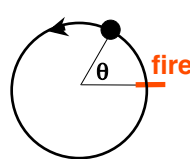
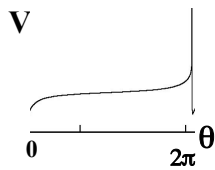
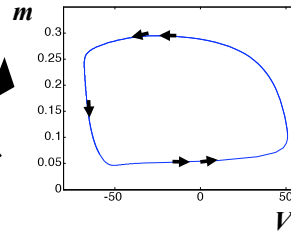
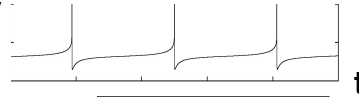
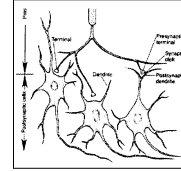


Reduction of neurons to phases

start with "biophysical"
neuron model

$$\begin{aligned}
 C\dot{V} &= -\bar{g}_{Na}m^3h(V-E_{Na}) - \bar{g}_K n^4(V-E_K) - \bar{g}_l(V-E_l) + I_a \\
 \dot{m} &= \alpha_m(V)(1-m) - \beta_m(V)m \\
 \dot{n} &= \alpha_n(V)(1-n) - \beta_n(V)n \\
 \dot{h} &= \alpha_h(V)(1-h) - \beta_h(V)h
 \end{aligned}$$

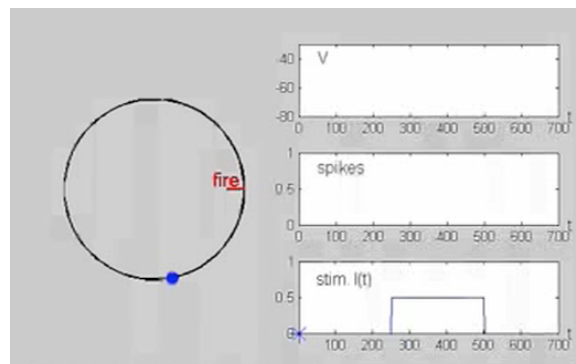


ALERT: Interesting methods here!

Winfree '74, Guckenheimer '75

1

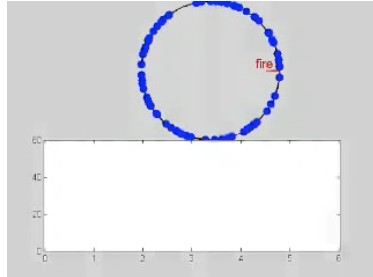
Phase dynamics



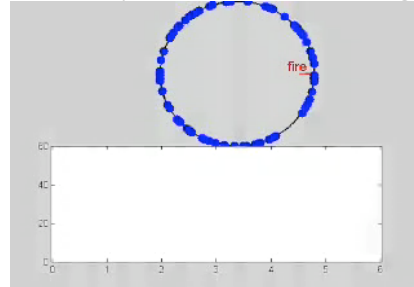
2

Spike trains, firing rates, and synchrony

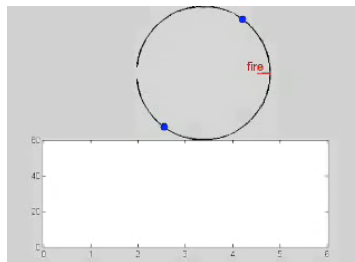
1. Decorrelated firing



2. Synchronized firing



3. Anti-synchronized, frequency-doubled firing



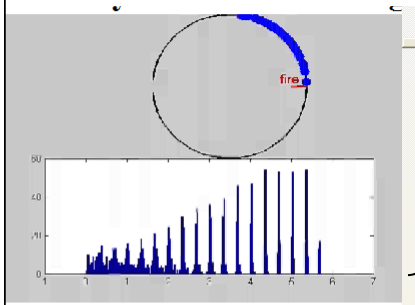
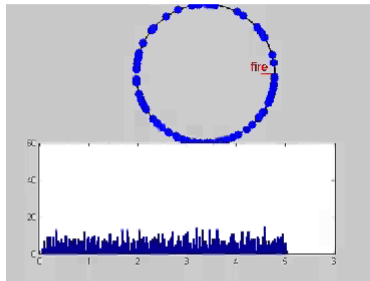
3

Roles for synchrony

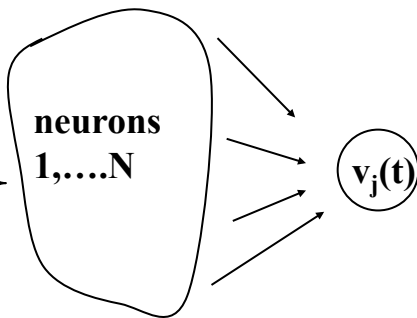
- 1) Synchrony allows information to propagate through “layers” of neurons
- 2) Synchrony enables new information processing strategies

4

A role for synchrony in signal transmission



Can the population trigger upstream cells? Answer depends on synchrony ... “synchrony controls salience of representation”

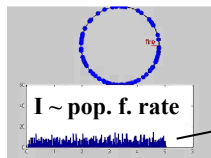


5

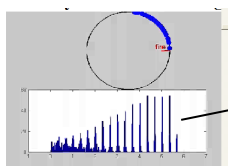
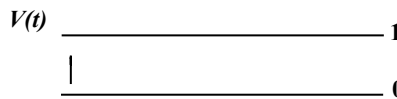
If average input $\langle I \rangle$ from upstream neurons insufficient to cause firing, need FLUCTUATIONS in I due to synchrony to drive V above spiking threshold (“detecting” upstream event)

$$\tau \frac{dV}{dt} = -V + k_1 + k_2 I \quad ; 0 \leq V \leq 1$$

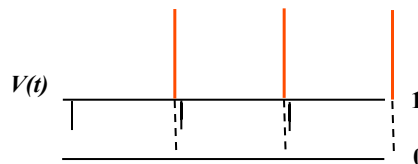
plus “reset” condition: $V \rightarrow 0$ and spike when passes 1



$I \sim \text{const}$



I fluctuates
 $\langle I \rangle$ same



Shelley, Cai, Rangan, Tao, McLaughlin, Shapley – Fluctuation driven firing (related)

6

Another role for synchrony ...

- Hypothesis

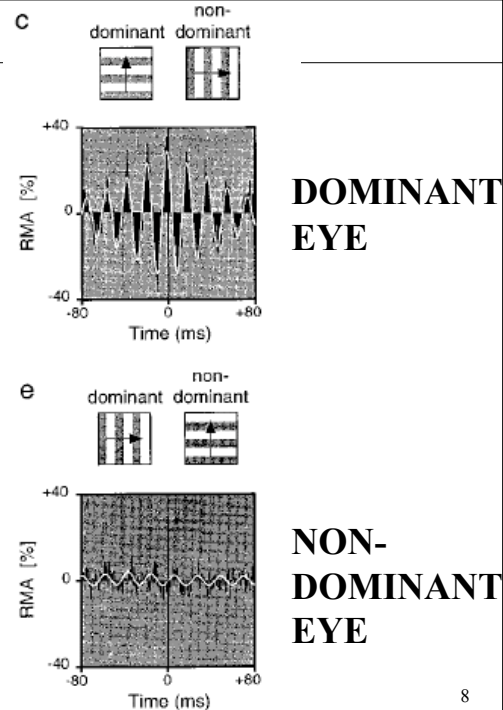
- alpha, beta, gamma rhythms set up “substrate” on which further neural computations are based.

- gamma (30-80 Hz) ... cognition ; synchrony at this frequency when “binding” together features of object, or in attention
 - beta (12-30 Hz) ... intense mental activity
 - alpha (8-12 Hz) ... wakefulness, reward?
 - delta (1-4 Hz) ... sleep

7

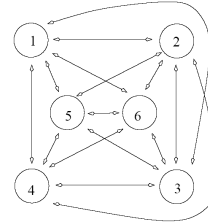
E.g. ...

- Measurements of synchrony in visual cortex during binocular rivalry task indicate *greater synchrony* among “currently” dominant neurons



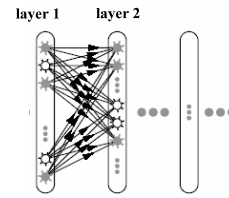
Three mechanisms for the generation of synchrony

1) Recurrent connections in a network

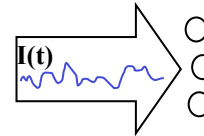


2) Feed-forward connections among layers

Diesmann, Gewaltig, Aertsen
Nature 402, 529, 1999.



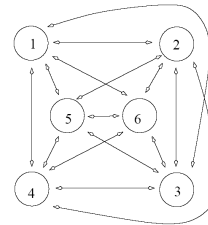
3) Shared, fluctuating inputs to a population Entrainment -- no connections!



9

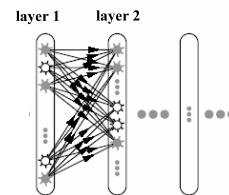
Three mechanisms for the generation of synchrony

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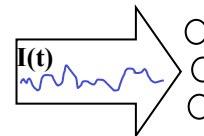


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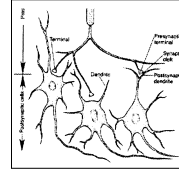
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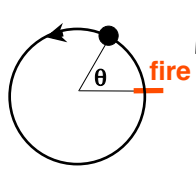
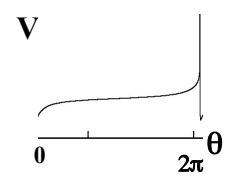
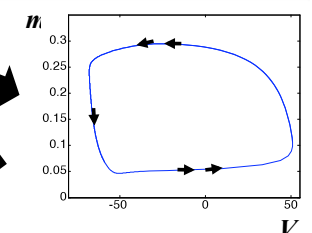
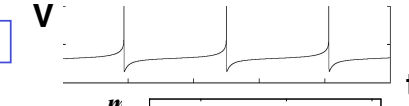
10

recall reduction of neurons to phases

start with biophysically plausible neuron model



$$\begin{aligned}
 CV &= -\bar{g}_{Na}m^3h(V - E_{Na}) - \bar{g}_K n^4(V - E_K) - \bar{g}_l(V - E_l) + I_a + I_{syn}(t) \\
 \dot{m} &= \alpha_m(V)(1 - m) - \beta_m(V)m \\
 \dot{n} &= \alpha_n(V)(1 - n) - \beta_n(V)n \\
 \dot{h} &= \alpha_h(V)(1 - h) - \beta_h(V)h
 \end{aligned}$$



ALERT: Interesting methods here!

Winfree '74, Guckenheimer '75

Reduction of neurons to phases

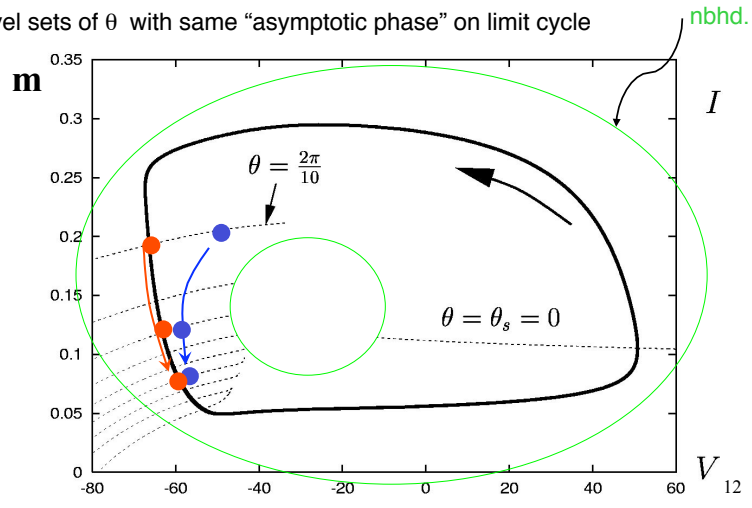
[Coddington and Levinson, 1955, Winfree, 1974, Guckenheimer, 1985]

In nbhd. of limit cycle, define variable $\theta(V, m, n, h)$ such that:

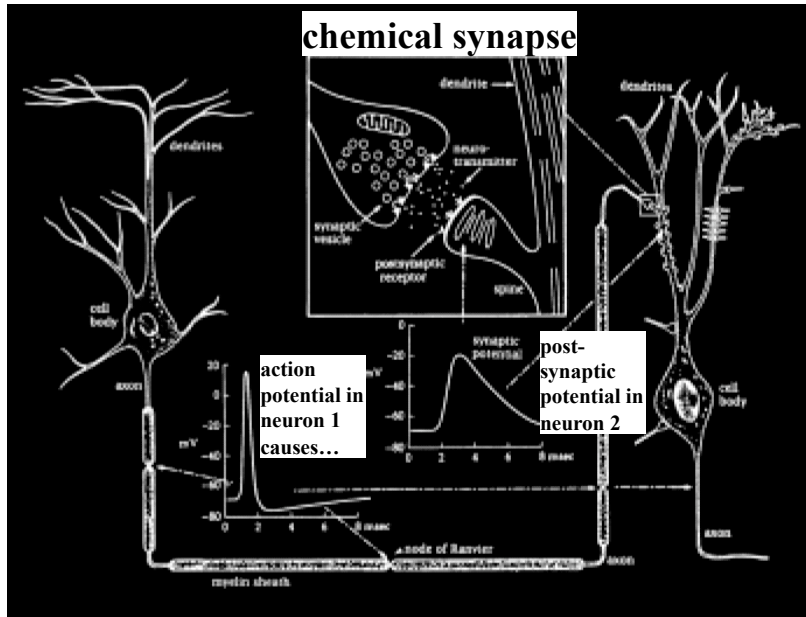
$$\frac{d\theta}{dt} = \omega \text{ along trajectories, where } \omega = \frac{2\pi}{T}$$

Strategy: start on limit cycle itself, where say $V(\theta) = V(\omega t)$.

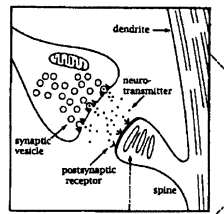
Then define level sets of θ with same "asymptotic phase" on limit cycle



Recall how neurons communicate...



13



Kandel and Schwartz

(Chemical) Synapse

$$C\dot{V} = -\bar{g}_{Na}m^3h(V - E_{Na}) - \bar{g}_K n^4(V - E_K) - \bar{g}_L(V - E_L) + I_a + \underbrace{I_{syn}(t)}_{\bar{g}_{syn}(t) * (V_{syn} - V)}$$

$$\dot{m} = \alpha_m(V)(1 - m) - \beta_m(V)m$$

$$\dot{n} = \alpha_n(V)(1 - n) - \beta_n(V)n$$

$$\dot{h} = \alpha_h(V)(1 - h) - \beta_h(V)h$$

Excitatory synapse: $V_{syn} > V_{rest}$

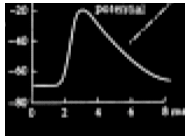
Inhibitory synapse: $V_{syn} < V_{rest}$

14

Approximating the synaptic current

$$\frac{dV}{dt} = \dots + \underbrace{I_{syn}(t)}_{g_{syn}(t) * (V_{syn} - V)}$$

assuming conductance impulse is brief, set $I_{syn}(t) = h * \delta(t)$



Excitatory synapse: $V_{syn} > V_{rest}$, $h > 0$

Inhibitory synapse: $V_{syn} < V_{rest}$, $h < 0$

$$V \rightarrow V + h\Delta V$$

15

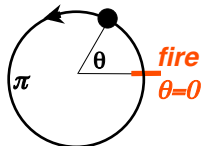
For phase dynamics ...

$$\frac{d\theta}{dt} = \omega + z(\theta) \times [I_{syn}(t)]$$

natural frequency

phase response curve
(phase sensitivity curve)

$$z(\theta) = \lim_{\Delta V \rightarrow 0} \frac{\Delta \theta}{\Delta V}$$

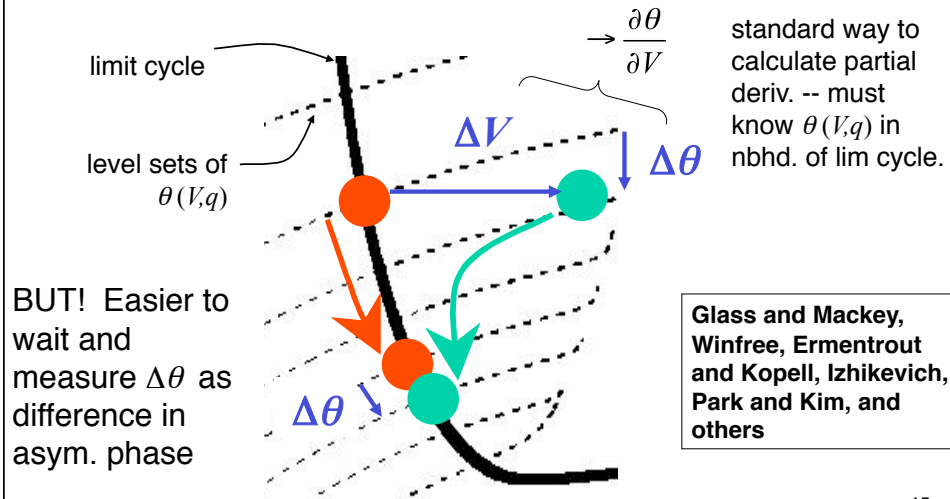


16

Finding $z(\theta)$.

Asymptotic phase property of field $\theta(V,q)$ gives nice way to calculate

$$z(\theta) = \lim_{\Delta V \rightarrow 0} \frac{\Delta \theta}{\Delta V}$$



17

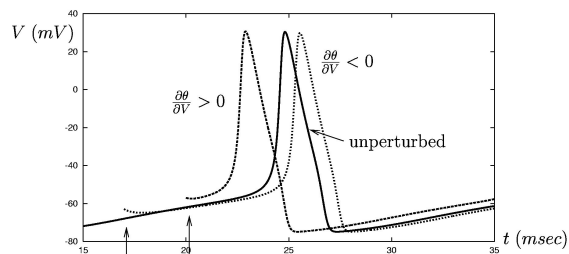
Finding $z(\theta)$.

Calculating the phase response curve:

- Perturb an uncoupled neuron with a brief voltage stimulus ΔV at different times in its cycle, parameterized by θ
- Measure the resulting phase-shift $\Delta \theta$ with respect to the unperturbed system

For Hodgkin-Huxley neurons with $I = 10 \mu A/cm^2$:

$$z(\theta) = \lim_{\Delta V \rightarrow 0} \frac{\Delta \theta}{\Delta V}$$



perturb with 5 mV stim.

Jeff Moehlis

18

Have phase dynamics ... that you could directly derive from the laboratory !

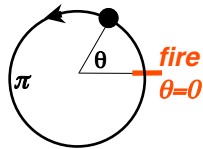
Glass and Mackey, Winfree

$$\frac{d\theta}{dt} = \omega + z(\theta) \times [I_{syn}(t)]$$

natural frequency

phase response curve
(phase sensitivity curve)

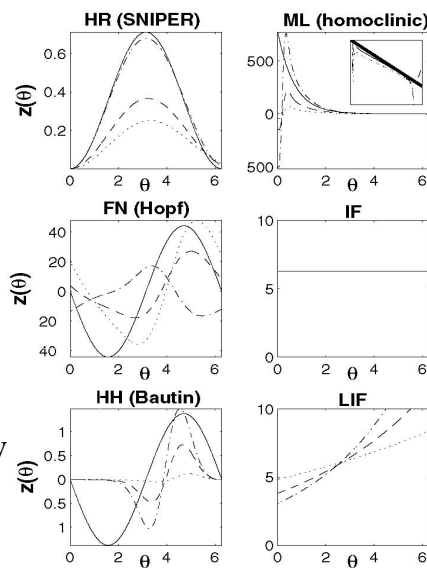
$$z(\theta) = \lim_{\Delta V \rightarrow 0} \frac{\Delta \theta}{\Delta V}$$



19

Phase response curves for different neurons look very different!

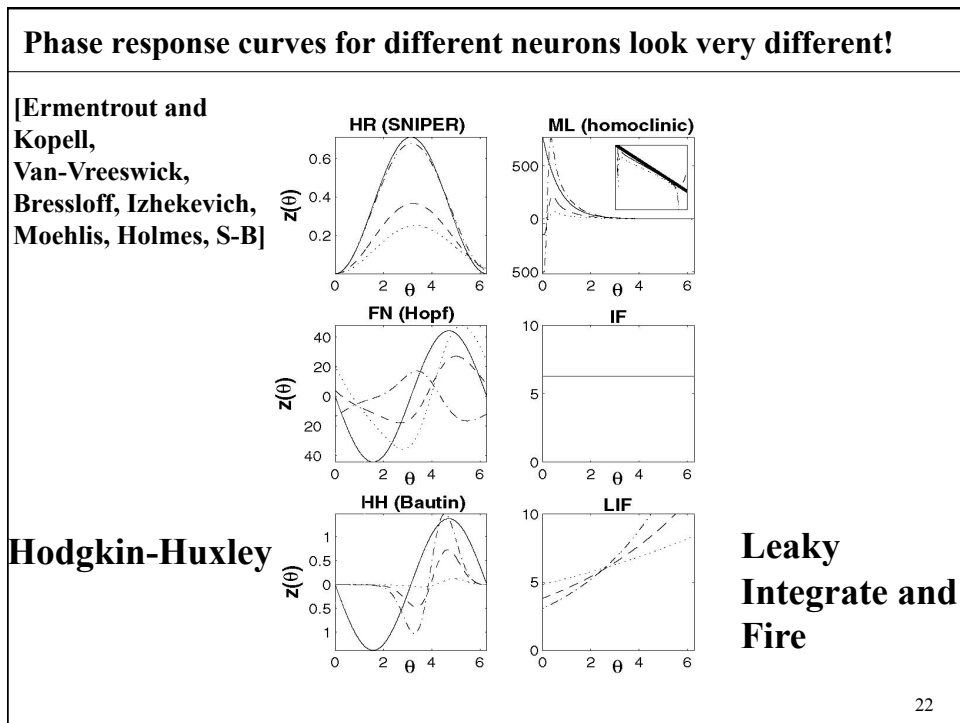
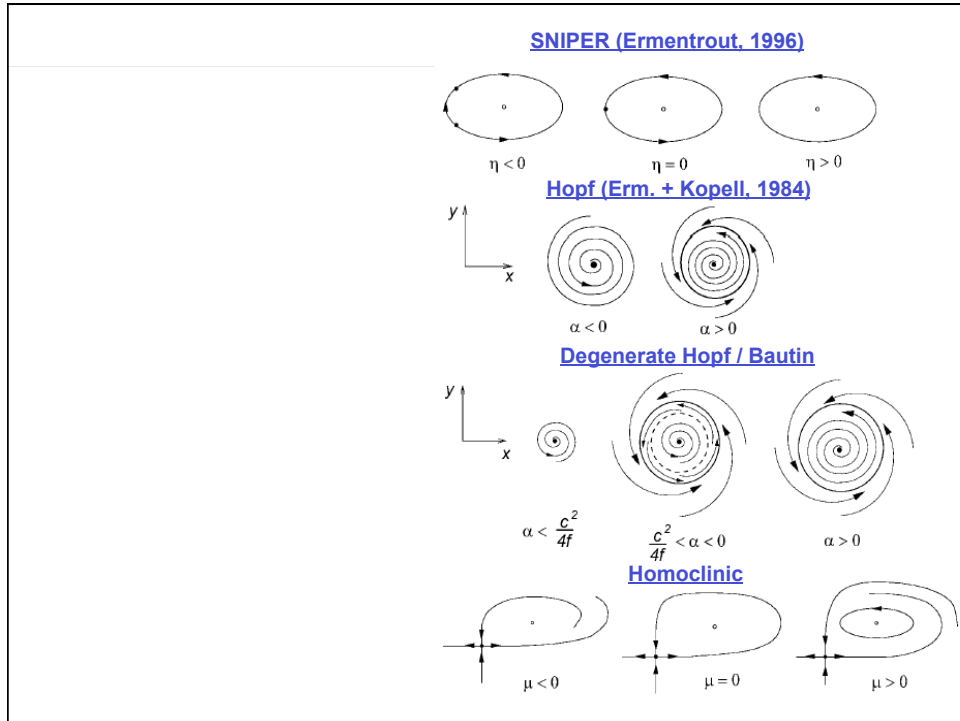
[Ermentrout and Kopell, Van-Vreeswick, Bressloff, Izhekevich, Moehlis, Holmes, S-B]



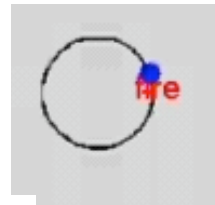
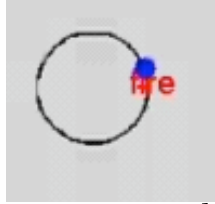
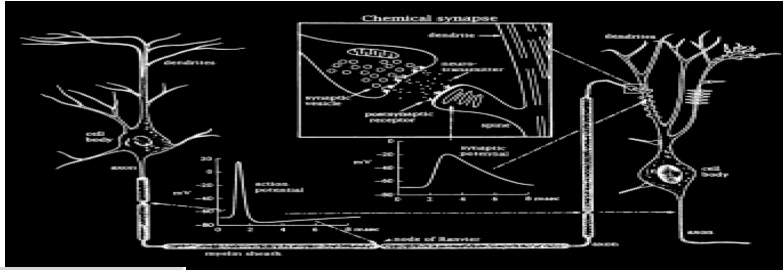
Hodgkin-Huxley

Leaky Integrate and Fire

20



Study synchrony in “network” of two coupled neurons



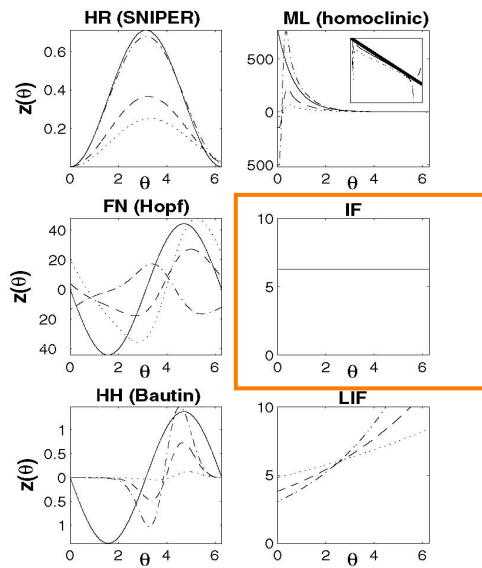
$I_{\text{syn}}(t)$

$$\frac{d\theta_1}{dt} = \omega + z(\theta_1) * h\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + z(\theta_2) * h\delta(t - t_1^j)$$

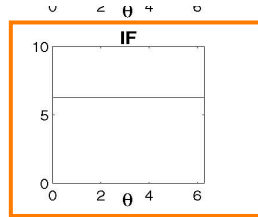
23

OK ... let's take the simplest imaginable case ...



24

OK ... let's take the simplest imaginable case ...



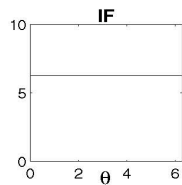
$$\frac{dV}{dt} = I_b \quad ; 0 \leq V \leq 1 \quad (1)$$

plus "reset" condition: $V \rightarrow 0$ and spike when passes 1

25

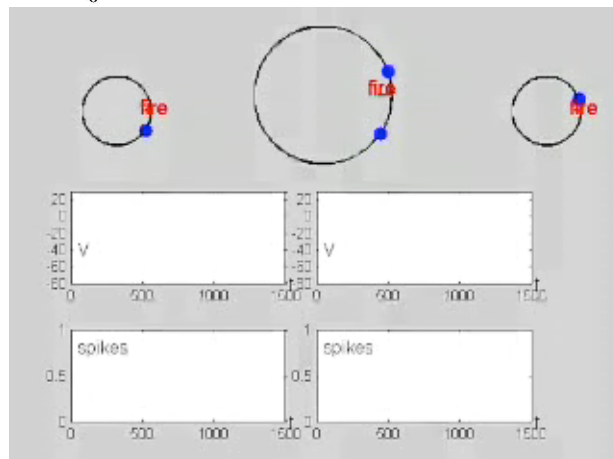
OK ... let's take the simplest imaginable case for z -- IF

PRC
 $z(\theta)$



$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$

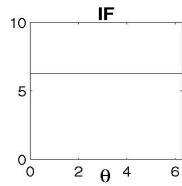


$h > 0$
excit.
synapse

26

OK ... let's take the simplest imaginable case for z -- IF

PRC
 $z(\theta)$



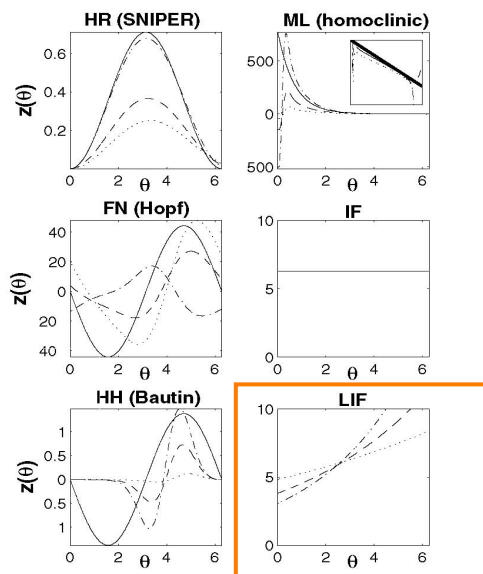
$$\frac{d\theta_1}{dt} = \omega + z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + z(\theta_2)\delta(t - t_1^j)$$

Moral: coupling two neurons together does **nothing** if this coupling is not voltage (phase) dependent

27

Next, consider the *leaky* integrate and fire model

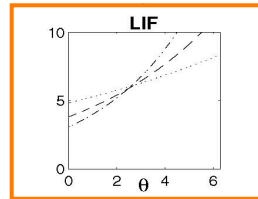


28

The Leaky integrate and fire model

$$\tau \frac{dV}{dt} = -V + I_b + I_{ext}(t) \quad ; 0 \leq V \leq 1 \quad (1)$$

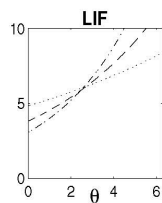
plus "reset" condition: $V \rightarrow 0$ and spike when passes 1



29

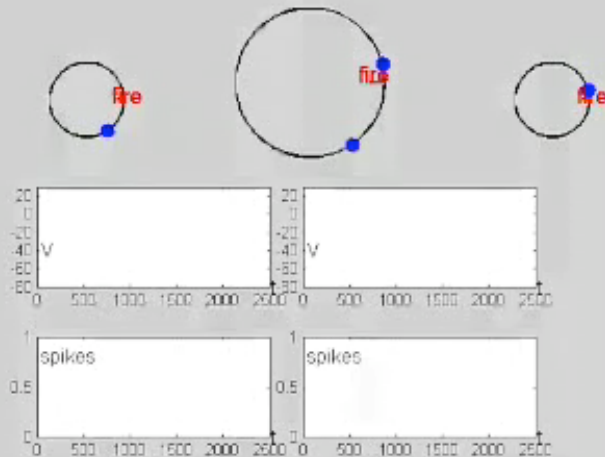
The Leaky integrate and fire model

PRC
 $z(\theta)$

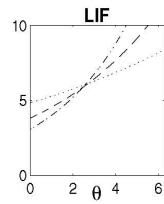


$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1) \delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2) \delta(t - t_1^j)$$



PRC
z(θ)



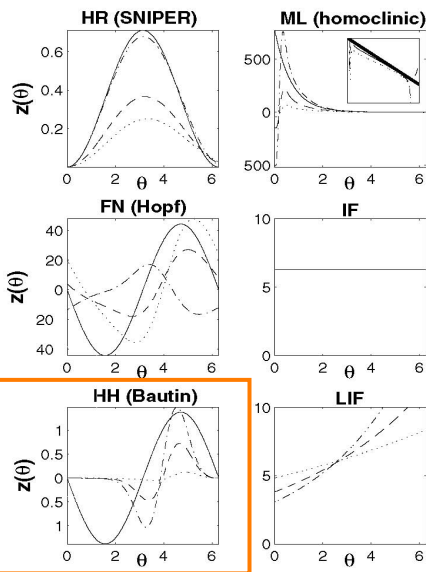
$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$

Moral: “Fast” excitatory coupling can synchronize LIF neurons ...

31

Next, back to Hodgkin-Huxley!

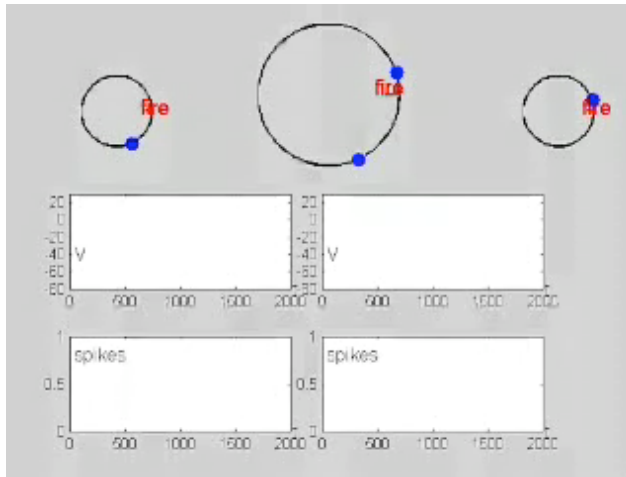
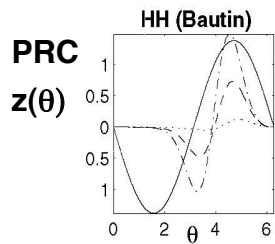


32

The Hodgkin-Huxley model

$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

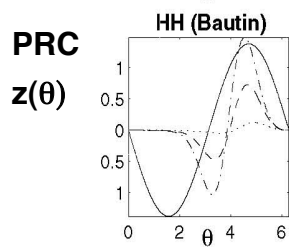
$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$



The Hodgkin-Huxley model

$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$



Moral: (again) “Fast” excitatory coupling can synchronize HH neurons ...

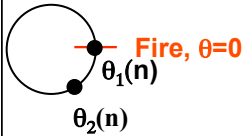
Analyze via Poincare map between firing times of θ_1

$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$

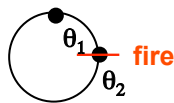
Nancy Kopell, Bard Ermentrout,
-- "weak coupling theory"

$$\text{Let } \theta_{12} = \theta_1 - \theta_2$$

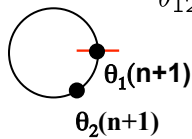


$$\theta_2 \mapsto \theta_2 + h z(-\theta_{12}(n)), \text{ or:}$$

$$\theta_{12}(n) \mapsto \theta_{12}(n) - h z(-\theta_{12}(n))$$



$$\theta_1 \mapsto \theta_1 + h z[\theta_{12}(n) - h z(-\theta_{12}(n))]$$



$$\theta_{12}(n+1) = \theta_{12}(n)$$

$$- h z(-\theta_{12}(n))$$

$$+ h z[\theta_{12}(n) - h z(-\theta_{12}(n))]$$

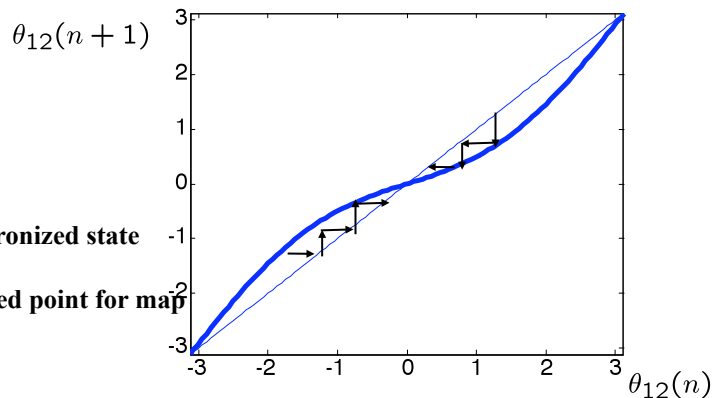
$$= \theta_{12}(n) + h \{z(\theta_{12}(n)) - z(-\theta_{12}(n))\} + \mathcal{O}(h^2)$$

Phase-difference map $\theta_{12} = \theta_1 - \theta_2$

$$\theta_{12}(n+1) = \theta_{12}(n) + h \{z(\theta_{12}(n)) - z(-\theta_{12}(n))\} + \mathcal{O}(h^2)$$

E.g., for HH neuron, $z(\theta) \sim -\sin(\theta)$, so

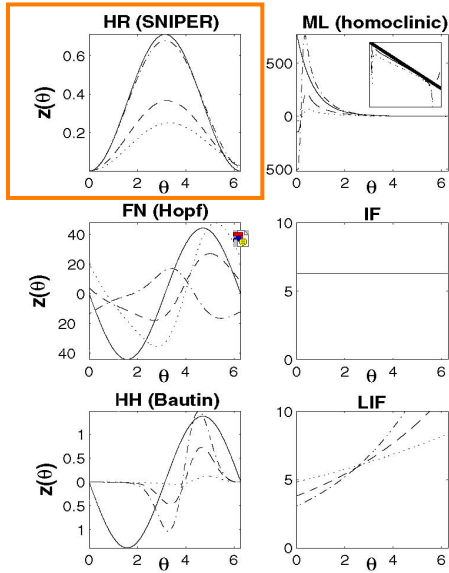
$$\theta_{12}(n+1) \approx \theta_{12}(n) - 2h \sin(\theta_{12})$$



See: synchronized state
 $\theta_{12}=0$
is stable fixed point for map

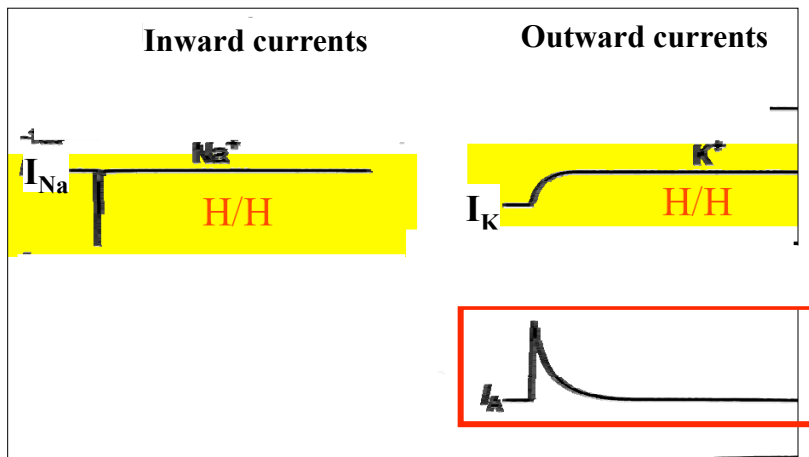
Let's try (as our last example)

Very common
in neural
models ...



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The “Hodgkin Huxley plus **A current**” model

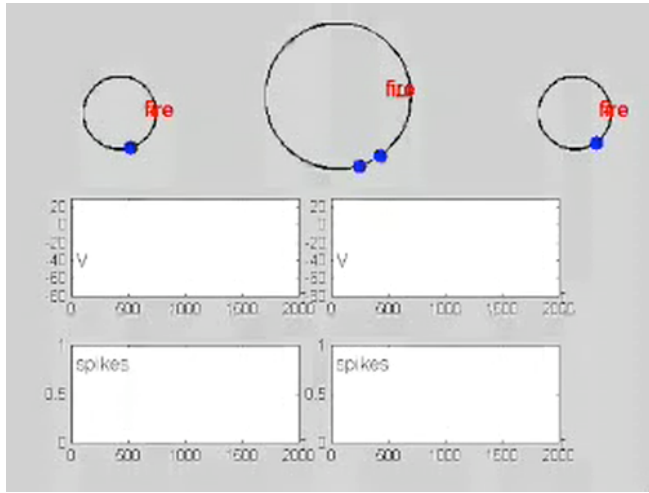


38

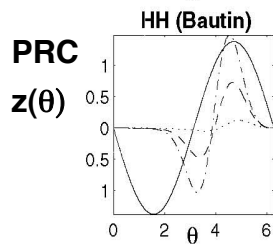
The “Hodgkin Huxley plus A current” model

$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$



The “Hodgkin Huxley plus A current” model



$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$

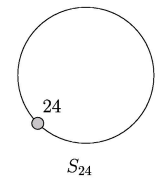
**Moral: Excitatory coupling actually
DESynchronizes HH neurons with A currents
Stable “anti-synchronized” state
However, inhibition *does* synchronize ...**

**“When inhibition, not excitation,
synchronizes...” Van Vreeswijk et al 1995**

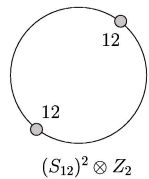
In fact, there are other types of stable antisynchronous states

- **N neurons, (slow) inhibitory synapses, Hodgkin-Huxley model:**

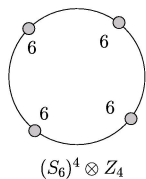
N=24



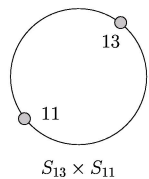
oscillators in phase



oscillators π out of phase



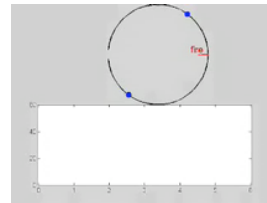
oscillators $\pi/2$ out of phase



oscillators $\delta \neq \pi$ out of phase

Multiple stable states

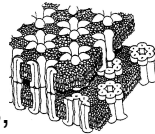
Each corresponds to a different effective frequency for the N neurons



Used by Rinzel to explain co-existence of delta (1-4 Hz) and “spindling” (8-14) Hz. rhythms [deep vs light sleep] – thalamo – cortical cells

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Beyond impulse coupling



Brain has gap junctions,

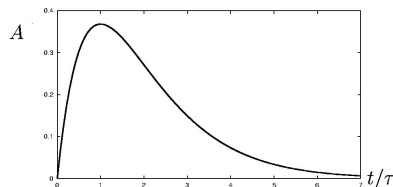
$$\dot{V}_i = \dots + \frac{\alpha_e}{N} \sum_{j=1}^N (V_j - V_i)$$

N = number of neurons

α_e = electrotonic coupling strength

as well as slow chemical synapses.

$$\dot{V}_i = \dots + \frac{\alpha_s}{N} (V_K - V_i) \sum_{j=1}^N A(t - t_j - \tau_d)$$



$$\frac{d\theta}{dt} = \omega + z(\theta) \times [I_{syn}(t)]$$

$$\frac{d\theta_i}{dt} = \omega + z(\theta_i) \sum_{j=1}^n I_j(\theta_j)$$

Kuramoto, Kopell, Ermentrout – average coupling functions:

$$f_{e,s}(\theta) = \frac{1}{2\pi} \int_0^{2\pi} z(\phi) I_{e,s}^{coup}(\theta + \phi) d\phi$$

get a system depending on phase differences only

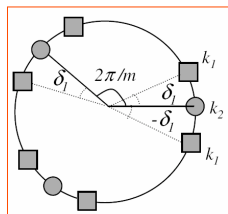
$$\frac{d\theta_i}{dt} = \omega + \underbrace{\frac{\alpha}{N} \sum_j f_e(\theta_j - \theta_i)}_{\text{electrotonic}} + \underbrace{\frac{\beta}{N-1} \sum_{j \neq i} f_s(\theta_j - \theta_i)}_{\text{synaptic}}$$

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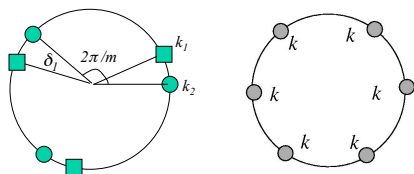
Symmetry arguments: exists huge variety of rotating equilibria

[Ashwin, Swift, Okuda, S-B.]

Proposition. f odd, satisfy inequality
→ solutions of form



Also, in general get:



$$\frac{d\theta}{dt} = \omega + z(\theta) \times [I_{syn}(t)]$$

$$\frac{d\theta_i}{dt} = \omega + z(\theta_i) \sum_{j=1}^n I_j(\theta_j)$$

Kuramoto, Kopell, Ermentrout -- average coupling functions:

$$f_{e,s}(\theta) = \frac{1}{2\pi} \int_0^{2\pi} z(\phi) I_{e,s}^{coup}(\theta + \phi) d\phi$$

get a system depending on phase differences only

$$\frac{d\theta_i}{dt} = \omega + \underbrace{\frac{\alpha}{N} \sum_j f_e(\theta_j - \theta_i)}_{\text{electrotonic}} + \underbrace{\frac{\beta}{N-1} \sum_{j \neq i} f_s(\theta_j - \theta_i)}_{\text{synaptic}}$$

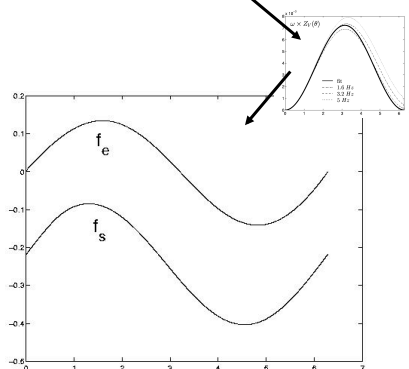
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Contrasts situation for sin coupling

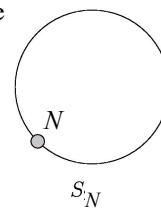
Coupling Functions

$$\frac{d\theta_i}{dt} = \omega + \underbrace{\frac{\alpha}{N} \sum_j f_e(\theta_j - \theta_i)}_{\text{electrotonic}} + \underbrace{\frac{\beta}{N-1} \sum_{j \neq i} f_s(\theta_j - \theta_i)}_{\text{synaptic}}$$

$$f_{e,s}(\theta) = \frac{1}{2\pi} \int_0^{2\pi} z(\phi) I_{e,s}^{coup}(\theta + \phi) d\phi$$



Proposition.
For $f(\cdot) = \sin(\cdot)$
in-phase state



oscillators in phase

is **globally stable**

[Use gradient dynamics]

[Strogatz, S-B, Kuramoto, Okuda]

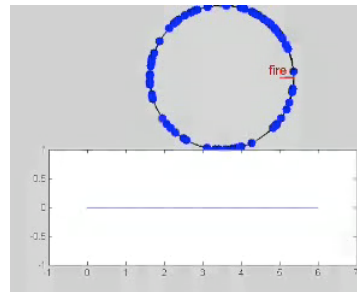
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Synchronized firing requires similar frequencies

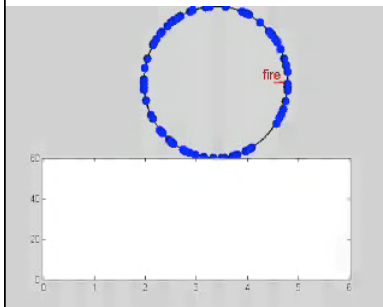
$$\omega_i = 3 \pm 0.5 \text{ Hz}$$

$$\frac{d\theta_i}{dt} = \omega_i + h \sum_{j=1}^n f(\theta_j - \theta_i)$$

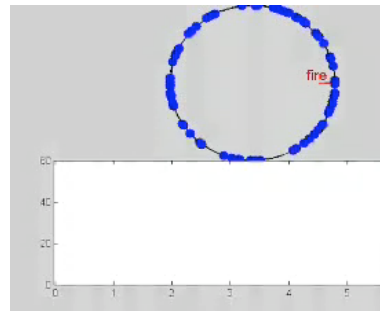
$i = 1, \dots, N$



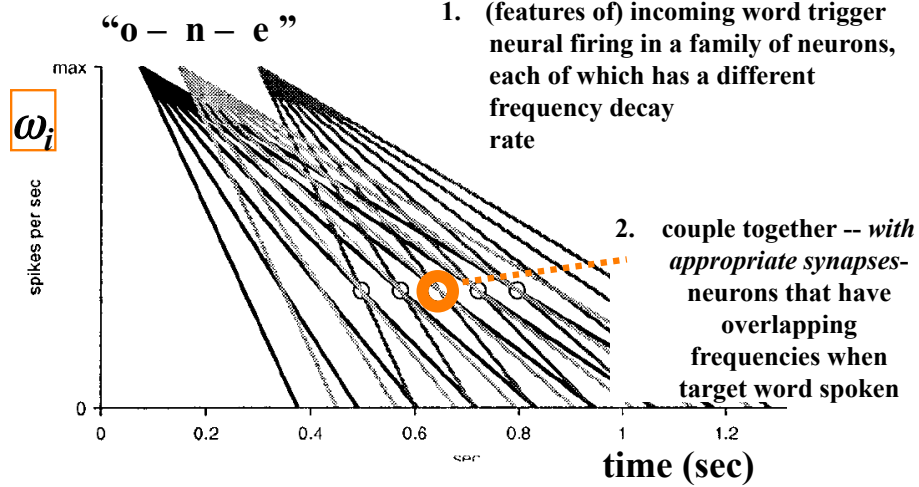
$$\omega_i = 3 \pm 1.0 \text{ Hz}$$



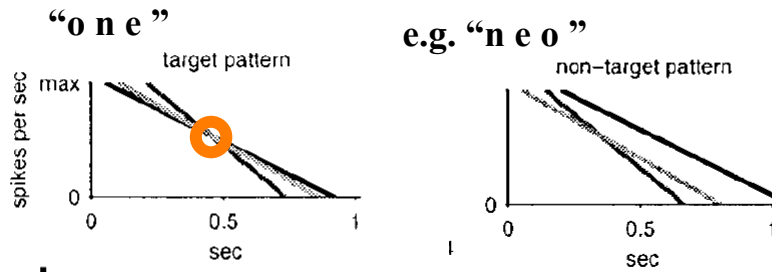
$$\omega_i = 3 \pm 1.5 \text{ Hz}$$



- this fact (!) allowed J. Hopfield and C. Brody to develop a new theory of speech recognition

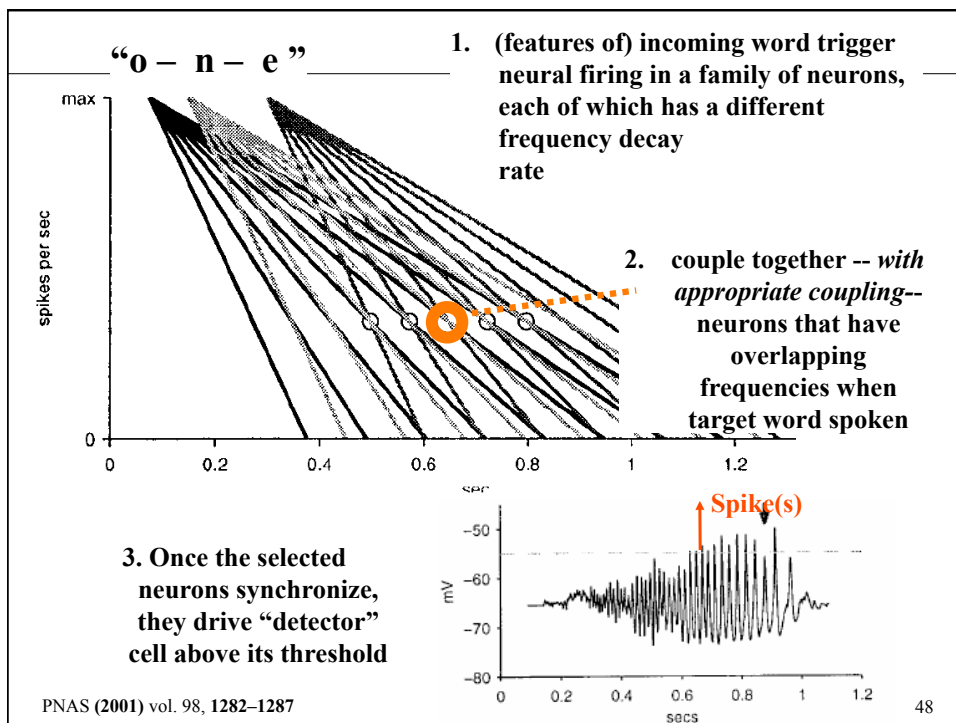


- “only” get overlap (among frequencies of selected neurons) when target word is presented



PNAS (2001) vol. 98, 1282–1287

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PNAS (2001) vol. 98, 1282–1287

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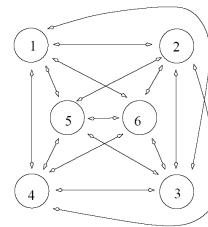
SUMMARY

- 1) Synchrony allows information to propagate through “layers” of neurons
 - Synchronized activity can be necessary to trigger “downstream” cells
- 2) Coupling and rhythms yield new computational strategies
 - Diverse neurons give diverse results
 - frequency-doubling and antiphase states
 - significance for computation and beautiful mathematics (N. Kopell)
 - Speech recognition (Hopfield and Brody) and may other applications!

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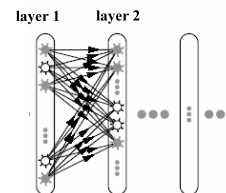
Three mechanisms for the generation of synchrony

1) Recurrent connections in a network

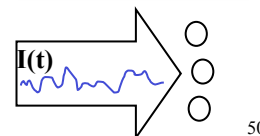


2) Feed-forward connections among layers

Diesmann, Gewaltig, Aertsen
Nature 402, 529, 1999.



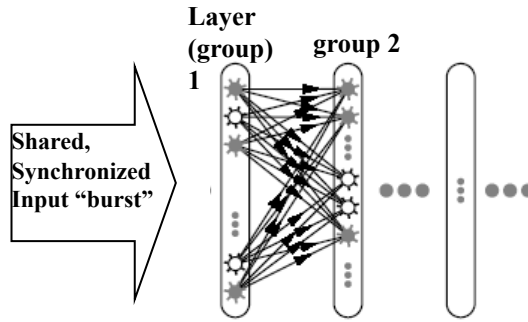
3) Shared, fluctuating inputs to a population Entrainment -- no connections!



A key question...Diesmann, Gewaltig, Aertsen; Nature 402, 529, 1999

- ONCE a synchronized “burst” of activity has been generated, can it be stably propagated through *layers* of cortical tissue? Or will it “dissipate”?

Feed-fwd. ONLY connections between successive neural groups



Diesmann, Gewaltig, Aertsen
Nature 402, 529, 1999.

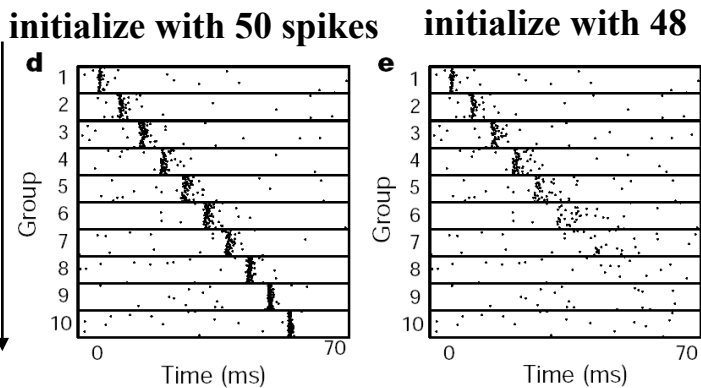
ABELES 1993 “synfire chains”

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A key question...

- ONCE a synchronized “burst” of activity has been generated, can it be stably propagated through *layers* of cortical tissue? Or will it “dissipate”?

Feed-fwd. ONLY connections between successive neural groups



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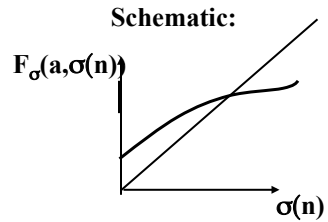
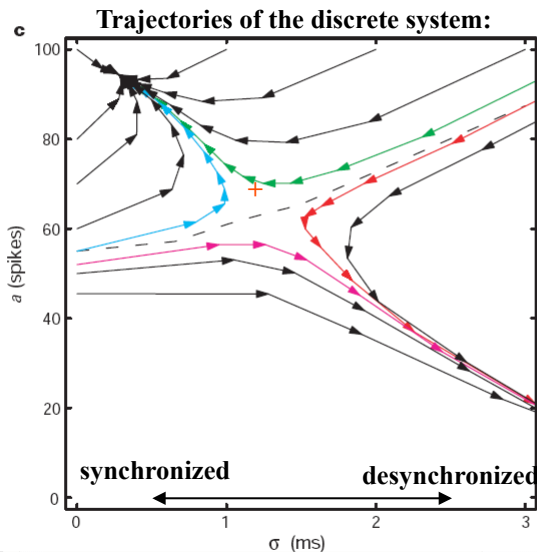
Answer: YES, if initiating spike volley suffic. large and synchronized

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Explain --

Numerically define a two dimensional map.
 $a(n)$, activity (number of cells that spikes in layer n)
 $\sigma(n)$, dispersion (spread in spike times at layer n).

$$(a(n+1), \sigma(n+1)) = F(a(n), \sigma(n)) .$$



See – synchrony
DEVELOPS across layers

Diesmann, Gewaltig, Aertsen
Nature 402, 529, 1999.

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- **Synchrony and feed forward networks at NYU:**

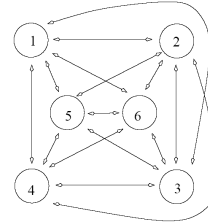
- Alex Reyes and collaborators

- Build virtual feed forward networks out of REAL NEURON(s)
- Analyze using phase or voltage density equations (Fokker-Planck, etc.)

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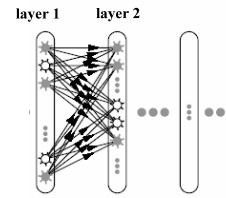
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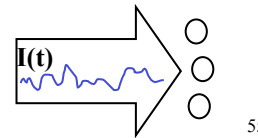


2) Feed-forward connections among layers

Diesmann, Gewaltig, Aertsen
Nature 402, 529, 1999.



3) Shared, fluctuating inputs to a population Entrainment -- no connections!



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Neurons produce reliable responses to fluctuating, but NOT constant (stepped) input

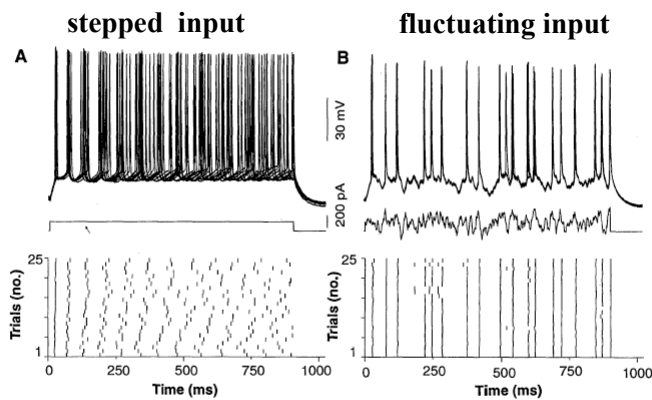


Fig. 1. Reliability of firing patterns of cortical neurons evoked by constant and fluctuating current. (A) In

Mainen and Sejnowski *data* from rat cortical neurons
Science 268 (1995) p. 1503

Spectrum of forcing matters – Hunter, Milton, and Cowan 1998
Explanation via Lyap. Exponents and phase models – Ritt 2003

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SUMMARY -- synchrony

- **Can arise in several ways:**
 - **Recurrent coupling**
 - **Feedforward coupling**
 - **Coordinated inputs**
- **Uses:**
 - **Synchronized activity can be necessary to trigger “downstream” cells**
 - **Coupling and rhythms yield new computational strategies**
 - See paper “We’ve got rhythm” by Nancy Kopell
 - Frequency-doubling and antiphase states (Rinzel, Golomb, Kopell)
 - Speech recognition (Hopfield and Brody) and may other applications!

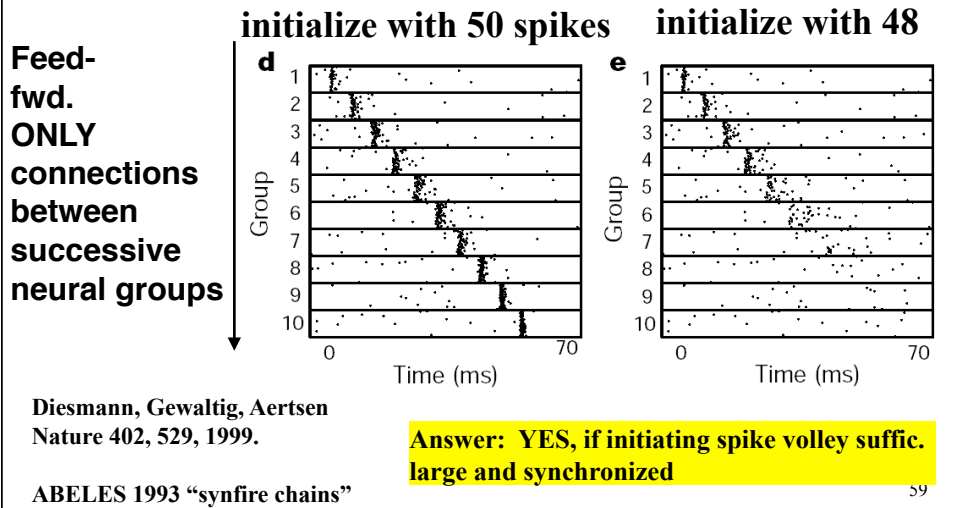
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- **extras**

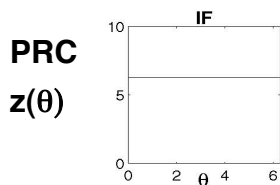
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A key question...

- ONCE a synchronized “burst” of activity has been generated, can it be stably propagated through *layers* of cortical tissue? Or will it “dissipate”?



OK ... let's take the simplest imaginable case for z -- IF



$$\frac{d\theta_1}{dt} = \omega + z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + z(\theta_2)\delta(t - t_1^j)$$

Moral: coupling two neurons together does nothing if this coupling is not voltage (phase) dependent

Note that, if we introduced reversal potentials

$$I_{\text{syn}} = \delta(t-t^j) (V_{\text{syn}} - V)$$

into the above, would recover voltage dependence and hence coupling would have some synchronizing effect

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Goal: simple phase description

natural
frequency

$$\frac{d\theta}{dt} = \omega$$

- Let $\mathbf{x} = \begin{pmatrix} V \\ q \end{pmatrix}$. Then we have defined coordinate change so that:

$$\frac{d\mathbf{x}}{dt} = \mathbf{F}(\mathbf{x}) \rightarrow \frac{d\theta}{dt} = \omega$$

where $\mathbf{F}(\mathbf{x})$ is 'original' neural vectorfield giving oscillations at freq. ω .

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Goal: simple phase description

natural
frequency

$$\frac{d\theta}{dt} = \underline{\omega} + \dots$$

- Let $\mathbf{x} = \begin{pmatrix} V \\ q \end{pmatrix}$. Then we have defined coordinate change so that:

$$\frac{d\mathbf{x}}{dt} = \mathbf{F}(\mathbf{x}) \rightarrow \frac{d\theta}{dt} = \omega$$

where $\mathbf{F}(\mathbf{x})$ is 'original' neural vectorfield giving oscillations at freq. ω .

- We're actually interested in effects of additional currents: $J(\mathbf{x}, t)$

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Goal: simple phase description

$$\frac{d\theta}{dt} = \overset{\substack{\text{natural} \\ \text{frequency}}}{\omega} + \dots$$

- Let $\mathbf{x} = \begin{pmatrix} V \\ q \end{pmatrix}$. Then we have defined coordinate change so that:

$$\frac{d\mathbf{x}}{dt} = \mathbf{F}(\mathbf{x}) \rightarrow \frac{d\theta}{dt} = \omega$$

where $\mathbf{F}(\mathbf{x})$ is 'original' neural vectorfield giving oscillations at freq. ω .

- We're actually interested in effects of additional currents: $J(\mathbf{x}, t)$ "perturbation"

$$\begin{aligned} \frac{d\mathbf{x}}{dt} = \mathbf{F}(\mathbf{x}) + \begin{pmatrix} J(\mathbf{x}, t) \\ 0 \end{pmatrix} &\rightarrow \frac{d\theta}{dt} = \frac{\partial \theta}{\partial \mathbf{x}} \cdot \left[\mathbf{F}(\mathbf{x}) + \begin{pmatrix} J(\mathbf{x}, t) \\ 0 \end{pmatrix} \right] \\ &\frac{d\theta}{dt} = \omega + \frac{\partial \theta}{\partial V} J(\mathbf{x}, t) \end{aligned}$$

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