Behavioral and Brain Sciences, vol. 20, No. 4, pp. 700-701, 1997

BBS Commentary

On the Computational Basis of Synchronized Codes

DeLiang Wang

Department of Computer and Information Science
and Center for Cognitive Science, The Ohio State University
Columbus, OH 43210-1277, USA

dwang@cis.ohio-state.edu; http://www.cis.ohio-state.edu/~dwang

Abstract

For scene analysis, it is important to ask the question of how synchronized population codes - the basic representation employed in the target article - are generated. Recent computational advances have resolved the critical challenges of rapid synchronization with local coupling and rapid desynchronization. The synchronized codes make real contributions to tackling the problem of scene analysis.

A fundamental aspect of perception is its ability to group elements of a perceived scene into coherent clusters (objects). This ability underlies perceptual processes such as perceptual organization, figure/ground segregation, and separation of multiple objects, and it is generally known as scene analysis (segmentation). Regarding this problem, Phillips and Singer (1997), in their general framework of cortical computation, have answered the following two basic questions explicitly. (1) How are coherent clusters represented in the brain? (2) What is the neurobiological substrate for the representation? Regarding the first question (the "binding problem"), the authors argue for synchronized population codes. That is, an object is represented by the synchronized firing activity of the scattered neurons coding different features of the object (Milner 1974; von der Malsburg 1981; Abeles 1982). As for the second question, the authors distinguish between receptive fields (RF) and contextual fields (CF), and argue that lateral CF connections linking RFs are the neurobiological substrate for the synchronized codes. There is another major question that needs to be addressed in the same context: (3) Given CF connections, *how* can the synchronized codes be generated? The question is a computational one, and is important for two reasons. First, it must be answered in order to explain how the brain analyzes various scenes in the framework of Phillips and Singer. Second, addressing this question would amount to constructing a computational system that does automatic scene analysis: an objective of great significance in its own right. Automatic scene analysis is a fundamental task of machine perception and a tremendously challenging engineering problem. This question, however, is not treated in any depth in the target article; dynamic grouping is touched upon in Sect. 3.4.3, but, from the computational perceptive, the functionality is simple and it is unclear how the networks generalize to handle realistic input patterns. On the other hand, there is a large body of literature that deals exclusively with this question, and major progress has been made. My commentary is focused on this issue as it has important implications on the computational foundation of the target article.

The discovery of long-range synchronous oscillations in the visual cortex (Eckhorn et al. 1988; Gray et al. 1989) triggered many computational studies on the synchronized codes. There are two major computational challenges. The first is how to achieve rapid synchronization within a population of locally coupled oscillators[1]. Earlier models proposed for achieving phase synchrony generally rely on all-to-all connections. However, a network with full connectivity indiscriminately connects and synchronizes all activated oscillators; it lacks topological information (Sporns et al. 1991; Wang 1993b). The indiscriminate grouping problem hinders this class of models from addressing real images. The second challenge is how to achieve fast desynchronization among different groups of oscillators representing distinct objects. We regard the rapidity of synchrony and desynchrony as particularly important, not only because speed is critical for real-time scene analysis but also because perception is very rapid. It is known that human subjects can segment and identify an object in a small fraction of a second (Biederman 1987; I. Biederman, personal communication, 1994). This suggests that both synchrony and desynchrony must be achieved in just a few cycles if the synchronized codes of 40 Hz rhythms (Eckhorn et al. 1988; Gray et al. 1989) are the underlying mechanism. Because of these two challenges, the synchronized codes have not contributed much to building successful artificial neural systems for analyzing real images.

Somers and Kopell (1993) and Wang (1993a; 1995) have independently recognized the severe limitations of widely used sinusoidal oscillators in generating global synchrony based on local coupling, and proposed to use different oscillator models to overcome the problem. More recently, Terman and Wang have proposed and analyzed locally excitatory globally inhibitory oscillator networks (LEGION) (Terman & Wang 1995; Wang & Terman 1995). In a LEGION network, each oscillator is modeled as a standard relaxation oscillator with two time scales (see also Somers & Kopell 1993). Local excitation is implemented by lateral coupling, and global inhibition is realized by a global inhibitor. Whether an oscillator can oscillate is determined by the external stimulus to the oscillator, and the connections in LEGION modify only the phases of oscillators. Thus, the LEGION network is fully compatible with the general RF/CF framework of the target article. The network exhibits a mechanism of *selective gating*, whereby an oscillator jumping up to the active phase rapidly recruits the oscillators stimulated by the same pattern, while preventing other oscillators from jumping up. We have proven that, with selective gating, the network rapidly achieves both synchronization within groups of oscillators that are stimulated by connected regions and desynchronization between different groups. To sum, the LEGION network provides an elegant solution to the two challenges outlined above.

A **B**

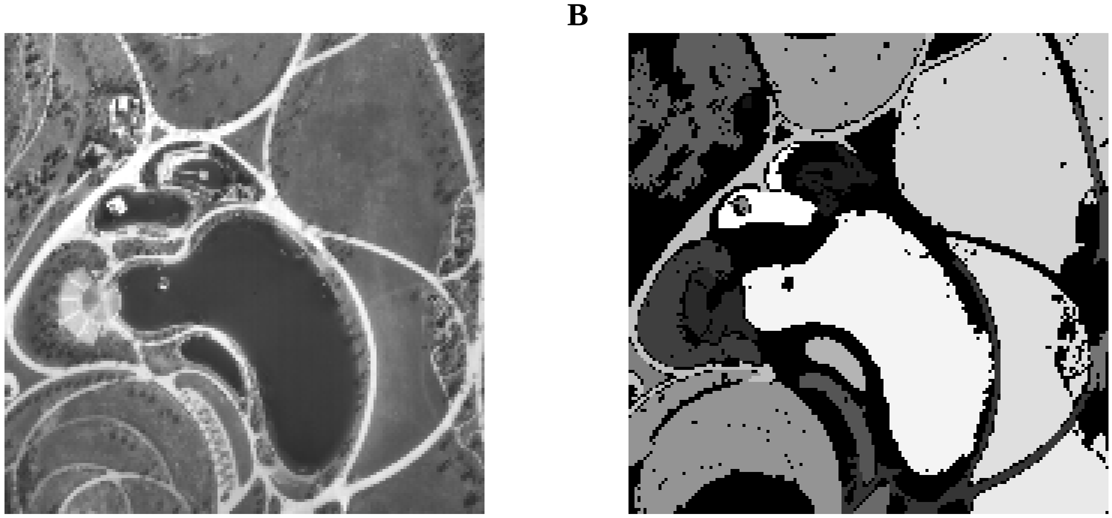

Figure 1. **A** A gray-level image consisting of 160x160 pixels. **B** The result of segmentation by a LEGION network with 160x160 oscillators. (from Wang and Terman, 1997)

The ability of LEGION in producing the synchronized codes presents a unique approach to addressing scene analysis. Wang and Terman (1997) applied LEGION to segmenting gray-level images, and reported very promising results. For gray-level images, each oscillator corresponds to a pixel, and two neighboring oscillators are connected with a weight proportional to corresponding pixel similarity. As an example, Fig. 1A shows one gray-level image, and Fig. 1B shows the result of segmentation. The entire image is segmented into 23 regions. Each region corresponds to a different density in the figure, indicating the phases of oscillators. In the simulation, different regions "pop out" alternately. As can be seen from Fig. 1B, almost all major regions in Fig. 1A are segmented. The black scattered regions in the figure represent the background that always remains inactive (see for details Wang & Terman, 1997). Other images, including MRI (magnetic resonance imaging) images and texture images, have also been successfully segmented.

In summary, I think it is important to ask the question of how the synchronized codes can be generated. Major advances have been made in addressing this question. In particular, the critical challenges of rapid synchrony based on lateral coupling and rapid desynchrony have been successfully resolved, and these synchronized codes make real contributions to tackling the hard engineering problem of scene analysis. These advances lay a sound computational ground for the theoretical framework of Phillips and Singer.

Acknowledgements Thanks to R. Lewis for helpful comments on an earlier version.

Notes

1. An "oscillator" here is used as a mathematical notion, and this does not necessarily imply an oscillatory (periodic) outcome. An oscillator is compatible with a spiking neuron.

References

Abeles, M. (1982) Local cortical circuits. Springer-Verlag.

Biederman, I. (1987) Recognition-by-component: A theory of human image understanding. Psychological Review 94: 115-147.

Eckhorn, R., Bauer, R., Jordan, W., Brosch, M., Kruse, W., Munk, M. & Reitboeck, H.J. (1988) Coherent oscillations: A mechanism of feature linking in the visual cortex. Biological Cybernetics 60: 121-130.

Gray, C. M., König, P., Engel, A. K. & Singer, W. (1989) Oscillatory responses in cat visual cortex exhibit inter-columnar synchronization which reflects global stimulus properties. Nature 338: 334-337.

Milner, P. M. (1974) A model for visual shape recognition. Psychological Review 81: 521-535.

Phillips, W.A. & Singer, W. (in press). In search of common foundations for coritical computation. Behavioral and Brain Sciences, in press.

Somers, D. & Kopell, N. (1993) Rapid synchrony through fast threshold modulation. Biological Cybernetics 68: 393-407.

Sporns, O., Tononi, G. & Edelman, G. M. (1991) Modeling perceptual grouping and figure-ground segregation by means of active re-entrant connections. Proceedings of the National Academy of Sciences USA 88: 129-133.

Terman, D. & Wang, D. L. (1995) Global competition and local cooperation in a network of neural oscillators. Physica D 81: 148-176.

von der Malsburg, C. (1981) The correlation theory of brain function. Internal Report 81-2, Max-Planck-Institute for Biophysical Chemistry.

Wang, D. L. (1993a) Modeling global synchrony in the visual cortex by locally coupled neural oscillators. Proceedings of the Fifteenth Annual Conference of the Cognitive Science Society, pp. 1058-1063.

Wang, D. L. (1993b) Pattern recognition: Neural networks in perspective. IEEE Expert 8: 52-60, August.

Wang, D. L. (1995) Emergent synchrony in locally coupled neural oscillators. IEEE Transactions on Neural Networks 6: 941-948.

Wang, D. L. & Terman, D. (1995) Locally excitatory globally inhibitory oscillator networks. IEEE Transactions on Neural Networks 6: 283-286.

Wang, D. L. & Terman, D. (1997) Image segmentation based on oscillatory correlation. Neural Computation 9: 805-836 (For errata see Neural Computation 9: 1623-1626).