



SHORT-TERM SYNAPTIC PLASTICITY IN THE
DETERMINISTIC TSODYKS-MARKRAM MODEL
LEADS TO UNPREDICTABLE NETWORK
DYNAMICS

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BACKGROUND

Short-term synaptic plasticity in the deterministic Tsodyks–Markram model leads to unpredictable network dynamics

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Contributed by Terrence J. Sejnowski, August 28, 2013 (sent for review April 13, 2013)

PNAS

AUTHOR INFORMATION

- HENRY MARKRAM
 - Spike timing dependent synaptic plasticity (1997)
 - Professor in EPFL
 - Head of Blue Brain Project
 - Simulated rat brain (100,000 columns of in the order of 10,000 neurons each)



The human brain — a spongy, three-pound mass of tissue — is the most complex living structure in the known universe.

Society for Neuroscience

SIGNIFICANCE

- ❖ With increasing life expectancy, neurological disorders drastically increase. (WHO)
- ❖ 1000+ diseases related to brain result in hospitalization and loss in productivity. (SFN)
- ❖ Storage capacity of brain is larger than any supercomputer and the complexity of network is way larger than a social network. (SFN)

BACKGROUND

- STSP : Temporal adjustment of synaptic strength in time-scales of ms to mins.
- STSP affects:
 - Network dynamics and brain function
 - Depression acts as activity regulator mechanism.
 - Facilitation is a way of implementing working memory.

BACKGROUND

- **Synaptic enhancement (facilitation, augmentation, potentiation)**

- ALL presynaptic mechanisms
- Increase in mean number of transmitter quanta without change in quantal size or postsynaptic effectiveness

Increased probability of release and perhaps an increased number of release sites

- Crucial role of calcium

Residual presynaptic intracellular calcium

BACKGROUND

■ **Synaptic depression**

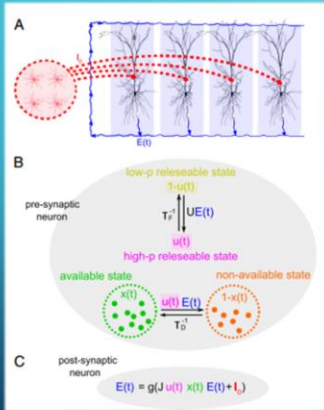
- MOSTLY presynaptic
- Depletion of pool of vesicles
- Decrease in number of transmitter quanta

Decrease in probability of release and perhaps a reduced release efficacy

MOTIVATION

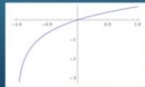
- Prove the existence of highly irregular and chaotic-like dynamics in the TM model.
- Identifying Shilnikov Chaos to account irregularities in the overall network activity.

MODEL



$$\begin{cases} \tau \dot{E}(t) = -E(t) + g(J u(t) x(t) E(t) + I_0) \\ \dot{x}(t) = \tau_D^{-1} (1 - x(t)) - u(t) E(t) x(t) \\ \dot{u}(t) = U E(t) (1 - u(t)) - \tau_f^{-1} (u(t) - U) \end{cases}$$

Symbol	Description	Value
τ	Time constant for rate dynamics	13 ms
τ_f	Time constant for synaptic facilitation	1,500 ms
τ_D	Time constant for synaptic depression	200 ms
U	Baseline for facilitation variable	0.3
J	Strength of recurrent connections	3.07
I_0	External inhibitory input	[-2, -1]
α	Normalization factor in the gain function	1.5



$$g(z) = \alpha \log(1 + \exp(\frac{z}{\alpha}))$$

METHODS

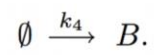
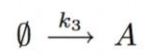
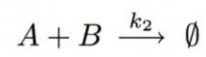
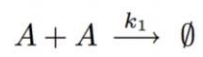
- XPPAUT AUTO
 - XPPAUT (freeware, simulation and analysis of differential equation models)
 - AUTO feature is used to obtain bifurcation diagram of the system.
 - Uses continuation techniques to numerically analyze sets of differential equations in an efficient manner

METHODS

- Gillespie Algorithm
 - Generates a statistically correct trajectory of a stochastic equation
 - Uses two random numbers to generate long trajectories, one for timestep and one for next state.

METHODS

- Gillespie Algorithm
 - EXAMPLE



METHODS

- Gillespie Algorithm

- EXAMPLE

- › Step 1: Generate two random numbers r_1 and r_2 in the range $(0, 1)$

- › Step 2: Compute the following variables

- › $\alpha_1 = A(t) (A(t)-1) k_1$

- › $\alpha_2 = A(t) B(t) k_2$

- › $\alpha_3 = k_3$

- › $\alpha_4 = k_4$

- › $\alpha_0 = \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4$

METHODS

- Gillespie Algorithm
 - EXAMPLE

$$\tau = \frac{1}{\alpha_0} \ln \left[\frac{1}{r_1} \right]$$

METHODS

- Gillespie Algorithm

- EXAMPLE

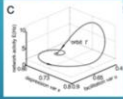
$$A(t + \tau) = \begin{cases} A(t) - 2 & \text{if } 0 \leq r_2 < \alpha_1/\alpha_0; \\ A(t) - 1 & \text{if } \alpha_1/\alpha_0 \leq r_2 < (\alpha_1 + \alpha_2)/\alpha_0; \\ A(t) + 1 & \text{if } (\alpha_1 + \alpha_2)/\alpha_0 \leq r_2 < (\alpha_1 + \alpha_2 + \alpha_3)/\alpha_0; \\ A(t) & \text{if } (\alpha_1 + \alpha_2 + \alpha_3)/\alpha_0 \leq r_2 < 1; \end{cases}$$

$$B(t + \tau) = \begin{cases} B(t) & \text{if } 0 \leq r_2 < \alpha_1/\alpha_0; \\ B(t) - 1 & \text{if } \alpha_1/\alpha_0 \leq r_2 < (\alpha_1 + \alpha_2)/\alpha_0; \\ B(t) & \text{if } (\alpha_1 + \alpha_2)/\alpha_0 \leq r_2 < (\alpha_1 + \alpha_2 + \alpha_3)/\alpha_0; \\ B(t) + 1 & \text{if } (\alpha_1 + \alpha_2 + \alpha_3)/\alpha_0 \leq r_2 < 1; \end{cases}$$

RESULTS

- Stability Analysis of System

HO @ $I = -1.76$
Shilnikov Chaos

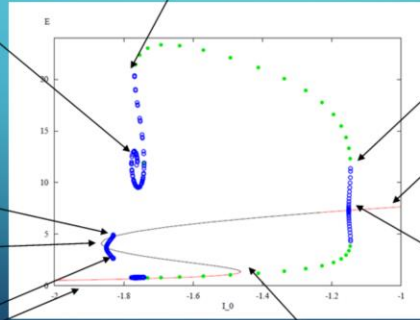


HO @ $I = -1.82$

SN @ $I = -1.86$

H @ $I = -1.84$

SNP @ $I = -1.77$



SNP @ $I = -1.14$

Up fixed point

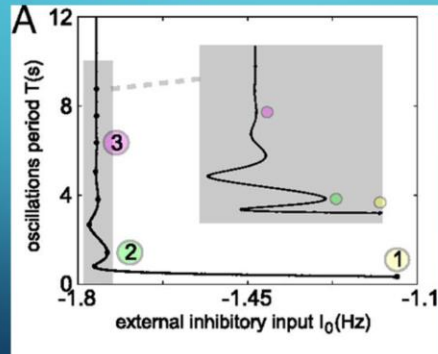
H @ $I = -1.15$

Down fixed point

SN @ $I = -1.46$

RESULTS

- Shilnikov Homoclinic Bifurcation



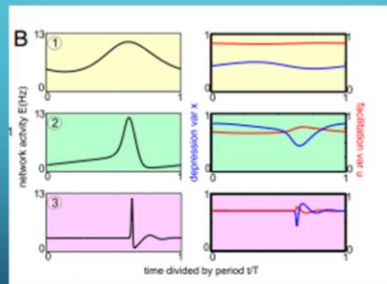
RESULTS

- Shilnikov Homoclinic Bifurcation

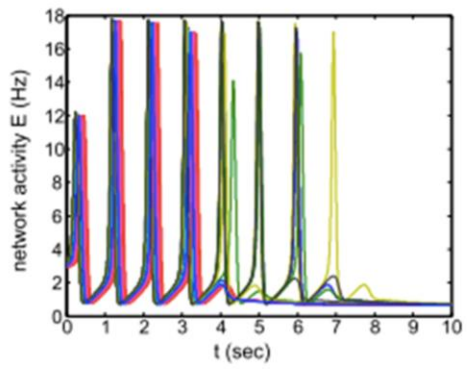
Far from homoclinic bifurcation

Closer to homoclinic bifurcation

At homoclinic bifurcation



RESULTS



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RESULTS

- Influence of Noise on Network Dynamics near Shilnikov Homoclinic Bifurcation

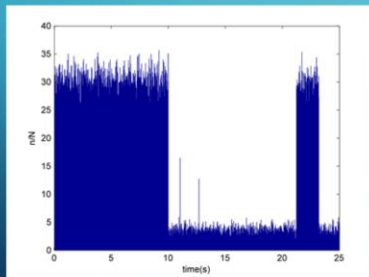
$$T_+(n, t) = NS \left(Ju(t)x(t) \frac{n}{N} + I_0 \right) / \tau, \quad T_-(n) = -n/\tau,$$

$$\begin{cases} \dot{x}(t) = \tau_D^{-1} (1 - x(t)) - u(t)x(t)n(t)/N \\ \dot{u}(t) = -\tau_F^{-1} (u(t) - U) + U(1 - u(t))n(t)/N. \end{cases}$$

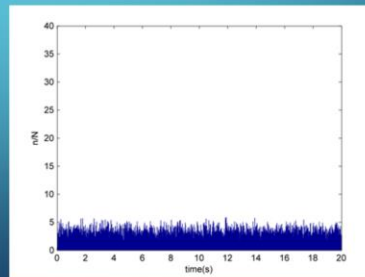
RESULTS

- Influence of Noise on Network Dynamics near Shilnikov Homoclinic Bifurcation

$\mu = -1.77$

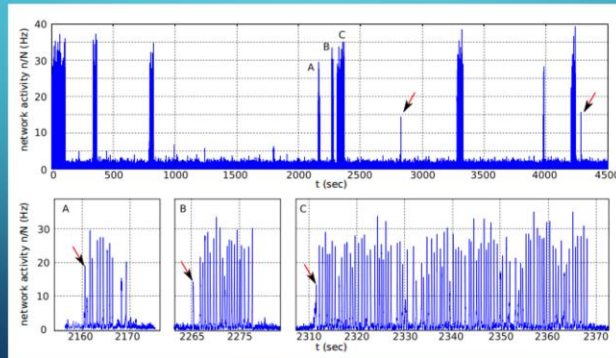


$\mu = -1.9$



RESULTS

- Influence of Noise on Network Dynamics near Shilnikov Homoclinic Bifurcation



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Spring board like dynamics

RESULTS

- Derivation of mean field description in large N limit

$$\frac{d}{dt}P(n,t) = T_+(n-1)P(n-1,t) + T_-(n+1)P(n+1,t) - [T_+(n) + T_-(n,t)]P(n,t).$$

$$\frac{d}{dt}P(z,t) = N(T_+(z-1/N)P(z-1/N,t) + T_-(z+1/N,t)P(z+1/N,t) - [T_+(z) + T_-(z,t)]P(z,t)).$$

$$T_+(n,t) = NS \left(Ju(t)x(t) \frac{n}{N} + I_0 \right) / \tau, \quad T_-(n) = -n/\tau,$$

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RESULTS

- Derivation of mean field description in large N limit:
 - Kramers-Moyal expansion of the master equation

$$\begin{cases} dz = A(z, x, u)dt + \frac{1}{\sqrt{N}}B(z, x, u)dW(t) \\ dx = (\tau_D^{-1}(1-x(t)) - u x z)dt \\ du = (-\tau_T^{-1}(u(t) - U) + U(1-u)z)dt \end{cases}$$

$$\begin{cases} A(z, x, u) = S(Ju x z + I_0) - z \\ B(z, x, u) = S(Ju x z + I_0) + z, \end{cases}$$

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RESULTS

- Derivation of mean field description in large N limit:
 - $N \rightarrow \infty$

$$\begin{cases} \tau \dot{E}(t) = -E(t) + S(Ju(t)x(t)E(t) + I_0) \\ \dot{x}(t) = \tau_D^{-1}(1-x(t)) - u(t)x(t)E(t) \\ \dot{u}(t) = -\tau_F^{-1}(u(t) - U) + U(1-u(t))E(t). \end{cases}$$

CONCLUSION

- Chaos is existing in the simple TM model for STSP dynamics.
- The chaos explains the irregularities in large scale brain dynamics.
- Effects of periodic or balanced inputs can be investigated.
- Feedback loop between inhibition and excitation is a reasonable candidate for self organizing tuning mechanism to the edge of chaos.