

Correlated neuronal activity can represent multiple binding solutions

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Abstract

The correlated activity of neurons is being regarded as candidate mechanism for binding the responses of different feature selective cells. Binding, however, is rarely unique, especially at levels beyond feature detection. In this article the dynamical properties of a network of coupled oscillators as a model for a mental representation of visual stimuli are investigated. Oscillator networks have been analyzed previously, but here a new coupling scheme and a biologically more relevant transfer function are used. A principal mode analysis of the activity shows that the network sensibly handles ambiguous segmentations of a visual stimulus.

Keywords: *oscillator network, binding, principal modes, segmentation*

1 Introduction

Multi-electrode recordings have revealed stimulus induced synchronization of cortical neurons. In addition to rate codes, the temporal correlation in the activity of neurons constitutes a coding dimension, in which the responses of cells, selective for features like edges, disparity etc., can be dynamically integrated [5].

Oscillator networks are a popular model to explain these observations. They have been used to model, e.g., contour integration and enhancement in the visual cortex [1], odor recognition [2] and binding across different feature dimensions [4]. Most of the investigations focus on the suppression of noise, spurious edges and other artefacts. This implies that the suppressed information could not be perceived. However, in a noisy image one can recognize the scene, but also single spots. In general, inputs permit different interpretations, depending on the context. For example, two parallel bars of the same color can be considered as two objects or as part of a grating. Other examples are flip figures like Rubin's vase or the Necker cube.

Here it is shown that the dynamics of a network of coupled oscillators simultaneously represents alternatives.

2 Model

On the macroscopic level, the dynamics of the mean activations of two mutually connected groups of excitatory (x) and inhibitory (y) neurons can be described by

$$\dot{x} = -\tau_x x - g_y(y) + L_0^{xx} g_x(x) + I_x + \eta_x \quad (1a)$$

$$\dot{y} = -\tau_y y + g_x(x) - I_y + \eta_y. \quad (1b)$$

Here τ_α ($\alpha \in \{x, y\}$) are constants that can be chosen to match refractory times of biological neurons, L_0^{xx} describes self-excitation of the excitatory population and η_α white noise, that models fluctuations within the populations. With external input I_α above threshold, the solutions of (1) are limit-cycle oscillations.

The transfer function is typically modeled by sigmoid-shaped functions. From a metabolic viewpoint it is not desirable for real neurons to reach saturating activity in every cycle. In this model a semi-linear transfer function,

$$g_\alpha(x) = \begin{cases} m_\alpha(x - \theta_\alpha) & \text{if } x > \theta_\alpha \\ 0 & \text{else} \end{cases}, \quad (2)$$

was used to prevent neurons from reaching saturation. Conditions, under which the dynamics of (1) is stable, analytically have been derived in [7].

The external input $I_\alpha = I_0 + I_{lat}^\alpha$ consists of static input from the feature detectors I_0 and input from neighboring oscillators via lateral connections I_{lat}^α . A preliminary study of the phase plane of (1) revealed, that the excitatory coupling $I_{lat}^x = \sum_{s \in S} L_s^{xx} x_s$ synchronizes oscillators, whereas the inhibitory coupling $I_{lat}^y = \sum_{s \in S} L_s^{yy} y_s$ desynchronizes them. S is the local neighborhood of the oscillator under consideration and $L^{\alpha\beta}$ ($\alpha, \beta \in \{x, y\}$) positive weights. Generally it was found, that connections originating from excitatory neurons have a synchronizing and those from inhibitory neurons a desynchronizing effect, so all connection types could have been used. Connections between excitatory and inhibitory neurons as well as the recurrent coupling of the inhibitory neuron were left out to keep the parameter space small. The static input was applied to the excitatory neurons exclusively. Applying it to the inhibitory neurons also does not change the behavior qualitatively [1].

To demonstrate the dynamic binding of visual stimuli within the color domain, a two - dimensional lattice was used (see figure 1), that represents a topographic mapping of the image. At every location, a hyper-column of four oscillators encodes the spectral properties. The properties of the color processing system are still discussed controversially, especially the actual number of color channels [3]. Here the channels red, green, blue and yellow were chosen.

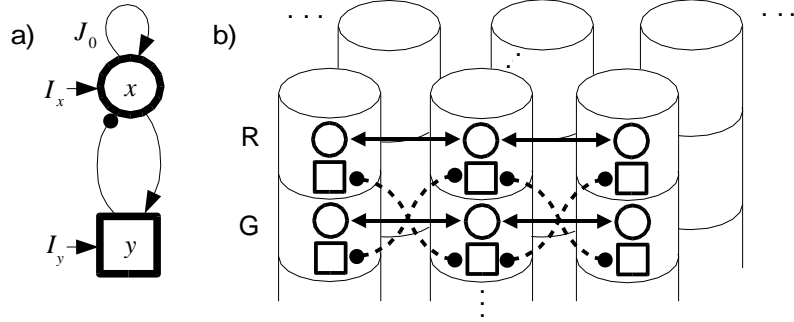


Figure 1: **a)** A single oscillator. **b)** Synchronizing (solid) and desynchronizing (dashed) connections between neighboring oscillators. R and G denote the red and green channel; the scheme has to be applied to other neighbors and the remaining channels as well.

The weight structure was isotropic and local. Oscillators receiving input from the same channel were coupled with synchronizing connections, those from different channels with desynchronizing connections. The connection scheme reflects the Gestalt principles of proximity and similarity.

The simplicity of the input representation allows a straightforward application to other feature dimensions like luminance or disparity.

3 Results

The stimulus in figure 2a) was applied to the network, and the system of equations (1) solved numerically. In order to show the relation to biological measurements, a cross-correlation analysis for the neurons with their receptive fields at the numbered positions in figure 2a) was carried out. The results are shown in figure 2b) and d). Cross-correlation, however, displays the dynamic properties of the network only locally.

From synergetics it is well known that the dynamics of complex systems is often governed by a few dominating states and can therefore be described by a small set of the corresponding order parameters. These states are the eigen- or principal modes of the system, the corresponding eigenvalues designate, how much of the variance is accounted for by that mode.

The principal modes have been computed as the eigenvectors of the covariance matrix $\mathbf{C} = \mathbf{x}^T \mathbf{x}$, where \mathbf{x} is a matrix with the activities of the excitatory neurons after a transient phase. The modes were ordered by descending eigenvalues (fig. 2d).

To assess the temporal evolution of the principal modes, the network state at any instant is considered as a weighted superposition of its principal modes \mathbf{v}_i , i.e. $\mathbf{x}(t) = \sum a_i(t) \mathbf{v}_i$. The time course of the order parameters $a_i(t)$ is shown in figure 2f).

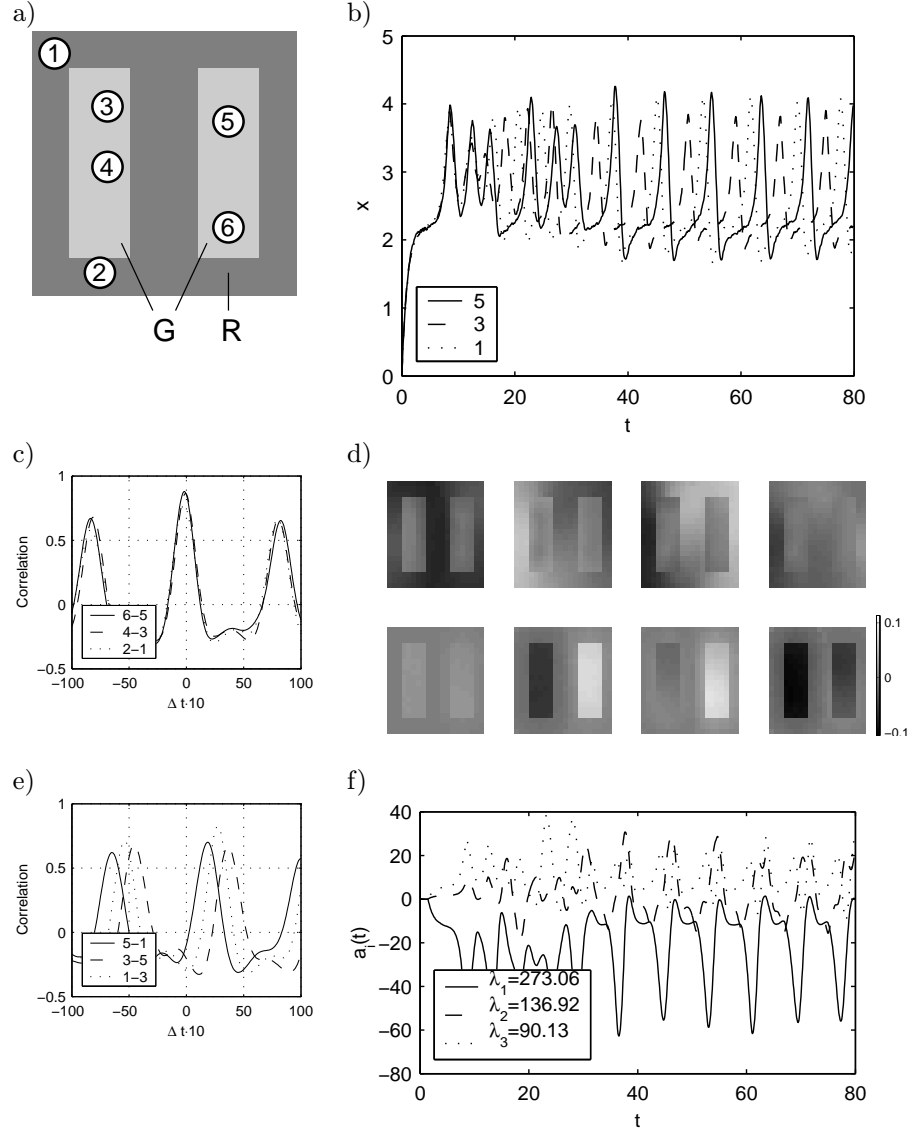


Figure 2: **a)** Stimulus. The bar displays the diameter of the neighborhood of an oscillator (S). **b)** Activity $x(t)$ of three oscillators. **c)** Cross-correlograms of oscillators in the same segment and in different segments (**e**). **d)** Principal modes with the four largest eigenvalues from left to right. Only the R (top) and G (bottom) channel are shown, since the other channels receive no input from the stimulus. **f)** Temporal evolution of the order parameters for the first (solid) and second (dashed) mode. Parameters: $\tau_x = \tau_y = 1$, $m_x = m_y = 2$, $\theta_x = 2$, $\theta_y = 1$, $I_0 = 2$, $L_0^{xx} = 0.1$, $\sum_{s \in S} L_s^{xx} = 1.1$, $\sum_{s \in S} L_s^{yy} = 0.3$

4 Discussion

After a transient phase the network exhibits stable oscillatory behavior. Oscillators that represent the same segment synchronize with approximately zero phase lag, whereas those for different segments have a phase lag different from zero. This represents the two bars being different objects.

The first principal mode exhibits the difference between the foreground (the two bars) and the background. This mode considers the bars to belong to the same segment. The second mode differentiates between the bars.

The influence of these two modes, expressed by the evolution of their order parameters a , alternates (figure 2f). The amplitudes of the order parameters for principal modes with lower eigenvalues are smaller. Therefore their influence on the network dynamics is smaller as well. Experiments with other stimuli yielded similar results.

According to [6], clusters of synchronously activated cells can be interpreted as a logically structured conceptual representation of a visual scene. The attractiveness of this theory lies in the fact that no "higher centers" and no computational facilities other than synchronized and desynchronized cells are required to achieve complex syntactic structure. Since the model developed here meets the assumptions of this theory, it gives an idea of how visual perceptions can be represented. The ability to account for ambiguous segmentations supports this view.

References

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