difference $\phi_1 - \phi_2$ is kept bounded while their amplitudes may be completely uncorrelated [1], i.e. $|\phi_1 - \phi_2| < M$, as $t \to \infty$. Here, the phase ϕ of an oscillator is defined as follows,

$$\phi = \Upsilon(\arctan(y/x)) \tag{1}$$

where x and y are variables of the oscillator and Υ represents the unwrap operation. Due to the unwrap operation, ϕ is always an increasing variable.

In order to study phase synchronization and desynchronization of chaotic oscillators we consider two almost identical coupled Rössler systems as follows:

$$\begin{aligned}
\dot{x}_{1,2} &= -\omega_{1,2} y_{1,2} - z_{1,2} + k(x_{2,1} - x_{1,2}), \\
\dot{y}_{1,2} &= \omega_{1,2} x_{1,2} + a y_{1,2}, \\
\dot{z}_{1,2} &= b + z_{1,2}(x_{1,2} - c),
\end{aligned} \tag{2}$$

where parameters $a = 0.15$, $b = 0.2$ and $c = 10$ are held constant with the same values used by Rosenblum et al. [2], $\omega_{1,2}$ governs the frequency of the oscillator and k is the coupling strength. Let $\Delta\omega$ be the difference between ω_1 and ω_2 and ϕ_1,ϕ_2 be the phases of the two oscillators.

For a fixed $\Delta\omega$, as k increases, we observe a transition from unsynchronized regime, i.e. $|\phi_1 - \phi_2| \to \infty$ as $t \to \infty$, to a synchronous state, where the phase difference does not grown with time. This transition is illustrated in Fig. 1. It is important to notice that while in complete synchronization of chaotic oscillators the fields coincide, here the instant fields $x_{1,2}$, $y_{1,2}$ and $z_{1,2}$ do not coincide, as illustrated in Fig. 2, which shows the uncorrelated chaotic amplitudes of two phase synchronized Rösller oscillators. Here the amplitudes of the Rössler oscillators are defined as follows [30]:

$$A = \sqrt{x^2 + y^2}. \tag{3}$$

III. Model Description

The proposed model is a two dimensional network of Rössler Oscillators and it is governed by the following equations:

$$\begin{aligned}
\dot{x}_{i,j} &= -\omega_{i,j} y_{i,j} - z_{i,j} + k\Delta^+ x_{i,j} + \eta_{i,j}\Delta^- x_{i,j}, \\
\dot{y}_{i,j} &= \omega_{i,j} x_{i,j} + a y_{i,j}, \\
\dot{z}_{i,j} &= b + z_{i,j}(x_{i,j} - c).
\end{aligned} \tag{4}$$

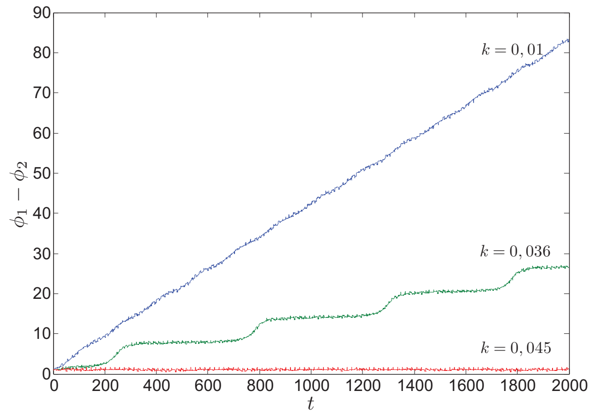


Fig. 1: Phase difference of two coupled Rössler systems versus time for nonsynchronous ($k = 0.01$), nearly synchronous ($k = 0.036$) and synchronous ($k = 0.045$) states. $\Delta\omega = 0.04$ ($\omega_1 = 0.98$ and $\omega_2 = 1.02$).

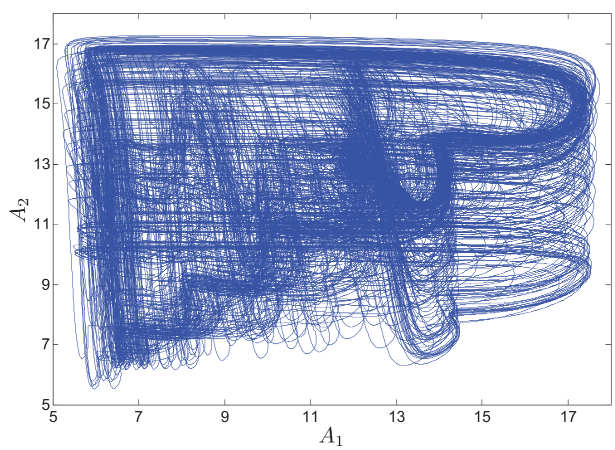


Fig. 2: Uncorrelated chaotic amplitudes A_1 and A_2 when $k = 0.045$ and $\Delta\omega = 0.04$ ($\omega_1 = 0.98$ and $\omega_2 = 1.02$).

where (i, j) is a lattice point with $1 \le i \le N$, $1 \le j \le M$. k is the positive coupling strength and is set accordingly to the scene. $\eta_{i,j}$ is a negative coupling strength which is set accordingly to the pixel contrast. $\omega_{i,j}$ is used to code pixel (i, j) intensity, as it will be explained later. $\Delta^+ x_{i,j}$ and $\Delta^- x_{i,j}$ are positive and negative coupling terms respectively. They are defined by:

$$\begin{aligned}
\Delta^{\pm} x_{i,j} \quad = \quad & \gamma_{i-1,j-1;i,j}(x_{i-1,j-1} - x_{i,j}) + \\
& \gamma_{i-1,j;i,j}(x_{i-1,j} - x_{i,j}) + \\
& \gamma_{i-1,j+1;i,j}(x_{i-1,j+1} - x_{i,j}) + \\
& \gamma_{i,j-1;i,j}(x_{i,j-1} - x_{i,j}) + \\
& \gamma_{i,j+1;i,j}(x_{i,j+1} - x_{i,j}) + \\
& \gamma_{i+1,j-1;i,j}(x_{i+1,j-1} - x_{i,j}) + \\
& \gamma_{i+1,j;i,j}(x_{i+1,j} - x_{i,j}) + \\
& \gamma_{i+1,j+1;i,j}(x_{i+1,j+1} - x_{i,j})
\end{aligned} \tag{5}$$

where

$$\gamma_{i,j;p,q} = \begin{cases} 1, & \text{if oscillator } (i,j) \text{ is coupled to } (p,q), \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

The segmentation and selection strategy is described below. Given an input image, the network is organized so that each oscillator represents a pixel of the image, which means that each oscillator receives a stimulation from its corresponding pixel in the image. In this model, the $\omega_{i,j}$ parameter of each oscillator is chosen to encode the intensity (gray level) of the corresponding pixel. The intensity is coded uniformly in $[1 - \frac{\Delta\omega}{2} \quad 1 + \frac{\Delta\omega}{2}]$ interval, where $\Delta\omega$ is set accordingly to the scene. As the system runs, the oscillators self-organize themselves according to a predefined similarity criterion, such that the connections in Δ^+ between pairs of neighboring oscillators with similar gray level will be maintained, while those connections between oscillators of very different gray level will be cut. Consequently, all oscillators belonging to the same segment will have their phases synchronized, while their amplitudes remain uncorrelated. In this way, objects in a given scene can be segmented. All the connections inside Δ^+ are adaptive, i.e., if two connected oscillators becomes unsynchronized ($|\phi_1 - \phi_2| > \pi$) at any time, the connection between them is immediately cut. So, if a pixel is incorrectly coupled to an object it will not disturb the object synchronization for long.

The proposed model also includes a negative coupling strength in order to disturb the synchronization among oscillators representing non-salient objects, so only the salient object remains synchronized. The connections in Δ^- are always on, which means that each oscillator is always connected to their 8-nearest-neighbors, except, of course, for the border oscillators which have less neighbors. While the positive coupling strength k is the same for every oscillator, the negative coupling strength $\eta_{i,j}$ is different for each oscillator and it is set accordingly to the contrast of the pixel in relation to the scene, as follows:

$$\eta_{i,j} = \alpha \frac{C_{i,j} - \min(C)}{\max(C)}, \tag{7}$$

where α is a negative constant (in this paper we fixed $\alpha = -0.02$) and $C_{i,j}$ is the contrast of pixel (i,j), which is given by:

$$C_{i,j} = \left(\sum_d |F^d_{i,j} - F^d_{\text{avg}}| \right)^\sigma, \tag{8}$$

where $F^d_{i,j}$ is the feature d value for pixel (i,j), σ is set accordingly to the scene, and F^d_{avg} is the mean value for feature d, which is given by:

$$F^d_{\text{avg}} = \frac{1}{N.M} \sum_{i=1}^{i=N} \sum_{j=1}^{j=M} F^d_{i,j}. \tag{9}$$

In this work 4 features were used, F^I, F^R, F^G and F^B, which corresponds to the values of intensity (I), red (R), green (G) and blue (B) components from each pixel respectively.

In oscillators which corresponding pixels have the highest contrast, the negative coupling strength tends to zero ($\eta \to 0$), thus the objects formed by high contrast pixels are nearly unaffected by negative strengths, at the same time that the positive strengths keep their oscillators synchronized in phase. Meanwhile, in oscillators which corresponding pixels have less contrast, the negative coupling strength is higher ($\eta \to \alpha$), thus these oscillators will repel each other. Finally, after some time, only the oscillators corresponding to the salient object will remain with their trajectories synchronized in phase while the other objects will have trajectories with different phases. These features satisfy the following essential requirements of a Visual Selection system:

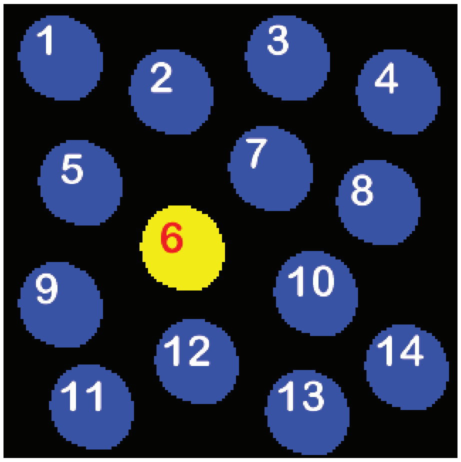
- considering as input one or a combination of features (Saliency Map), the neural network must highlight (select) the region of the image where the focus of attention should be directed;
- all other locations of the visual input must be suppressed by the system in order to keep the focus of attention on just one of the active objects.

IV. Computer Simulations

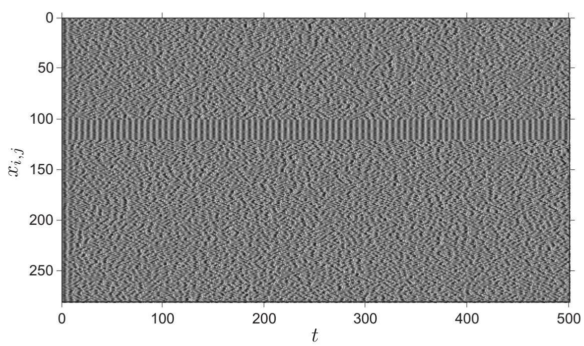
In this section, we present the simulation results of visual selection tasks by using the proposed model on synthetic and real images. We consider the salient object to be the one which has the largest intensity and color contrast to the other parts of the image. This assumption receives direct support from biological experiments, which show that feature contrast is more important than absolute value of features in visual searching tasks performed by biological visual systems [31], [32].

The first experiment was carried out by using the artificial image shown in Fig. 3a, which has 14 objects, 13 of them are blue and only one is yellow (object number 6), thus becoming the salient object. The free parameters were set as follows: $k = 0.005$, $\sigma = 1.0$ and $\Delta\omega = 0.2$. Fig. 3b shows the behavior of 20 randomly chosen oscillators (pixels) from each object, where each line corresponds to an oscillator. Dark colors represent the lowest values for the component x of the corresponding oscillator, while bright colors represent the higher values. From lines 101 to 120 we can see that the oscillators corresponding to the salient object are phase synchronized (see the formed pattern), while the rest of the oscillators have their phases uncorrelated. Fig. 3c shows the oscillators phase growth through time, and it is easier to notice that the oscillators corresponding to the salient object form a plain platform, while the other oscillators have different phases. Notice that the numbers appearing in Fig. 3a were not in the image presented to the system, they were only used so that the reader can easily locate the corresponding pixels in the results in Figs. 3b and 3c.

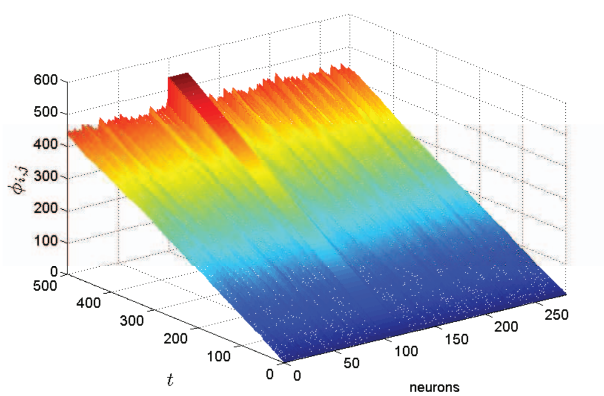
The second experiment was carried out by using the artificial image shown in Fig. 4a, like in Fig. 3a there are 14 objects, and again the yellow one (object number 6) is the salient. However, in this case there is less contrast between



(a) Source image (160×160 pixels).



(b) Oscillators behavior.



(c) Phase growth.

Fig. 3: Artificial image with 14 objects.

the salient object and the others. The free parameters were set as follows: $k = 0.005$, $\sigma = 1.0$ and $\Delta\omega = 0.2$, the same values that were used in the previous experiment, so that we can observe what happens when there is less contrast in the scene. Fig. 4b shows the behavior of 20 randomly chosen oscillators (pixels) from each object, where each line corresponds to an oscillator. From lines 101 to 120 we can see the oscillators corresponding to the salient object, and again the formed pattern clearly indicates that these oscillators are phase synchronized, however phases from oscillators corresponding to other objects are not completely uncorrelated. Actually, some of the oscillators even show phase synchronized behavior for short periods, which means they are not sufficiently inhibited by the salient object. Fig. 4c shows the oscillators phase growth through time, and in this case, although the oscillators corresponding to the salient object still form a plain platform, there are other oscillators that have high phase growth, however they form an irregular platform, since they cannot keep their phase synchronization plateau for long. Notice that we could easily prevent this behavior by setting a higher value for the σ parameter, compensating for the less contrast in the scene. In order to confirm the above mentioned behavior, we ran the same experiment again with all the same parameters, except for σ, which had its value raised from 1 to 4. The results are shown in Figs. 4d and 4e, and now we can observe that the salient object was able to completely inhibit the other objects to be phase synchronized, as it was expected. Once more, numbers appearing in Fig. 4a were not in the image presented to the system.

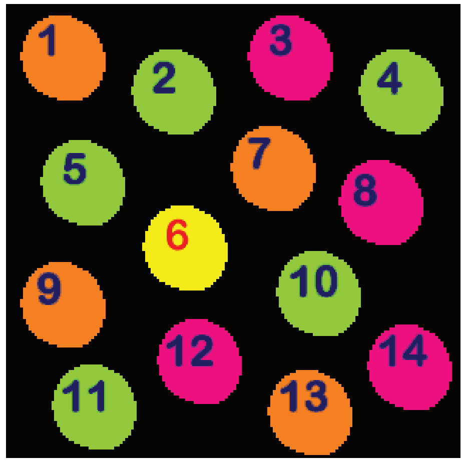
Our third experiment is performed by using the real image shown by Fig. 5a, where the salient object is the “bird”, which contrasts with the “sky”. The free parameters were set as follows: $k = 0.02$, $\sigma = 1.0$ and $\Delta\omega = 0.02$. In Fig. 5b we can see the behavior of 300 randomly chosen oscillators (pixels) from the image, the first 150 lines corresponds to the background “sky” and the other 150 lines corresponds to the “bird”. Fig. 5c shows the oscillators phase growth through time. Both graphics show that the system chooses to deliver attention to the “bird” as it was expected.

Our forth experiment is performed by using the real image shown by Fig. 6a, the salient object “dog” is linearly non-separable, since it is surrounded by the background “grass”. The free parameters were set to: $k = 0.2$, $\sigma = 2.0$ and $\Delta\omega = 0.02$. In Fig. 6b we can see the behavior of 300 randomly chosen oscillators (pixels) from the image, the first 150 lines corresponds to the “grass” and the other 150 lines corresponds to the “dog”. Fig. 6c shows the oscillators phase growth through time. Again, it is easier to notice that the system chooses to deliver attention to the “dog” as it was expected.

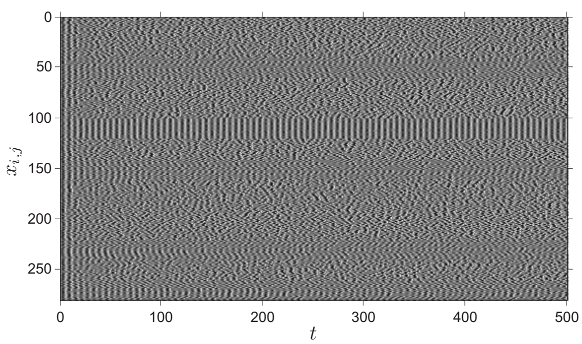
Our last experiment is performed by using another real image, shown by Fig. 7a, with several objects. The free parameters were set as follows: $k = 0.02$, $\sigma = 1.0$ and $\Delta\omega = 0.02$. Fig. 7b shows the behavior of 300 randomly chosen oscillators (pixels) from the image, so the first 150 lines corresponds to the “leaves” and the other 150 lines corresponds to the “flower”. Fig. 7c shows the oscillators phase growth through time. Our model selected the “flower”, which agrees to our visual inspection.

V. Conclusions

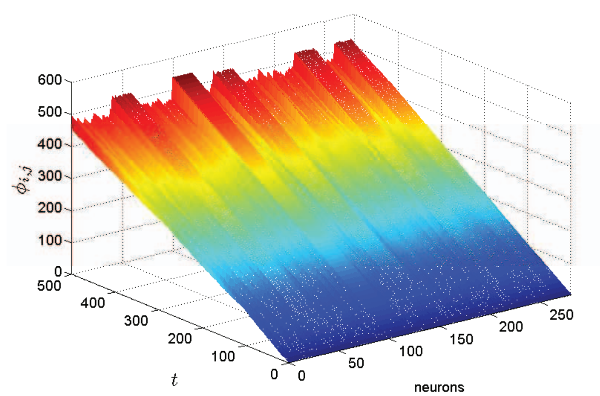
This paper presented a visual selection mechanism based on a network composed of chaotic Rössler oscillators, taking advantage of its phase synchronization behavior. This mechanism can be seen as part of a visual attention system, which is responsible for selecting one of several regions of interest



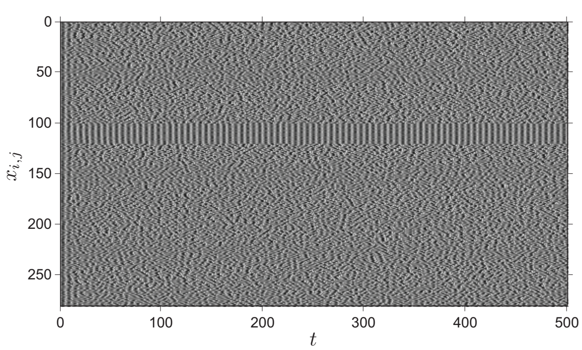
(a) Source image (160 × 160 pixels).



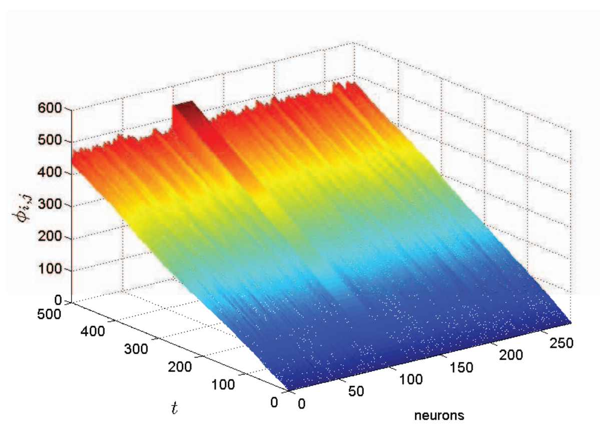
(b) Oscillators behavior, $\sigma = 1$.



(c) Phase growth, $\sigma = 1$.



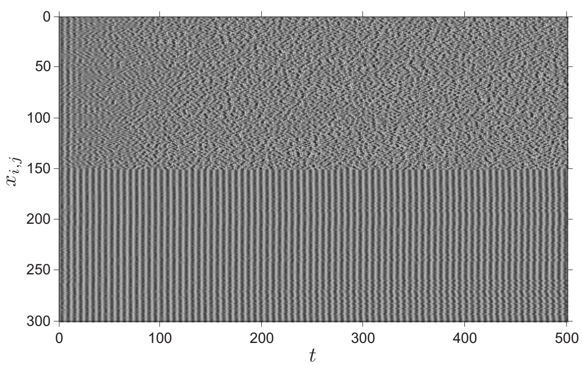
(d) Oscillators behavior, $\sigma = 4$.



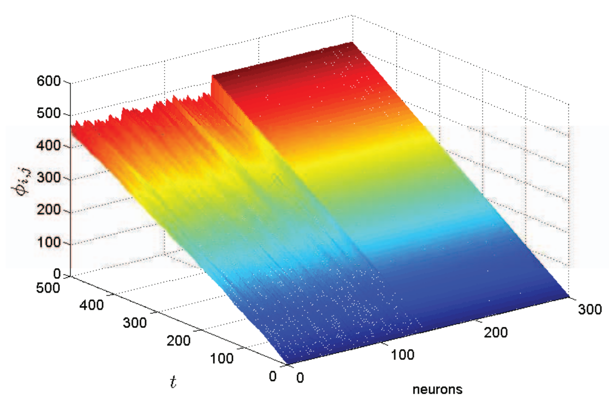
(e) Phase growth, $\sigma = 4$.

Fig. 4: Artificial image with 14 objects and less contrast.

(a) Source image (320×240 pixels).



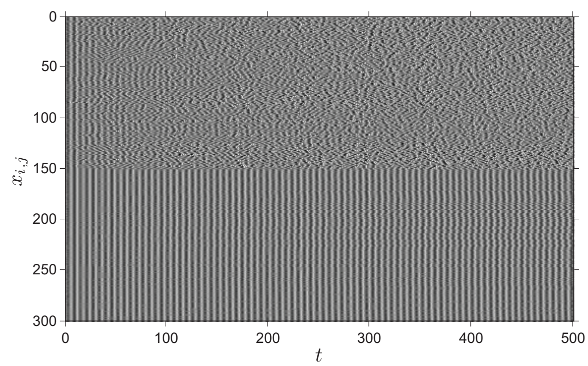
(b) Oscillators behavior.



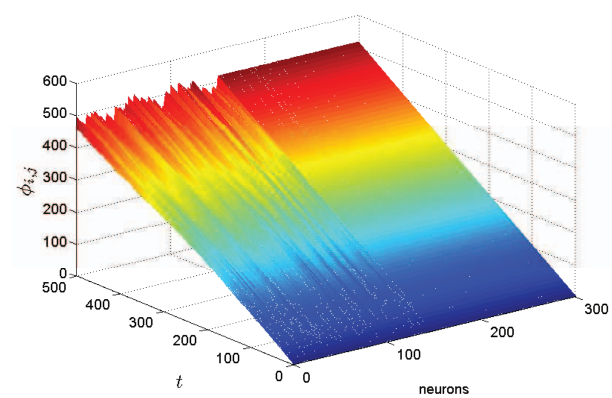
(c) Phase growth.

Fig. 5: Real Image - "Bird".

(a) Source image (320×240 pixels).



(b) Oscillators behavior.



(c) Phase growth.

Fig. 6: Real Image - "Dog".

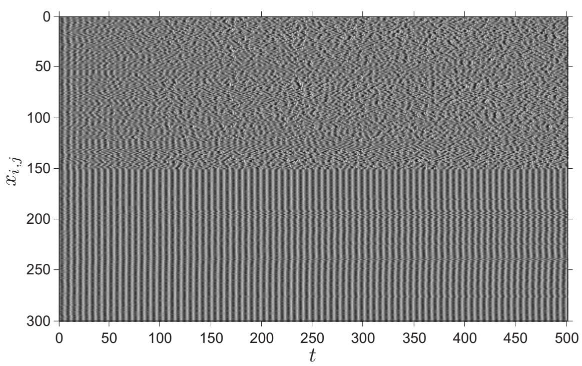
into the visual input image. The proposed model utilize the properties of chaos and phase synchronization to discriminate the salient object from the visual input while keeping the non-salient, or less salient, objects unsynchronized.

Computer simulations have shown that our model can be applied as an object selection model. Also, it is important to notice the robustness of the nontrivial phase synchronization, which requires only a small coupling strength in order to keep the oscillators phase synchronized. Moreover, phase synchronization can also be observed in nonidentical systems, which is a more plausible case that typically takes place in nature, where subsystems are never identical.

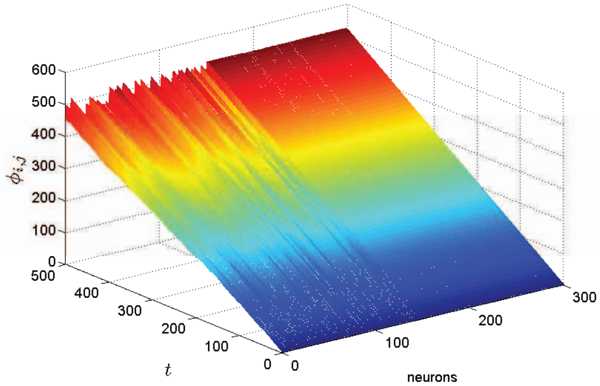
The model considers the contrast between an object and the whole scene, but it could be easily modified in order to consider the contrast between an object and its neighborhood as well, thus detecting the salient object in more homogeneous scenes, where although an object is not so different from all the others, it still gets the focus of attention due to the contrast among itself and its closer neighbors.

In this work the free parameters were set empirically

(a) Source image (320 × 240 pixels).



(b) Oscillators behavior.



(c) Phase growth.

Fig. 7: Real Image - "Flower".

according to the input image. The σ parameter defines how much the salient object will inhibit the other objects in the scene, as demonstrated in the second experiment. When the salient object is homogenous there is no harm in setting a high value for σ. However, when the scene presents a larger and more heterogenous salient object, the σ parameter has to be chosen carefully in order to prevent the salient object from inhibiting other parts of itself if this is not a desirable behavior. The other parameters are also sensitive, the positive coupling strength k cannot be set too low because it would not be able to keep the salient object synchronized, and neither it can be set too high because it would delay or even prevent the inhibition of non-salient objects. The $\Delta\omega$ parameter defines how much the oscillators will differ from each other based on their respective pixel intensity, and consequently it will also define their different oscillation speeds and how much their phases growth tend to be different when they are not coupled. Therefore, $\Delta\omega$ has to be carefully chosen, as it directly affects the synchronization of the salient object and the inhibition of the non-salient ones. As a future work, we intend to develop some mechanism to optimize these parameters automatically.

REFERENCES

[1] A. Pikovsky, M. Rosenblum, and J. Kurths, *Synchronization: A universal concept in nonlinear sciences*. Cambridge University Press, 2001.

[2] M. G. Rosenblum, A. S. Pikovsky, and J. Kurths, "Phase synchronization of chaotic oscillators," *Phisical Review Letters*, vol. 76, no. 7, pp. 1804–1807, March 1996.

[3] R. Eckhorn, R. Bauer, W. Jordan, M. Brosch, W. Kruse, M. Munk, and H. J. Reitboeck, "Coherent oscillation: A mechanism of feature linking in the visual cortex?" *Biological Cybernetics*, vol. 60, pp. 121–130, 1988.

[4] K. Engel, P. Knig, A. K. Kreiter, and W. Singer, "Interhemispheric synchronization of oscillatory neuronal responses in cat visual cortex," *Science*, vol. 252, pp. 1177–1178, 1991.

[5] P. Fries, J. H. Reynolds, A. E. Rorie, and R. Desimone, "Modulation of oscillatory neuronal synchronization by selective visual attention," *Science*, vol. 291, no. 5508, pp. 1560–1563, 2001.

[6] P. Gong, A. R. Nikolaev, and C. van Leeuwen, "Scale-invariant fluctuations of the dynamical synchronization in human brain electrical activity," *Neuroscience Letter*, vol. 336, pp. 33–36, 2003.

[7] M. Grey, P. Knig, A. K. Engel, and W. Singer, "Oscillatory responses in cat visual cortex exhibit inter-columnar synchronization which reflects global stimulus properties," *Nature*, vol. 338, pp. 334–337, 1989.

[8] Y. J. Kim, M. Grabowecky, K. A. Paller, K. Muthu, and S. Suzuki, "Attention induces synchronization-based response gain in steady-state visual evoked potentials," *Nature Neuroscience*, vol. 10, no. 1, pp. 117–125, 2007.

[9] V. N. Murthy and E. E. Fetz, "Coherent 25- to 35-hz oscillations in the sensorimotor cortex of awake behaving monkeys," *Academy Sci. USA*, vol. 89, pp. 5670–5674, 1992.

[10] C. von der Malsburg, "The correlation theory of brain function," Internal report 81-2: Max-Planck Institute for Biophysical Chemistry, Gttingen, Germany, Tech. Rep., 1981.

[11] D. Terman and D. L. Wang, "Global competition and local cooperation in a network of neural oscillators," *Physica D*, vol. 81, pp. 148–176, 1995.

[12] C. von der Malsburg and W. Schneider, "A neural cocktail-party processor," *Biological Cybernetics*, vol. 54, pp. 29–40, 1986.

[13] D. L. Wang and D. Terman, "Image segmentation based on oscillatory correlation," *Neural Computation*, vol. 9, pp. 805–836, 1997.

[14] D. L. Wang, "The time dimension for scene analysis," *IEEE Transactions on Neural Networks*, vol. 16, no. 6, pp. 1401–1426, 2005.

[15] D. Hansel, "Synchronization and computation in a chaotic neural network," *Physical Review Letters*, vol. 68, no. 5, pp. 718–721, 1992.

[16] L. Zhao and E. E. N. Macau, "A network of dynamically coupled chaotic maps for scene segmentation," *IEEE Transactions on Neural Networks*, vol. 12, no. 6, pp. 1375–1385, 2001.

[17] L. Zhao, E. E. N. Macau, and N. Omar, "Scene segmentation of the chaotic oscillator network," *International Journal of Bifurcation and Chaos*, vol. 10, no. 7, pp. 1697–1708, 2000.

[18] W. J. Jermakowicz and V. A. Casagrande, "Neural networks a century after cajal," *Brain Research Reviews*, vol. 55, no. 2, pp. 264–284, 2007.

[19] C. Buia and P. Tiesinga, "Attentional modulation of firing rate and synchrony in a model cortical network," *Journal of Computational Neuroscience*, vol. 20, pp. 247–264, 2006.

[20] E. Niebur and C. Koch, "A model for neuronal implementation of selective visual attention based on temporal correlation among neurons," *Journal of Computational Neuroscience*, vol. 1, pp. 141–158, 1994.
[21] F. Shic and B. Scassellati, "A behavioral analysis of computational models of visual attention," *International Journal of Computer Vision*, vol. 73, no. 2, pp. 159–177, 2007.
[22] J. K. Tsotsos, "On the relative complexity of active vs. passive visual search," *International Journal of Computer Vision*, vol. 7, pp. 127–141, 1992.
[23] L. Itti and C. Koch, "Computational modelling of visual attention," *Nature Reviews Neuroscience*, vol. 2, pp. 194–203, 2001.
[24] L. Carota, G. Indiveri, and V. Dante, "A softwarehardware selective attention system," *Neurocomputing*, vol. 58-60, pp. 647–653, 2004.
[25] D. L. Wang, "Object selection based on oscillatory correlation," *Neural Networks*, vol. 12, pp. 579–592, 1999.
[26] Y. Kazanovich and R. Borisyuk, "Object selection by an oscillatory neural network," *Biosystems*, vol. 67, pp. 103–111, 2002.
[27] M. G. Quiles, L. Zhao, and R. Romero, "A selection mechanism based on a pulse-coupled neural network," in *The 20th International Joint Conference on Neural Networks (IJCNN)*, Orlando-US, 2007, pp. 1–6.
[28] L. Zhao, F. Breve, M. Quiles, and R. Romero, "Visual selection and shifting mechanisms based on a network of chaotic wilson-cowan oscillators," in *The 3rd International Conference on Natural Computation (ICNC'07)*, Haikou-China, 2007, pp. 1–6.
[29] F. Varela, J.-P. Lachaux, E. Rodriguez, and J. Martinerie, "The brainweb: Phase synchronization and large-scale integration," *Nature Reviews Neuroscience*, vol. 2, pp. 229–239, April 2001.
[30] G. V. Osipov, A. S. Pikovsky, M. G. Rosenblum, and J. Kurths, "Phase synchronization effects in a lattice of nonidentical rössler oscillators," *Phys. Rev. E*, vol. 55, no. 3, pp. 2353–2361, Mar 1997.
[31] J. M. Wolfe and T. S. Horowitz, "What attributes guide the deployment of visual attention and how do they do it?" *Nature Reviews Neuroscience*, vol. 5, no. 6, pp. 495–501, June 2004.
[32] S. Yantis, "How visual salience wins the battle for awareness," *Nature Neuroscience*, vol. 8, no. 8, pp. 975–977, 2005.