



Massachusetts
Institute of
Technology



Learning Cycle-Linear Hybrid Automata for Excitable Cells

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Joint work with

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HSCC 2007

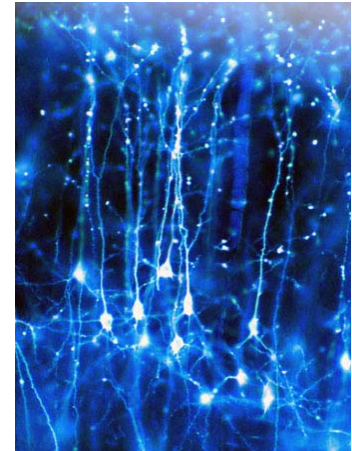
Pisa, Italy

Outline

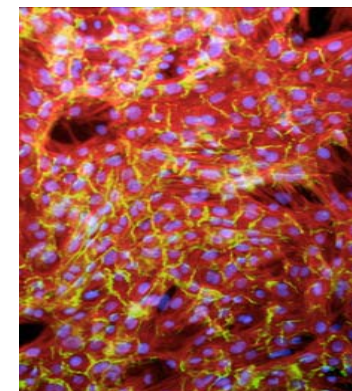
- Excitable cells
- Hybrid model for excitable cells
- Conclusions and future directions

Excitable Cells

- An excitable cell generates electrical pulses or *action potentials* in *response* to electrical stimulation
 - Examples: neurons, cardiac cells, smooth muscle cells
- **Local regeneration** allows electric signal propagation without damping
- Building block for electrical signaling in brain, heart, and muscles



Neurons of a squirrel
University College London

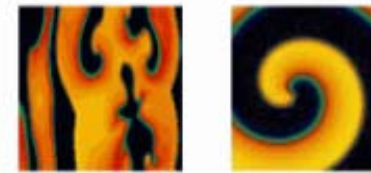
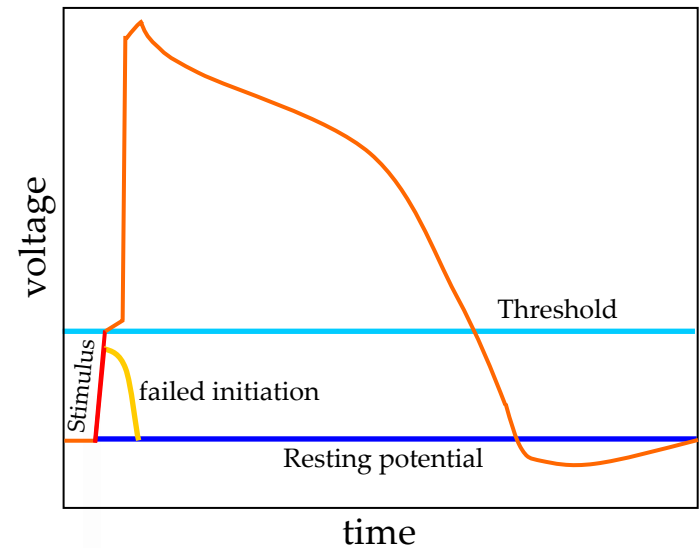


Artificial cardiac tissue
University of Washington

Interaction of Excitable Cells

- Action Potential (AP) depends on stimulus, membrane voltage of neighboring cells, state of cell itself
- Normal: *synchronous pulses*, spiral waves
- Abnormal: *incoherent pulses*, wave breakup
 - Leads to cardiac arrhythmia, epilepsy

Schematic Action Potential

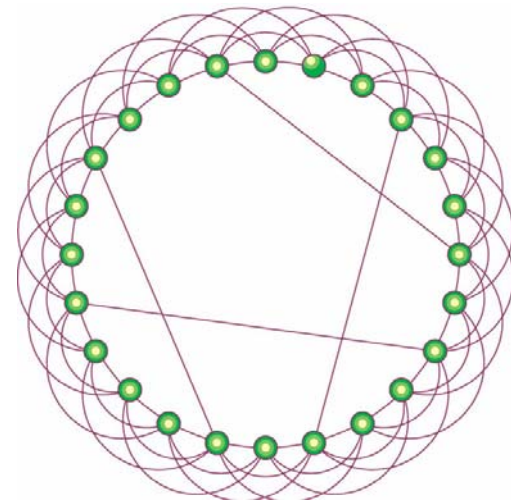


Macro Models of Action Potentials

- Cellular automata
- Oscillators and uniform coupling between cells
[Kuramoto '84]
- Small-world network of coupled oscillators
[Watts & Strogatz '98]

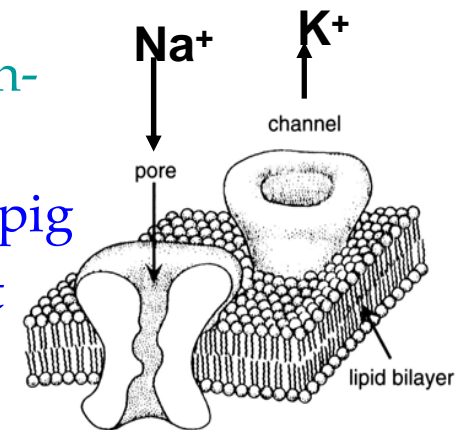
$$\frac{\partial \theta_i}{\partial t} = \omega_i + \frac{K}{N} \sum_{j=1}^N \sin(\theta_j - \theta_i)$$

$i = 1 \dots N$



Micro Models for Action Potentials

- Membrane potential for squid giant axon [Hodgkin-Huxley '52]
- Luo-Rudy model (1991) for cardiac cells of guinea pig
- Neo-Natal Rat (NRR) model for cardiac cells of rat



$$C \dot{V} = \bar{g}_{Na} m^3 h (V_{Na} - V) + \bar{g}_K n^4 (V_K - V) + g_L (V_L - V) + I_{st}$$

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

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

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

$$\alpha_h(V) = 0.07 e^{-\frac{V}{20}}$$

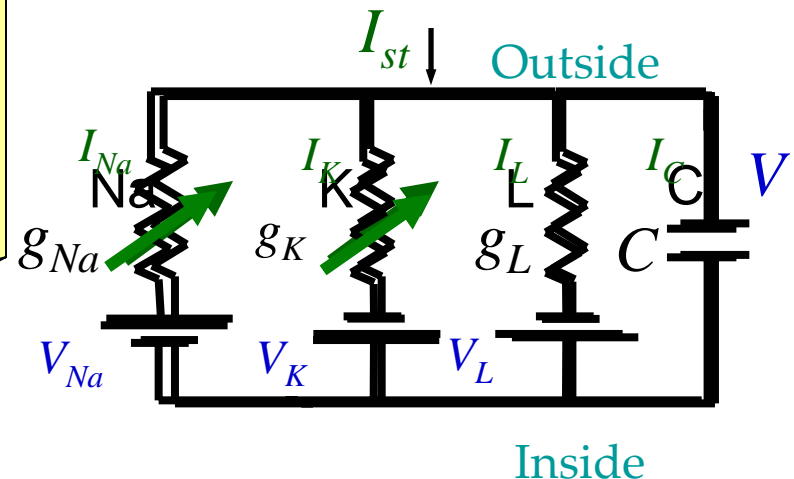
$$\beta_h(V) = \frac{1}{e^{3-0.1V} + 1}$$

$$\alpha_m(V) = \frac{(2.5 - 0.1 V)}{e^{2.5-0.1V} - 1}$$

$$\beta_m(V) = 4e^{-\frac{V}{18}}$$

$$\alpha_n(V) = \frac{(0.1 - 0.01 V)}{e^{1-0.1V} - 1}$$

$$\beta_n(V) = 0.125e^{-\frac{V}{80}}$$



- Large state-space
- Nonlinear differential equations
- Multiple spatial and temporal scales

Micro

Realistic, but not analyzable.
Simulation is slow.

Macro

Analyzable but unrealistic

$$\frac{\partial \theta_i}{\partial t} = \omega_i + \frac{K}{N} \sum_{j=1}^N \sin(\theta_j - \theta_i)$$

$i=1 \dots N$

$$c\dot{v} = \bar{g}_{Na} m^3 h (V_{Na} - V) + \bar{g}_K m^4 (V_K - V) + \bar{g}_L (V_L - V) + I_{st}$$

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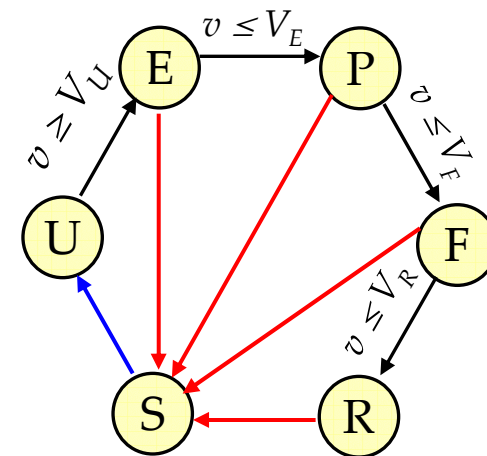
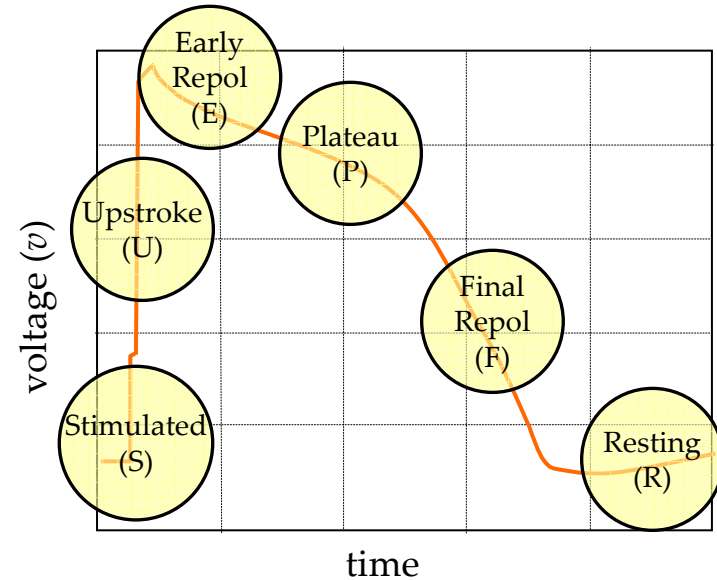
Linear Hybrid Approximations for Action Potentials

- **Suppose**, AP can be partitioned into modes so that in mode M , v can be approximated by:

$$x_i = b_{Mi} x_i$$

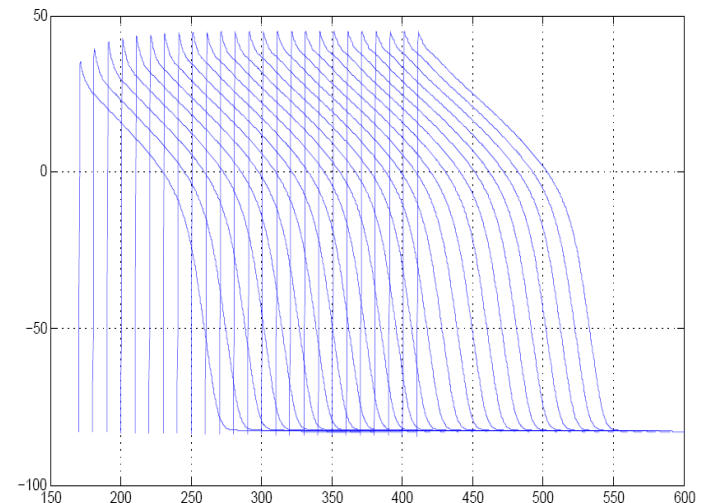
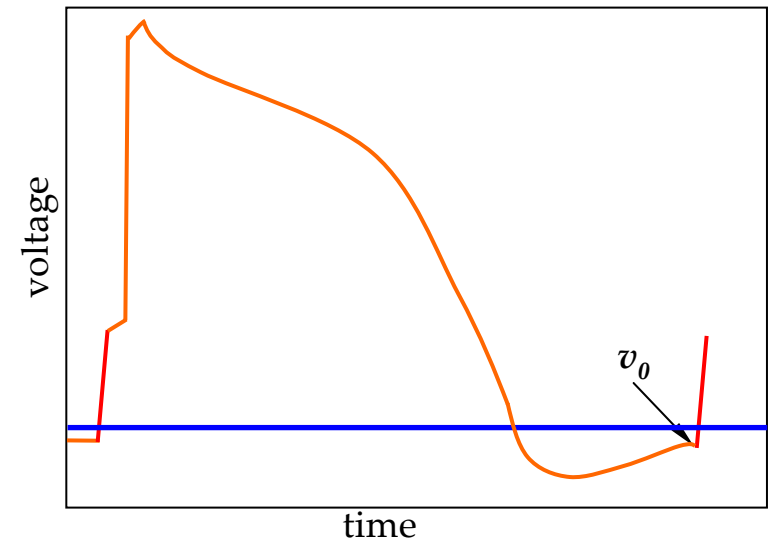
$$v = \sum_i x_i, M \in \{S, U, E, P, F, R\}$$

- b_{Mi} 's can be found by **Prony's method** which fits sum of exponentials to data
- Mode switches
 - at the beginning and end of stimulus
 - when v crosses threshold voltages V_M
- **But**, stimulus can appear at any M
 - State of cell at the time of arrival of stimulus influences behavior of cell for the next AP
 - b_{Mi} 's history dependent



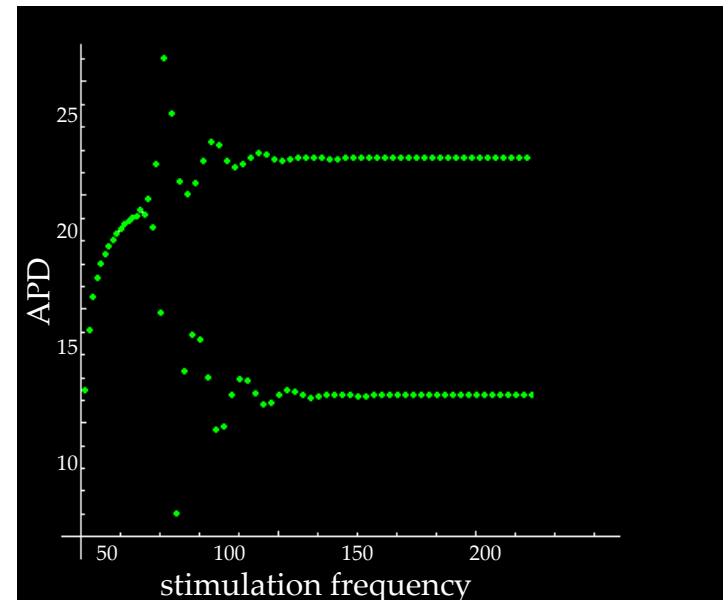
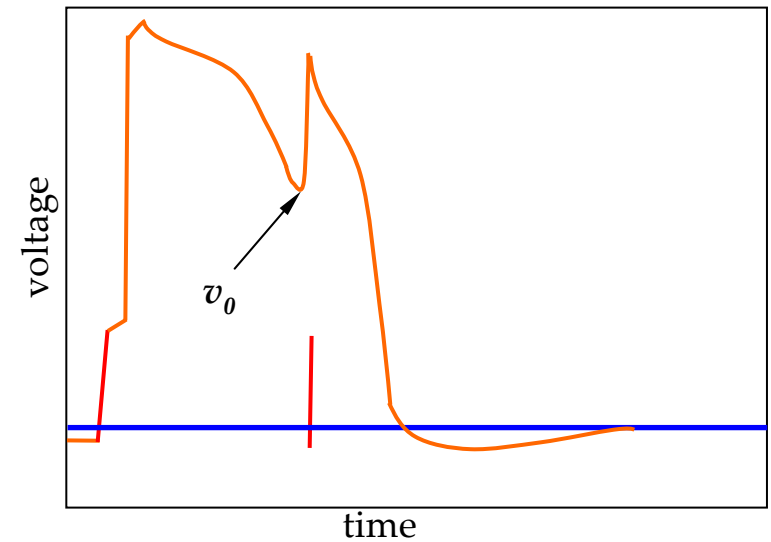
History Dependence of APs

- Frequency of stimulation determines voltage (v_0) at the time of appearance of stimulus, which influences shape of next AP
- Lower frequency: *longer resting time* and v_0 closer to *resting voltage* results in *longer AP*
- Higher frequency: *shorter AP*



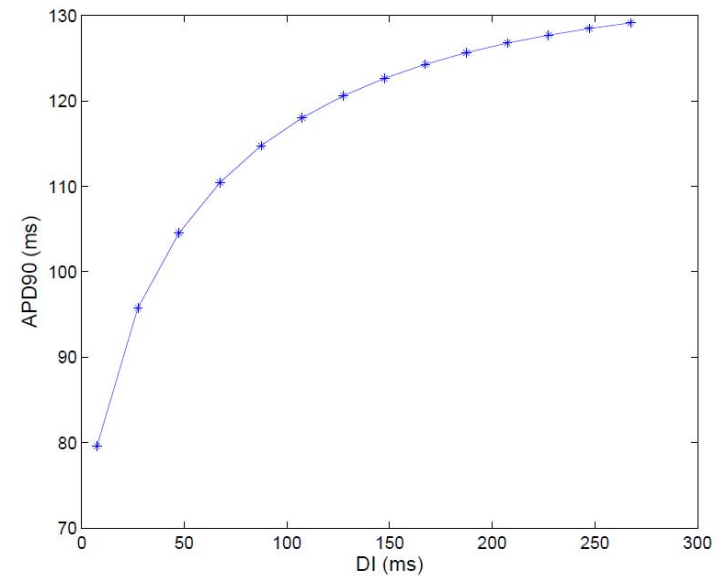
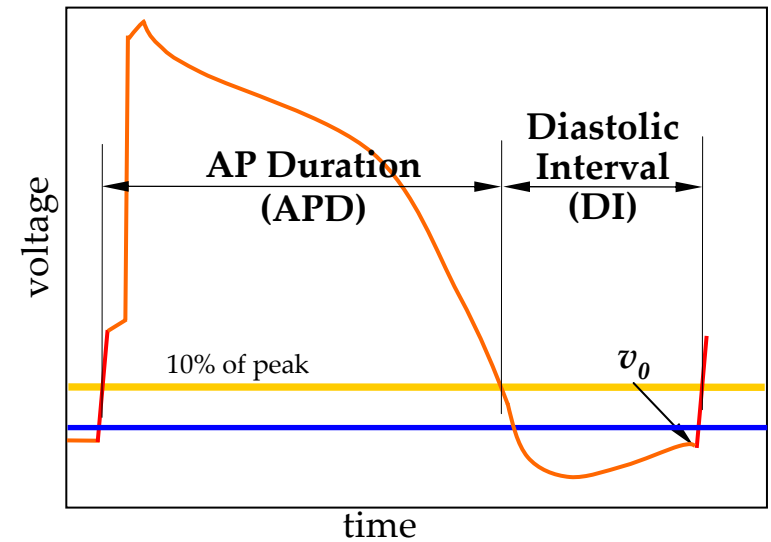
History Dependence of APs

- Frequency of stimulation determines voltage (v_0) at the time of appearance of stimulus, which influences shape of next AP
- Even higher frequency: conjoined AP, bifurcation



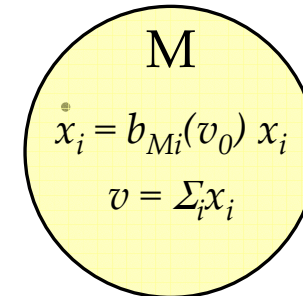
History Dependence and Restitution

- Frequency of stimulation determines voltage (v_0) at the time of appearance of stimulus, which influences shape of next AP
- *Restitution curve*: APD vs. DI
 - Slope > 1 indicates breakup of spiral waves under high frequency stimulation
 - Local to global behavior

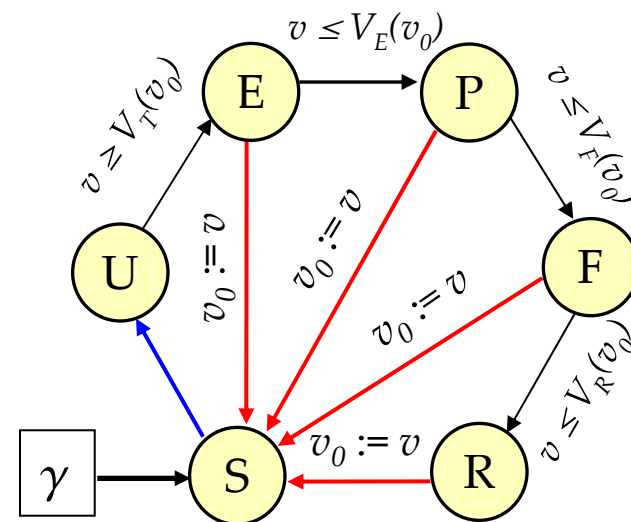


Cycle Linear Hybrid Automata (CLHA)

- Uncountable family of modes
 - $M = \mathcal{E} \times \mathcal{R}$: *Epoch* and *Regime*
 - $(\mathcal{R}, <)$ is a total order
- Linear dynamics in each mode
- **Unique** $\gamma \in \mathcal{R}$ that is visited infinitely many times
- There exists a *snapshot function* $\mathcal{S}: X \rightarrow \mathcal{E}$, such that for any switch $(x_1, \epsilon_1, r_1) \rightarrow (x_2, \epsilon_2, r_2)$
 - (i) $r_2 = \gamma$ and $\epsilon_2 = \mathcal{S}(x_1)$, or
 - (ii) $r_2 \neq \gamma$, $\epsilon_2 = \epsilon_1$ and $r_2 < r_1$
- $\mathcal{R} = \{S, U, E, P, F, R\}$
 \mathcal{E} determined by v_0



$M \in \{S, U, E, P, F, R\}$



Identifying CLHA Parameters for a single AP

For each mode, we seek a solution for LTI:

$$\dot{x} = bx, \quad x(0) = a,$$

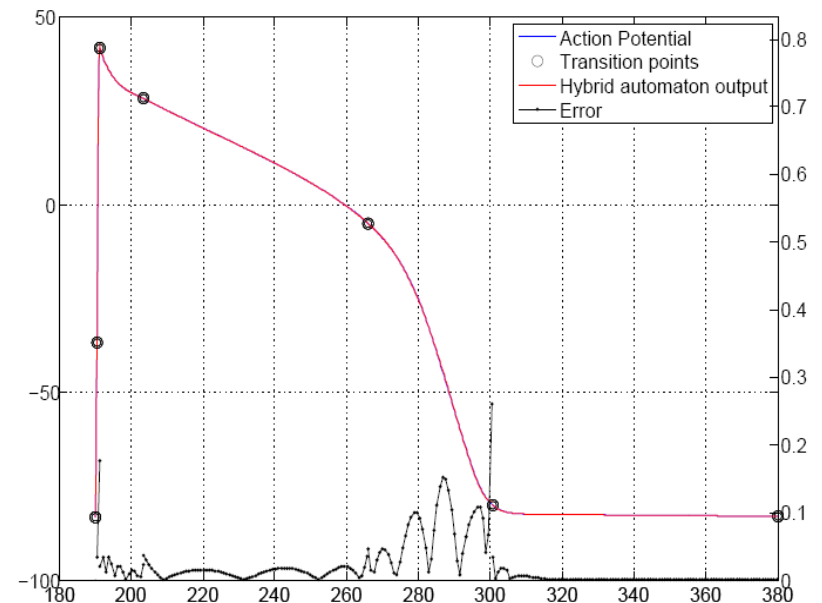
$$b = \text{diag}(b_1, \dots, b_n), \quad a = [a_1 \dots a_n]^T$$

$$v = \sum_{i=1}^n x_i$$

Observable solution is a sum of exponentials:

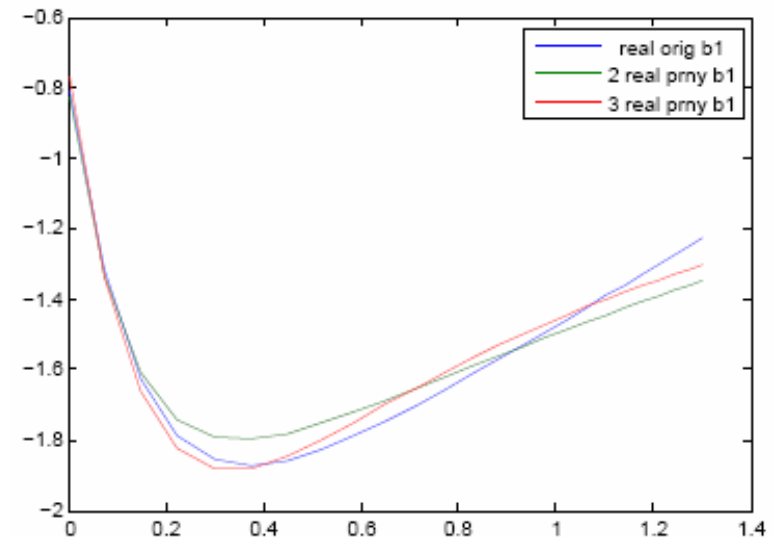
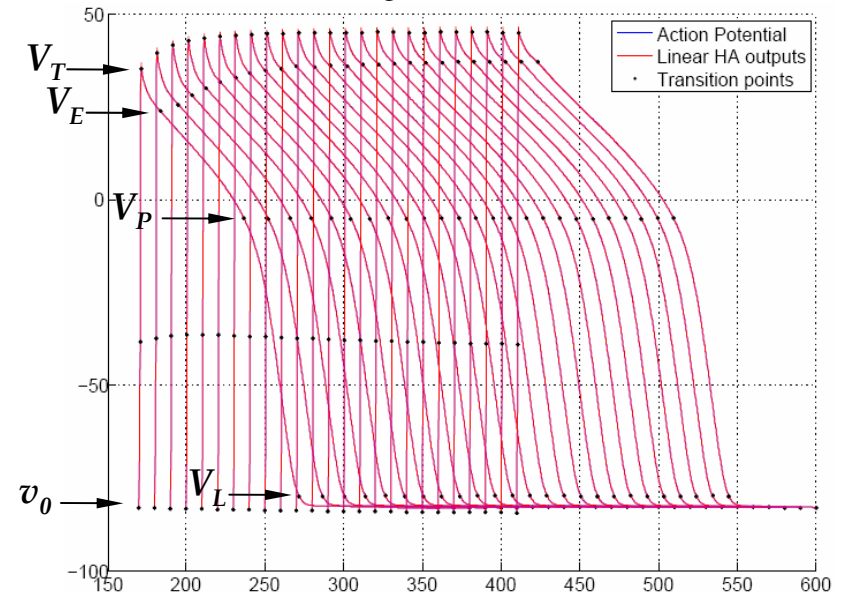
$$v = \sum_{i=1}^n a_i e^{b_i t}$$

- Curve segments are **Convex, concave or both**
- **Consequences:**
 - **Solutions:** might require at least **two** exponentials
 - **Coefficients** a_i and b_i : positive/negative or real/complex
- **Exponential fitting: Modified Prony's method**
[Osborne and Smyth '95]



Parameters as Functions of History Variable

- Parameters:
 - Threshold voltages V_S, V_E, \dots
 - Coefficients of differential equations $b_{S1}, b_{S2}, b_{E1}, \dots$
 - Coefficients in reset maps
- From each stimulation frequency in the training set, we get a corresponding value for $b_{S1}, b_{S2}, \dots, V_S, V_E, \dots$
- Apply Prony's method (a second time) to obtain b_{S1} as a function of v_0 :
 - $b_{M1}(v_0) = c_{M1} \exp(v_0 d_{M1}) + c'_{M1} \exp(v_0 d'_{M1})$, for each $M \in \{S, U, E, P, F, R\}$
 - $V_T(v_0) = c_T \exp(v_0 d_T) + c'_T \exp(v_0 d'_T)$

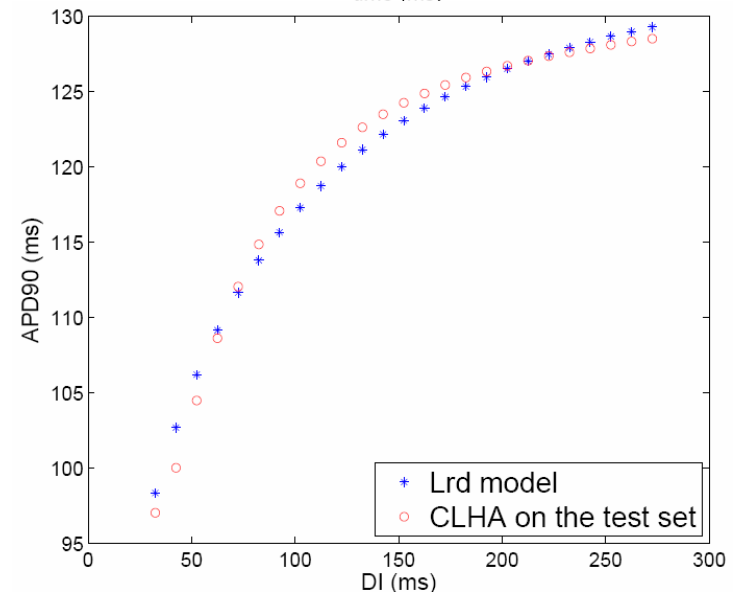
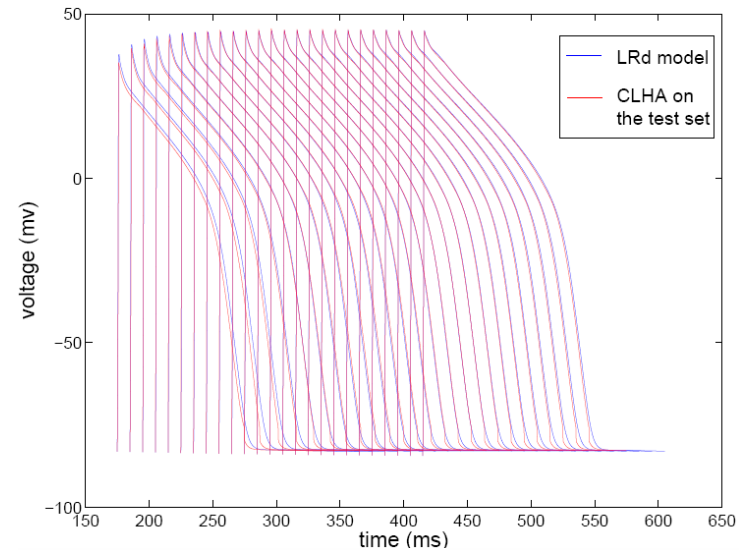


Contributions and Simulation Results

- CLHA as a model for almost periodic systems
- Iterative process to obtain excitable cell model with desired accuracy
- Simulation efficiency (> 8 times faster)
- [True, Entcheva, et al.]
- Biological interpretation of state variables x_1, x_2 ; restitution curve
- Spiral wave generation and breakup

Spiral waves

Breakup



Future Directions

- CLHA for stimulation with different shapes
- CLHAs coupled through---pulses or diffusion---for analyzing synchronization conditions
- Specification of spatiotemporal voltage patterns
- Distributed control through targeted stimulation