Towards a realistic model of cortical dynamics at criticality

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Background

A significant portion of communication between neurons in the mammalian brain is mediated by bursts of electrical pulses that propagate from neuron to neuron via chemical synapses. These pulses are called action potentials or ***spikes***. Just as knowledge of collective properties of feathers making up bird wings can illuminate the study of avian flight, elucidating ***collective dynamics*** of neuronal populations can advance our understanding of how large networks of neurons can give rise to behavior and cognition.

Critical dynamics

Many natural systems, including snow avalanches, earthquakes and schools of fish, exhibit critical dynamics. Interestingly, avalanches of neuronal spikes have been observed in cortices ("the bark/rind of the brain", or commonly known as grey matter) of anesthetized and awake animals, and also in cultured cortical slices[1]. The observed avalanches are essentially cascades of spikes that vary in size and duration, just as there are snow avalanches of various sizes and durations.

A few motivations behind the study of critical dynamics in neuronal networks are as follows:

1) Maximization of the repertoire of networks states/patterns that can be exploited for recognition, learning, spontaneous explorative/creative thoughts, etc.;
2) Maximization of the range of signals that could be received;
3) Enablement of information binding across different brain regions, e.g., the binding of visual and auditory information in identifying someone familiar.

Asynchronous irregular (AI) dynamics

Besides critical dynamics, other types of dynamics have been observed. In particular, asynchronous irregular dynamics is of interest. ***Asynchronous*** means that pairs of neurons are not firing in synchrony. ***Irregular*** means that spike timing of individual neurons is hard to predict. Cortical networks from anesthetized rats and awake macaques have been known to exhibit highly asynchronous spike activity[2,3].

The AI state is important for the following reasons:

1) It provides a substrate for robust signal propagation[4];
2) It enhances learning so that training processes are faster and the trained network outputs are more accurate and robust against noise[5].

The goal

For the aforementioned reasons, building neuronal networks that jointly exhibit ***spontaneous*** critical and AI dynamics is of interest. The spontaneous network state is analogous to a daydreaming/idling brain where the network is free to explore the space that its dynamics allow. There is no external drive stimulating the network. Once given an initial kick, the network can subsequently maintain its own activity without further external support.

Network model

The network consists of 4000 adaptive exponential integrate-and-fire (AdEx) [6] neurons, 3200 (80%) of which are excitatory pyramidal neurons and 800 (20%) of which are inhibitory fast-spiking neurons. Connection densities and strengths are chosen so that the network exhibits critical and asynchronous irregular dynamics.

References

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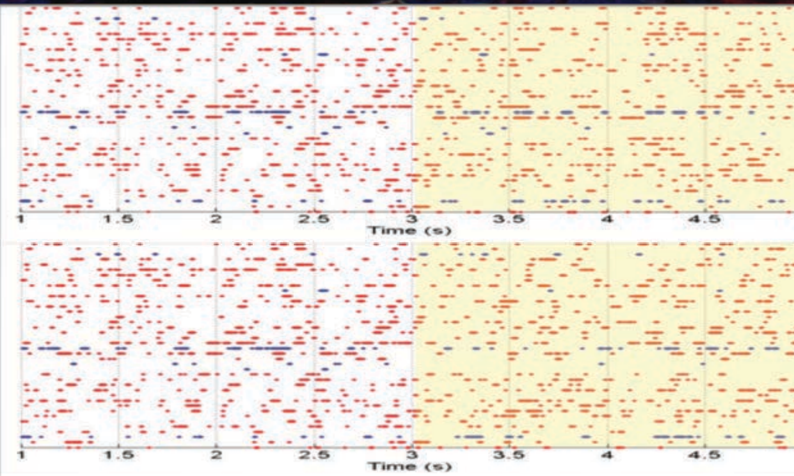

Fig.1 – Spike rasters of 30 randomly sampled neurons out of 4000

Red/blue dots are spikes from excitatory/inhibitory neurons, respectively. Top plot is the original raster. Bottom plot is obtained from perturbing a single neuron's electric potential by 1% at *t=3s*. Note the drastic difference in the two highlighted (yellow) patterns soon after *t=3s*. *Hint: Visually, the blue dots are easier to track; their patterns clearly fail to match after t=3s.*

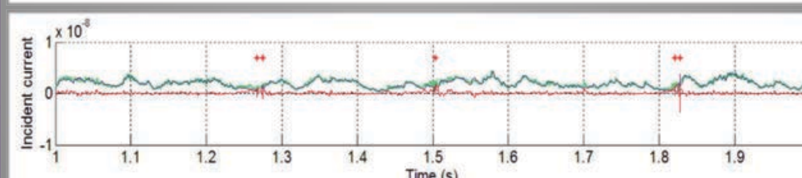

Fig.2 – Network recurrence-mediated excitation-inhibition balance

The thick green and thin purple traces are respectively the net excitatory and inhibitory currents incident on a randomly chosen neuron. The red trace is their difference. The two currents often annihilate each other. Occasionally, the green trace creeps above the purple one and a spike precipitates (*).

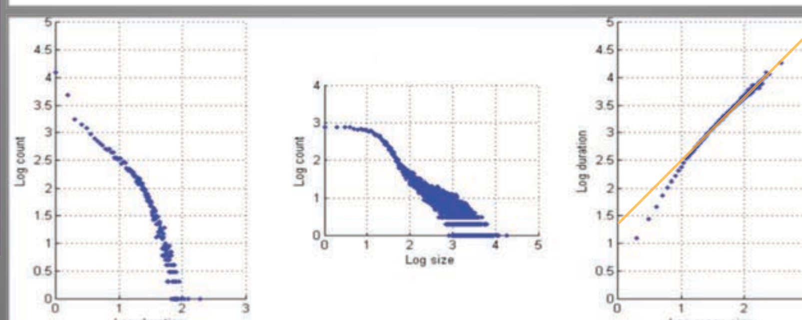

Fig.3 – Distributions of (left) avalanche duration, (middle) avalanche size, and (right) avalanche duration as a function of avalanche size

Power-laws should manifest themselves as straight lines on $\log_{10}$-$\log_{10}$ plots. Avalanche duration appears to be subcritical. Avalanche duration exhibits a large spread in values. Avalanche duration as a function of avalanche size follows a linear relationship with an exponent of ~1.2.

Results

1) Spontaneous activity

Upon termination of an initial stimulation from 0s to 1s, the network is able to remain active indefinitely (see Fig.1) with no subsequent stimulation.

2) Excitation-inhibition balance[7]

As shown in Fig.2, traces of excitatory and inhibitory currents incident upon the sampled neuron counterbalance each other with high temporal precision. This results in a net incident current that is close to zero. Transient deviations away from such balance trigger spike generation. The balance is a direct consequence of recurrent connections between a large number of neurons within the network. In its simplest form, an example of recurrence is having two excitatory (inhibitory) neurons sending projections to each other so that they mutually excite (inhibit) each other.

3) Critical dynamics

One signature of criticality is the presence of multiple power-laws with exponents that are interrelated. Power-laws appear as straight lines on log-log plots. For neuronal avalanches, there are three power-law distributions associated with avalanche duration and size (Fig.3). The duration distribution (left panel of Fig.3) clearly exhibits a relatively steeper slope for long avalanches. Finite size of the network and the network's balancing dynamics could have produced such behavior; this effect remains to be tested. One can only conclude that the exponent associated with duration as a function of size distribution (right panel of Fig.3) mimics empirical data closely[1].

A more stringent and convincing test for criticality is avalanche profile collapse[1]. The idea is that avalanche duration and size across *all* scales (though constrained by finite network size) can be collapsed onto a single common profile when the network is indeed critical. Data from the model, consisted of over 30,000 avalanches recorded over 20 minutes, suggests the presence of such a collapse (see Fig.4). This is indicative of criticality.

4) Asynchronous irregular (AI) dynamics

From Fig.1, it is clear that network dynamics is AI. Correlation coefficient (CC) and coefficient of variation (CV) are two commonly used statistics that quantify synchrony and regularity, respectively. Their values are respectively less than 0.01 and greater than 1, indicating asynchronous and irregular spiking. This AI state is highly sensitive to perturbations, as could be seen in the pair of plots in Fig.1. The top scenario differs from the bottom one in one respect – in the bottom scenario, the electric potential of ***one of the 4000 cells is perturbed by a mere 1% at t=3s***. Within about *0.1s* immediately after the perturbation, the pattern of sampled spikes across the ***whole*** network completely alters itself compared to the unperturbed case. This is the proverbial butterfly effect, where tiny local perturbations propagate very rapidly to alter the global trajectory of the system. Here, a miniscule local perturbation is imposed upon a single neuron and the subsequent dramatic global changes involve all 4000 neurons of the network.

Future directions

- Examine the conditions under which criticality can emerge in neuronal networks via homeostatic and plasticity mechanisms.
- Impose network topologies that are consistent with cortical architecture to compare the information processing capabilities of critical networks and of other types of networks.

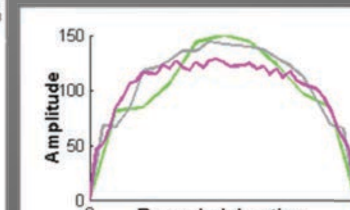

Fig.4 – Avalanche profile collapse

The green, grey, and magenta curves are *re-scaled*[1] mean avalanche shapes of duration 25ms, 50ms, and 100ms (1.0, 1.3, 1.6 in $\log_{10}$ in Fig.3), respectively. The mean shapes are estimated from 620, 343, and 117 instances of avalanches, respectively.