

Emergent Synchrony in Locally Coupled Neural Oscillators

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Abstract—The discovery of long range synchronous oscillations in the visual cortex has triggered much interest in understanding the underlying neural mechanisms and in exploring possible applications of neural oscillations. Many neural models thus proposed end up relying on global connections, leading to the question of whether lateral connections alone can produce remote synchronization. With a formulation different from frequently used phase models, we find that locally coupled neural oscillators can yield global synchrony. The model employs a previously suggested mechanism that the efficacy of the connections is allowed to change on a fast time scale. Based on the known connectivity of the visual cortex, the model outputs closely resemble the experimental findings. Furthermore, we illustrate the potential of locally connected oscillator networks in perceptual grouping and pattern segmentation, which seems missing in globally connected ones.

I. INTRODUCTION

A fundamental aspect of perception is to bind spatially separate sensory features to form coherent objects, essential for object identification, segmentation of different objects, and figure/ground segregation. Theoretical considerations point to the temporal correlation of feature detectors as a binding mechanism [1]–[3]. The temporal correlation theory [1] asserts that in the brain remote cells coding different sensory features are bound together if their temporal activities (such as firing patterns) show strong correlation. Thus, an object may be analyzed and represented by cell groups across different brain regions, generally consistent with known neurobiological findings [4]. As shown in von der Malsburg and Schneider [3], neural oscillations provide a natural way of implementing temporal correlation, whereby synchronized oscillators form an oscillator group to represent the common object, and groups desynchronized from each other represent different objects. More recently it was demonstrated that the cat visual cortex exhibits 40–60 Hz stimulus-dependent oscillations, and synchronization exists in spatially remote columns (up to 7 mm) which reflects global stimulus properties [5], [6]. Later experiments further show that phase-locking can occur between the striate cortex and the extrastriate cortex [7],

between the two striate cortices of the two brain hemispheres [8], and across the sensorimotor cortex [9].

Since the discovery of stimulus-driven oscillations and long-range synchronization in the visual cortex, many theoretical attempts have been made to interpret the phenomenon of global phase locking with no phase shift (to be called phase locking hereafter) [10]–[14]. Others have employed computational characteristics of temporal oscillations for solving problems of pattern segmentation and figure/ground segregation [3], [15]–[18], and associative memory [19], [20]. Most of these models rely on a globally connected oscillator network to reach synchronization (phase entrainment) across the network. A frequently used scheme is the phase model [11], [12], [15] which represents each oscillator by a sole phase variable and describes mutual coupling by an odd periodic function such as sine. The simplest form of the phase model can be defined as

$$\frac{d\theta_i}{dt} = \omega_i + \sum_j \sin(\theta_j - \theta_i) \quad (1)$$

where θ_i is the phase of oscillator i and ω_i represents the internal frequency and/or the external input. Characteristics of the systems of coupled phase models have been extensively analyzed in mathematics and theoretical physics (known as the X-Y models) literature [21]–[26]. While global coupling readily yields phase locking, a system with only local coupling does not seem to be able to generate global synchrony in the presence of noise.

Although Sporns *et al.* [10] and Chawanya *et al.* [14] used local connections in simulating the experimental data, their simulations only demonstrated correlation of a few oscillators and their models do not seem to be capable of producing long-range synchrony. An exception is the model by König and Schillen [13] who simulated global synchrony with local connections. Their model is based on delays between an excitatory unit and an inhibitory unit to generate oscillations. In particular, the model requires an assumption that the delay from the excitatory unit of an oscillator X to the inhibitory unit of X is on the same order as the delay between the coupled oscillators, namely the delay from the excitatory unit of X to the inhibitory units of all local oscillators that X projects to.

We consider it critically important to form synchrony using only local connections, to support useful computations, particularly pattern segmentation, by neural oscillations. The reason is that long-range, all-to-all connections lose geometrical relationships among oscillators, important for perceptual grouping,

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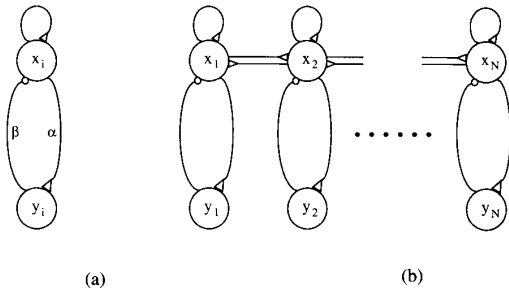


Fig. 1. (a) Basic oscillator model formed by a feedback loop between an excitatory unit x_i and an inhibitory unit y_i . α and β are mutual connection strengths. (b) A chain of N oscillators. Small triangles indicate excitatory connections, and small circles inhibitory connections.

thus leading to indiscriminate synchronization. This point will be emphasized in Section IV. This paper reports a new model that can demonstrate stable long-range synchrony based on only local coupling in a network of neural oscillators. Based on plausible neural mechanisms, we use the model to simulate the experimental data of synchronous oscillations in the visual cortex. Also, we illustrate how such a network may be used to solve the engineering problem of pattern segmentation. A preliminary version of this work has been presented previously [27].

II. MODEL DESCRIPTION

As the building block, the model of a single oscillator is defined in the simplest form as a feedback loop between an excitatory unit and an inhibitory unit [Fig. 1(a)]

$$\frac{dx_i}{dt} = -x_i + g_x(x_i - \beta y_i + S_i + I_i + \rho) \quad (2a)$$

$$\frac{dy_i}{dt} = -\gamma y_i + g_y(\alpha x_i) \quad (2b)$$

$$g_r(\nu) = \frac{1}{1 + \exp[-(\nu - \theta_r)/T]}, r \in \{x, y\} \quad (2c)$$

where α and β are positive parameters describing the coupling between the two units. Adding an inhibitory feedback to the inhibitory unit as in [17] and [19] does not seem to change the qualitative behavior. S_i represents the inputs from other oscillators and I_i represents external stimulation. λ is a decay parameter, and ρ denotes the amplitude of a Gaussian noise term. $g_r(\nu)$ is a sigmoid gain function with threshold θ_r , where $r \in \{x, y\}$, and parameter T .

Equation (2) is essentially a simplification of the system proposed by Wilson and Cowan [28], and it has been shown that the system produces oscillations within a wide range of parameters [19], [28], [29]. Fig. 2 shows a typical limit cycle drawn on the x - y plane, as exhibited by a single oscillator. The two nullclines split the x - y plane into four regions. Within each region, dx/dt and dy/dt have unique signs. For example, $dx/dt < 0$ and $dy/dt < 0$ in the upper-left region (where the starting point lies in). Thus, both x and

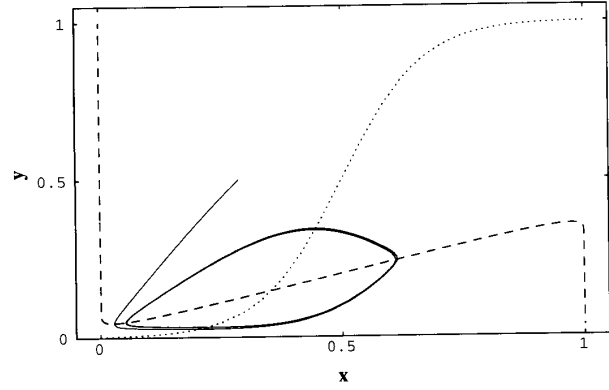


Fig. 2. Nullclines and limit cycle trajectory of a single oscillator as shown in the phase plane. The x -nullcline ($dx/dt = 0$) is shown by the dashed curve and the y -nullcline ($dy/dt = 0$) is shown by the dotted curve. The oscillator started from a randomly generated point, the end point near (0.3, 0.5), and it quickly fell in the trajectory of a limit cycle. The parameters for this simulation are $a = 0.3$, $b = 2.5$, $r = 0.01$, $\theta_x = 0.2$, $\theta_y = 0.15$, $T = 0.025$, $l = 1.0$, and $I = 0.2$. 2000 integration steps.

y decrease in this region until the trajectory intersects with the x -nullcline. After the intersection, the trajectory moves into the lower-left region where $dx/dt > 0$ and thus x starts to increase. Following this type of qualitative analysis, one can see why (2) gives rise to oscillations. As in the following simulations, the equations were numerically solved with the simple Euler method, where $\Delta t = 0.01$. The results were also confirmed using the fourth-order Runge-Kutta method. The oscillator model can be biologically interpreted as a mean field approximation to a network of excitatory and inhibitory neurons [10], [30], [31].

To see the detailed behavior of an isolated single oscillator, Fig. 3 presents the simulation of the system with different parameters. Fig. 3(a) shows that if the external input is very small, the oscillator will be silent; but if the input is very high, the system reaches a saturation point. Oscillations (limit cycles) occur between the two extremes. In other words, oscillations are driven by input, as opposed to the phase model where oscillation is built into the system. Fig. 3(b) shows that γ controls the frequency of oscillations, and Fig. 3(c) demonstrates that α has a major influence on the amplitude of oscillations.

Weak coupling between oscillators (S_i is relatively small) does not disrupt the oscillatory behaviors of individual oscillators. To study the properties of a network of oscillators, first a chain of N oscillators is constructed with only neighboring coupling between excitatory units, as shown in Fig. 1(b). We define the coupling as

$$S_i = \begin{cases} W(x_{i-1} + x_{i+1}) & \text{if } 1 < i < N \\ 2Wx_2 & \text{if } i = 1 \\ 2Wx_{N-1} & \text{if } i = N \end{cases} \quad (3)$$

where W is a connection weight. Note that the weights connecting to the two end oscillators 1 and N double those of the connections to the other interior ones in the chain. We

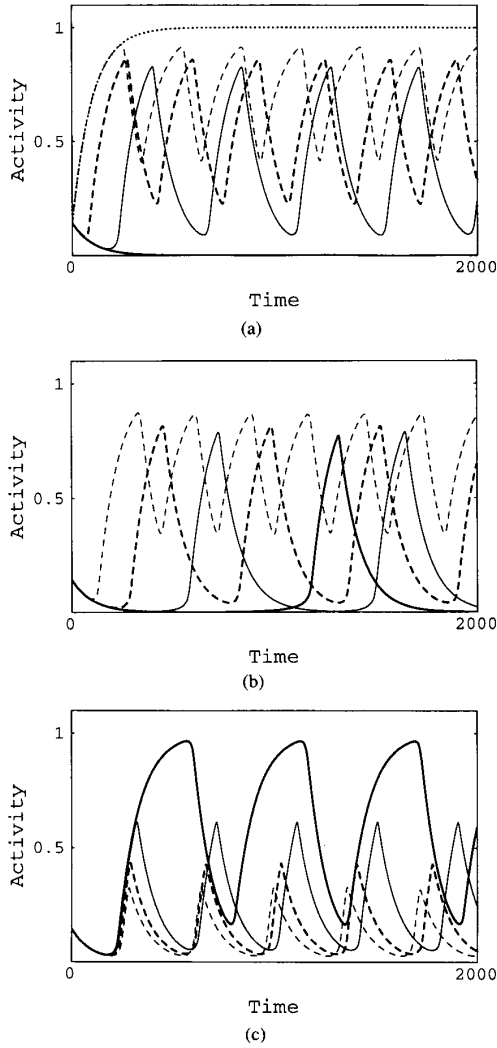


Fig. 3. Behavior of a single oscillator. (a) Effect of varying external input. Solid thick, $I = 0.0$; solid thin, $I = 0.2$; dashed thick, $I = 0.4$; dashed thin, $I = 0.8$; dotted, $I = 1.6$. $\lambda = 1.0$ and $\alpha = 0.2$. (b) Effect of varying λ . Solid thick, $\lambda = 0.2$; solid thin, $\lambda = 0.4$; dashed thick, $\lambda = 0.8$; dashed thin, $\lambda = 1.6$. $I = 0.2$ and $\alpha = 0.2$. (c) Effect of varying α . Solid thick, $\alpha = 0.15$; solid thin, $\alpha = 0.3$; dashed thick, $\alpha = 0.45$; dashed thin, $\alpha = 0.6$. $I = 0.2$ and $\lambda = 1.0$. The other parameters are the same as in Fig. 2. 2000 integration steps.

found, remarkably, with uniform external input and random values for x_i and y_i (namely random phases) initially, that the chain with coupling (3) is synchronized after an initial period of rapid phase transitions.¹ The synchronization is absent, however, if the connections to the end oscillators are equally strong as to the interior ones. Instead we found phase shifts across the chain. Fig. 4 presents a simulation with $N = 30$. Note that there were small phase differences when

¹Independent of my study (see [27] and also [32]), Somers and Kopell [33] demonstrated phase synchrony in a ring of oscillators. Their oscillators differ from ours in the use of two time scales for the excitatory and inhibitory units of an oscillators (so-called relaxation oscillators).

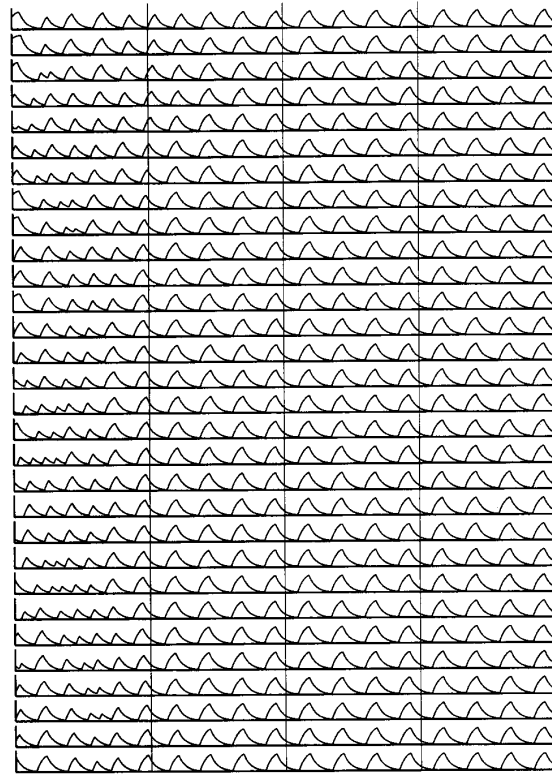


Fig. 4. Synchrony in a chain of oscillators. The input $I_i = 0.8$, and the initial values $x_i(0)$ and $y_i(0)$ were randomly generated within the range $[0, 0.8]$. The height of the ordinate of each oscillator is one. $W = 0.6$ and $N = 30$. The parameters $\alpha = 0.2, \theta_x = 0.6$, and the remaining ones are the same as in Fig. 2. 8000 integration steps. Vertical lines are drawn to help identify phase relations among the oscillators.

nearly stable limit cycles started to occur, but the differences diminished as time went on.

A chain of oscillators using the phase model has been extensively studied for modeling swimming behaviors in fish [21], [22]. Cohen *et al.* [21] noted that phase-locking with no phase shift can be reached with a chain of identical oscillators. Phase-locking, however, cannot be produced if there is inhomogeneous input to a chain, contradicting the experimental conditions of Gray *et al.* [6], where synchrony can occur even if two stimulus bars are not connected (more discussion in the next section). For this reason, the chain model was considered not proper for modeling the phase locking experiments [11]. But, as will be clear later, our model does not suffer from this problem.

Equation (3) is not a necessary condition for phase-locking. Let us call an oscillator active if it receives an external stimulus. We observed that in a system defined by (2), as long as the overall (sum of) weights of the connections converging on every active oscillator from all other active oscillators are kept constant, phase-locking occurs. This condition is called the equal weight condition. Equation (3) is a special case of this condition. It is easy to show that without noise ($\rho = 0$) homogeneous inputs lead to the solution of synchronized oscillations to (2). When the system is in synchrony, $x_i = x_j$,

for $i, j = 1, \dots, N$. With the equal weight condition, we have $S_i = S_j$, and thus $dx_i/dt = dx_j/dt$, and $dy_i/dt = dy_j/dt$, for $i, j = 1, \dots, N$. Therefore, the system will keep the synchrony in its evolution. We are presently unable to prove the stability of the synchronized solution. Extensive numerical simulations have been conducted however, and we found that the system is stable with respect to perturbations by noise once it reaches synchronous oscillations.² Intuitively, positive coupling between neighboring oscillators serves to drive the oscillators close to each other in phase and it can also correct small discrepancies among the phases of the oscillators. We have tested one dimensional chains of up to 256 oscillators and two dimensional grids of up to 100 by 100, and synchrony in such systems is stable. So even the conclusion concerning long range synchrony might not be established when the size of the network tends to infinity, the significance of the system studied here does not vanish because almost all practical applications of oscillator networks, such as image analysis (see Section IV), require only limited sizes.

The equal weight condition is easily achieved if one allows connection weights to be dynamically modified on a fast time scale, an idea first introduced by von der Malsburg [1]. In this scheme, there is a pair of connection weights from oscillator j to i , one permanent T_{ij} , and another dynamic J_{ij} (so called Malsburg synapses, see [35]). Permanent links reflect the hardwired structure of a network, while dynamic links quickly change from time to time. In computations, though, only dynamic links formed on the basis of permanent links play an effective role. The equal weight condition can be naturally realized by a modification rule of dynamic links which combines a Hebbian rule [36] that emphasizes coactivation of oscillators i and j and a normalization of all incoming connections to an oscillator. More specifically, it can be implemented by a two-step procedure: First update dynamic links and then normalization

$$\Delta J_{ij} = \delta T_{ij} h(x_i) h(x_j) \quad (4a)$$

$$J_{ij} = \gamma (J_{ij} + \Delta J_{ij}) / \left[\varepsilon + \sum_k (J_{ik} + \Delta J_{ik}) \right] \quad (4b)$$

where δ and γ are positive parameters, and function $h(x)$ measures whether x is active. It is here simply defined as $h(x) = 1$ if $\langle x \rangle$ is greater than a constant and $h(x) = 0$ otherwise, where the angular bracket $\langle x \rangle$ stands for temporal averaging of the activity x . ε ($\varepsilon \ll 1$) is introduced to prevent division by zero. Note that weight normalization of this form is commonly used in neural network models for competitive learning [37], [38].

²We note that this result appears in contradiction with the well-known theorem of Mermin and Wagner [34] in statistical mechanics. The theorem states that no long-range order (synchrony) exists in one- or two-dimensional isotropic Heisenberg models (X-Y models). The fact that our system (2) is not an equilibrium statistical mechanical system and it is not isotropic (see Figs. 2 and 3) makes it not subject to the theorem. On the other hand, sinusoidal oscillators, such as the one defined in (1), tend to be isotropic and are probably subject to the theorem. This might account for the qualitative difference between nonsinusoidal and sinusoidal oscillators. (Kopell and Somers [33] have also realized the qualitative difference between sinusoidal and relaxation oscillators). The author is indebted to Drs. J. Cheyres and C. Jayaprakash who assured him of this observation.

With introduction of fast changing synapses, the equal weight condition in (3) can now be reached by dynamics in (4) from a natural condition $S_i = T(x_{i-1} + x_{i+1})$, $1 \leq i \leq N$, and $x_0 = x_{N+1} = 0$ defined for permanent links, where T is the strength of every permanent link. In other words, the same permanent link is established for only neighboring oscillators, and there is no permanent connection beyond nearest neighbors. Because of this, dynamic links can be established for only neighboring oscillators according to (4a). Since the entire chain is stimulated, $h(x_i) = 1$ for $1 \leq i \leq N$. Following (4), after a very brief beginning period, $J_{ij} = \gamma/2$ if oscillators i and j are nearest neighbors and $i \neq 1$ or N . Additionally, $J_{12} = J_{N,N-1} = \gamma$. This connection pattern of dynamic (effective) links is equivalent to (3) if one lets $W = \gamma/2$.

It should be obvious that the result concerning global synchrony extends to oscillator networks of higher dimensions than one-dimensional (1-D). A prototype of (two-dimensional (2-D) network is illustrated in the next section. Also, the result is established for lateral connections beyond nearest neighbors. Indeed, more extensive connections can speed up the synchronization process. In a sense, synchrony in fully connected networks is a special case of our result based on local coupling.

III. MODELING CORTICAL OSCILLATIONS

With the above analysis, we now simulate the experiments of Gray *et al.* [6] with a two-dimensional layer of 10×24 oscillators. The oscillator layer is constructed such that each oscillator laterally connects to its eight nearest neighbors, 16 second nearest neighbors, and 24 third nearest neighbors. Each oscillator is assumed to represent a single distinct receptive field. The permanent coupling strengths are isotropic and fall off with distance. This kind of lateral connections is present in the primary visual cortex in the form of horizontal connections [39]. Proper dynamic connections are formed according to (4). Following the experimental configurations, Fig. 5 presents the model response to two light bars each corresponding to 2×7 oscillators separated by zero, two, and four oscillator positions. Oscillators under the bars were uniformly stimulated while other oscillators received no input. Cross-correlations were computed for two oscillators within a bar and between the bars and then normalized for each trial.³ Our simulation results are presented in the similar format as used by König and Schillen [13], which illustrates the results in a way readily comparable with the corresponding experimental results. The upper panels of Fig. 5 show stimulus configurations, and the lower panels present the correlograms. The cross-correlations within a bar (dashed lines) are compared to those between bars (solid lines). When two bars formed a single long bar [Fig. 5(a)], the between-bar correlation was as good as the within-bar correlation, showing that phase-locking was reached across the entire long bar. When two bars were separated by two oscillator positions, the between-bar correlation is a little weaker than the within-bar correlation, but is still significant.

³The cross correlation $C(\tau)$ between two time functions $x_1(t)$ and $x_2(t)$ is $C(\tau) = \langle x_1(t)x_2(t+\tau) \rangle$.

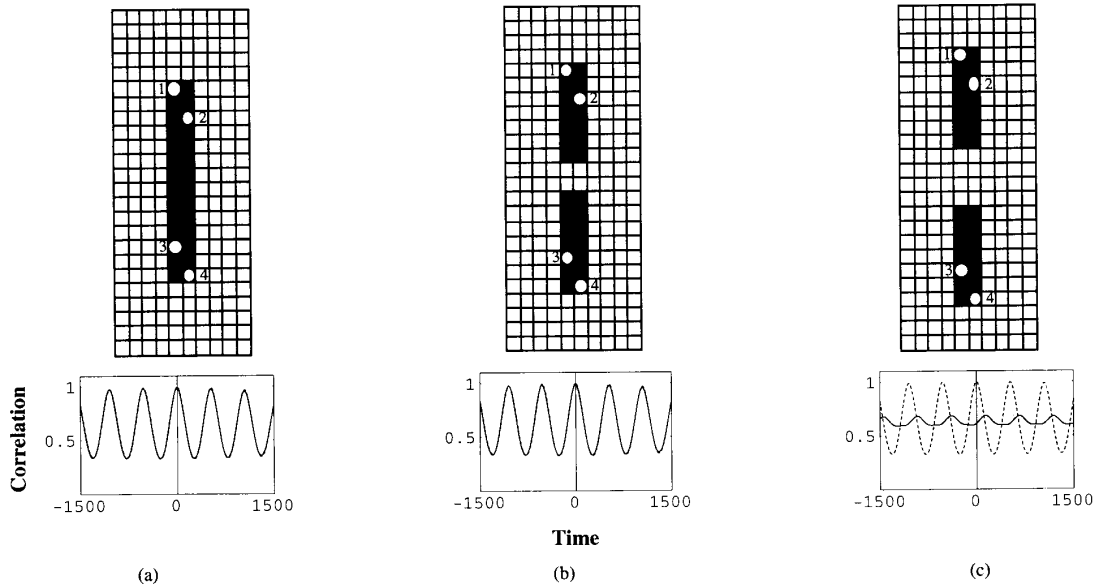


Fig. 5. Cross-correlation within and between two bars in a two-dimensional layer of locally coupled oscillators. The ratio of the coupling strengths of nearest, second nearest, and third nearest neighbors is 2:1.6:1, respectively. The overall incoming connection strength for each oscillator was normalized to 1.25. (a) The two bars form a single long bar. (b) The two bars are separated by two oscillator positions. (c) The two bars are separated by 4 positions. The dashed lines are the normalized cross-correlation within (1-2, 3-4) and the solid lines between (1-3) the two bars. The average of 10 simulations is shown as in the experiments of Gray *et al.* [6]. The oscillators under the bars received external input $I_i = 0.8$, and the remaining ones received no external input. The initial values $x_i(0)$ and $y_i(0)$ were randomly generated within the range $[0, 0.5]$. The rest of the parameters are the same as in Fig. 4. Cross-correlations were computed for a time interval of 10000 integration steps after omitting the initial 3000 steps.

The correlations in Fig. 5(b), however, are weaker than in Fig. 5(a), because the configuration in Fig. 5(b) took longer to reach phase-locking due to weaker links between the two bars. All these results well match the experimental data [6]. In Fig. 5(c), however, the between-bar correlation is minimal while the within-bar correlation is almost perfect, showing that phase-locking was readily reached within each bar but there was no phase relationship between the two bars. Note that, in this case, there was no direct link between the two bars. The simulation results demonstrate that the visual cortex with its own lateral (horizontal) connections is capable of producing phase-locking of stimulus-driven oscillations, without resort to a global phase coordinator [11], all-to-all connections [12], or fixed phase relations among oscillators [13].

In terms of the oscillator activities, the similar pattern of Fig. 4 occurred in the two-dimensional case, i.e., a period of rapid transitions appeared in the beginning and it then gave way to stable oscillations with phase locking. The conduction delays between oscillators have been neglected in the above modeling (there is always one discretization step delay in numerical integration), because the delays resulting from neighboring projections are generally much smaller than the periods of the oscillators. Introducing some delays in the horizontal connections does not necessarily yield phase shifts, as one might expect, since neighboring oscillators are mutually connected and they receive external input simultaneously. Our preliminary observations show that up to 0.5 ms delay (assuming 40 Hz oscillations) between neighboring oscillators does not prevent the chain from reaching synchronous oscillations.

IV. WHY LOCAL CONNECTIONS?

Temporal correlation promises to provide a conceptual framework for object segmentation and figure/ground segregation [1], [3], [15]–[18], a tremendous problem facing the current technology of general pattern recognition [40]. There is an outstanding obstacle to this idea, however, if synchrony can only be produced with long-range connections as in associative memory models or with a global phase coordinator (they are computationally equivalent). A network with long-range connections is dimensionless, and loses the critical information of geometry. Thus it would lead to indiscriminate synchronization among all object features, contrary to Gestalt laws of perceptual grouping that emphasizes spatial and temporal relationships of the objects [41], [42]. This point can be clearly illustrated in Fig. 6(a), where two objects, a desk lamp and a cup, are placed on a two-dimensional 15×15 grid. One can easily segment them solely on the basis of connectedness, which turns out to be one of the most important Gestalt grouping principles [42]. If the oscillators on the grid are fully connected, however, there would be no way to segment the two, since an active oscillator, say, triggered by the cup image, projects indiscriminately to the other oscillators activated by the cup as well as the ones activated by the desk lamp. This is the case even we take into account the orientation sensitivity, so that only the oscillators triggered by the same orientation are fully connected as used in [12] and [15].

We believe that the mechanism elucidated here provides a way out of this predicament. Sensory segmentation can

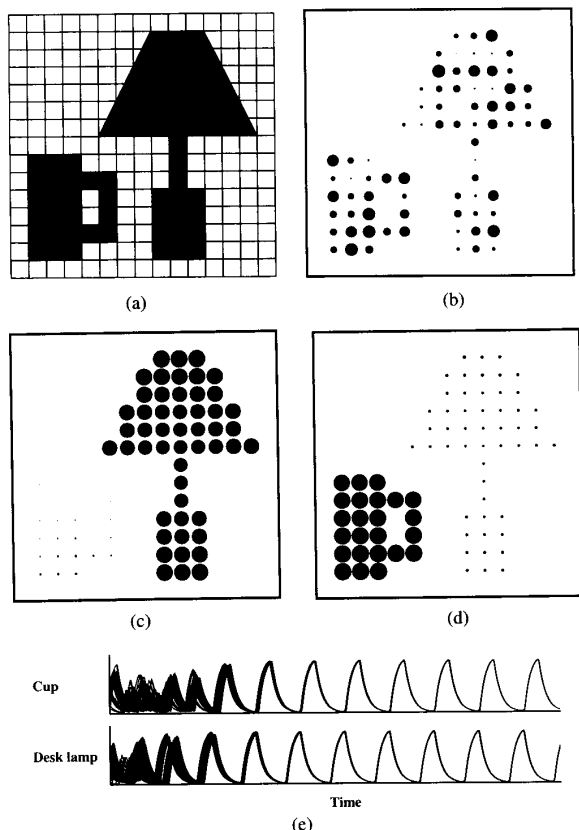


Fig. 6. Pattern segmentation based on local coupling of neural oscillators. (a) The two images, representing a "cup" and a "desk lamp," are presented to a 15×15 matrix of oscillators with nearest neighbor connections (See also [38]). (b) A snapshot of the activities of the oscillator grid at the beginning of dynamic evolution. (c). A snapshot of the activities of the oscillator matrix several cycles after the beginning. (d) Another snapshot taken shortly after (c) In these displays, the x activity of an oscillator is denoted by the radius of the corresponding circle, and only the oscillators with nonzero activity are shown. (e) The upper trace shows the combined temporal activities of the oscillators representing the cup image, and the lower trace shows those representing the desk lamp image. The height of each ordinate is one. Stimulated oscillators received external input $I_i = 0.7$, and $I_i = 0$ for the remaining ones. The initial values $x_i(0)$ and $y_i(0)$ were randomly generated within the range $[0, 0.8]$. The parameters for a single oscillator are the same as in Fig. 2 except that $\alpha = 0.6$; $\theta_x = 0.7$. The overall incoming connection strength for each oscillator was normalized to 1.5. 7000 integration steps.

now be accomplished based on general architectures with connections only in neighboring units. The two-dimensional matrix of Fig. 5 can readily serve for segmentation based on connectedness and proximity, known to be essential for perceptual grouping. Let us demonstrate it by solving the segmentation problem of Fig. 6(a). Each cross point in the grid is represented by an oscillator defined in Section II, and each oscillator is only connected to its four nearest neighbors except boundary ones where we assume no wrap-around. The objects are presented to the model simply by setting the inputs to the oscillators covered by the objects to a high value. Thus, the stimulated oscillators are activated, while the others are inactive. The phases of the activated oscillators were initially randomized. With the dynamic links in place, the

oscillators belonging to the same connected region are quickly entrained. That is, the oscillators constituting the cup image are synchronized, and the same is true for those constituting the desk lamp image. But since there is no interconnections between the two objects, their oscillations are not correlated. The rest of Fig. 6 shows the simulation results. Fig. 6(b) shows a snapshot (instant activity) of the oscillator network shortly after the images were applied to the network. As is clear from the figure, the phases of the oscillators were fairly random. But, just a few cycles later, the oscillators representing each object were synchronized, which can be seen by the same amplitudes of oscillations exhibited by those oscillators. Fig. 6(c) and 6(d) show two other snapshots after synchrony across each image was established, where in Fig. 6(c) the desk lamp image dominates and in Fig. 6(d) the cup dominates. The entire temporal process of reaching synchrony within each object is shown in Fig. 6(e), where the two traces represent the combined oscillatory activities of the oscillators belonging to the two objects respectively. The synchronized oscillations within each object are clearly shown just a few cycles after the beginning of dynamic evolution.

In the above simulation, no attempt was made to desynchronize the oscillators belonging to different objects, which should be included in a full system of pattern segmentation. We can achieve desynchronization by introducing a global inhibitor that receives inputs from the entire network and inhibits back. Equivalently, the global inhibitor can be replaced by long-range weak mutual inhibitions (see [19] for such an example). Desynchronization among different patterns will be dealt with in a different paper. It now suffices to mention that we can separate the phases of several patterns by using a global inhibitor to an oscillator network discussed in this paper.

V. DISCUSSION

This paper provides a mechanism for reaching emergent synchrony in a network of oscillators by only local connections. There are two main parts to this mechanism: 1) a more detailed, possibly more plausible, oscillator model is used and 2) the dynamic normalization principle (4) to ensure the equal weight condition for the communication among the oscillators. Dynamic normalization provides a quantitative procedure for the idea of dynamic links, which has been argued to be neurally plausible (see [1] and [35]). Based on this mechanism, the simulation results of synchronous oscillations in the visual cortex well match the corresponding experimental results. We note that the models of Sporns *et al.* [10], König and Schillen [13], and Chawanya *et al.* [14] can also simulate the experimental results based on local coupling. Our model differs from Sporns *et al.* [10] and Chawanya *et al.* [14] in that we provide a general mechanism of reaching global synchronization based on local connections. As stated in the introduction, the model of König and Schillen [13] relies on specific delay relations to obtain phase synchronization, while ours does not.

Perhaps more importantly, we consider that synchronous oscillations based on local connections represent a significant step towards solving engineering problems of pattern segmen-

tation and figure/ground segregation. Although a number of attempts have been made to use neural oscillations for solving the problem of sensory segmentation [3], [12], [15], [17], [18], the progress in general is very limited and does not meet people's expectations (see [1]). We think that the lack of a local mechanism has been one of the major difficulties to be overcome before neural oscillations can play a significant role in machine pattern analysis.

The network architecture illustrated in Section IV lays a ground for a novel approach to neural pattern segmentation. The permanent connection pattern [T_{ij} 's of (4)] of the network defines the innate architecture, which is simple and sufficiently general. Dynamic connections (J_{ij} 's) are formed on the basis of the permanent connections and current input patterns. Synchronous oscillations make the result of segmentation readily utilizable—a simple threshold function would do the job. The neighborhood connectivity pattern preserves the geometrical structures of the objects. If one allows lateral connections beyond nearest neighbors or adds more layered structures of the network, both the capability and the flexibility of pattern segmentation should be markedly enhanced. These features are very attractive compared to the traditional approach of image segmentation, where edge detection is followed by contour detection and then a process of labeling different regions based on closed contours, among other heuristics [43], [44]. The approach offered here directly operates on objects, without the detour of detecting contours from regions and then forming regions based on contours, often an ambiguous process.

Of course, pattern segmentation involves many issues other than the separation of connected regions, such as segmentation based on depth (see [18] for an interesting handling by synchronous oscillations), object occlusion, segment intersection, and so on. Although its eventual applicability to pattern segmentation must be judged by future research, the basic principle of the approach introduced here, namely, the emergent properties from local communications, will be, we believe, a fundamental part of a successful system of real-time image understanding.

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