### Transient spatiotemporal chaos collapses into periodic and steady states in an electrically-coupled neural ring network Keegan Keplinger (kmkeplinger@alaska.edu) and Renate Wackerbauer, Complex Dynamical Systems Group, Physics Department, University of Alaska, Fairbanks, © 2012.

### Introduction

Chaotic behavior in a spatially extended system is often referred to as **spatio**temporal chaos. The trajectories of a system as it evolves through state space are described by irregular spatial and temporal patterns.

In mathematical biology, spatiotemporal chaos has been demonstrated in chemotaxis models (Painter & Hillen, 2011) predator-prey models (Sherratt, J. & Fowler, A., 1995) and the Hogdkin-Huxley neural model (Wang, Lu, & Chen,

**Transient chaos** is a special case of chaotic dynamics in which the system dynamics collapses without external perturbation. Rather, collapse is an intrinsic property of the system.

Here, we diffusively couple many **spiking neurons** into a ring network and find that the network dynamics can collapse on to two different species of attractor: the **limit cycle** and the **steady-state** solution.





## The Morris-Lecar Model

The Morris-Lecar model was derived empirically from the barnacle giant muscle fiber (Morris & Lecar, 1981). The **system equations** describe the *membrane potential* (V) of the neuron as a function of ion currents and the *state* of the potassium channel (n). The applied current (I<sub>app</sub>) is the **bifurcation parameter**.

The **channel equations** describe each current's value across the membrane as it depends on each channel's Nernst potential ( $V_{c_{\alpha}}$  and  $V_{\mu}$ ).

Each channel has a voltage-dependent activation function associated with it. The potassium channel has an additional term,  $\tau_{n}$ , describing the *time-course* of potassium channel activation.

> stable

> > unstable focu

limit cycle boundarie

**Parameters:**  $C = 20 [uF/cm^2]$  -Membrane Capacitance,  $gK = 8 [uS/cm^2]$  - Potassium conductance, gl = 2 [uS/cm^2] - Leak Conductance, Vl = -60 [uS/cm^2] - Leak Equilibirium Potential, VCa = 120 [mV] - Ca Equilibrium Potential, VK = -80 [mV] - K Equilibrium Potential, V1 = -1.2 [mV] - Potential when Mss = .5, V2 = 18 [mV] - reciprocal slope of Mss voltage dependence, T0 = 15 [s] - - time constant, gCa = 4 [uS/cm^2] Class I Calcium Conductance, V3 = 14.95 - Potential when Nss = .5, V4 = 17.4[mV] reciprocal slop of Nss voltage dependence

## Stability Analysis

The nullclines of the system describe where each of the system equations equals zero, and thus no change in that variable occurs. At their intersection, the system is in equilibrium. If the equilibrium point is unstable, the slightest perturbation will push trajectories away.

Figure: A bifurcation diagram (right) demonstrates how the fixed points in the system change as a function of the bifurcation parameter. A **saddle-node bifurcation** occurs around  $I_{ann} = 38.8$  mA. This study is restricted to the **excitable** parameter regime  $I_{ann} < 38.8$ , where the neuron remains at resting potential until acted upon by an external perturbation. Phaseplots (**below**) depict the nullclines.



References: [1] Morris, C. and Lecar, H. (1981) Voltage oscillations in the barnacle giant muscle fiber. Biophys. J. 35: 193 - 213. [2] Painter, K., Hillen, T. (2011) Spatio-temporal Chaos in the wake of invasion. PNAS 92 (7), 2524-2528. [4] Stone, L., Ezrati, S. (1996). Chaos, Cycles and Spatiotemporal Dynamics in Plant Ecology. British Ecological Society 84 (2), 279-291. [5] Tel, T. and Lai, S. (1996). Chaos, Cycles and Spatiotemporal Dynamics in Plant Ecology. British Ecological Society 84 (2), 279-291. [5] Tel, T. and Lai, S. (1996). Chaos, Cycles and Spatiotemporal Dynamics in Plant Ecology. British Ecological Society 84 (2), 279-291. [5] Tel, T. and Lai, S. (1996). Chaos, Cycles and Spatiotemporal Dynamics in Plant Ecology. British Ecological Society 84 (2), 279-291. [5] Tel, T. and Lai, S. (1996). Chaos, Cycles and Spatiotemporal Dynamics in Plant Ecology. British Ecolog Y.C. (2007). Chaotic Transients in spatially extended systems. Physics Reports 460 (6), 245-275. [6] Wackerbauer, R. and Showalter, K. (2003). Collapse of Spatiotemporal Chaos. Phys. Rev. Lett. 91. [7] Wang, Q., Lu, Q., Chen, G. (2007). Ordered bursting synchronization and complex wave propagation in a ring neuronal network, Physica A: Statistical Mechanics and its Applications 374 (2), 69-878.





Excitable Cell

# Electrically Coupled Neural Network

A coupled ring network consists of several Morris-Lecar neurons. Each neuron's membrane potential is coupled to the membrane potential of its neighbor through a **diffusive coupling term**:

$$\dot{V}_i = f(V, n) + D(V_{i+1} + V_{i-1} - 2V_i)$$



Figures: a single kicker neuron spreads activity through the network (right). The vertical axis represents time (descending). The horizontal axis represents individual neurons in the network. The membrane potential is described by the color (blue: resting potential). Below: the effect of several kickers as the bifurcation parameter is increased. Starting from the left,  $I_{app} = 28.5, 30, 32, 38$ .



#### **Applied Current**

The Morris-Lecar ring network is a **chaotic** system. Measurements of the maximum Ly**apunov exponent** ( $\lambda$ ) result in a positive number, showing that solutions that start near  $<_{0.015}$ each other in phase space diverge exponentially.

As the bifurcation parameter is increased (**top**) the Lyapunov exponent **decreases**. When the network size increases (**bottom**), the Lyapunov exponent **increases**.

Figures: Lyapunov exponent on the vertical axis with time on the horizontal axis (**right**). For measurements  $\frown$  0.02 across the bifurcation parameter, N = 100. Measurements across network size are for a constant bifurcation parameter,  $I_{app} = 32$ .

Transient chaos is characterized by a sudden collapse of chaotic dynamics in the absence of external perturbations, indicating that collapse is an intrinsic property of many deterministic systems.

Figures: The Morris-Lecar ring network exhibits transient chaos that can collapse on to two species of attractor: the stable fixed point in which the whole network falls to the resting potential (left), or a limit cycle, in which activity cycles around the network periodically (right).

Lifetime analysis shows that prior to collapse, chaotic behavior can persist over large temporal scales. These lifetimes increase exponentially as the bifurcation parameter (**left**) is increased.. Lifetimes also tend to increase as the network size (**right**) is increased, as is common for systems exhibiting transient spatiotemporal chaos (Wackerbauer & Showalter, 2003).

Figures: Lifetimes of transient chaotic behavior across I (**left**) and system size (**right**).

Periodic collapse behavior is more common near particular bifurcation parameter, and increases uniformly with the network size. Lifetime analysis (above) shows that both periodic and steady states have the same average lifetime, but the histogram details a wider distribution for the  $\frac{1}{2}$ steady-state solutions.

28.5 29 29.5 30 30.5 Applied Current, I [mA] Periodic Collapse

32 33 34 35 36 37 3

Applied Current ImA

Lifetimes, N = 50

total mean steady mean

periodic mean

**Figures:** Probability of a collapse to periodic behavior (**left**) as a function of I<sub>app</sub>. A histogram of lifetimes (**right**); steady (blue) and periodic (red) for  $I_{app} = 32$ .

## Existence of Chaos







# Transient Basins of Attraction





A basin of attraction gives the set of initial conditions for which a particular attractor is reached. Here, the "transient" basin of attraction is computed. A set of neurons are moved to a point in phase space and the network is allowed to evolve deterministically for 1000ms. At that point, the state of the network is determined.

Only a particular subset of neurons are represented by the color of the phase point. All other neurons in the network are either at resting potential, or relaxed on the chaotic saddle, depend ing on the study (see **Basin Figures** 2 & 3).

Basin Figure 1: The basin represents the initial conditions for which the system reached an attractor (blue - steady state, green - periodic) or those for which the system dynamics did not collapse (red).

# Mechanisms of Collapse

A transient basin study demonstrates two distinct mechanisms for collapse in the diffusively-coupled ring network. For a network mostly at rest, periodic solutions are more probable for higher current values, but for an active network relaxed on the attractor, the lower current values carry a higher probability of collapsing onto the limit cycle. As the perturbation size is increased, the probability of periodic collapse begins to spread to higher applied current. On the other hand, such large synchronized perturbations are unlikely in the closed system that experiences no external perturbation with the exception of a near collapse. In a near collapse, most neurons fall to the rest state except a small cluster of neurons that may either reactivate the network, or collapse its dynamics. This moves the network closer to the rest regime, where larger applied current is associated with a higher chance of collapse to the periodic state. These data suggest distinct collapse mechanisms dominate interactions in different regions of the parameter space.

#### Basin Figure 2:

Right: the network at rest is perturbed with two kickers at varied distances from each other. The basin becomes indistinguishable from a single neuron perturbation around a distance of six.

#### **Basin Figure 3:**

Below: an active network is initiated by randomly perturbing 1/5 of the neurons and letting the trajectories approach the vicinity of the chaotic saddle that drives the chaotic behavior. Then a fraction of neurons (vertical axis) are perturbed at random locations in the network.





#### **Applied Current**

The empirically-derived Morris-Lecar neuron model makes a powerful element for a network study, allowing a compromise between complexity and computational efficiency. The system can express drastic changes over short temporal scales shifting from an active chaotic state to simple periodic or steady-state behavior. Correlation studies reveal no long-term spatial or temporal correlation between members of the ensemble and collapse comes suddenly, without warning. System collapse is an intrinsic property, occurring in the absence of external influence.

Chaos can persist in the network for long lifetimes, but the system always inevitably collapses to either a periodic (on) or steady (off) state. That complicated interactions with a binary result can occur in a diffusively-coupled system of spiking neurons implies a significant role for gap junctions in neural computation, especially with respect to lateral information transfer in parallel wired transmission. Gap junctions serve as gateways between cells. In the CNS, both astrocytes and neurons rely on gap junctions for intercellular communication. In neurons, gap junction coupling is sufficient to evoke action potentials and can synchronize activity across a network (Velazquez & Carlen, 2000). Gap junctions have been found connecting axons in the adult hippocampus (Hamzei-Schiani et al, 2007) and throughout the adult cerebral cortex (Nadarajah et al, 1998). They have also been shown, in conjunction with inhibitory synapses, to modulate inspiratory motoneuron synchronization (Bou-Flores, C. & Berger, A., 2000).

#### Gap Junction References:

Bou-Flores, C. & Berger, A. (2000). Gap Junctions and Inhibitory Synapses Modulate Inspiratory Motoneuron Synchronization. Journal of Neurophysiology 85 (4), 1543-1551 /elazquez, JLP and Carlen PL (2000). Gap junctions, synchrony and seizures, Trends in Neurosciences 23 (2), 68-74.









### Discussion

Hamzei-Sichani, F et al (2007). Gap junctions on hippocampal mossy fiber axons demonstrated by thin-section electron microscopy and freeze-fracture replica immunogold labeling. PNAS 104 (30), 12548-12553. Nadarajah, B et al (1998). Gap junctions in the adult cerebral cortex: Regional differences in their distribution and cellular expression of connexins. The Journal of Comparative Neurology 376 (2) 326-342.