

My Research Experience (Duke in a nutshell)

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Outline

- Introduction
- Governing Equations
- Numerical methods
- Parallelization
- Luo Rudy Dynamic (LRD)
- Cable experiments
- Membrane dynamics

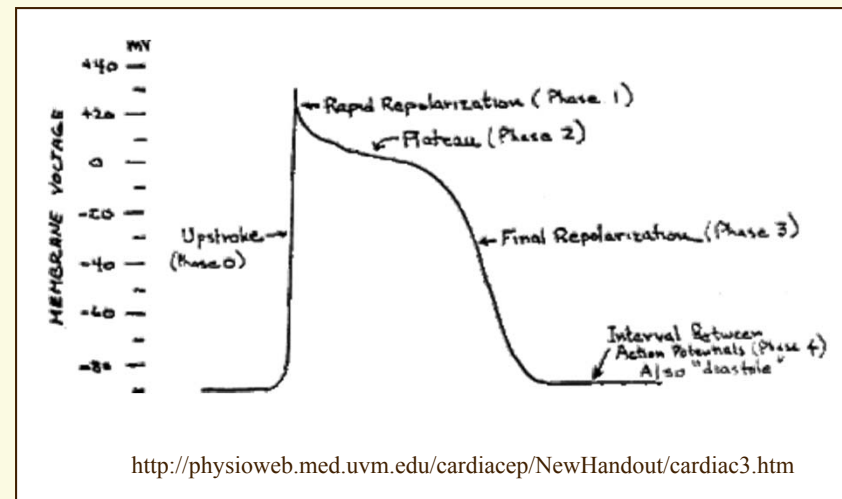
Introduction

📄 Computational Modeling

- Collects much more data than experiments
- Can be implemented without loss of life
- Can test new methods with minimal human error

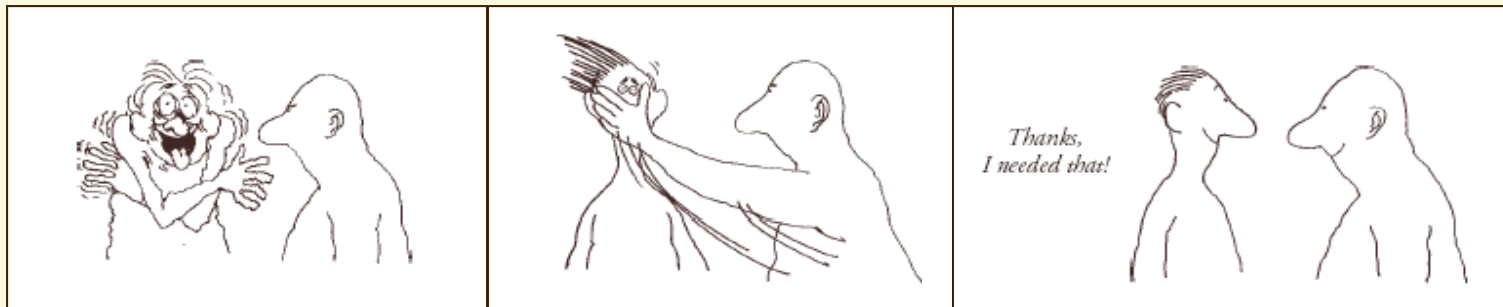
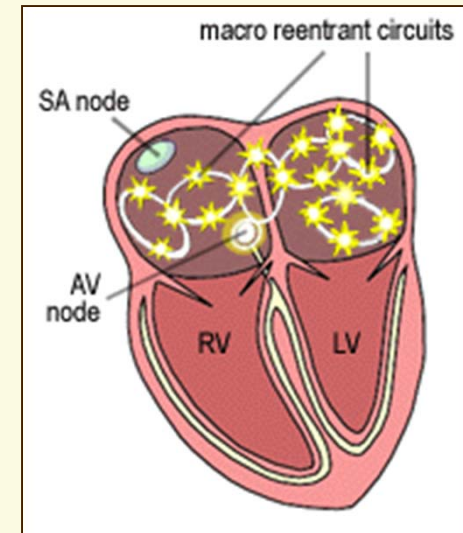
📄 Model Characteristics

- Domain Structure
- Homogeneity
- Isotropy
- Membrane dynamics
- Numerical Methods
- Stimulus Type



Introduction

- Attempt to model different arrhythmias
 - Re-entry, Tachycardia, Fibrillation, etc
 - Condition - region reactivated by the same wavefront
 - Requires uni-directional block
- Defibrillation is one solution
 - large voltage applied across a tissue to simultaneously depolarize all tissue
 - 95% of tissue must meet defibrillation threshold (DFT) for successful cardioversion.

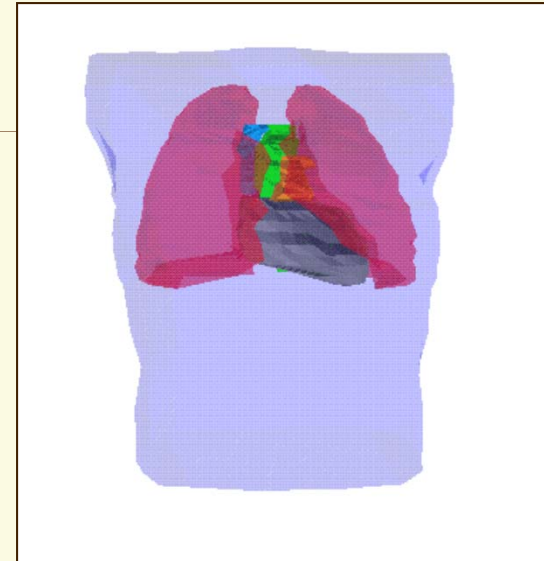


Introduction



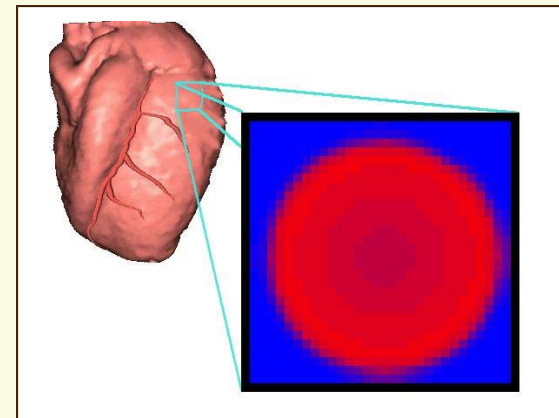
Full scale model

- Complex 3-D mesh of torso
- different tissues and conductivities



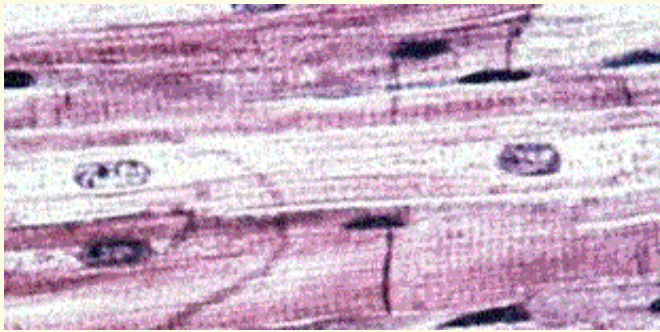
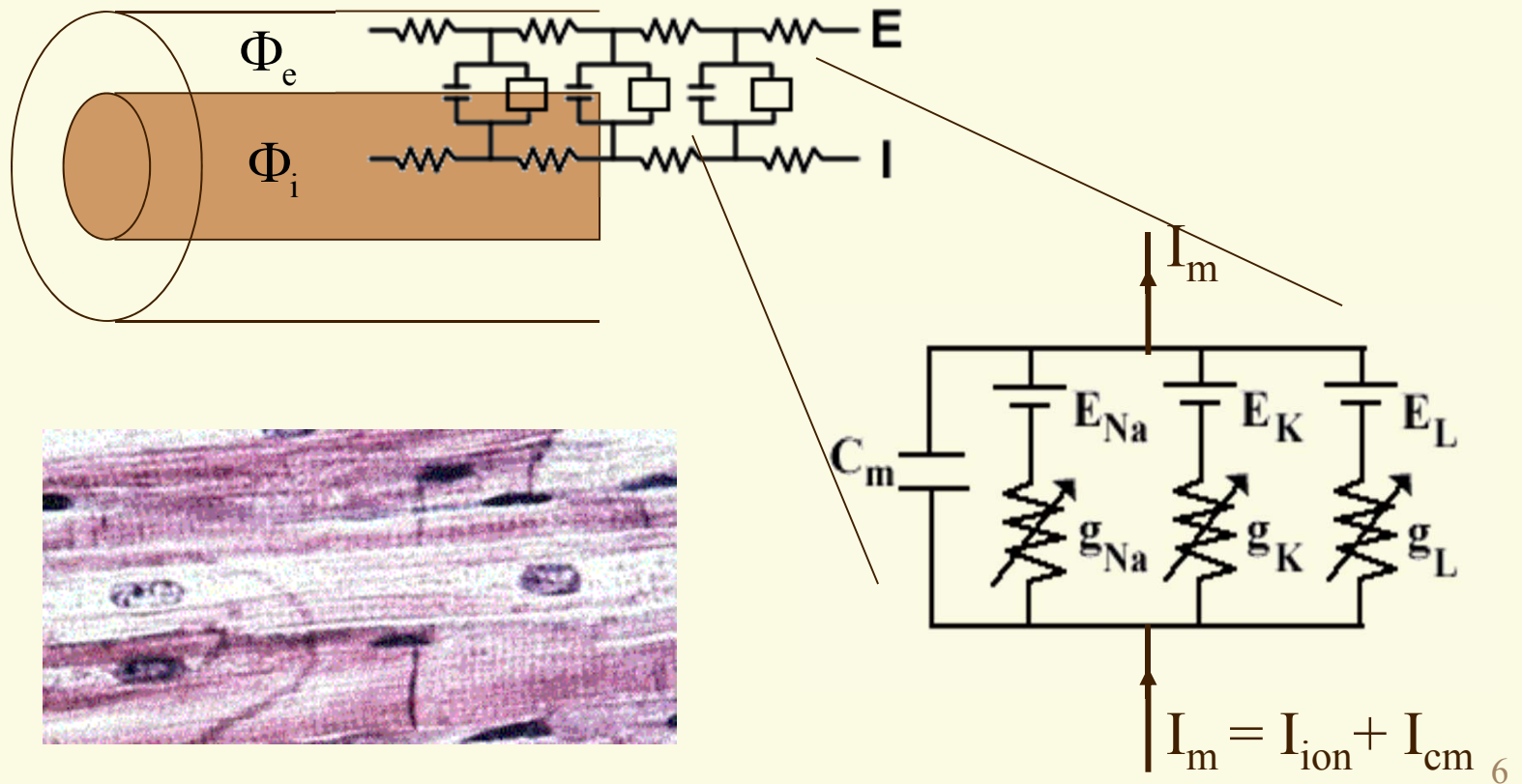
Simplified model

- Simple mesh of cells (2-D, Square)
- Single tissue type (homogenous)
- Isotropic
- 4 connections for each cell



Resistor Model of Cell

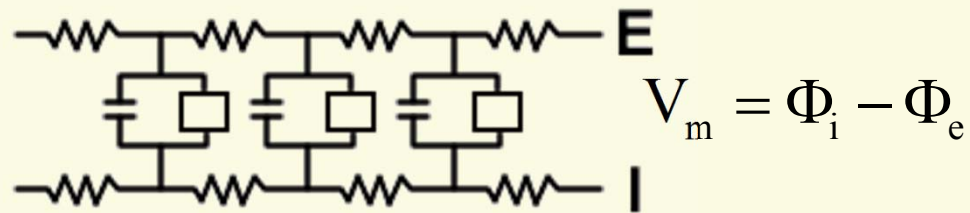
☞ Represented as a series of resistors joined in parallel by an RC circuit



Governing Equations

Bidomain

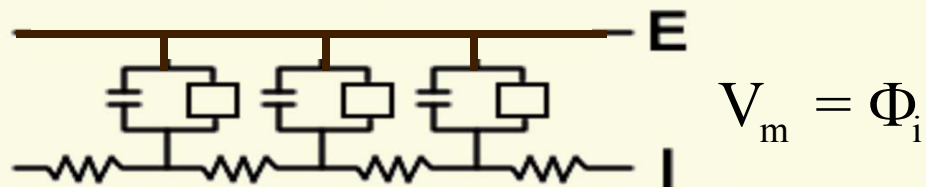
$$\nabla \cdot (\sigma_i \nabla \Phi_i) = \beta \left(C_m \frac{dV_m}{dt} + I_{\text{ion}} \right) \quad \nabla \cdot (\sigma_e \nabla \Phi_e) = -\beta \left(C_m \frac{dV_m}{dt} + I_{\text{ion}} \right)$$



Monodomain

$$\nabla \cdot (\sigma_i \nabla V_m) = \beta \left(C_m \frac{dV_m}{dt} + I_{\text{ion}} \right)$$

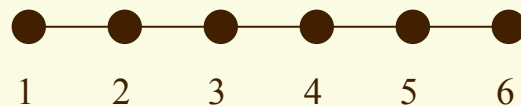
Assumes: $\sigma_e = \infty$ ($R_e = 0$) $\therefore \Phi_e = 0$



LHS - Current Diffusion

$$\nabla \cdot (\sigma \nabla V_m) \rightarrow M V_m$$

Numerical Approximation (Finite difference)



(1-D homogenous cable)

$$M \rightarrow \left(\sigma \frac{d}{dx} \frac{d}{dx} \right)$$

$$\frac{d^2 V_{m(i)}}{dx^2} = \frac{V_{m(i-1)} - 2V_{m(i)} + V_{m(i+1)}}{\Delta x^2}$$

$$M = \frac{\sigma}{\Delta x^2} \begin{bmatrix} 0 & & & & & \\ 1 & -2 & 1 & & & \\ & 1 & -2 & 1 & & \\ & & 1 & -2 & 1 & \\ & & & 1 & -2 & 1 \\ & & & & & 0 \end{bmatrix}$$

Boundary Condition needed

Computational Issues

📄 Simple EP models can get computationally expensive

- domain size
- domain structure/complexity
- membrane model
- time step required for dynamics

📄 Motivation: Attempt to speed up computation time while preserving quality of results.

$$\nabla \cdot (\sigma \nabla V_m) = \beta \left(C_m \frac{dV_m}{dt} + I_{\text{ion}} \right)$$

Numerical Methods

📄 Explicit - Forward Euler

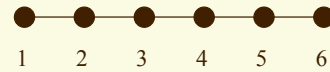
$$\nabla \cdot (\sigma \nabla V_m) = \beta \left(C_m \frac{dV_m}{dt} + I_{\text{ion}} \right) \longrightarrow M V_m^t = \beta \left(C_m \frac{V_m^{t+1} - V_m^t}{\Delta t} + I_{\text{ion}}^t \right)$$

Rearranging:

$$V_m^{t+1} = V_m^t + \frac{\Delta t}{C_m} \left(\frac{1}{\beta} M V_m^t - I_{\text{ion}}^t \right)$$

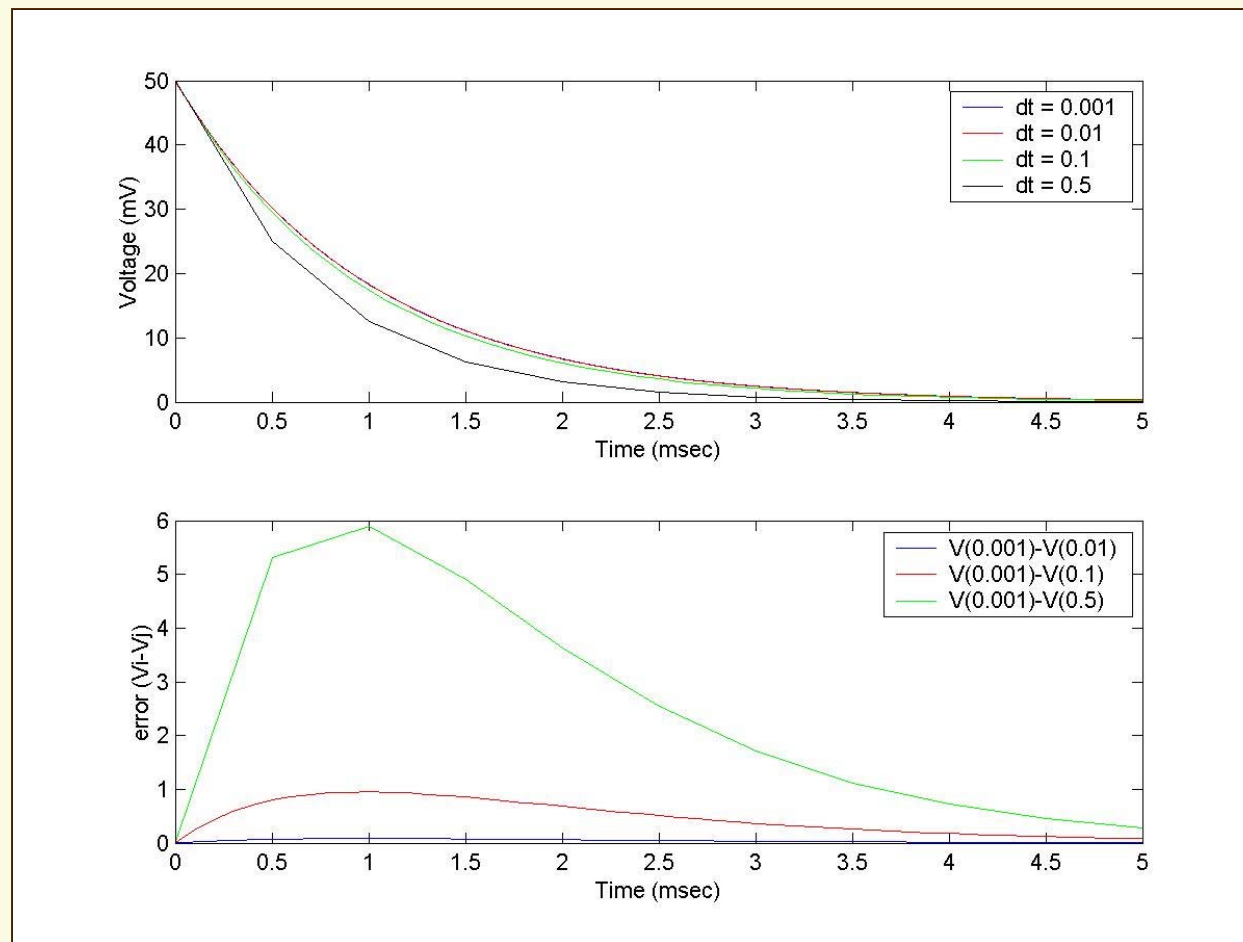
$$V_m^{t+1} = f(V_m^t, I_{\text{ion}}^t)$$

Methods - FE



$$V_m^{t+1} = V_m^t + \frac{\Delta t}{C_m} \left(\frac{1}{\beta} M V_m^t - I_{ion}^t \right)$$

Issues: Choosing optimal dt is critical!



Methods

📄 Semi-Implicit

$$MV_m = \beta \left(C_m \frac{dV_m}{dt} + I_{\text{ion}} \right) \longrightarrow MV_m^{t+1} = \beta \left(C_m \frac{V_m^{t+1} - V_m^t}{\Delta t} + I_{\text{ion}}^t \right)$$

Rearranging:

$$\left(M - \frac{\beta C_m}{\Delta t} I \right) V_m^{t+1} = -\frac{\beta C_m}{\Delta t} V_m^t + \beta I_{\text{ion}}^t$$

$$Ax = b$$

$$x = A^{-1}b$$

Method - SI

$$\left(M - \frac{\beta C_m}{\Delta t} I \right) V_m^{t+1} = -\frac{\beta C_m}{\Delta t} V_m^t + \beta I_{ion}^t$$

Issues:

– A^{-1} requires that $\left(M - \frac{\beta C_m}{\Delta t} I \right)$ be non-singular

- i.e. $\left(\frac{\beta C_m}{\Delta t} \right)$ cannot be an eigenvalue of $\left(M - \frac{\beta C_m}{\Delta t} I \right)$

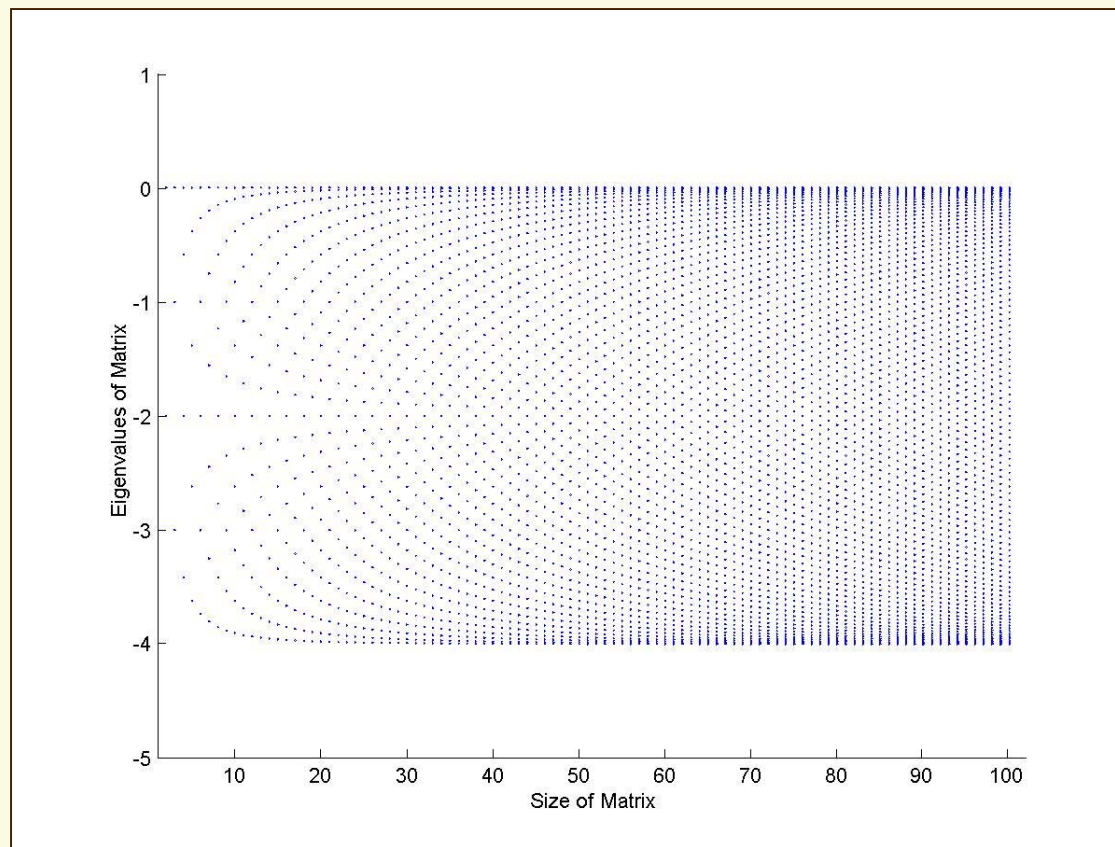
Recall:

$$\det(A - \lambda I) = 0$$

$$\det(\text{Singular}) = 0$$

Results - Semi Implicit

📄 All eigenvalues range from $[-4,0]$

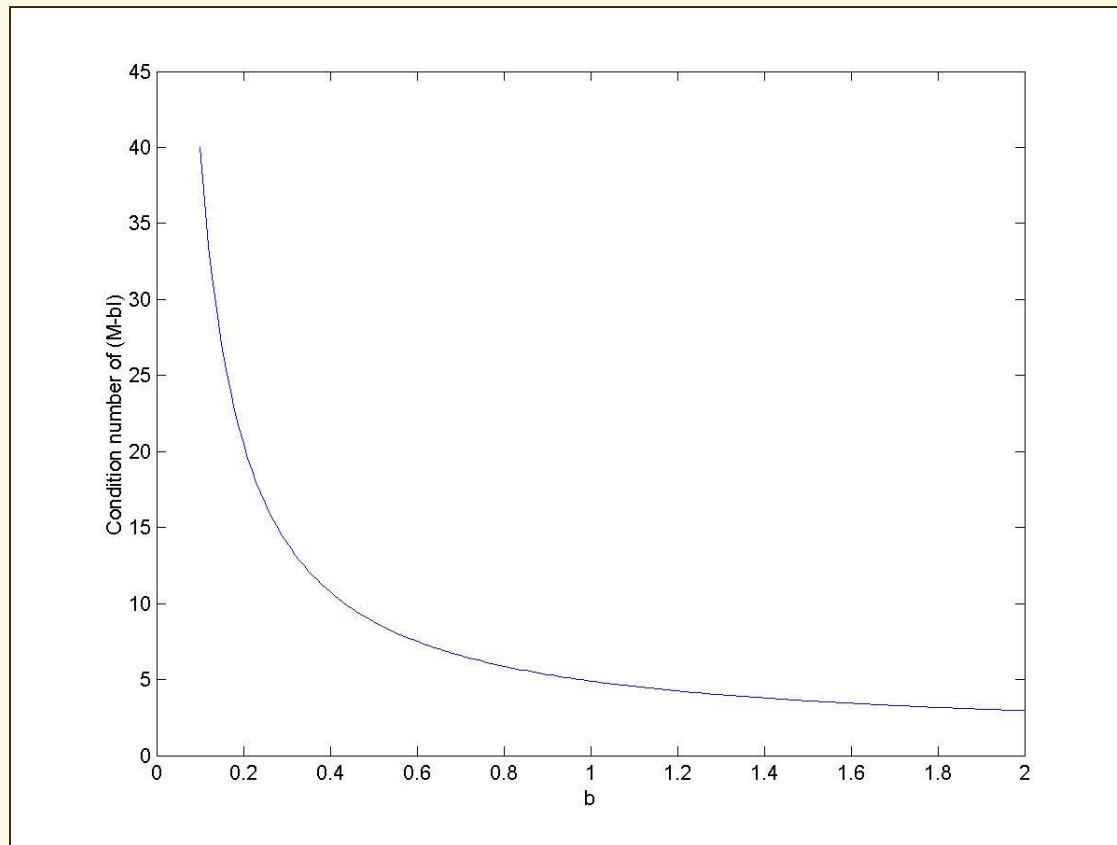


$$\left(\frac{\beta C_m}{\Delta t}\right) \neq 0$$

M is already
singular

$$\therefore \left(\frac{\beta C_m}{\Delta t}\right) > 0$$

Results - Semi Implicit $\left(M - \frac{\beta C_m}{\Delta t} I\right) V_m^{t+1} = -\frac{\beta C_m}{\Delta t} V_m^t + \beta I_{ion}^t$



Where:

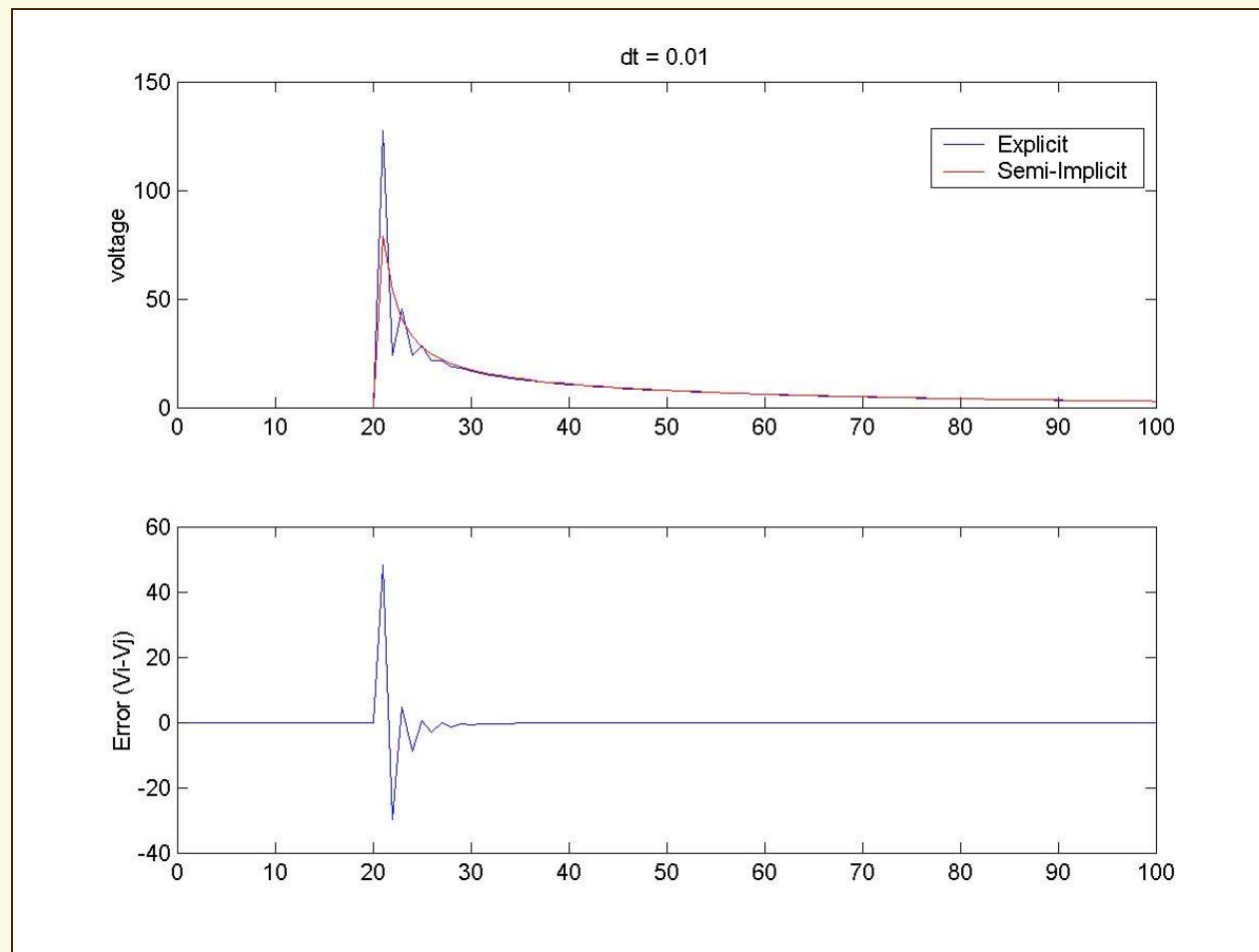
$$b = \left(\frac{\beta C_m}{\Delta t}\right)$$

$$K(M) = 3.6e16$$

(Size = 10)


Results - Both

Semi Implicit is more stable at larger values of dt



Methods

Implicit

$$MV_m = \beta \left(C_m \frac{dV_m}{dt} + I_{\text{ion}} \right) \longrightarrow MV_m^{t+1} = \beta \left(C_m \frac{V_m^{t+1} - V_m^t}{\Delta t} + I_{\text{ion}}^{t+1} \right)$$


Rearranging:

$$MV_m^{t+1} - \beta \left(C_m \frac{V_m^{t+1} - V_m^t}{\Delta t} + I_{\text{ion}}^{t+1} \right) = 0$$

Recall: $I_{\text{ion}}^{t+1} = f(V_m^{t+1})$

Use non-linear solver
Very Expensive!

Summary

Forward Euler

- less operations per iteration
- needs small dt (more total iterations needed)
- less stable

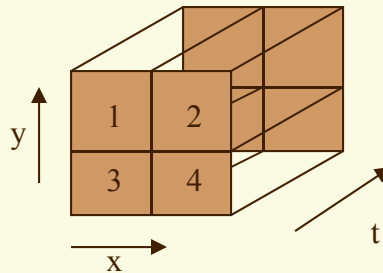
Semi-implicit

- more operations per iteration
- can use larger dt (less total iterations needed)
- more stable

Parallel distribution for 2-D domain

Essentially a 3-D problem (x,y,time)

- Can only divide up in space, since voltages at $t+1$ are dependent on values at t



Implement Domain Decomposition Method

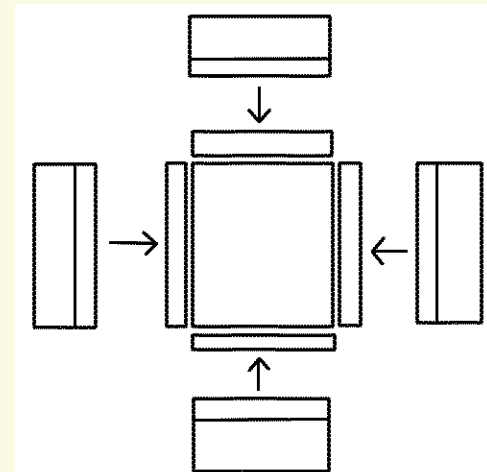
- Processors will exchange information with other processors that share common boundaries

After I_{ion} is determined...

- Recall the equation for Forward Euler:

$$V_m^{t+1} = V_m^t + \frac{\Delta t}{C_m} \left(\frac{1}{\beta} M V_m^t - I_{ion}^t \right)$$

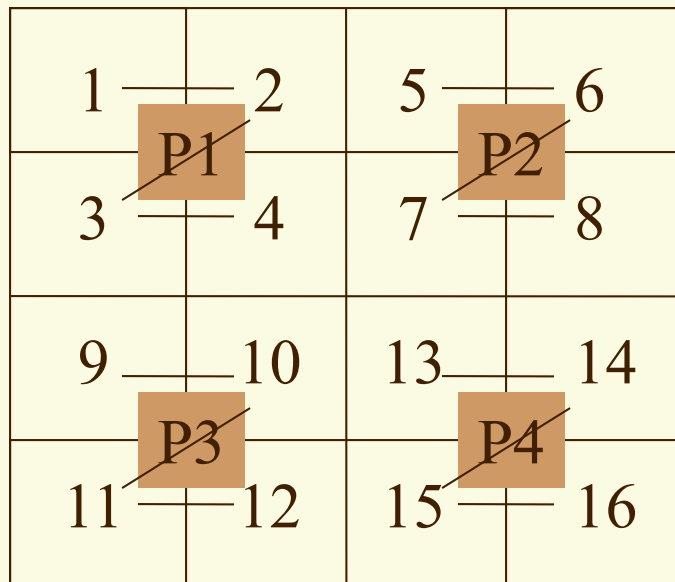
- Data must be exchanged prior to current diffusion to consider current passing over processor boundaries.



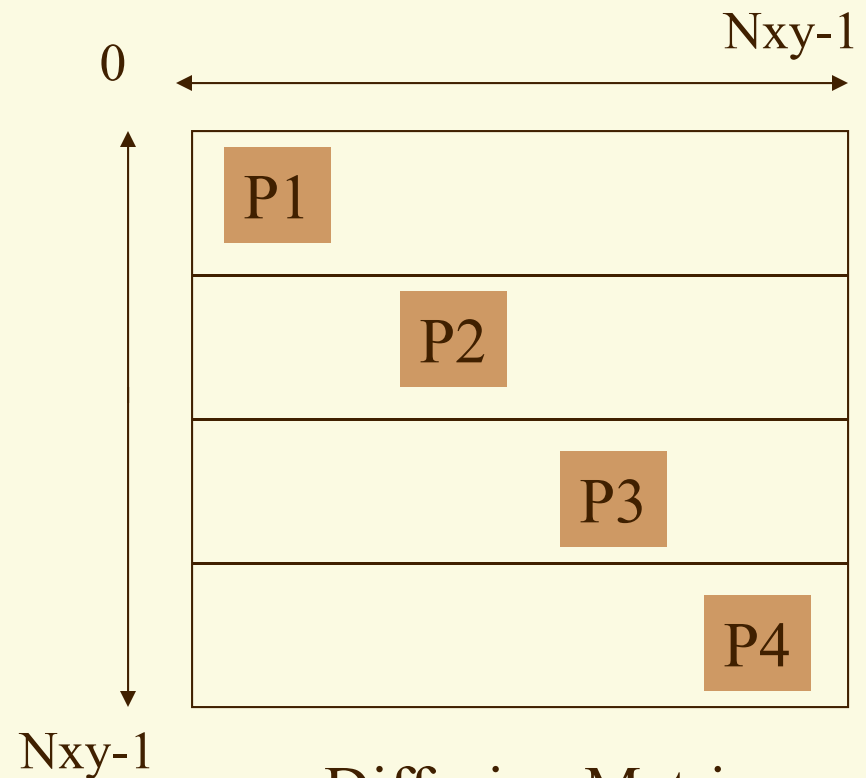
- Only a fraction of the M matrix will be required for each sub domain
 - How can we take advantage of this structure?

Morton ordering (z ordering)

📄 This technique was used to help group nearby nodes together in the diffusion matrix



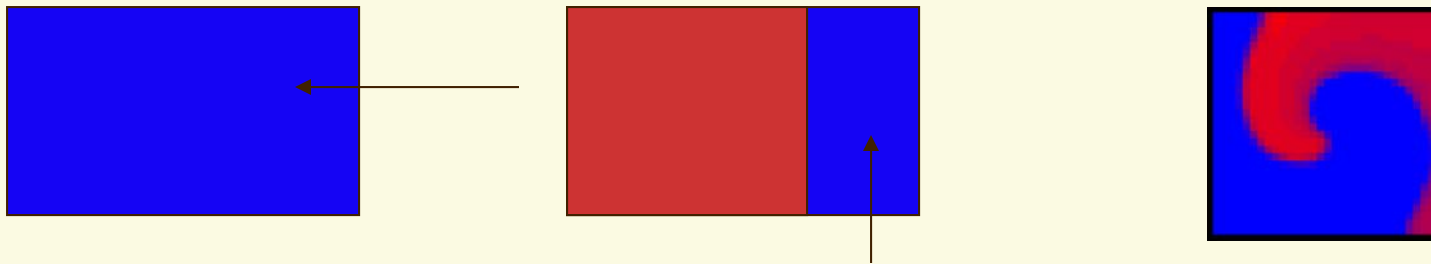
Domain layout



Diffusion Matrix

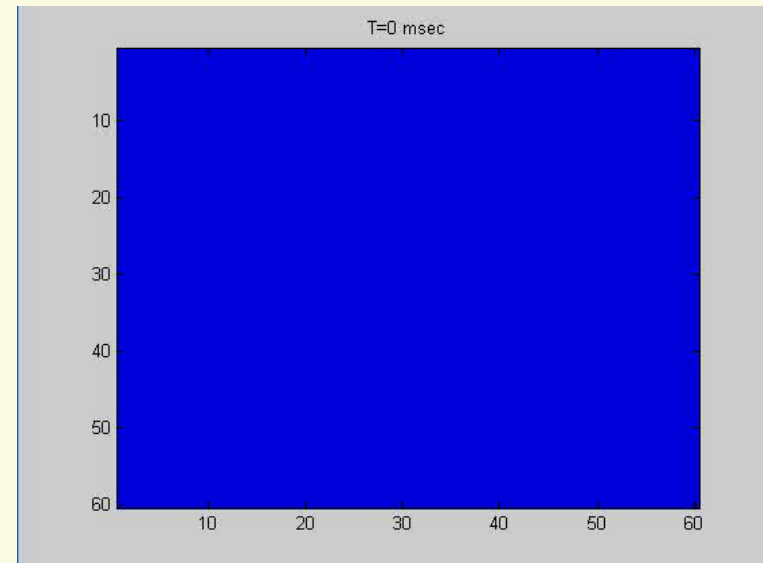
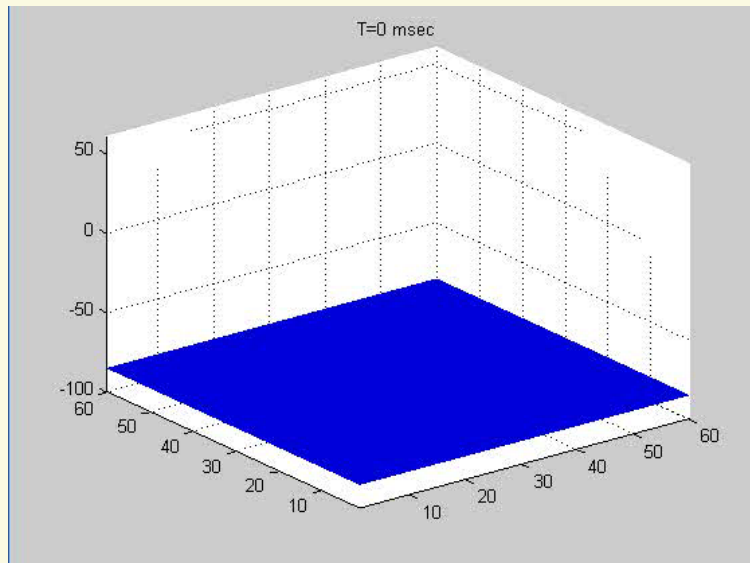
Once program is complete...

- ☞ A stimulus can be applied and studied
- ☞ Re-entry is difficult to achieve within small domain
- ☞ There is one sure-fire method to always achieve re-entry

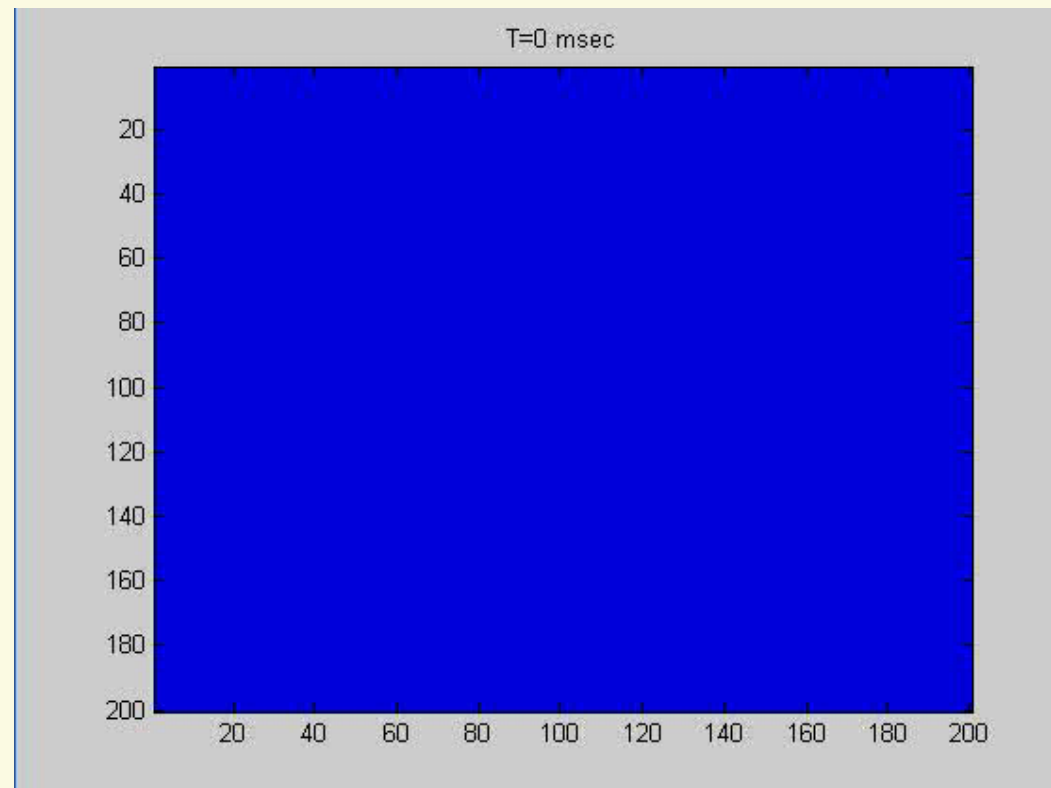


Visualization

- 📄 A Matlab script was used to manipulate data
 - Data must be rearranged from z-ordered vector format into a rectangular matrix



More Movies



Double Spirals

Performance Results

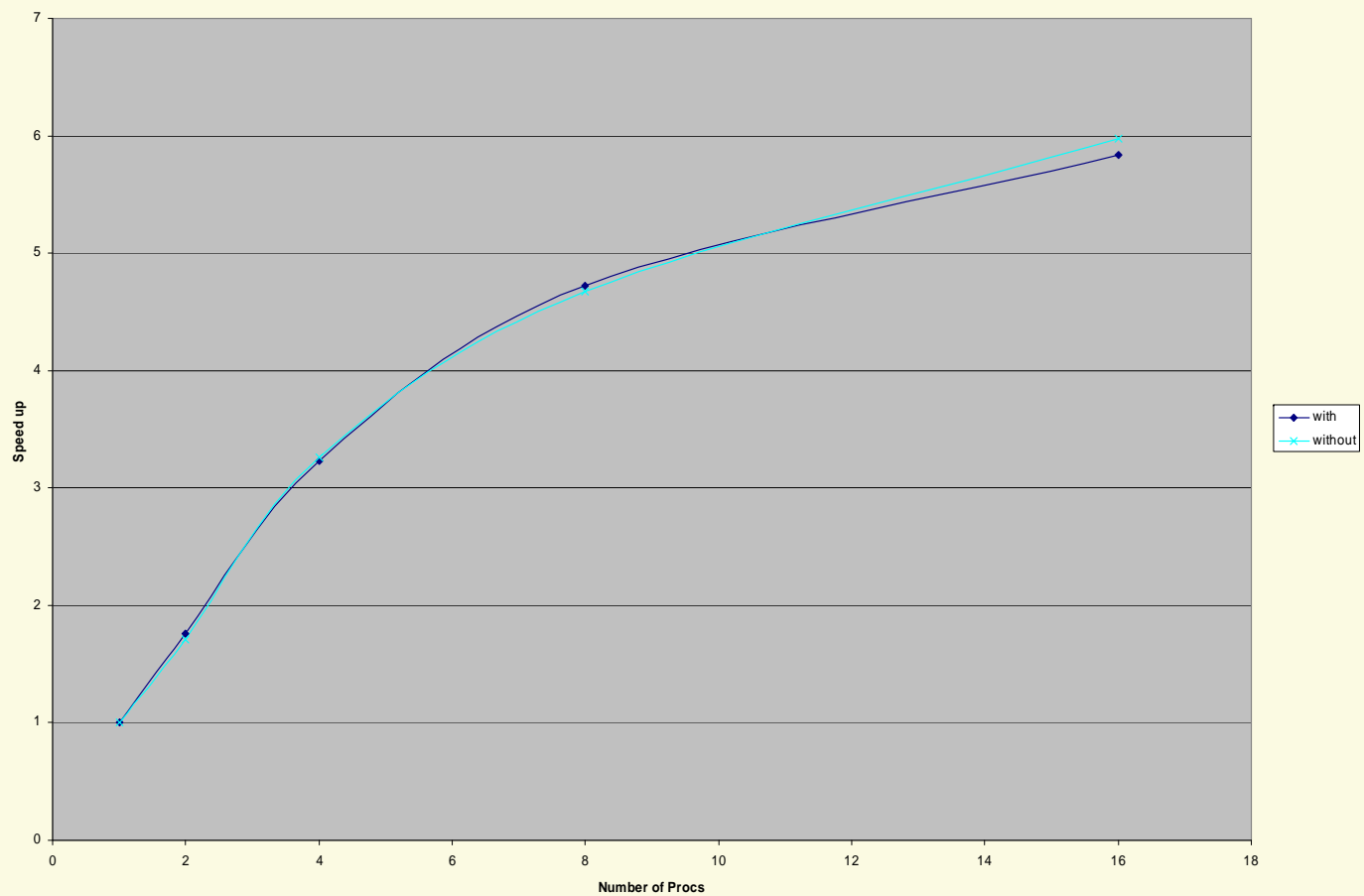
📄 Speed up: (20 nodes x 20 nodes x 3000 time steps)

With File I/O # of Procs	Time	Speed up		w/o File I/O # of Procs	Time	Speed up
1	16.59	1		1	15.63	1
2	9.41	1.76		2	9.09	1.71
4	5.13	3.23		4	4.79	3.26
8	3.58	4.72		8	3.34	4.67
16	2.84	5.84		16	2.61	5.98

(full matrix)

File I/O is the writing of voltage data to file.
This was turned off for benchmarking purposes

Performance Results



Luo Rudy Equations

Fast Sodium current

$$I_{Na} = 23(m^3)(h)(j)(V - E_{Na})$$

For $V \geq -40$ mV

$$\beta_h = \frac{1}{0.13(1 + e^{\frac{V+10.66}{-11.1}})} \quad \alpha_h = \alpha_j = 0.0$$

$$\beta_j = \frac{(0.3)e^{-2.535(V)(10^{-7})}}{1 + e^{-0.1(V+32)}}$$

For $V < -40$ mV

$$\alpha_h = (0.135)e^{\frac{80+V}{-6.8}} \quad \beta_j = (0.1212) \frac{e^{(-0.01052V)}}{1 + e^{-0.1378(V+40.14)}}$$

$$\beta_h = (3.56)e^{(0.079V)} + 3.1(10^5)e^{(0.35V)}$$

For all range of V

$$\beta_m = (0.08)e^{\frac{-V}{11}} \quad \alpha_m = (0.32) \frac{(V+47.13)}{1 - e^{-0.1(V+47.13)}}$$

Slow inward current

$$E_{si} = 7.7 - (13.0287) \ln([Ca]_i)$$

$$I_{si} = (0.09)(d)(f)(V - E_{si})$$

$$\alpha_d = (0.095) \frac{e^{-0.01(V-5)}}{1 + e^{-0.072(V-5)}}$$

$$\beta_d = (0.07) \frac{e^{-0.017(V+44)}}{1 + e^{0.05(V+44)}}$$

$$\alpha_f = (0.012) \frac{e^{-0.008(V+28)}}{1 + e^{0.15(V+28)}}$$

$$\beta_f = (0.0065) \frac{e^{-0.02(V+30)}}{1 + e^{-0.2(V+30)}}$$

Calcium Uptake

$$\frac{d([Ca]_i)}{dt} = -(I_{si})(10^{-4}) + 0.07(10^{-4} - [Ca]_i)$$

Luo Rudy Equations

Outward currents

Time-dependent potassium current

$$I_K = \bar{G}_K(X)(X_i)(V-E_K) \quad \alpha_x = (0.0005) \frac{e^{0.083(V+50)}}{1+e^{0.057(V+50)}}$$

$$\bar{G}_K = 0.282 \sqrt{\frac{[K]_o}{5.4}} \quad \beta_x = (0.0013) \frac{e^{-0.06(V+20)}}{1+e^{-0.04(V+20)}}$$

For $V > -100\text{mV}$

$$X_i = 2.837 \frac{(e^{0.04(V+77)} - 1)}{(V+77)e^{0.04(V+35)}}$$

For $V \leq -100\text{ mV}$

$$X_i = 1$$

Total time-independent potassium current

$$I_{K1(T)} = I_{K1} + I_{Kp} + I_b$$

Time-independent potassium current

$$I_{K1} = (\bar{G}_{K1})(K1_\infty)(V-E_{Kp}) \quad \bar{G}_{K1} = (0.6047) \sqrt{\frac{[K]_o}{5.4}}$$

$$\alpha_{K1} = \frac{1.02}{1+e^{0.2385(V-E_{K1}-59.215)}}$$

$$\beta_{K1} = \frac{(0.49124)e^{0.08032(V-E_{K1}+5.476)} + e^{0.06175(V-E_{K1}-594.31)}}{1+e^{-0.5143(V-E_{K1}+4.753)}}$$

Plateau potassium current

$$I_{Kp} = 0.0183(Kp)(V-E_{Kp}) \quad E_{Kp} = E_{K1}$$

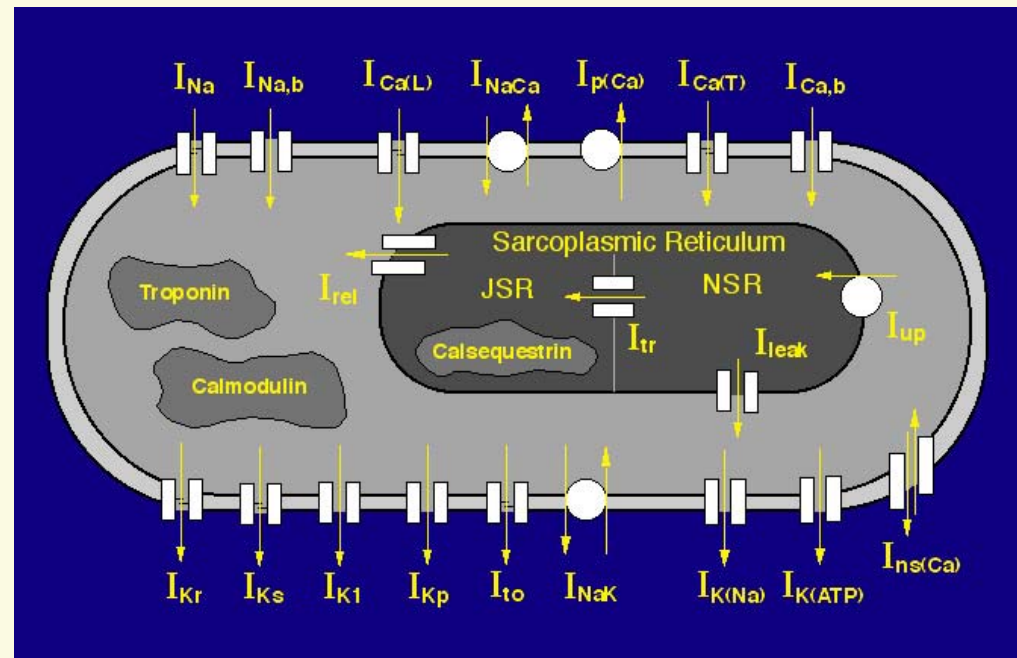
$$Kp = \frac{1}{1+e^{\frac{7.488-V}{5.98}}}$$

Background current

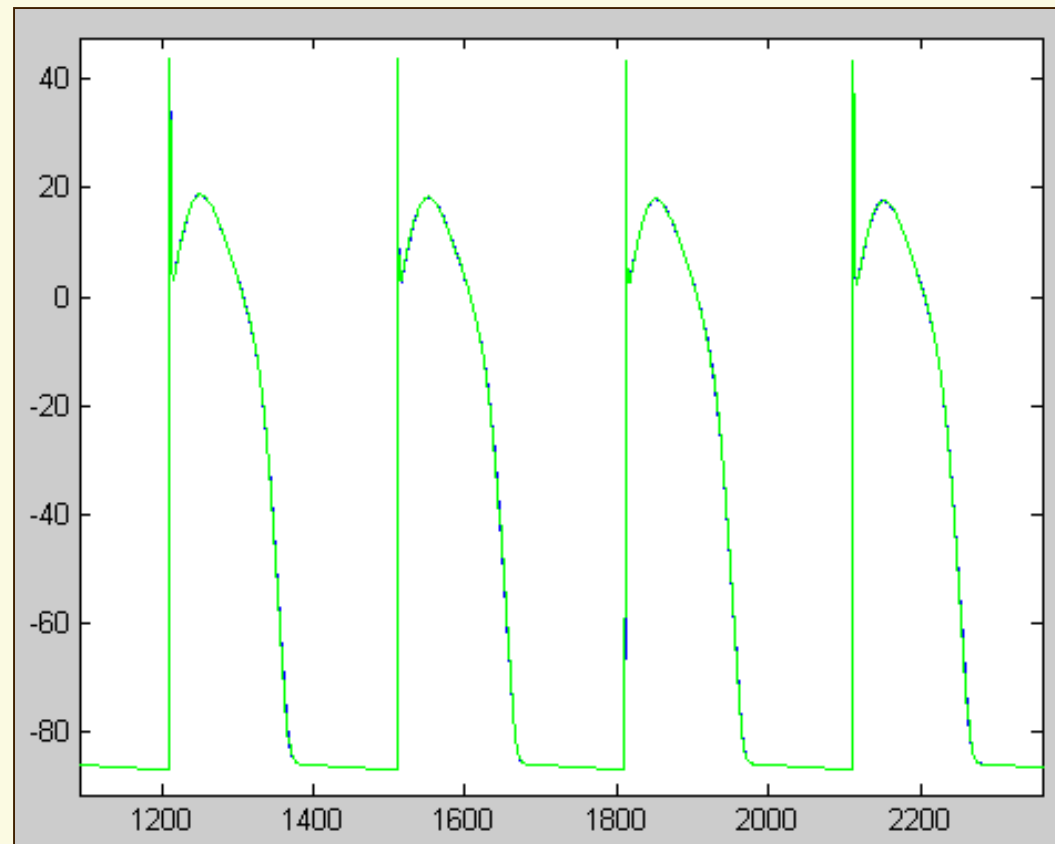
$$I_b = 0.03921(V+59.87)$$

Luo Rudy Dynamic (LRD)

- More complex than Luo Rudy I (LRI)
- More currents and concentrations
- Event dependent internal currents
 - CICR
- Ca²⁺ overload
 - csqn > csqnth
- Cleft concentrations
- Physiological currents
 - Ito, Ikna, Insns, Insk

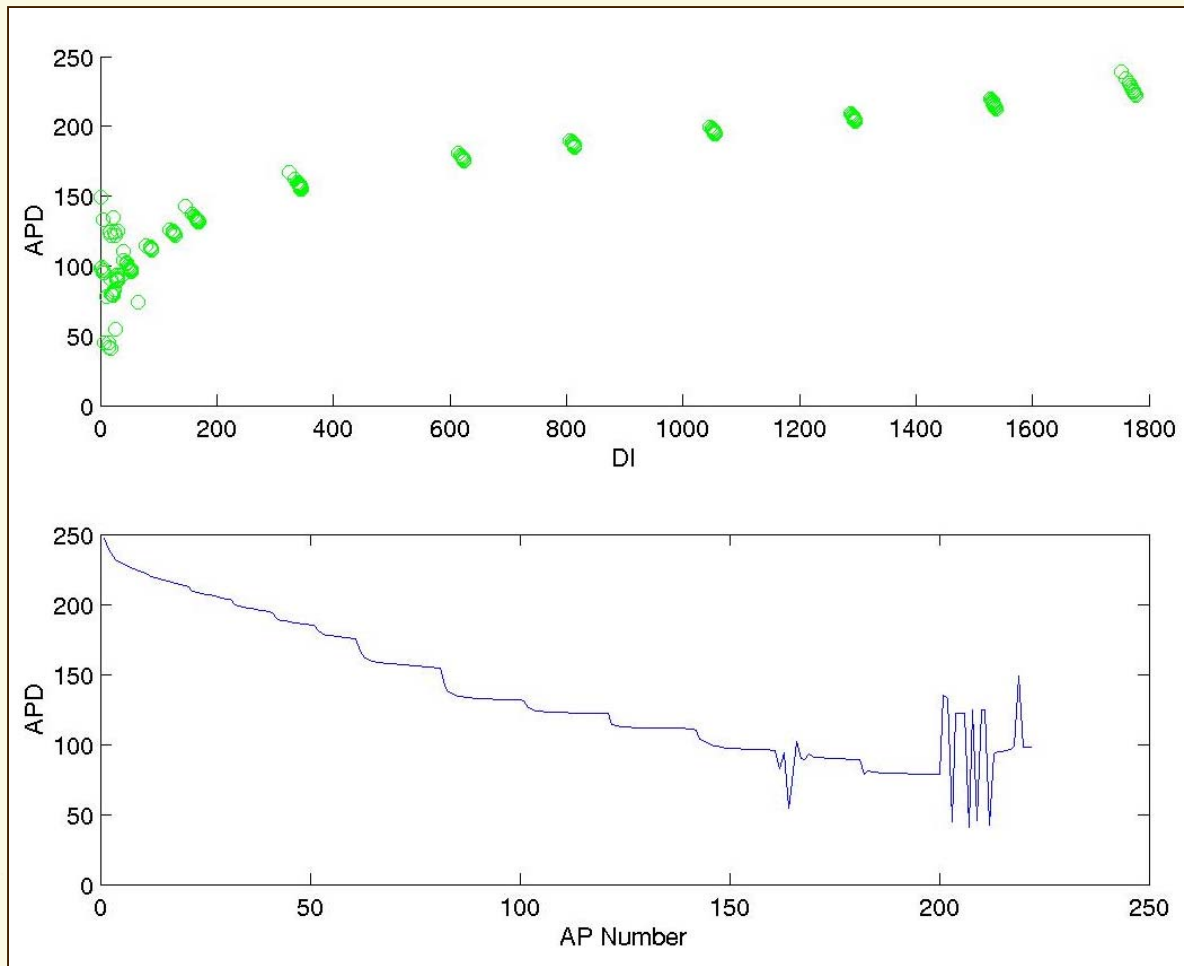


LRD – Action potential



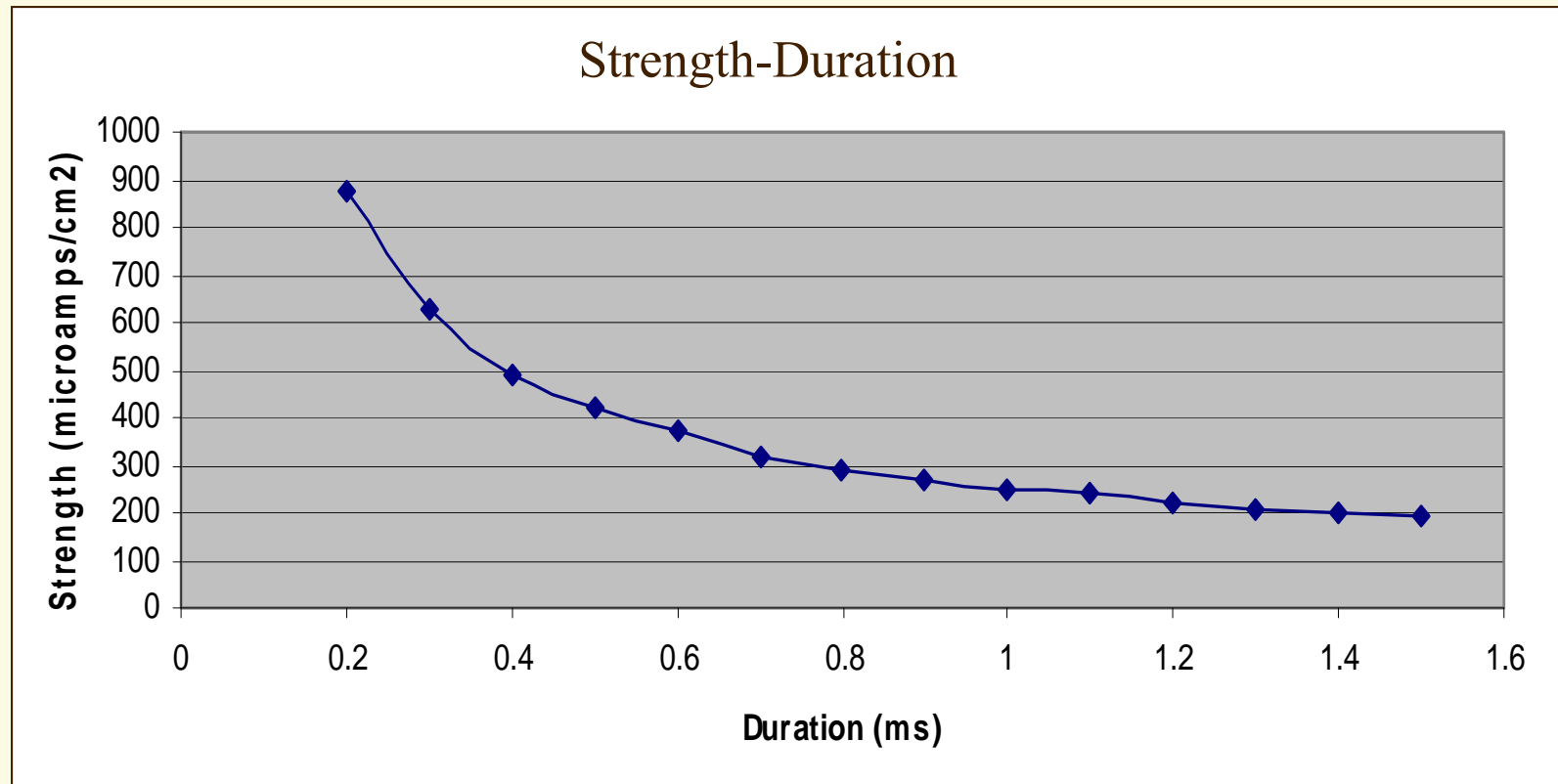
$$\text{Error} = \frac{\sqrt{\sum (x_1 - x_2)^2}}{\text{length}[x_1]} = 0.0230 \text{ mV}$$

LRD – Pacing Downsweep

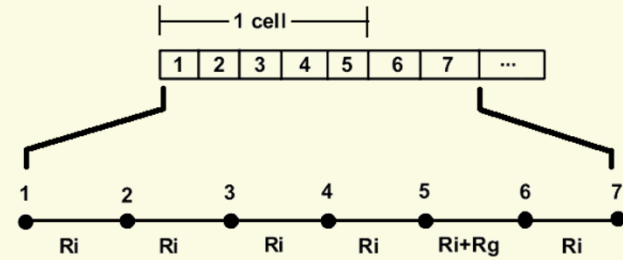


# of Stim	BCL	
10	2000	
10	1750	
10	1500	
10	1250	
10	1000	
10	800	
20	500	
20	300	
20	250	
20	200	
20	150	
20	100	
20	70	
20	50	32

Cable Experiments – LR I



Gap Junction Resistance



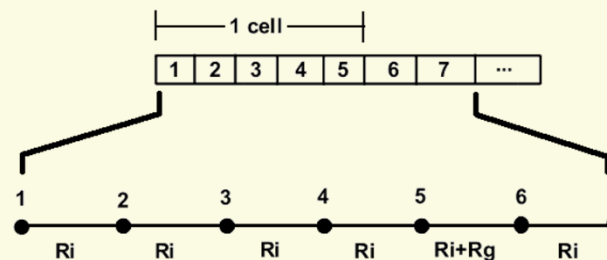
Rg	Pavg	CVavg	CVcell	CVgap
0	0.15	135	266.66	266.66
0.0015	0.3	95	200	80
0.003	0.45	76.25	235.29	72.72
0.01	1.15	47.15	400	44.44
0.05	5.15	21.05	1333.33	26.66
0.1	10.15	14.05	1600	18.77
0.5	50.15	3.68	10000	8.84
0.6	60.15	2.9412	20000	7.27
0.7	70.15	1.957	26666.67	7.27

$$R_g = \Omega\text{cm}^2$$

$$P_{\text{avg}} = \text{k}\Omega\text{cm}$$

$$CV = \text{cm/sec}$$

GNa



GNA %	GNA	CV
0	0	0
1	0.32	0
5	1.6	0
10	3.2	32.4
20	6.4	52.4
30	9.6	62.89
40	12.8	70.5
50	16	76.22
60	19.2	80.99
70	22.4	84.8
80	25.6	88.6
90	28.8	91.47
100	32	94.33
125	40	100.04
150	48	104.81
200	64	113.39

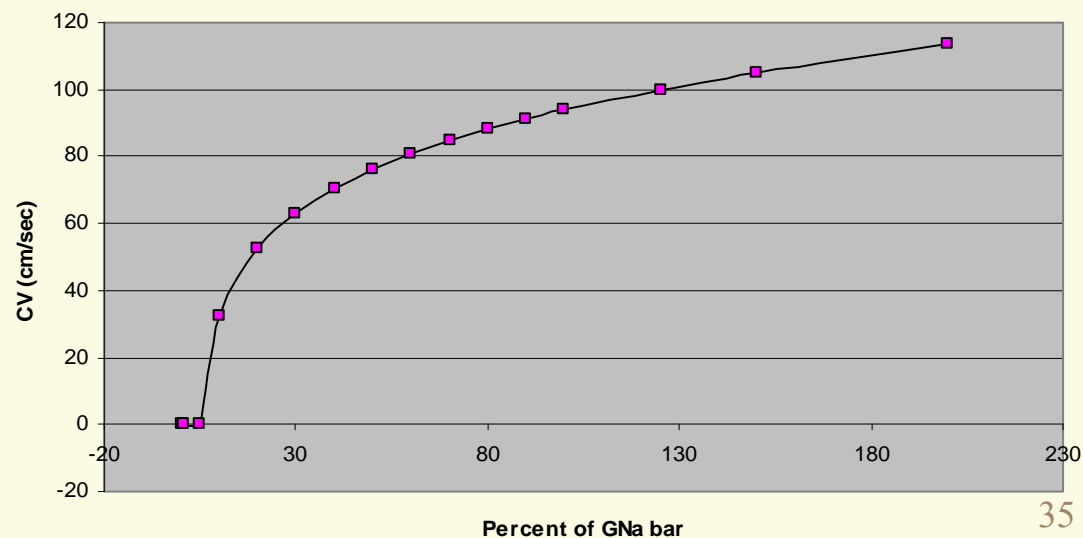
$$I_{Na} = \bar{G}_{Na} (m^3 h j) (V_m - E_{Na})$$

$$R_g = 1.5 \Omega \text{cm}^2$$

$$G_{Na} = \text{mS/cm}^2$$

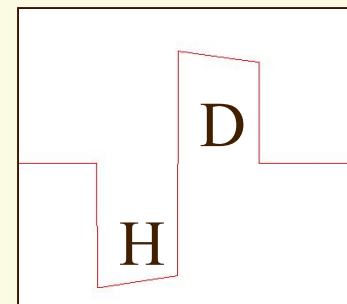
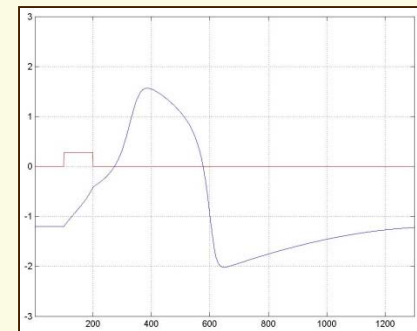
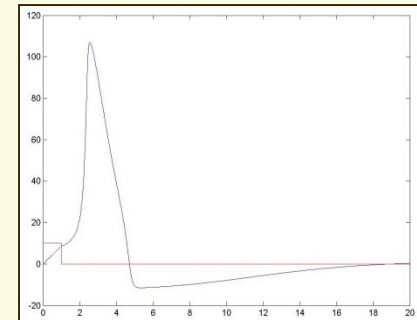
$$CV = \text{cm/sec}$$

Gna vs CV



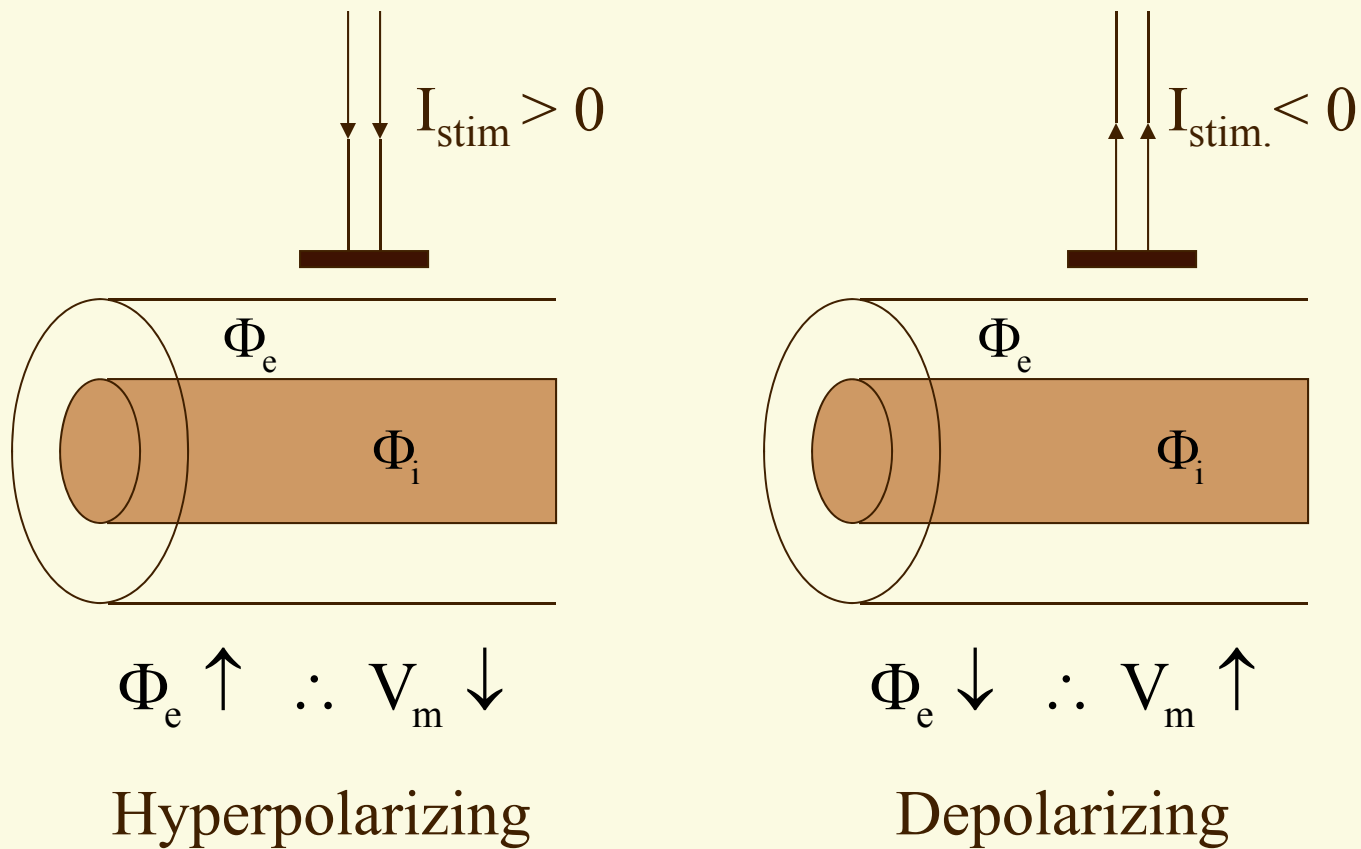
Fitzhugh-Nagumo (FN) vs Hodgkin-Huxley (HH)

- HH (4-D) accurately represents physiology
 - Fast Variables (V, m)
 - Slow Variables (n, h)
- FN (2-D) is a reduced version of HH considers only the fast changing variables (x, y)
 - simplicity makes it a good tool to understand fundamentals of “excitability”
- FN loses some realistic behavior
 - Bi-phasic stimulus
 - Decreases threshold (HH)
 - Increases threshold (FN)

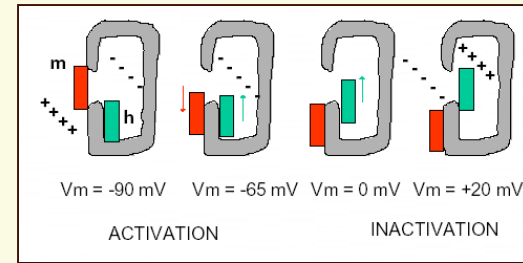


Stimulation (extracellular)

$$V_m = \Phi_i - \Phi_e$$



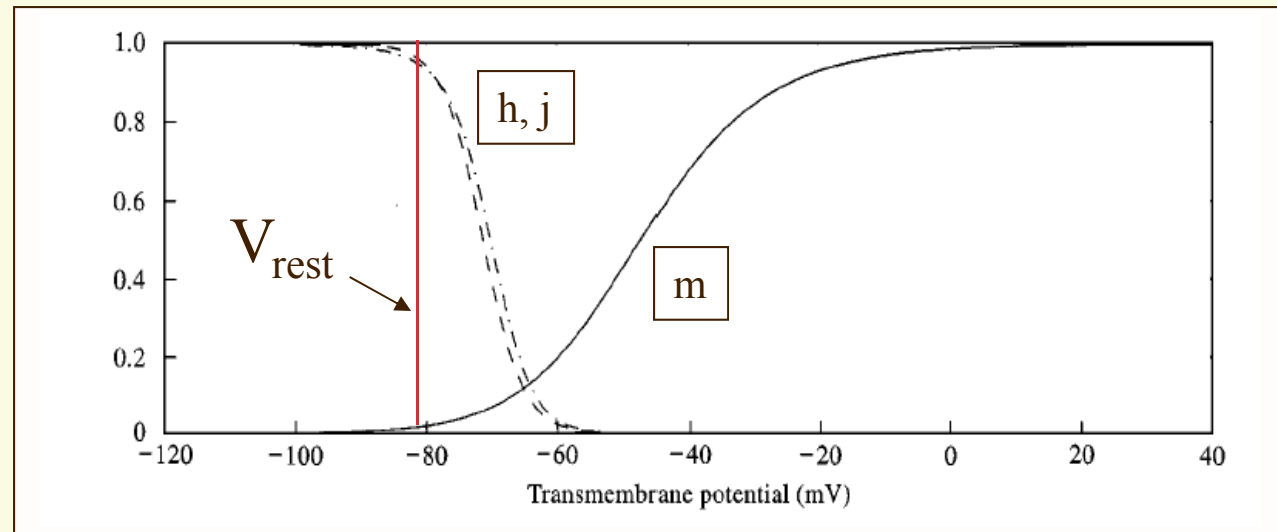
Gate performance for HH



Activation occurs when I_{Na} is large enough to overcome outward currents

$$I_{Na} = \bar{G}_{Na} (m^3 h j) (V_m - E_{Na})$$

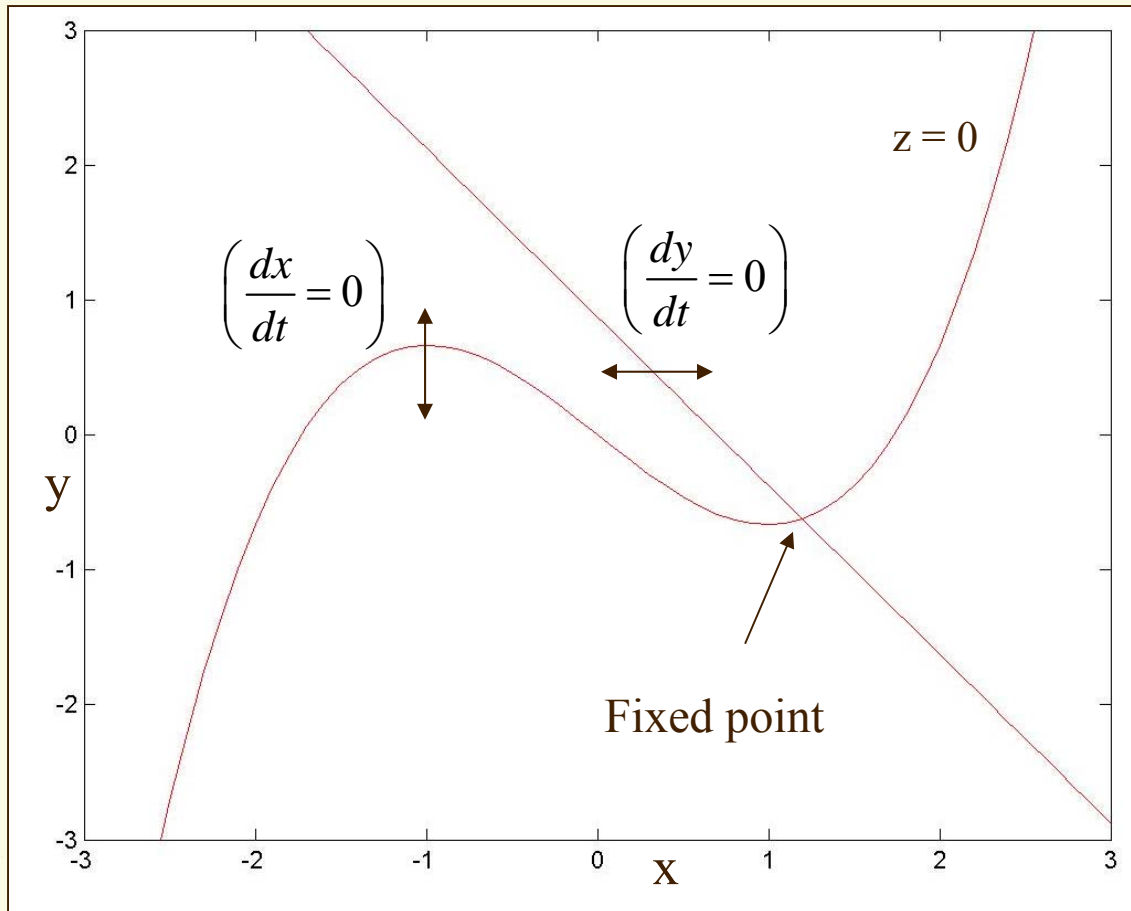
τ_m is "small" $\rightarrow m \approx m_\infty$ (fast)
 τ_h, τ_j is "large" $\rightarrow h \neq h_\infty, j \neq j_\infty$ (slow)



Due to slow variables, a hyperpolarizing pre-pulse reduces the activation threshold which would require a smaller depolarizing pulse!³⁸

Nullclines

$$\frac{dx}{dt} = c \left(y + x - \frac{x^3}{3} + z \right) \quad \frac{dy}{dt} = - \frac{(x - a + by)}{c}$$



nullclines

$$y = \frac{x^3}{3} - x - z \quad \left(\frac{dx}{dt} = 0 \right)$$

$$y = \frac{a - x}{b} \quad \left(\frac{dy}{dt} = 0 \right)$$

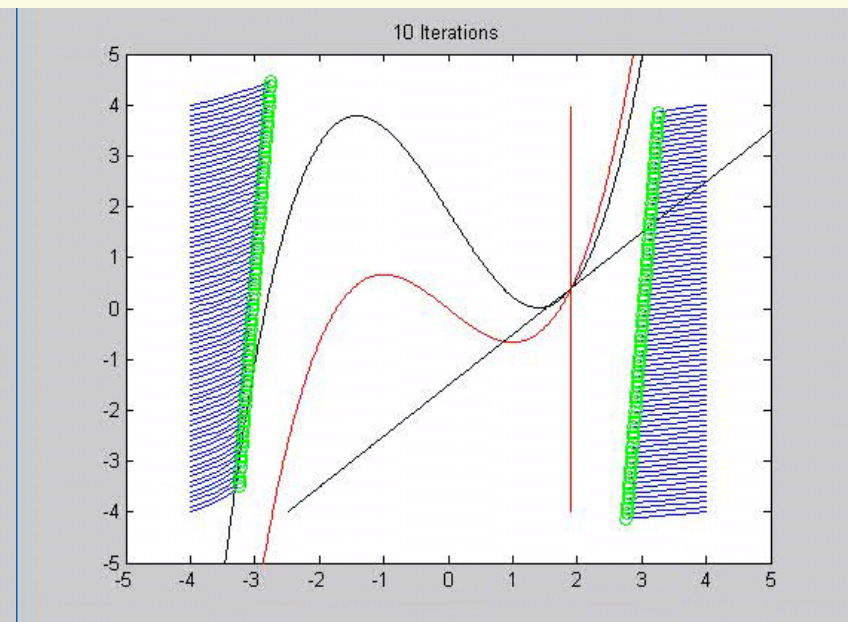
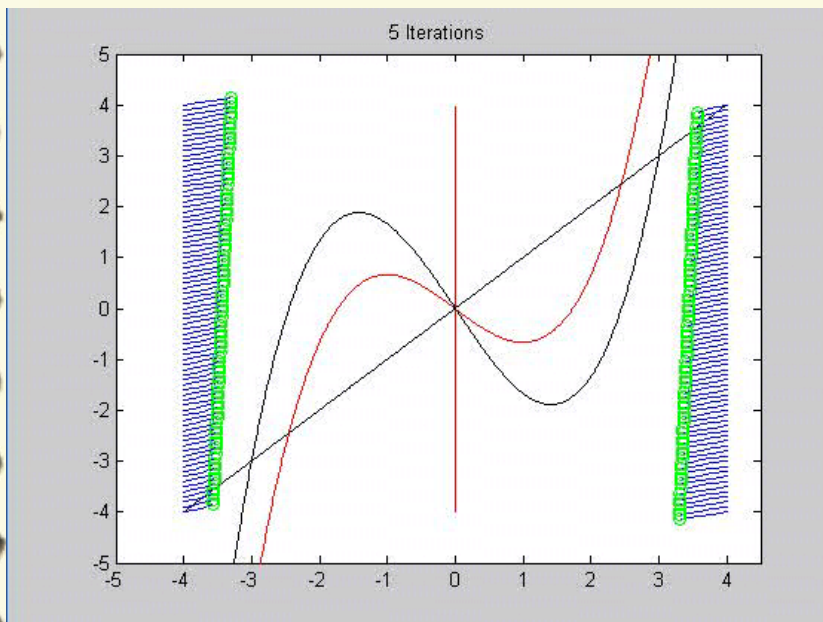
$$a = 0.7$$

$$b = 0.8$$

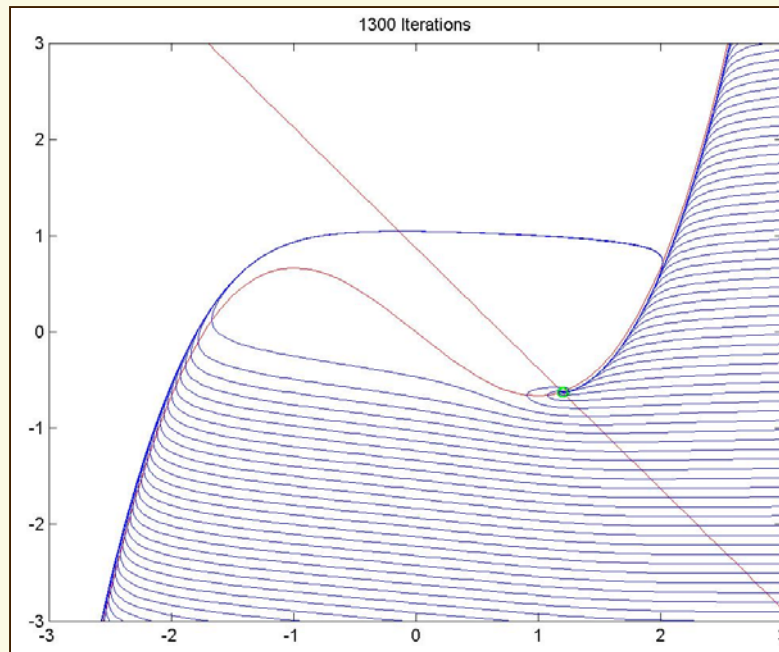
$$c = 3$$

Cubic nullclines

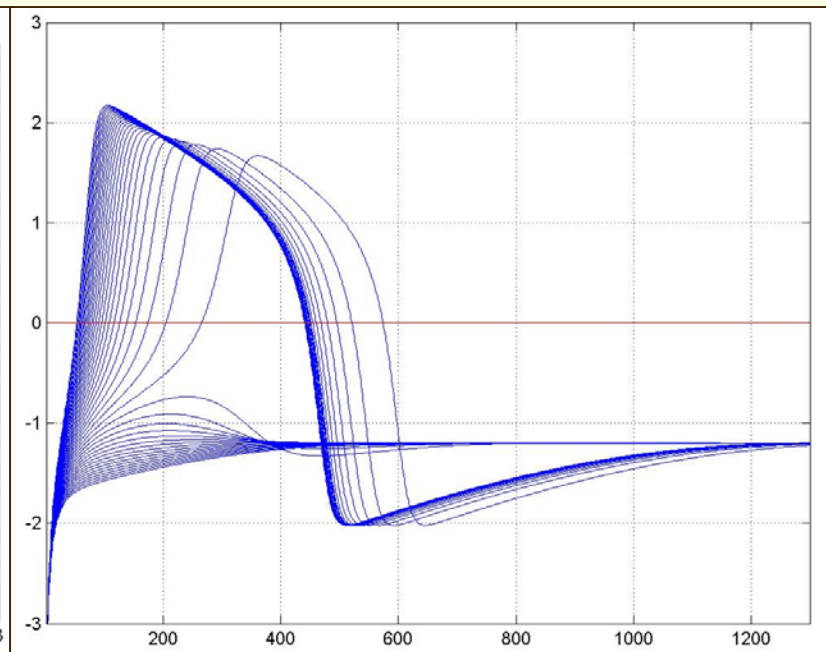
- ☞ Produce oscillatory dynamics
- ☞ Shifting linear nullcline changes orbit
 - can cause limit cycle to collapse to single point



Phase Space $x = 4$ ($z = 0$)

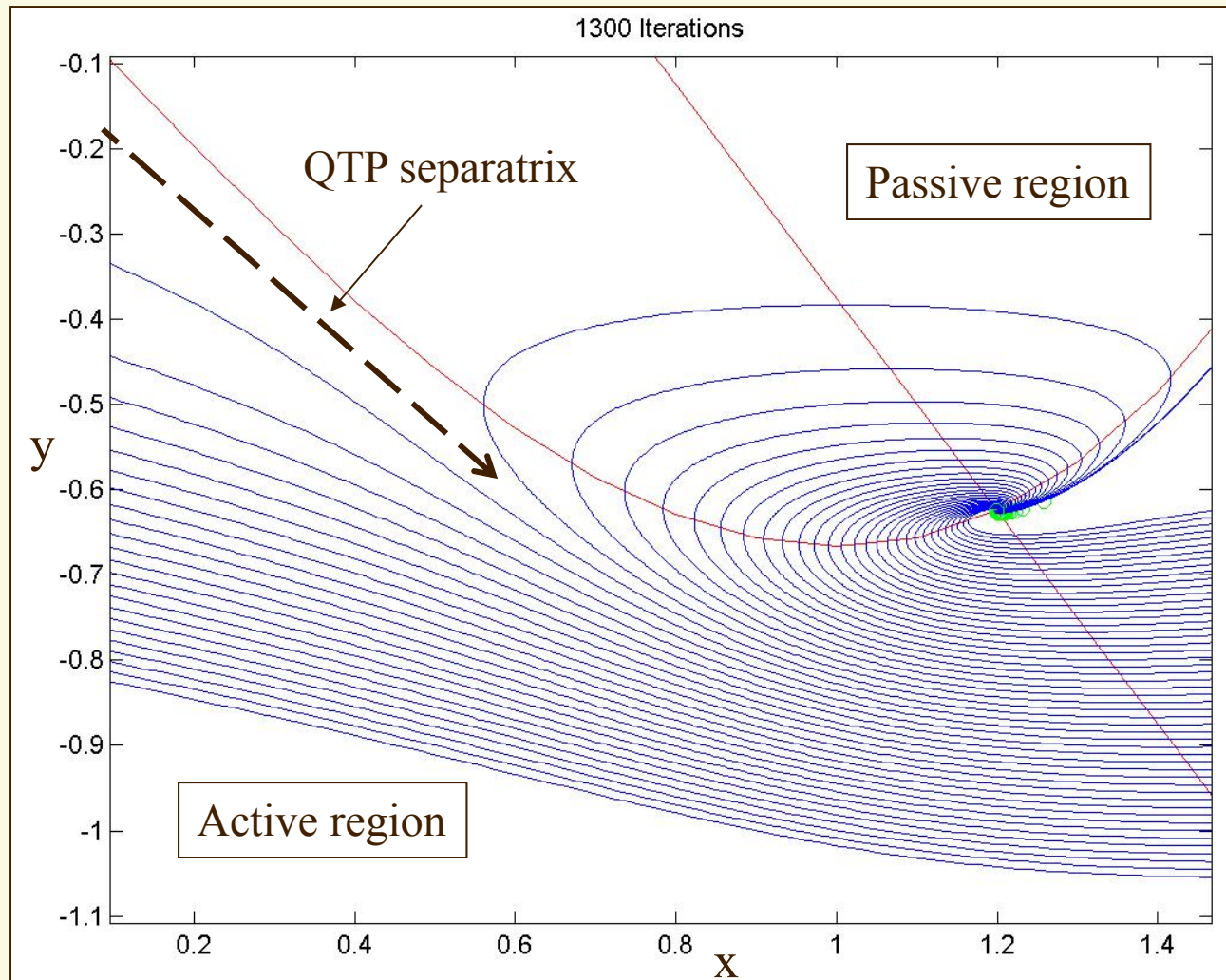


x vs y

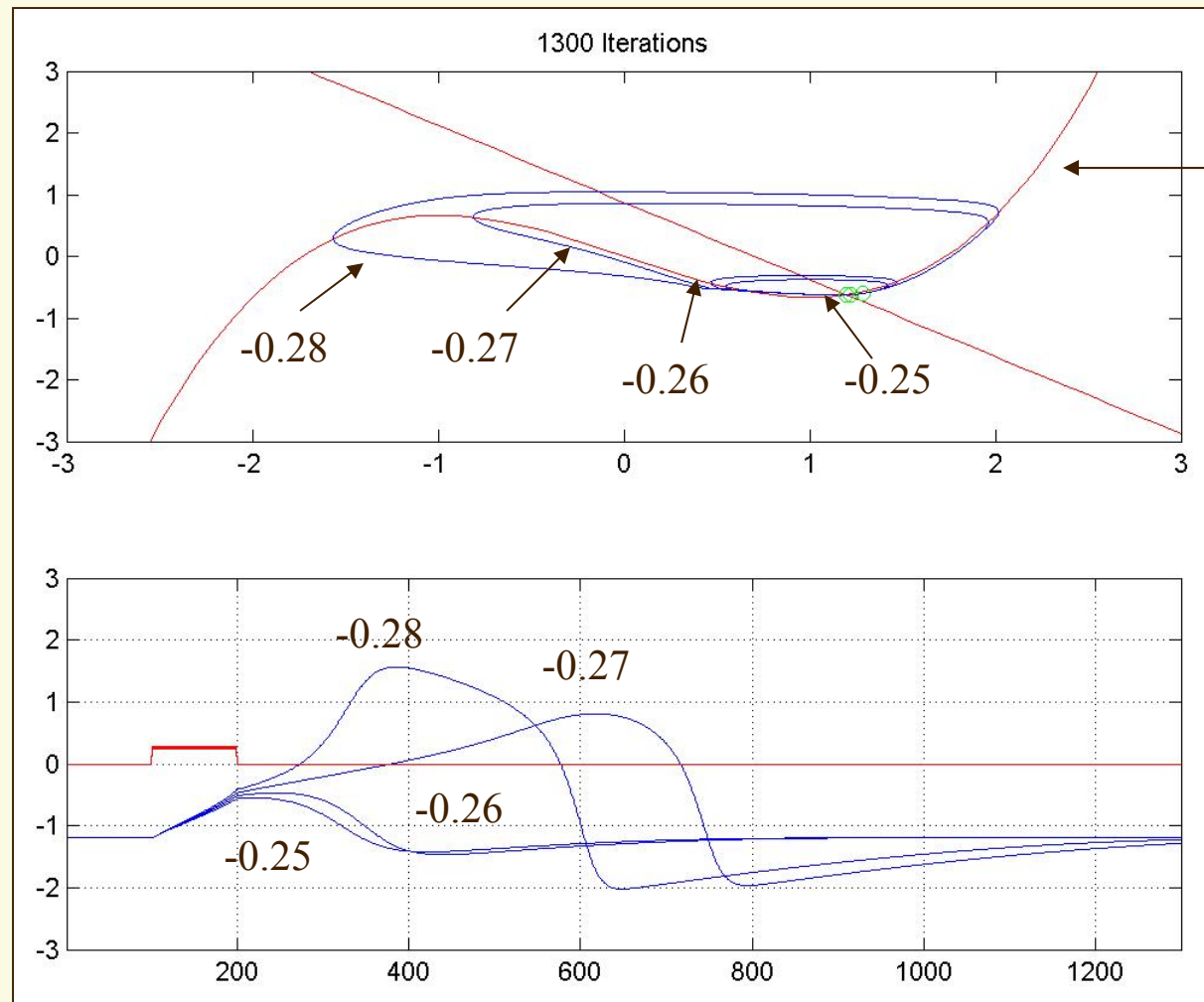


x vs iteration number

Phase Space $x = 4$ ($z = 0$)

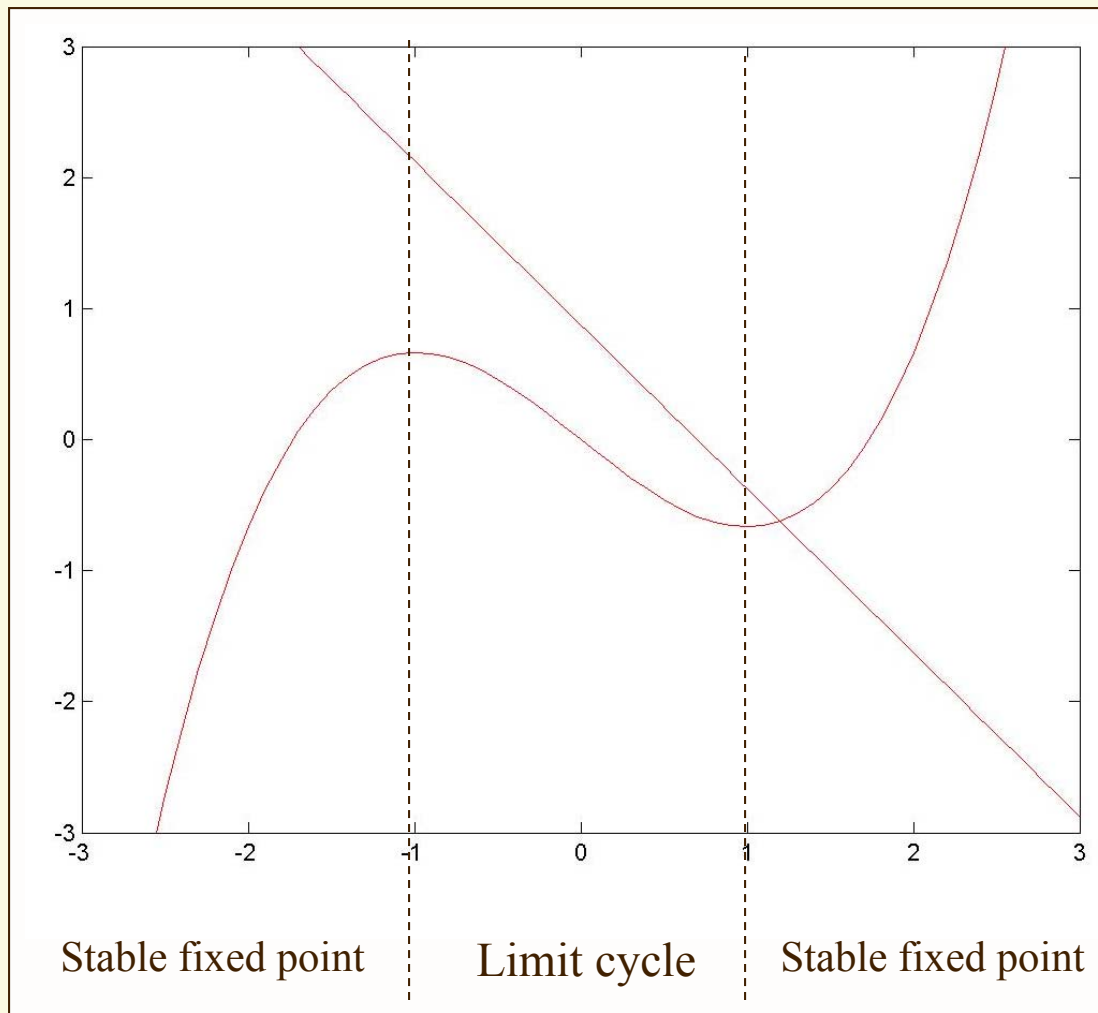


Variations in stimulation strength (z)



Nullcline
for $z = 0$

Intersection behavior

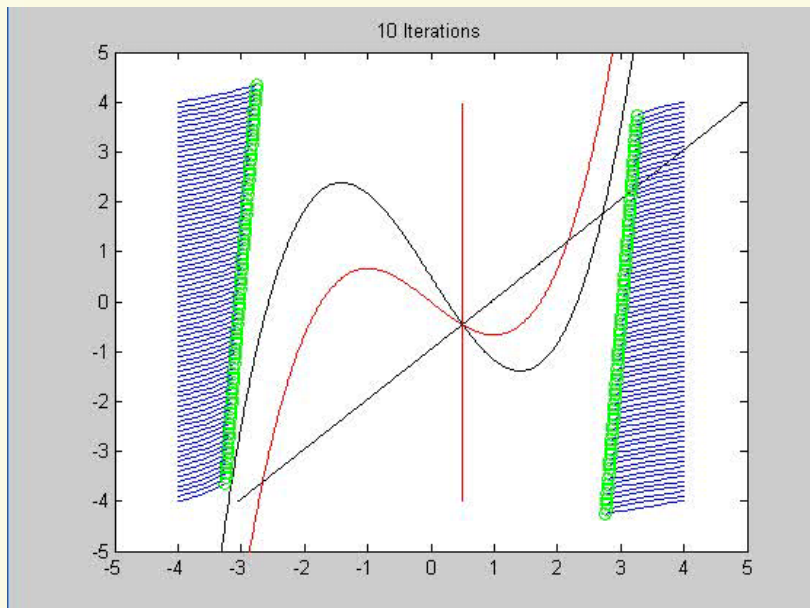


nullclines

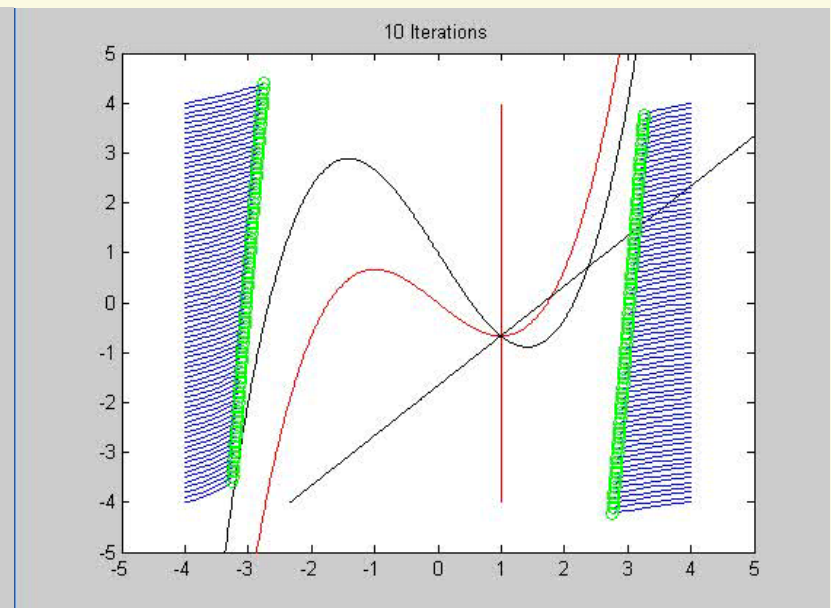
$$y = \frac{x^3}{3} - x - z \quad \left(\frac{dx}{dt} = 0 \right)$$

$$y = \frac{a - x}{b} \quad \left(\frac{dy}{dt} = 0 \right)$$

More Movies



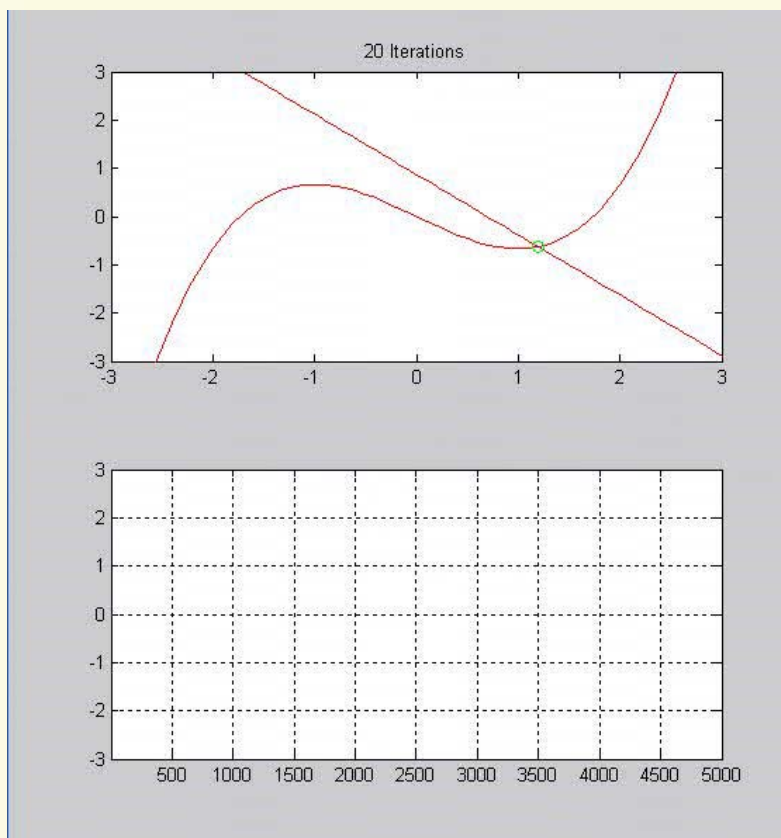
Limit Cycle



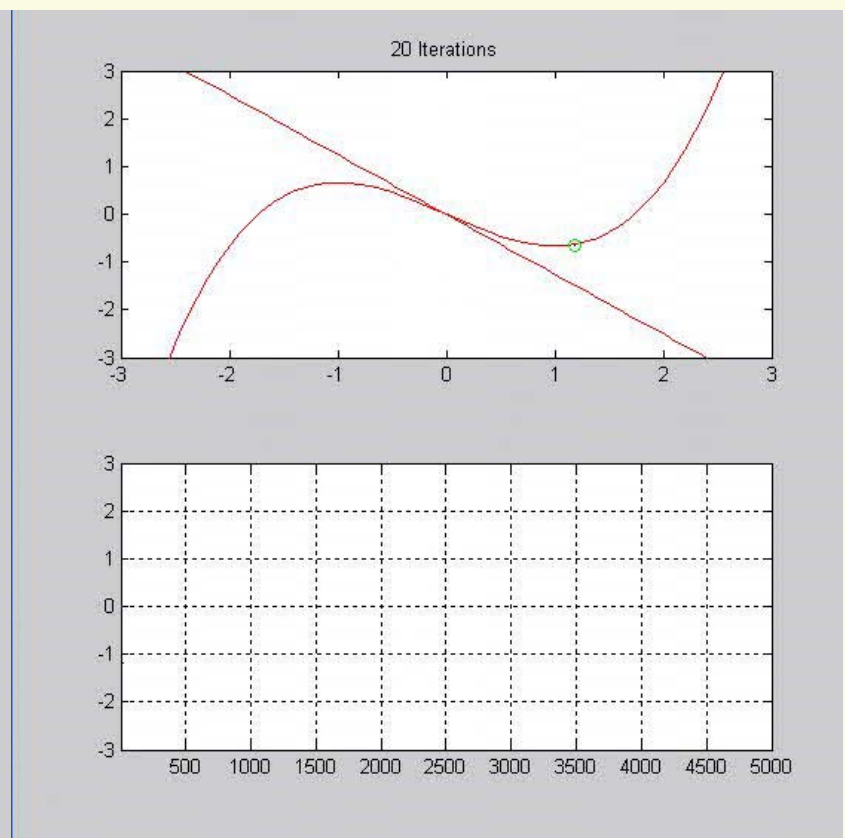
Limit Cycle

Movies

$$\frac{dx}{dt} = c \left(y + x - \frac{x^3}{3} + z \right) \quad \frac{dy}{dt} = - \frac{(x - a + by)}{c}$$



Long stim (z)



a = 0, no stim

Conclusions

- 📄 HH is a better representation of the physiology
- 📄 FN is a reduced version of HH
 - only considers fast changing variables
- 📄 FN is a good simple tool to understand why systems can be excitable.
 - People have trouble visualizing systems in 4 dimensions.
 - Contains important characteristics of action potential

Thank you!

