

Cost-Efficiency Neural Representation

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Abstract— Brains are believed to be capable of information processing with remarkable efficiency but low metabolic cost. Here we provide computational evidence that salient features of irregular firing, oscillations and criticality in cortical activity can be simultaneously accounted in a generic neural circuit capturing the excitation-inhibition balance with realistic synaptic dynamics. Their simultaneous organization achieves maximal information efficiency and minimal firing rate.

1. Introduction

Cortical information processing with synaptic transmission and action potentials is metabolically expensive [1]. Therefore, neural codes are required to achieve "economy of impulses" [2] by reducing mean spike rate and increasing energy efficiency, e.g. representational capacity per energy unit. Cost-efficiency of neural codes is likely an underlying design principle for constraining cortical activity level and organizing cortical activity patterns. The constraint on neuronal firing rate can be understood by taking into consideration the relative energy distribution for spikes and resting states [3]. However, so far, the connection of cost-efficiency with cortical activity patterns is still lacking.

Cortical activities represent neural codes by generating various spatiotemporal spike patterns, with salient features at multiple scales: irregular firings [4,5], synchronized oscillations [6,7] and neuronal avalanches [8,9]. They have been studied separately in different models about different implications for information processing, such as accuracy and speed of information relay by firing rate [10,11], coordination and communication between neural populations [12,13], and sensitivity to signals and perturbations [14].

Here we demonstrate that cost-efficient neural representation is reflected in the co-organization of these multi-scale features in neuronal network model.

2. Model

We simulate large random networks of excitatory-inhibitory (E-I) spiking neurons with E-I ratio 4:1 and connection probability 0.2 (Fig. 1A). The network is biologically plausible with conductance-based integrate-and-fire (IF) neurons (Fig. 1B) interacting through

voltage-dependent synaptic currents [15]. Each neuron also receives external excitatory projections independently. The conductance change due to a pre-synaptic spike is modeled as a bi-exponential function with conduction delay time $\tau \Gamma_1$, rise time $\tau \Gamma_1$ and decay time $\tau \Gamma_2$ (Fig. 1C). The coupling strengths are chosen to realize a balanced state, where neurons fire irregularly [10]. We study the parameter space of excitatory and inhibitory decay times ($\tau\tau$) for various dynamical modes and costefficiency of the corresponding spike patterns.

3. Results

In this model, with suitable pair of parameters (τ_{de} , τ_{di}), cortical activities can indeed multi-scale simultaneously generated. There are three different dynamical states with different synchrony degree: asynchronous irregular state (both decay times are large, e.g., τ_{de} =6ms, τ_{di} =6ms), moderately synchronized state (inhibitory synapses are relatively slower, e.g. τ_{de} =4ms, τ_{di} =10ms) and highly synchronized state (excitation very fast and inhibition much slower, e.g. τ_{de} =2ms, τ_{di} =14ms)). The moderately synchronized state is the most interesting regime. Here we can observe the co-organization of multilevel dynamics: (1) The firing activity of individual neurons is irregular, with CV (standard deviation over mean of inter-spike intervals (ISI)) close to 1, indicating that the spiking train is very close to random poison process. (2) However, the whole network displays collective oscillations in the gamma band (40-60 Hz), where the oscillation power increases with the degree of synchronization. (3) The oscillations are induced by constantly changing clustering of the neuronal firing like neural avalanches. Interestingly, the distribution of the avalanche size follows a power-law distribution in this region, suggesting that the system is at the self-organized critical state due to the interaction between excitatory and inhibitory populations. The co-organization of the dynamical modes is shown in Fig. 2.

Importantly, in the regime of co-organization of the multi-level dynamical modes as experimentally observed, the firing patterns are cost-efficient. The firing rate in this regime is minimal, while the energy efficiency of the neural representation $\eta = H/E$ is maximal. Here H (the

entropy) measures the abundance of different spike patterns, and E=nr+m is the average energy expenditure per pattern (m spikes among n neurons), with r being the energy usage for resting neurons relative to a spike (1/r) measures the relative energy constraint level on the spike patterns [3]). Here we considered both the binary case (Fig. 3A,C) where in a time window we examine whether a neuron is active or not, irrespective of how many spikes, and the analogy case (Fig. 3B,D) by taking the number of spikes into account. The neuron representation is cost-efficient in both cases.

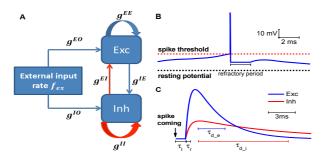


Fig. 1 Schematics of network architecture, neuronal integration and spike, synaptic conductance traces. (A) The local recurrent neuronal network consists of excitatory (Exc) and inhibitory (Inh) spiking neurons with synaptic connections (blue, excitatory; red, inhibitory) and external inputs. (B) The IF neurons with refractory period

and leaky current. (C) The unitary conductance response to a pre-synaptic spike is described by a bi-exponential function with latency τ_l , rise time τ_r and decay time τ_d . Parameters from [15].

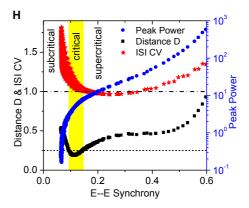


Fig. 2. Co-existence of multi-scale cortical activities at moderately synchronized states. ISI CV (red), distance of avalanche size distribution from power-law (black) and peak power of network oscillations (blue) vs. E--E Synchrony (synchronization between the spikes of excitatory neurons), showing the co-existence of irregular firings, synchronized oscillations and neuronal avalanches at moderately synchronized states.

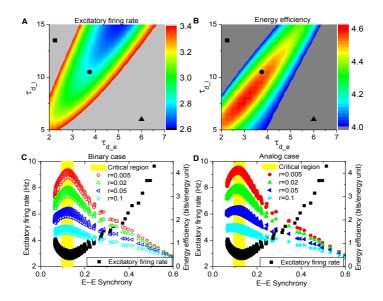


Fig. 3. Cost-efficient neural representation in critical region. (A, B) Average excitatory firing rate (A) and energy efficiency η of analog patterns at r=0 (B) in the parameter space (τ_{de} , τ_{di}) (unit: ms). (C, D) Energy efficiency η at various r (colors) and average excitatory firing rate (black) with respect to E--E Synchrony for both binary (C) and analog (D) cases. Cost-efficiency is achieved robustly in the critical region across the empirical range of r.

3. Conclusion

We showed that experimentally observed salient features of neural activity, including irregular firing of individual neurons, collective oscillations of the network and self-organized critical states can be accounted simultaneously in a biologically realistic E-I balanced network, and such co-organization of the dynamical modes achieves cost-efficient neural representation. It will be interesting to study in the future how the cost-efficient neural dynamics are employed in neural information processing, memory and learning.

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References

- [1] D. Attwell, S. B. Laughlin, An energy budget for signaling in the grey matter of the brain. *J. Cereb. Blood Flow Metab.* **21**, 1133-1145 (2001).
- [2] H. Barlow, in *Information Processing in the Nervous System*. (Springer, 1969), pp. 209-230.
- [3] W. B. Levy, R. A. Baxter, Energy efficient neural codes. *Neural Comput.* **8**, 531-543 (1996).
- [4] W. R. Softky, C. Koch, The highly irregular firing of cortical cells is inconsistent with temporal integration of random EPSPs. *J. Neurosci.* **13**, 334-350 (1993).
- [5] M. N. Shadlen, W. T. Newsome, The variable discharge of cortical neurons: implications for connectivity, computation, and information coding. *J. Neurosci.* **18**, 3870-3896 (1998).

- [6] G. Buzsáki, A. Draguhn, Neuronal oscillations in cortical networks. *Science* **304**, 1926-1929 (2004).
- [7] P. Fries, D. Nikolić, W. Singer, The gamma cycle. *Trends Neurosci.* **30**, 309-316 (2007).
- [8] J. M. Beggs, D. Plenz, Neuronal avalanches in neocortical circuits. *J. Neurosci.* **23**, 11167-11177 (2003).
- [9] T. Petermann, T. C. Thiagarajan, M. A. Lebedev, M. A. Nicolelis, D. R. Chialvo, D. Plenz, Spontaneous cortical activity in awake monkeys composed of neuronal avalanches. *Proc. Natl. Acad. Sci. U.S.A.* 106, 15921-15926 (2009).
- [10] C. van Vreeswijk, H. Sompolinsky, Chaos in neuronal networks with balanced excitatory and inhibitory activity. *Science* **274**, 1724-1726 (1996).
- [11] T. J. Sejnowski, O. Paulsen, Network oscillations: emerging computational principles. *J. Neurosci.* **26**, 1673-1676 (2006).
- [12] P. Fries, Neuronal gamma-band synchronization as a fundamental process in cortical computation. *Annu. Rev. Neurosci.* **32**, 209-224 (2009).
- [13] X.-J. Wang, Neurophysiological and computational principles of cortical rhythms in cognition. *Physiol. Rev.* **90**, 1195-1268 (2010).
- [14] W. L. Shew, H. Yang, T. Petermann, R. Roy, D. Plenz, Neuronal avalanches imply maximum dynamic range in cortical networks at criticality. *J. Neurosci.* **29**, 15595-15600 (2009).
- [15] N. Brunel, X.-J. Wang, What determines the frequency of fast network oscillations with irregular neural discharges? I. Synaptic dynamics and excitation-inhibition balance. *J. Neurophysiol.* **90**, 415-430 (2003).