Efficient Signal Processing in Random Networks that Generate Variability: A comparison of internally generated and externally induced variability

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Abstract

The Source of cortical variability and its influence on signal processing remain an open question. We address the latter, by studying two types of randomly connected networks of quadratic integrate-and-fire neurons with balanced excitation-inhibition that produce irregular spontaneous activity patterns: (a) a deterministic network with strong synaptic interactions that actively generates variability by chaotic dynamics (internal noise) and (b) a stochastic network that has weak synaptic interactions but receives noisy input (external noise), e.g. by stochastic vesicle releases. These networks of spiking neurons are analytically tractable in the limit of a large network-size and channel-time-constant. Despite the difference in their sources of variability, spontaneous activity patterns of these two models are indistinguishable unless majority of neurons are simultaneously recorded. We characterize the network behavior with dynamic mean field analysis and reveal a single-parameter family that allows interpolation between the two networks, sharing nearly identical spontaneous activity. Despite the close similarity in the spontaneous activity, the two networks exhibit remarkably different sensitivity to external stimuli. Input to the former network reverberates internally and can be successfully read out over long time. Contrarily, input to the latter network rapidly decays and can be read out only for short time. The difference between the two networks is further enhanced if input synapses undergo activity-dependent plasticity, producing significant difference in the ability to decode external input from neural activity. We show that, this difference naturally leads to distinct performance of the two networks to integrate spatio-temporally distinct signals from multiple sources. Unlike its stochastic counterpart, the deterministic chaotic network activity can serve as a reservoir to perform near optimal Bayesian integration and Monte-Carlo sampling from the posterior distribution. We describe implications of the differences between deterministic and stochastic neural computation on population coding and neural plasticity.

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Additional Details

In this study, we investigated two versions of (Fig. 1A) randomly connected networks of $N = 3000$ quadratic integrate-and-fire (QIF) neurons with balanced excitation-inhibition that produce irregular spontaneous activity patterns, where the ratio of the membrane time constant and the slow synaptic time constant that averages spike input was set to a low value of 0.05, mimicking the operation of NMDA and GABAb receptors. The irregularities in the spontaneous condition are caused by the following two different sources, i.e. (a) internal strong synaptic interactions without any external noise, which actively generate variability resulting in a deterministic chaotic network, and (b) weak internal synaptic connections receiving external noise, e.g., by stochastic vesicle releases, in a stochastic network. Keeping Dale's principle, the coupling strengths were randomly drawn from a distribution with zero mean and a standard deviation proportional to $g/\sqrt{N}$, where g controls the strength of synaptic connections in the network. This model is analytically tractable in the limit of large N and in the limit of slow synaptic time constant. Using dynamic mean field theory we characterize the dynamics of the QIF networks in the rate limit, and show that there exists a single parameter family with the same baseline statistics. In order for the two networks to have the same baseline statistics, the noise must satisfy $\Gamma(\tau) = \left[1 - \left(\frac{\tilde{g}}{g}\right)^2\right](c(\tau) - \ddot{c}(\tau))$, where $\tilde{g}$ represents the magnitude of synaptic strength of an interpolating network, i.e. fixing $g = 1$ and changing $\tilde{g} = 1$ to $\tilde{g} = 0$ one can interpolate between a strongly connected deterministic chaotic network to a very weakly connected stochastic network, without altering the spontaneous activity statistics (Fig.1B). However, this family can exhibit remarkably different sensitivity to external input depending on $\tilde{g}$. The larger the synaptic interactions are, the more longer the effect of the input, with the deterministic chaotic network showing much larger change in spiking probability as compared to the purely stochastic network, after being stimulated with a brief input (Fig. 1C).

Interestingly, we found that the origin of variability in the network can also influence learning. When synapses that provide external input to the two networks undergo typical Hebbian activity dependent plasticity, the learning outcome is greatly enhanced in the deterministically chaotic model than in the stochastic model, as observed by the significant difference of the signal-to-noise ratio in Fig 1D. The input can be decoded from the internal activity (Figs. 1E left and right) of the network with $\tilde{g} = 1$ much better, than the network with $\tilde{g} = 0$. Finally, we demonstrate that this difference in encoding external stimulus naturally leads to distinct performance for the two networks to optimally integrate signals from two sources at different time points. The networks were driven by two input pulses (t_1 and t_2) sampled from different Gaussian distributions (i.e $t_1 \in N(\mu_1, \sigma_1)$ and $t_2 \in N(\mu_2, \sigma_2)$). We show that (Fig. 1F), the deterministic chaotic network activity serves as a much better reservoir for probabilistic computation and Monte-Carlo sampling. Specifically, one linear output neuron reading out information from the network can sample possible output from the optimal Bayesian posterior distribution and the other can generate a pulse signal at the time point (t^*) that maximizes the posterior distribution $P(t|t_1, t_2; \mu, \sigma)$. This property was numerically confirmed by comparing the Kullback-Libler divergence (Fig. 1G) between the desired Bayes-optimal distribution and the actual distribution learned by each network. In sum, we have shown that the deterministic chaotic network performs significantly better than the weakly connected stochastic network in representing inputs, learning inputs, as well as optimally integrating inputs by sampling.

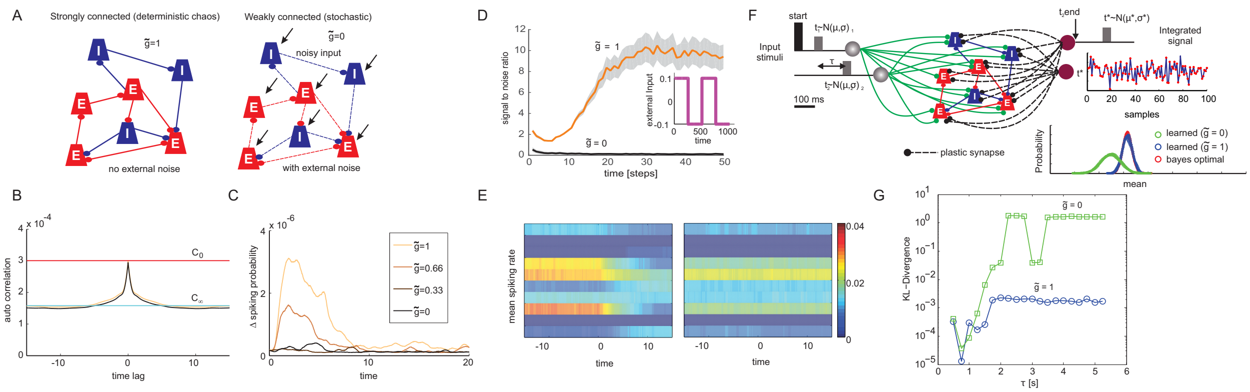

Figure 1: (A) Schematic illustrations of networks considered in the present study. The left network consists of strongly coupled neurons without noise, while the right network consists of weak coupling among neurons with noisy input. (B) Nearly identical rate autocorrelation functions in the two networks. The red line (C_0) represents the value of the autocorrelation at time 0 and cyan line (C_∞) is the value of autocorrelation function in the limit of large t. (C) Change in spiking probability for different network connectivity strengths ($\tilde{g}$), after being stimulated by brief input. (D) Signal-to-noise ratio comparison for the two networks driven by an external input (inset) with the input synapses undergoing Hebbian plasticity. A modification of the Oja's plasticity rule was used. The grey shaded region shows standard deviation across 20 trials. (E) Mean spiking rate for the two networks. left-deterministic chaotic network and right-stochastic network. (F)The network setup for learning the Bayes-optimal integrated signal for two temporally delayed pulsed inputs sampled from different Gaussian distributions. (G) KL-divergence comparison between the desired optimal output distribution and the learned distribution by both the networks, with increasing time delay τ between the two input stimuli.

Acknowledgments

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