

Information coding and oscillatory activity in synfire neural networks with and without inhibitory coupling

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Abstract

When a population spike (pulse-packet) propagates through a feed-forward network with random excitatory connections, it either evolves to a sustained stable level of synchronous activity, or fades away (Diesmann et al. 1999; Cateau and Fukai, 2001). Here, I demonstrated that in the presence of noise, the probability of the survival of the pulse-packet (or equivalently the firing rate of output neurons) reflects the intensity of the input. Furthermore, inhibitory coupling between layers can result in quasi-periodic alternation between several levels of firing activity. These results were obtained by analyzing the evolution of pulse packet activity as a Markov chain. For the Markov chain analysis, the output of the chain is a linear mapping of the input into a lower dimensional space, and the eigenvalues and eigenvectors of the transition matrix determine the dynamics of the evolution. Synchronous propagation of firing activity in successive pools of neurons was simulated in networks of integrate and fire and compartmental model neurons and the activation of each pool was observed to be predominantly depending on the number of cells that fired in the previous pool, consistent with the discrete Markov process. Simulation results agreed with the numerical solutions of the Markov model. When inhibitory coupling between layers were included in the Markov model, some eigenvalues became complex numbers, implying oscillatory dynamics. The quasi-periodic dynamics was validated with simulation with leaky integrate and fire neurons. The networks demonstrated different modes of quasi-periodic activity as the inhibition or excitation parameters of the network were varied.

Summary of research

Here I developed a simple mathematical framework based on discrete Markov chains for understanding and analyzing synfire chains (Figure 1) in presence of randomness or noise. Many neurons show considerable irregularity in their sequence of action potentials in recordings in vivo (Holt et al. 1996). Recent intracellular recording reveals considerable fluctuations in the voltage of the membrane of cortical cells below threshold due to synaptic input from other cells (Destexhe and Pare 1999). Applying mean field analysis when the network size is small (pool size of a few hundreds or less) is prone to discretization error (false limit cycles due to truncation) and stochasticity (uncertainties in each iteration add up, so the information is lost). Probabilistic approaches such as Markov process models provides a natural extension to validate the results of the mean field analysis, and can give estimates of the effect of the network size on the dynamics of the network. The model was motivated by the observation that in a network of

compartmental model neurons (with Hodgkin-Huxley type voltage dependent ion channels), the output jitter is a function of the output rate (Figure 2). Consequently, the conditional probability of firing of j neurons provided that i neurons fire in the previous iteration does not depend on the previous states of the system.

Including noise in the network model and use of Markov formalism allow to simplify the behavior of randomly connected pools of neurons to a feedforward chain of linear nodes. Although the cortical networks are not strictly connected at random, they still inherit the properties of the randomly connected model under study when $\sigma_{\xi} > 1.5\sigma_w\sqrt{n}$, where σ_w and σ_{ξ} reflect the standard deviations of synaptic efficacy, and the stochastic component of the threshold, respectively. The Markov chain model captured the main aspects of the evolution of the activity of the firing volley in the chain (Figure 3). The dynamical regime of activity was shown to depend on the distribution of synaptic efficacies and thresholds. Our analysis suggest that stochastic, randomly connected, excitatory chains can convey information by converting the ensemble coding of the input to the rate coding in the output layer. Similar results were also recently reported in simulation with leaky integrate and fire neurons (van Rossum et al. 2002).

The Markov model can give insight the stability of the dynamical regime in the case of networks with inhibitory coupling between layers. For a carefully selected range of parameters, the transition matrix has subdominant non-trivial eigenvalues close to one, and a complex (damping oscillatory or quasiperiodic) dynamics emerges (Figure 4). Complex dynamics might be useful for coding information but when the transition matrix has a subdominant non-unity eigenvalue then the chain is ill-conditioned in the sense that the system is sensitive to small perturbations in the transition probabilities (Meyer 1994). I could demonstrate that a small change of the parameters of the network leads to different dynamics and input-output mapping. The possibility of existence of modes of activation that are largely invariant to changes in parameters of the system is to be determined to justify the reliability of information coding in such modes.

References

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Figure 1. Schematic drawing of the connectivity pattern in a synfire chain. Pools size is n . Left: Synfire chain with purely excitatory connections. Right: Synfire with excitatory and inhibitory connections. Small circles represent inhibitory interneurons.

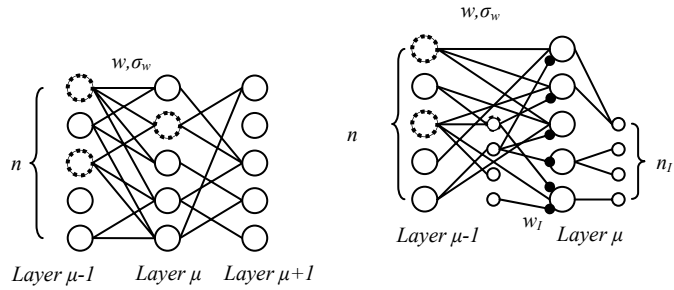


Figure 2. (a) Transfer function of a randomly connected network. Desynchronization of the input shifts the transfer function of the layer to the right. (b) Effect of input activity and synchrony on output synchrony. (c) The output synchrony depends mostly on the output activity, and for most of the outputs falls in a narrow range (between 1 and 1.2). The dark line is the average of all input jitters. (d) The relation between output synchrony and output activity seem to be preserved in three consecutive iterations in a four-layer network.

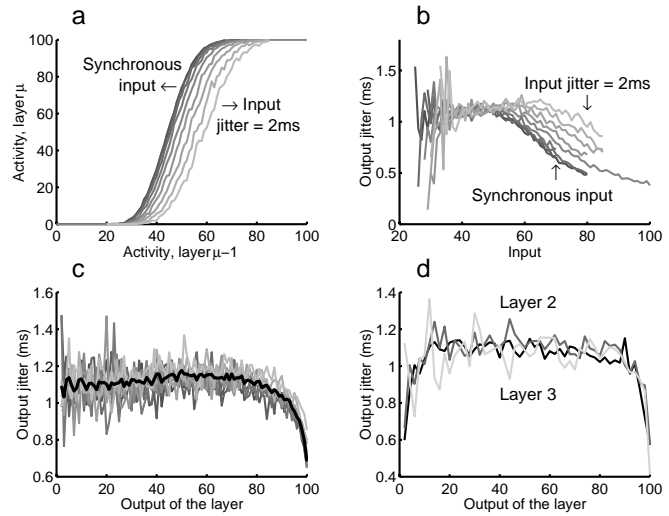


Figure 3. Transition matrices of first to fourth iteration (A , A_2 , A_3 , and A_4 , respectively) estimated from simulation results of the four layer compartmental model with a pool size of 100 (a-c) compared with the model (e-f).

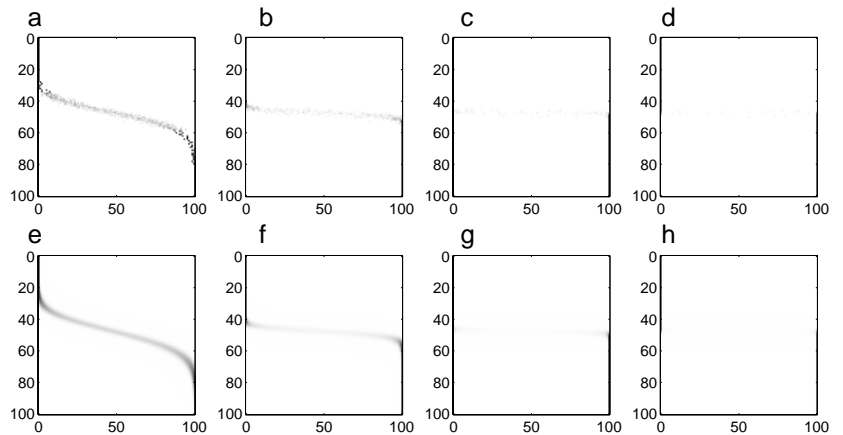


Figure 4. Quasiperiodic dynamics in an excitatory-inhibitory network with 400 neurons in each layer. (a), transfer function of each layer. (b), transition matrix (white =0, black =1), (c) the expected output for each iteration. 100 out of 400 cells fired at input (iteration zero). (d) Simulation (based on the transition matrix) of two trials for the same input. The two waveforms are desynchronized at later iterations, and gradually cancel out each other in the average (c).

