Rapid temporal modulation of synchrony in cortical interneuron networks with synaptic depression

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Abstract

The synchrony of neurons in extrastriate visual cortex is modulated by selective attention even when there are only small changes in firing rate. We used Hodgkin-Huxley type models of cortical neurons to investigate the mechanism by which the degree of synchrony can be modulated independently of changes in firing rates.

The synchrony of local networks of model cortical interneurons interacting through inhibitory synapses with synaptic depression was modulated on a fast time scale by selectively activating a fraction of the interneurons. The activated interneurons became rapidly synchronized without changing significantly the firing rate of other neurons.

Key words: synchronization, reliability, gamma oscillations

1 Introduction

Selective attention greatly enhances the ability of the visual system to detect visual stimuli and to store and recall these stimuli. The neural correlate of selective attention has recently been studied in macaque monkeys [5, 3]. A key finding is that attention modulates both the mean firing rate of a neuron in response to a stimulus [5] and the coherence of spiking with other neurons responsive to the stimulus [3]. Increased synchrony can boost the impact of spikes on subsequent cortical areas to which these neurons project [6]. These results suggest that mean activity and the degree of coherence may represent independent signals that can be independently controlled. It is, however, unclear biophysically what mechanisms are responsible.

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Previously we found that interneuron networks can dynamically modulate their synchrony on time scales of 100 ms with only moderate changes in the mean firing rate [8]. Synchrony arose by competition between two groups of interneurons and required a specific range of synaptic background activity. Here we study how synaptic depression [1] affects the synchrony modulation in a interneuron network and we compare it to the case in which synaptic depression is absent.

2 Methods

2.1 Network model

The model consisted of a network of N interneurons connected all-to-all. Each neuron had a sodium I_{Na}, a potassium I_K and a leak current I_L and was driven by a white noise current η with mean I_i and variance $2D$. The equation for the membrane potential V reads:

$$C_m \frac{dV}{dt} = -I_{Na} - I_K - I_L + \eta(t) + I_{syn}, \tag{1}$$

here $C_m = 1\mu F/cm^2$ is the membrane capacitance (normalized by area), and I_{syn} is the synaptic input from other neurons in the network. For the first N_A neurons the current was $I_i = I_A + \delta I_i$ $(i = 1, \cdots N_A)$, for the remainder it was $I_i = I_B + \delta I_i$ $(i = N_A + 1, \cdots, N)$. Heterogeneity in neural properties was represented by δI_i, which was drawn from a Gaussian distribution with a standard deviation σ_I. I_A was increased from I to $I + \Delta I$ during a 500 ms interval between $t = 1000$ and 1500 ms, I_B was equal to I for the duration of the simulation. The neurons were connected by inhibitory synapses with unitary strength g_{syn}/N and time constant $\tau_{syn} = 10$ ms. When a presynaptic spike occurred the synaptic conductance was increased by $g_{syn}S_j$, where j was the label of the afferent neuron. S_j described the depression at the synapse receiving the spike [1] and obeyed the differential equation

$$\tau_d \frac{dS_j}{dt} = 1 - S_j, \tag{2}$$

with the time constant $\tau_d = 300$ ms. Each time a presynaptic spike occured S_j was multiplied by a factor $f_{dep} = 0.75$. The model used here was adapted from that introduced by Wang & Buzsaki (1996). The standard set of parameters was $N = 1000$, $N_A = 250$, $N_B = N - N_A = 750$, $I = 0.7$ $\mu A/cm^2$, $\Delta I = 0.3$ $\mu A/cm^2$, $g_{syn} = 0.4$ mS/cm^2, $\sigma_I = 0.02$ $\mu A/cm^2$ and $D = 0.02$ mV^2/ms.

2.2 Statistical analysis

Spike times were recorded when the membrane potential (V in Eq. 1) crossed 0 mV from below. N is the total number of neurons in the network, N_s is the number of spikes (by all neurons) generated during a given simulation run. For some calculations it is convenient to pool the spike times of all neurons together into one set, $\{t_1, \cdots, t_\nu, \cdots, t_{N_s}\}$, ordered from low to high values. The ordered set is indexed by ν, where $\nu = 1$ is the earliest spike and $\nu = N_s$ is the latest. The CV_P measure is based on the idea that during synchronous states the minimum distance between spikes of different neurons is reduced compared with asynchronous states. The interspike interval of the *combined* set of network spikes is $\tau_\nu = t_{\nu+1} - t_\nu$. Note that these interspike intervals are between *different* neurons. The coefficient of variation is

$$CV_P = \frac{\sqrt{\langle \tau_\nu^2 \rangle_\nu - \langle \tau_\nu \rangle_\nu^2}}{\langle \tau_\nu \rangle_\nu},$$

where P stands for population and $\langle\rangle_\nu$ denotes the average over all intervals. The higher the value of CV_p, the more synchronous the network is.

3 Results

Competition leads to dynamical modulation of synchrony. We study the dynamics of an all-to-all connected interneuron network. Key parameters are: mean level of depolarizing current I, variance $2D$ of the white noise current and neuronal heterogeneity modeled as a dispersion σ_I in the driving current across neurons. These three parameters can account for changes occuring *in vivo* in the level of background synaptic activity, and the effect of neurotransmitters and neuromodulators. Previous work shows that synchrony is only stable up to $\sigma_I \approx 0.10 \mu A/cm^2$ [9] and $D \approx 0.10 mV^2/ms$ [7]; for higher values, only the asynchronous state is stable. For moderate values of σ_I and D (below these critical values), synchrony is only stable for a large enough driving current I.

Based on these results it is expected that applying a current pulse to the network in a low synchrony state will lead to increased synchrony. Representative simulation results are shown in Fig. 1. There were $N = 1000$ neurons in the network, the other parameters were $D = 0.02\ mV^2/ms$ and $\sigma_I = 0.02\ \mu A/cm^2$. Initially the driving current was $I = 0.7\ \mu A/cm^2$. In this baseline state the mean firing rate per neuron was $f = 8.18\ Hz$. When the depolarizing current was increased during the time-interval between 1000 ms and 1500 ms to only

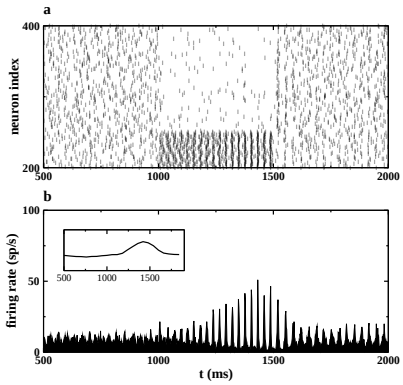

Fig. 1. Synchrony modulation by competition without synaptic depression [8]. (a) Rastergram showing the spike trains of 200 out of the 1000 neurons. Driving current $I = 0.7\ \mu A/cm^2$ was increased to $I = 1.0\ \mu A/cm^2$ during the time interval between 1000 ms and 1500 ms for the bottom 50 neurons. The top 150 neurons received baseline current throughout the simulation. (b) Spike time histogram of all the network neurons. Parameters for these simulations were: $\sigma_I = 0.02\ \mu A/cm^2$, $D = 0.02\ mV^2/ms$, $g_{syn} = 0.4\ mS/cm^2$ and $\tau_{syn} = 10\ ms$. (inset) Sliding-window average of the coefficient of variation (CV_P) of the interspike intervals between all the network neurons.

250 of the 1000 interneurons, a robust increase in synchrony was observed (Fig. 1). During that period the mean firing rate only weakly increased from $f = 8.18\ Hz$ to $f = 9.48\ Hz$. It is also possible to induce synchrony by increasing the driving current to all neurons in the network. However, the necessary increase in current is much higher than used in Fig. 1, and the resulting firing rate increase is also much higher compared with the competitive mechanism.

In Fig. 2, the corresponding situation for synapses with depression is shown. To obtain synchrony by competition we used a driving current $I = 0.9\ \mu A/cm^2$ and a synaptic strength $g_syn = 0.6\ mS/cm^2$. The mean firing rate per neuron was $f = 19.49\ Hz$ initially ($t < 1000\ ms$) and $f = 23.97\ Hz$ after the activation of 250 neurons in the time interval ($1000\ ms, 1500\ ms$). The increased synchrony of the activated neurons suppressed the non-activated neurons to a lesser extent compared to the previous case, because the synaptic depression reduced the strength of the synapses that received higher rates of inputs. As a consequence, at the end of the activation period there is a small gap in the activity of the 250 activated neurons, due to the stronger inhibitory synapses with the non-activated neurons. We explored the dynamics for different values of the driving current and synaptic strength. The increase in synchrony without significant change in the firing rate occurred for a wider range of parameter values, indicating that synchrony by competition is more robust with depression.

4 Discussion

Synchrony by competition is effective when the baseline state is asynchronous

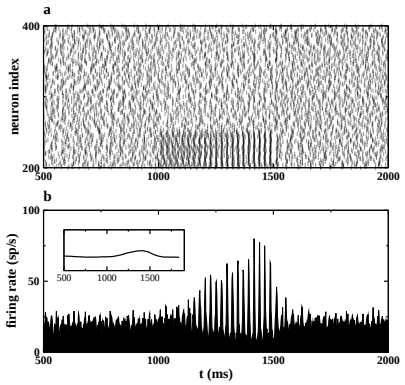

Fig. 2. Synchrony modulation by competition with synaptic depression. (a) Rastergram showing the spike trains of 200 out of the 1000 neurons. Driving current $I = 0.9\ \mu A/cm^2$ was increased to $I = 1.2\ \mu A/cm^2$ during the time interval between 1000 ms and 1500 ms for the bottom 50 neurons. The top 150 neurons received baseline current throughout the simulation. (b) Spike time histogram of all the network neurons. Parameters for these simulations were: $\sigma_I = 0.02\ \mu A/cm^2$, $D = 0.02\ mV^2/ms$, $g_{syn} = 0.6\ mS/cm^2$ and $\tau_{syn} = 10\ ms$. (inset) Sliding-window average of the coefficient of variation (CV_P) of the interspike intervals between all the network neurons.

and reached quickly from a synchronized network state (corresponding to an initial condition with all neurons having a similar membrane potential). The activated state should be synchronous and should be established quickly from an asynchronous state (corresponding to an initial condition with a wide dispersion of membrane potential across different neurons). In a previous study [7] the focus was on the degree of synchronization in the asymptotic state of the network. Here we study a network with competition between otherwise identical neurons and the focus is on the effect of the synaptic depression on the speed of the transition between synchronous and asynchronous states. Our preliminary results indicate that synaptic depression increases the parameter range for which synchrony by competition is obtained. Notably, the speed with which the network can switch between synchronous and asynchronous states is not afftected.

An important issue is whether and to what extent the results reported here generalize to other models. When the maximum conductance of the sodium and potassium current in the model were varied by less than 10%, we obtained similar results to those reported here [8]. Hence, there is robustness against small changes in model-neuron parameters. The key requirements are that the model network has a synchronous state in the gamma frequency range, an asynchronous state, and that the degree of synchrony depends on the coupling strength and driving current. These properties hold across different Hodgkin-Huxley type models [9, 10, 4] and for leaky integrate-and-fire model neurons [2, 4]. This suggests that synchrony modulation by competition will also be present in these models.

References

[1] LF Abbott, JA Varela, K Sen, and SB Nelson. Synaptic depression and cortical gain control. *Science*, 275:220–224, 1997.

[2] N Brunel and V Hakim. Fast global oscillations in networks of integrate-and-fire neurons with low firing rates. *Neural Computation*, 11:1621–1671, 1999.

[3] P Fries, JH Reynolds, AE Rorie, and R Desimone. Modulation of oscillatory neuronal synchronization by selective visual attention. *Science*, 291:1560–1563, 2001.

[4] D Hansel and D Golomb. The number of synaptic inputs and the synchrony of large sparse neuronal networks. *Neural Comput*, 12:1095–1139, 2000.

[5] CJ McAdams and JH Maunsell. Effects of attention on orientation-tuning functions of single neurons in macaque cortical area V4. *J Neurosci*, 19:431–441, 1999.

[6] E Salinas and TJ Sejnowski. Impact of correlated synaptic input on output variability in simple neuronal models. *J Neurosci*, 20:6193–6209, 2000.

[7] PHE Tiesinga and JV José. Robust gamma oscillations in networks of inhibitory hippocampal interneurons. *Network*, 11:1–23, 2000.

[8] P.H.E. Tiesinga and T.J. Sejnowski. Rapid temporal modulation of synchrony by competition in cortical interneuron networks. *Neural Computation*, 16, 2004. in press.

[9] XJ Wang and G Buzsáki. Gamma oscillation by synaptic inhibition in a hippocampal interneuronal network model. *J. Neurosci.*, 16:6402–6413, 1996.

[10] JA White, CC Chow, J Ritt, Soto-Treviño C, and N Kopell. Synchronization and oscillatory dynamics in heterogeneous, mutually inhibited neurons. *J. Comput. Neurosci.*, 5:5–16, 1998.