Depletion-enhanced synchronization in reverberatory bursts

Chun-Chung Chen, Chih-Hsu Huang, Yuting Huang, C. K. Chan

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Computational Neuroscience:
A Bridge to Artificial Intelligence
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Laboratory of Computing Biological Networks

Bursting of cultured neurons on MEA

In vitro neuronal networks

680 • The Journal of Neuroscience, January 19, 2005 • 25(3):680 – 688

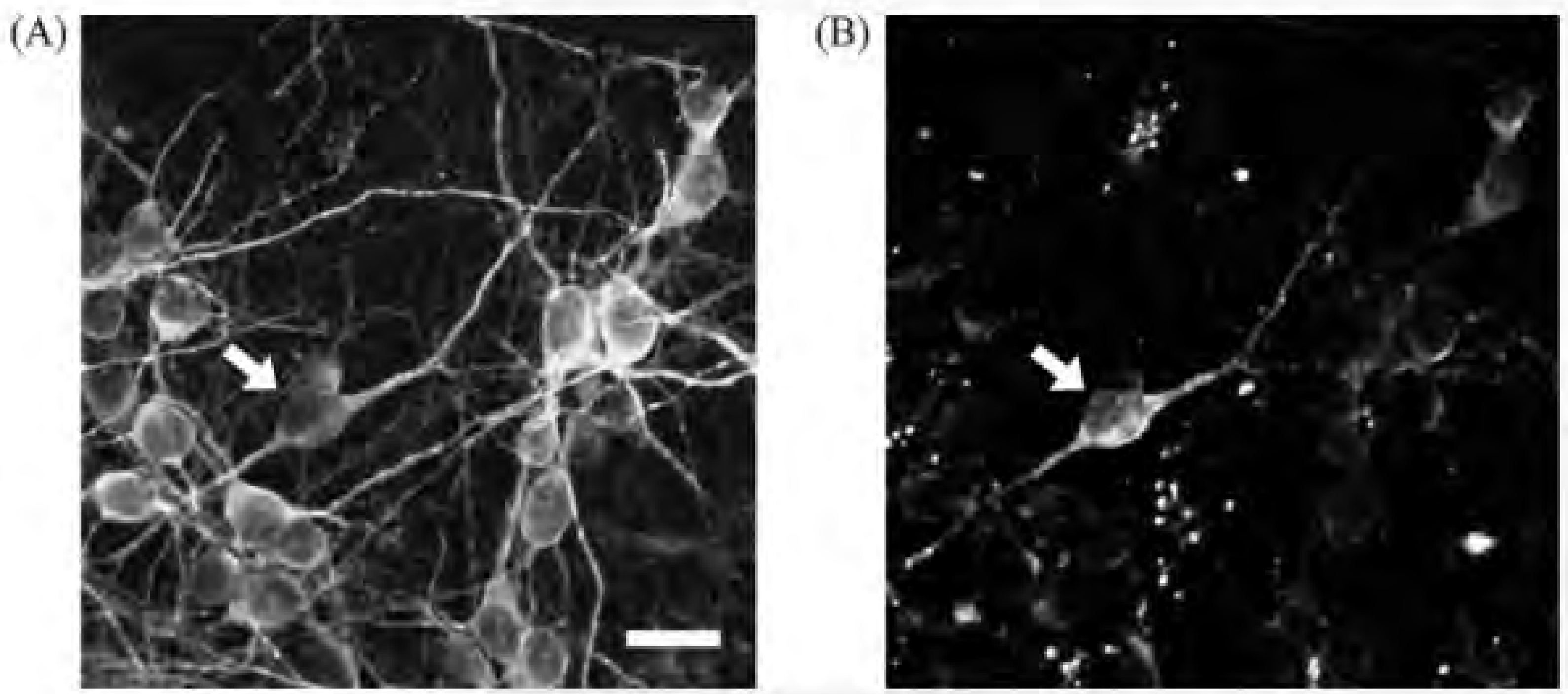
Behavioral/Systems/Cognitive

Controlling Bursting in Cortical Cultures with Closed-Loop Multi-Electrode Stimulation

Daniel A. Wagenaar,[1] Radhika Madhavan,[2] Jerome Pine,[1] and Steve M. Potter[2]

[1]Department of Physics, California Institute of Technology, Pasadena, California 91125, and [2]Department of Biomedical Engineering, Georgia Institute of Technology and Emory University Medical School, Atlanta, Georgia 30332-0535

In vitro neuronal networks



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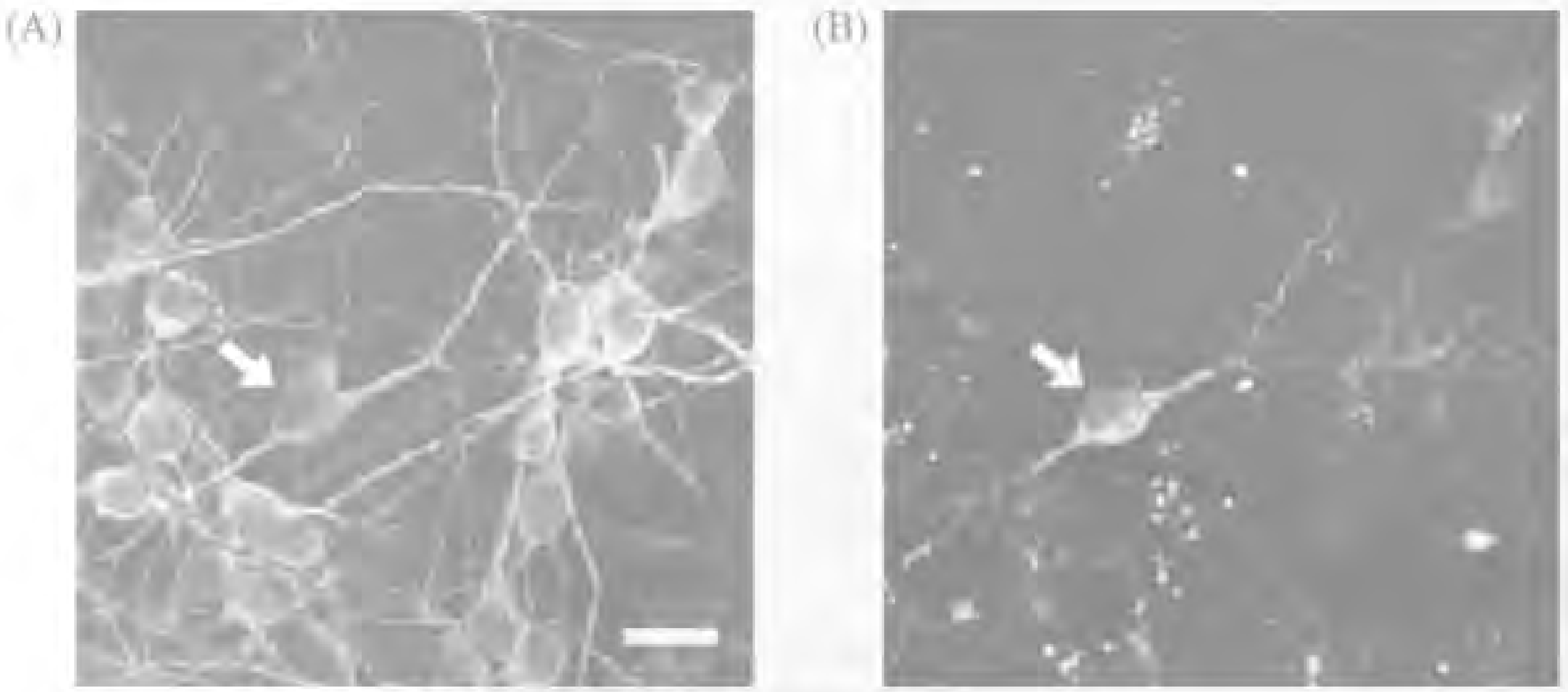

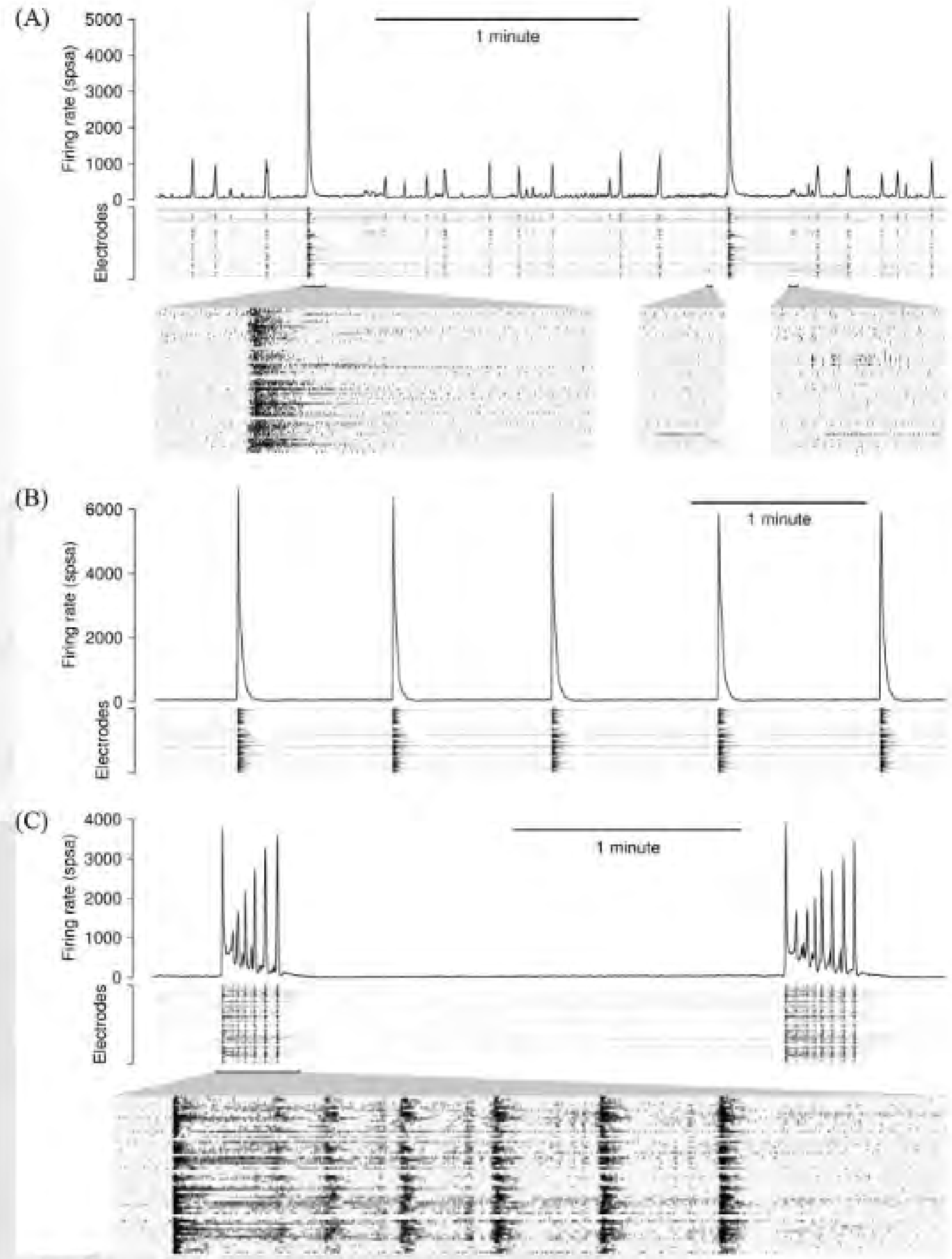

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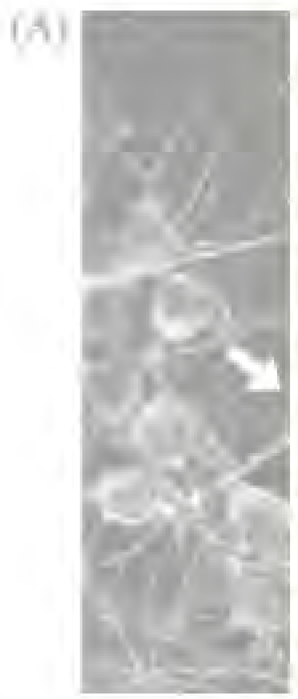
In vitro neuronal networks

http://www.biomedcentral.com/1471-2202/7/11



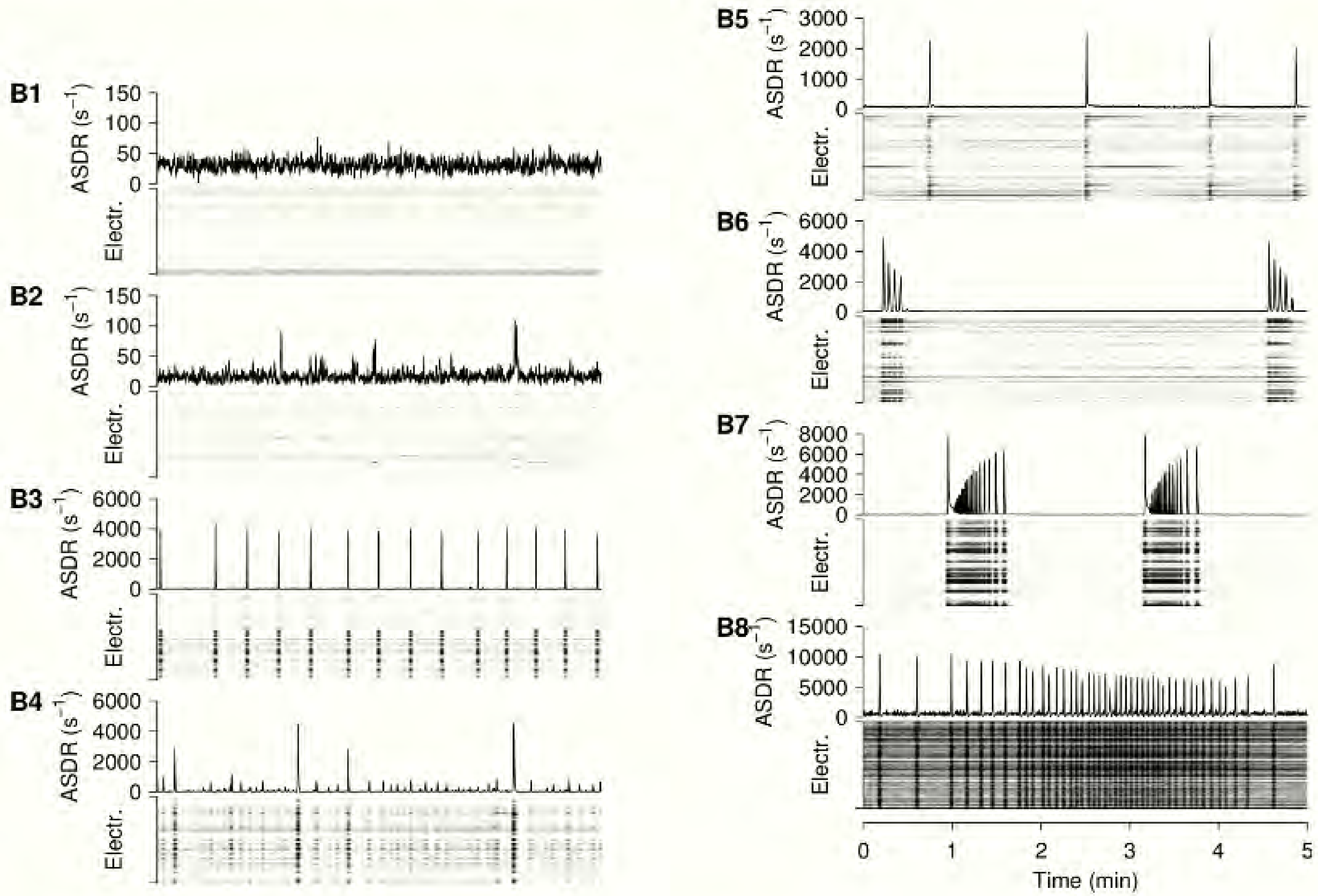


Figure 3
Classification of observed bursting behaviors. A Overview of the different classes of bursting behavior observed in our cultures. Numbers in parentheses indicate plating batch. Vertical bars indicate partial medium replacement times. Hash patterns indicate burst frequency for all types of burst patterns except superbursts. In batch 3, three cultures received full medium replacements (indicated by thicker bars in the lower three cultures of batch 3). One culture in batch 6 got infected after 20 div, and had to be discarded. **B** Examples of burst pattern classes, with array-wide spike detection rates and gray-scale rasters for all electrodes, all taken from dense cultures. **B1** No bursting. **B2** Tiny bursts. **B3** Fixed size bursts. **B4** Variably sized bursts. **B5** Long-tailed bursts. **B6** Regular superbursts. **B7** Inverted superbursts. **B8** Dramatic burst rate variation. Gray scales are as in Figure 1.

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Wagenaar, Pine, Potter, BMC Neuroscience 2006, 7:11

Phenomenological models with multiple-time-scale dynamical systems

Multi-scale dynamical system

The Journal of Neuroscience, April 15, 2000, *20*(8):3041–3056

Modeling of Spontaneous Activity in Developing Spinal Cord Using Activity-Dependent Depression in an Excitatory Network

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Multi-scale dynamical system

θ-model

$$\tau_a \dot{a} = a_\infty(n \cdot d \cdot a) - a,$$

$$\tau_d \dot{d} = d_\infty(a) - d,$$

$$\tau_\theta \dot{\theta} = \theta_\infty(a) - \theta.$$

s-model

$$\tau_a \dot{a} = a_\infty(n \cdot s \cdot d \cdot a) - a,$$

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The parameter n measures the connectivity in the network. All of the x_∞ functions are sigmoidal.

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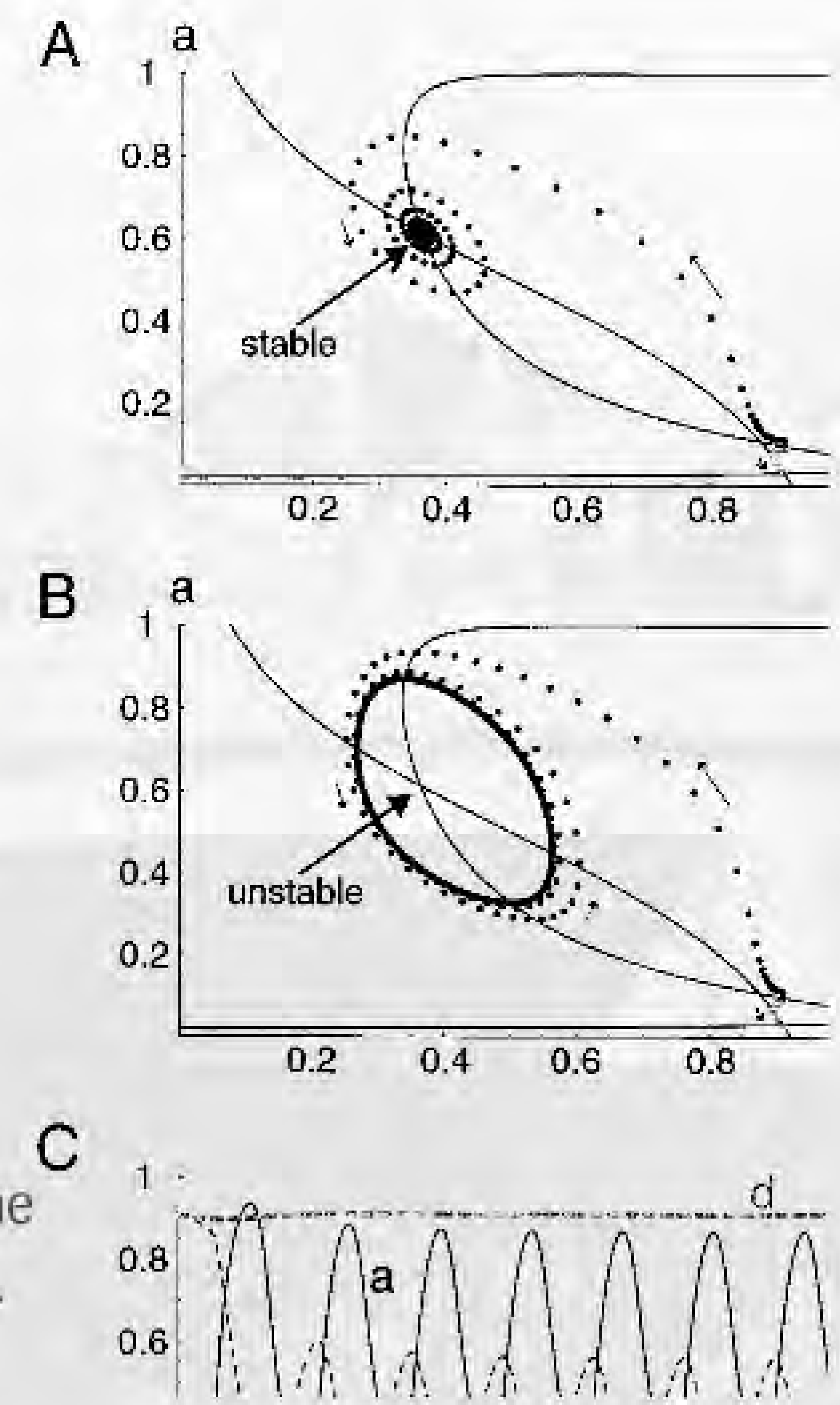

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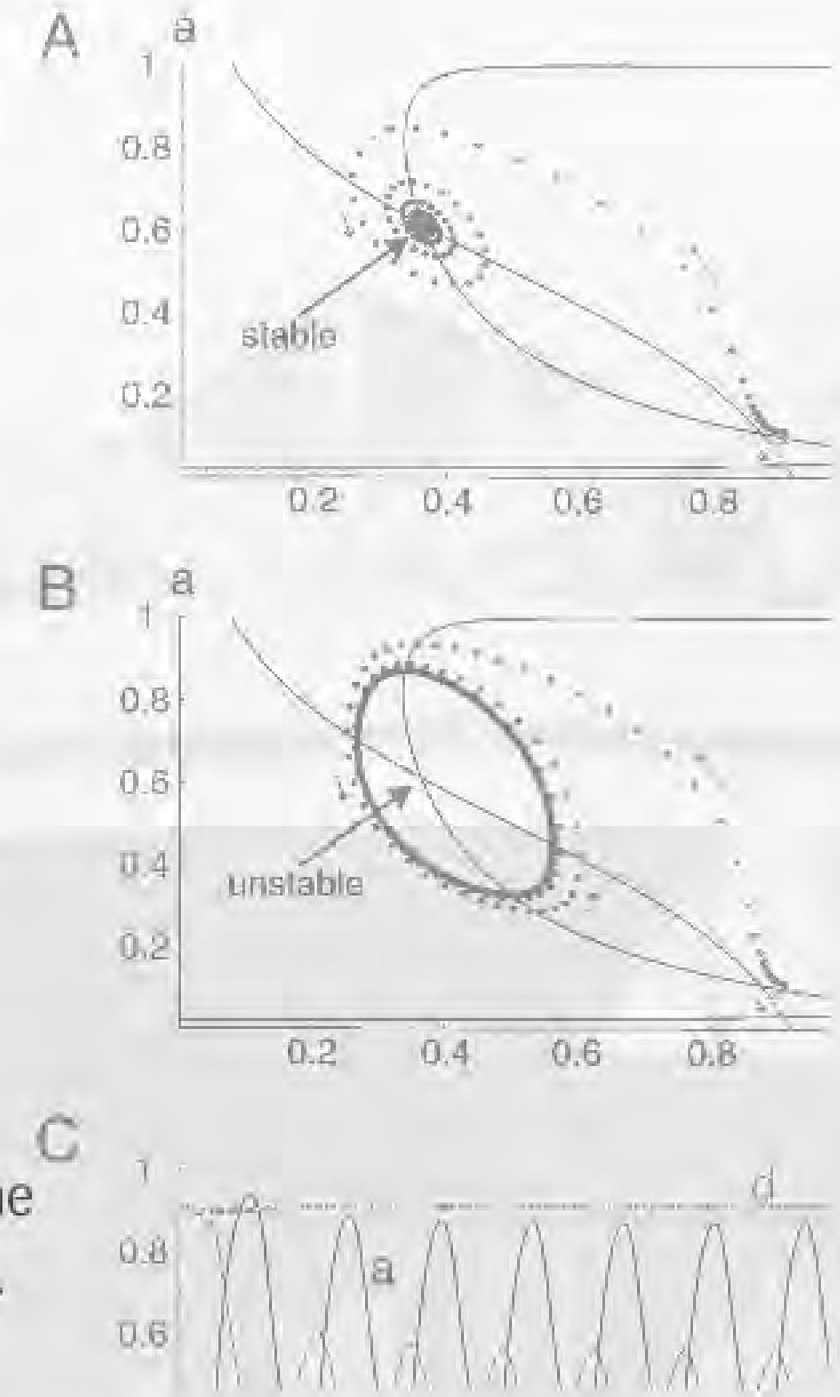

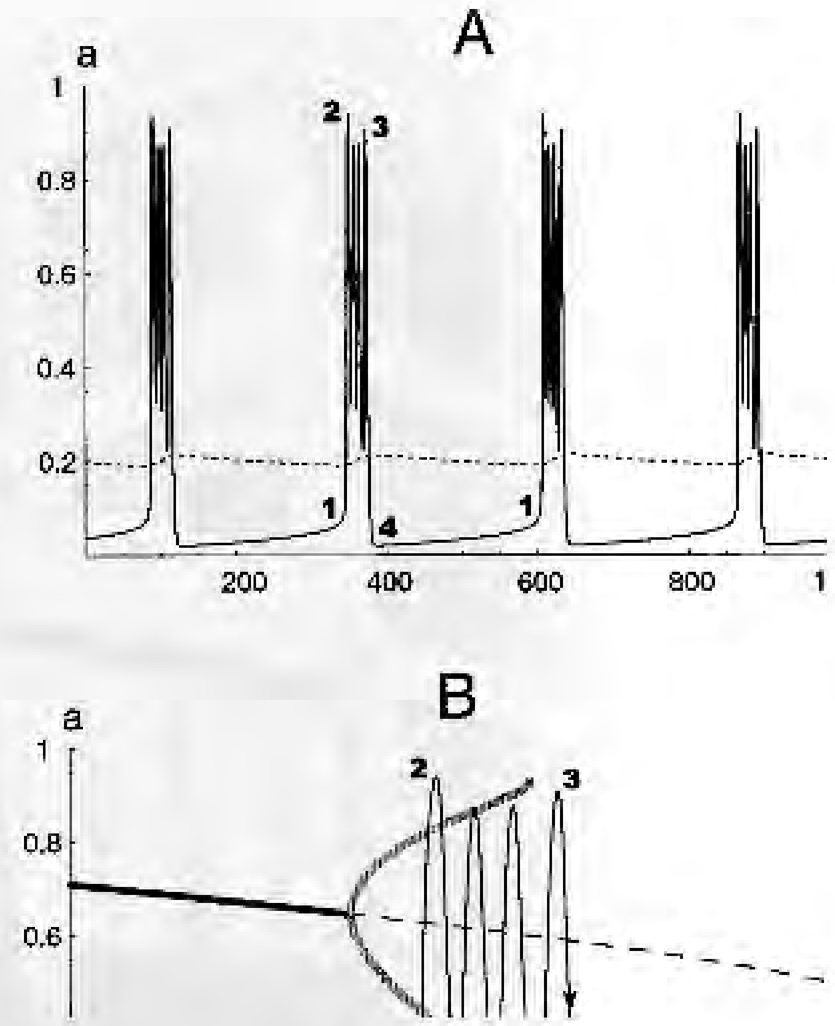

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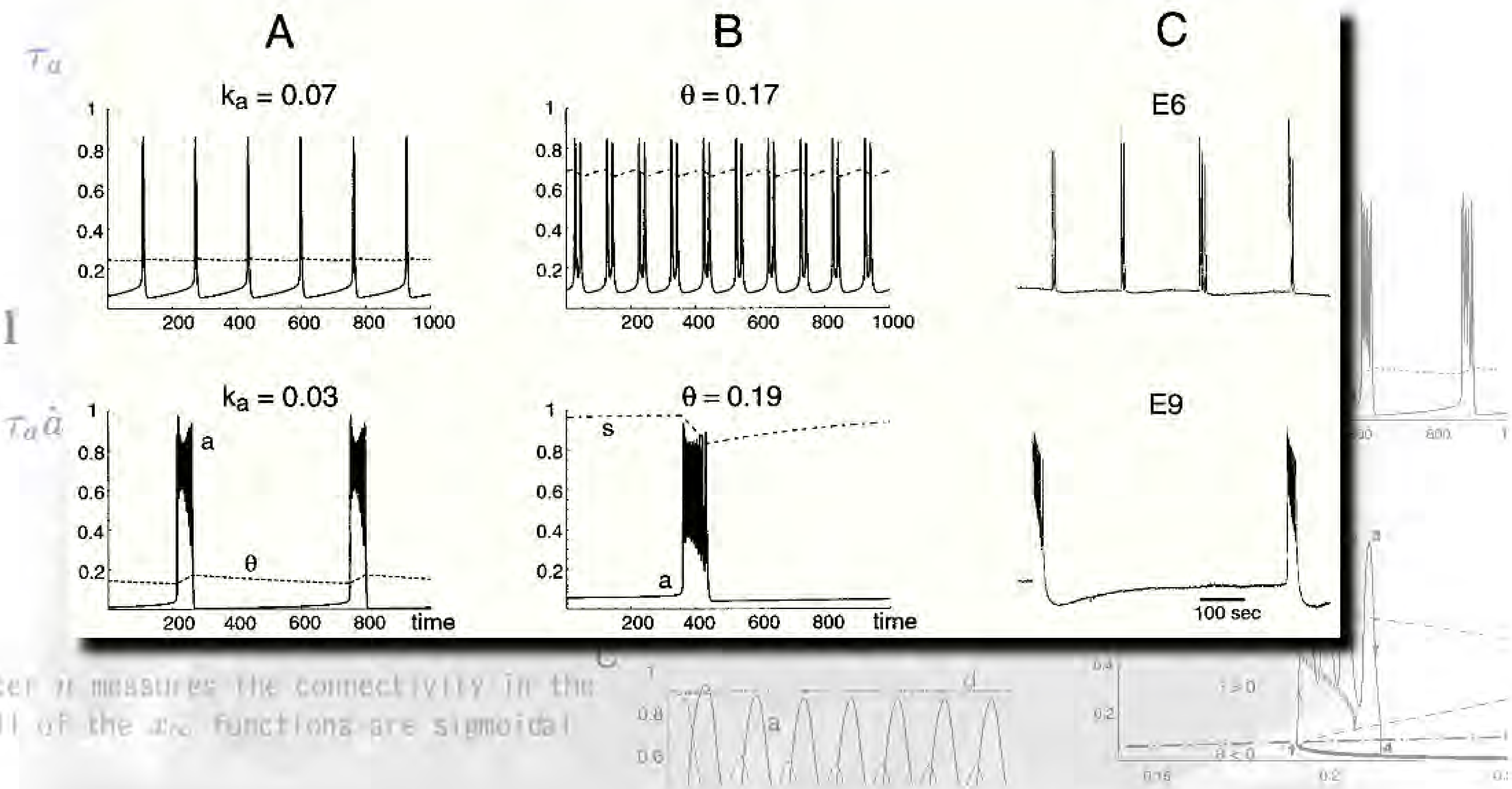

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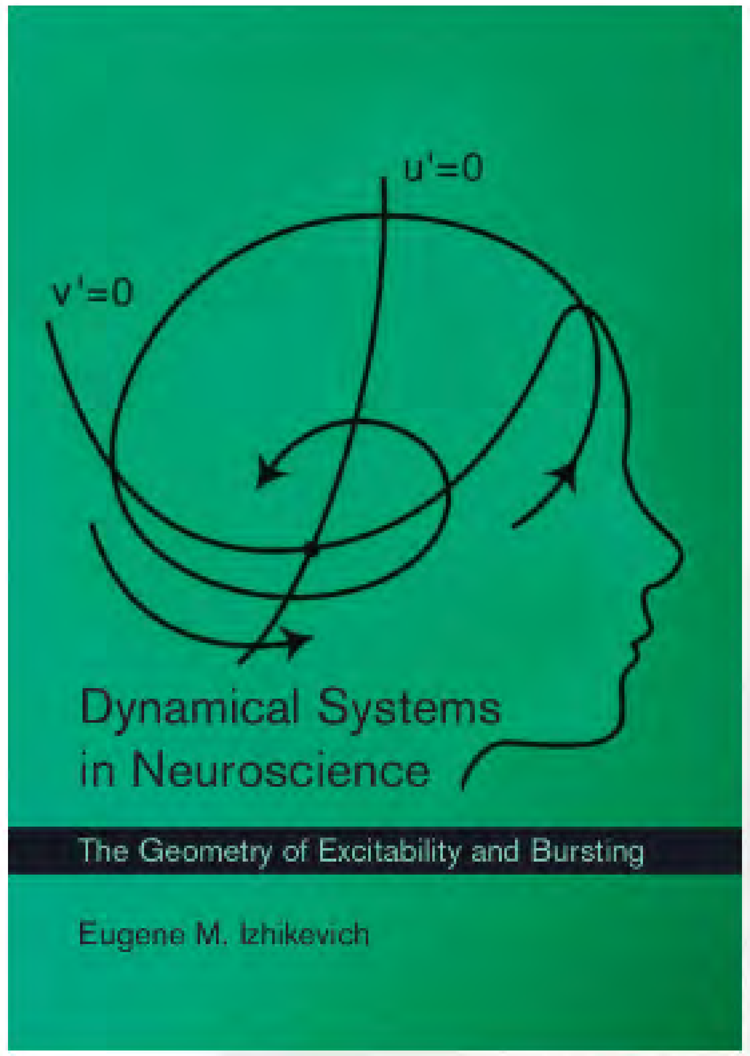
Transient oscillation dynamics: bursting systems



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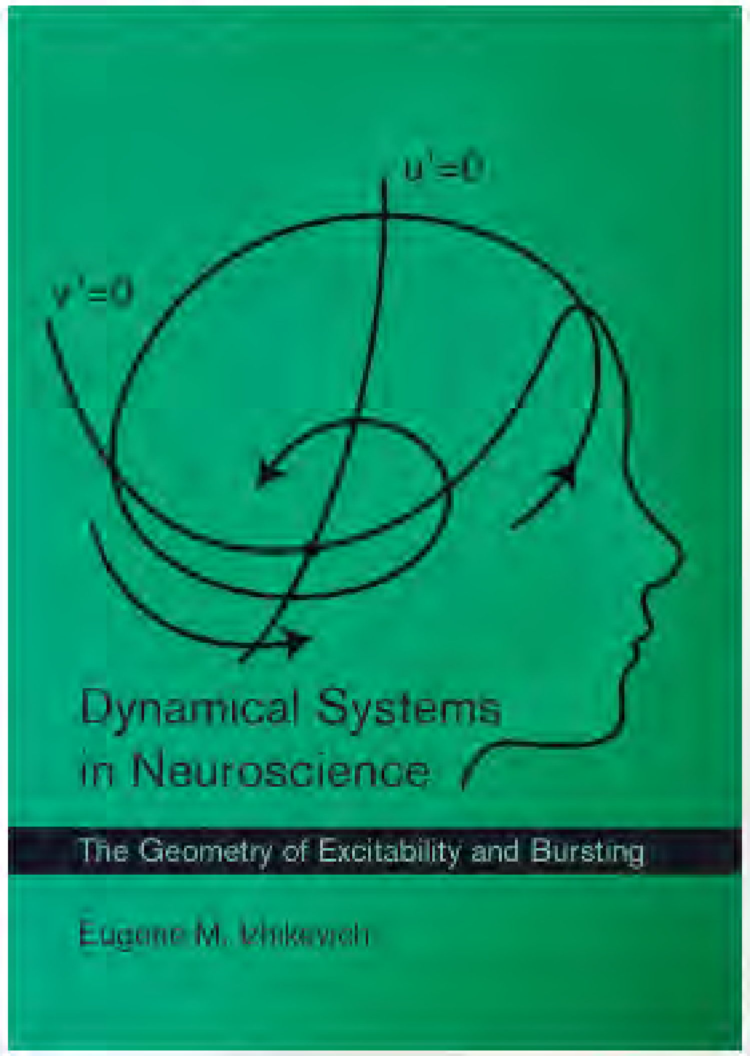


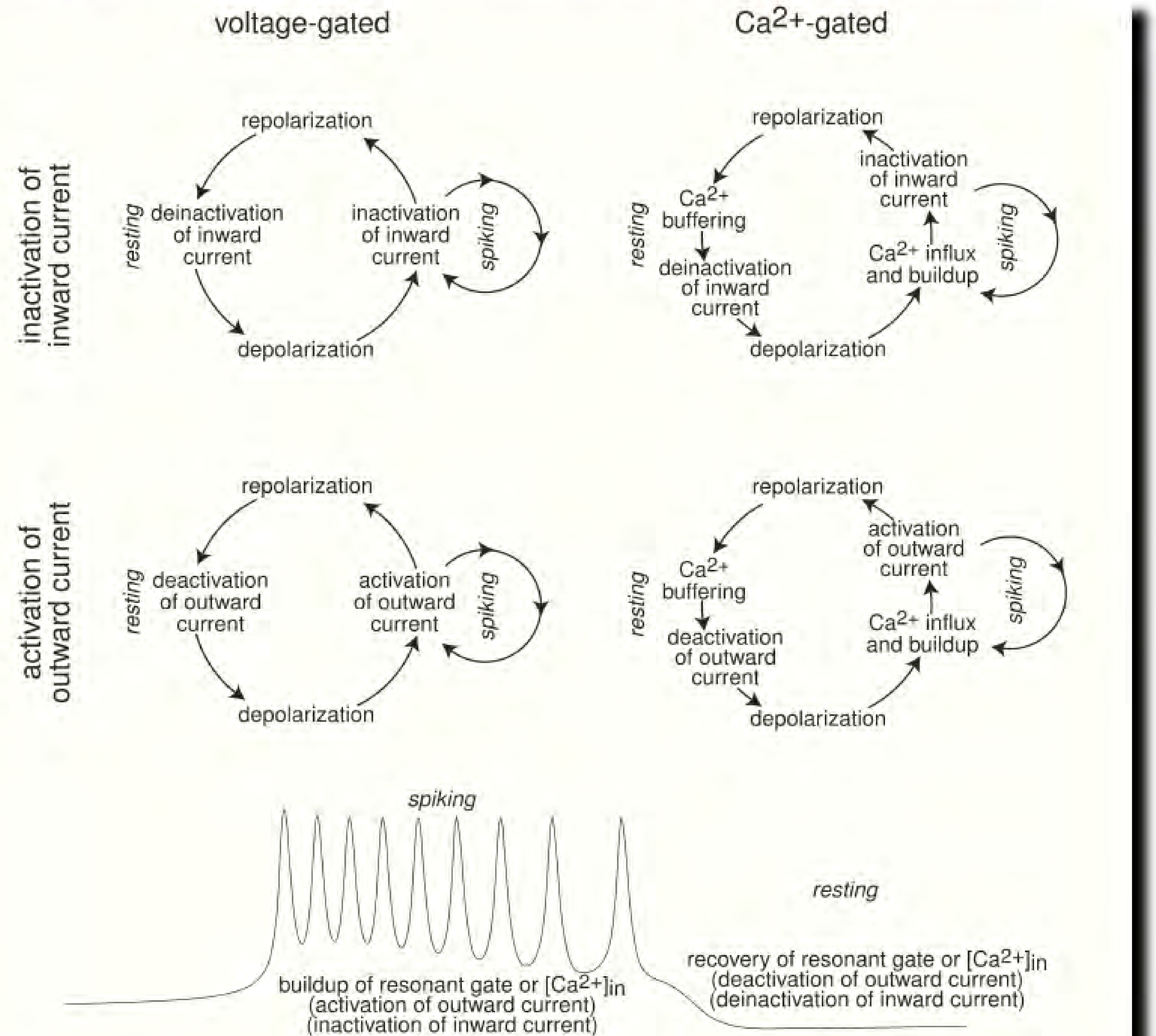
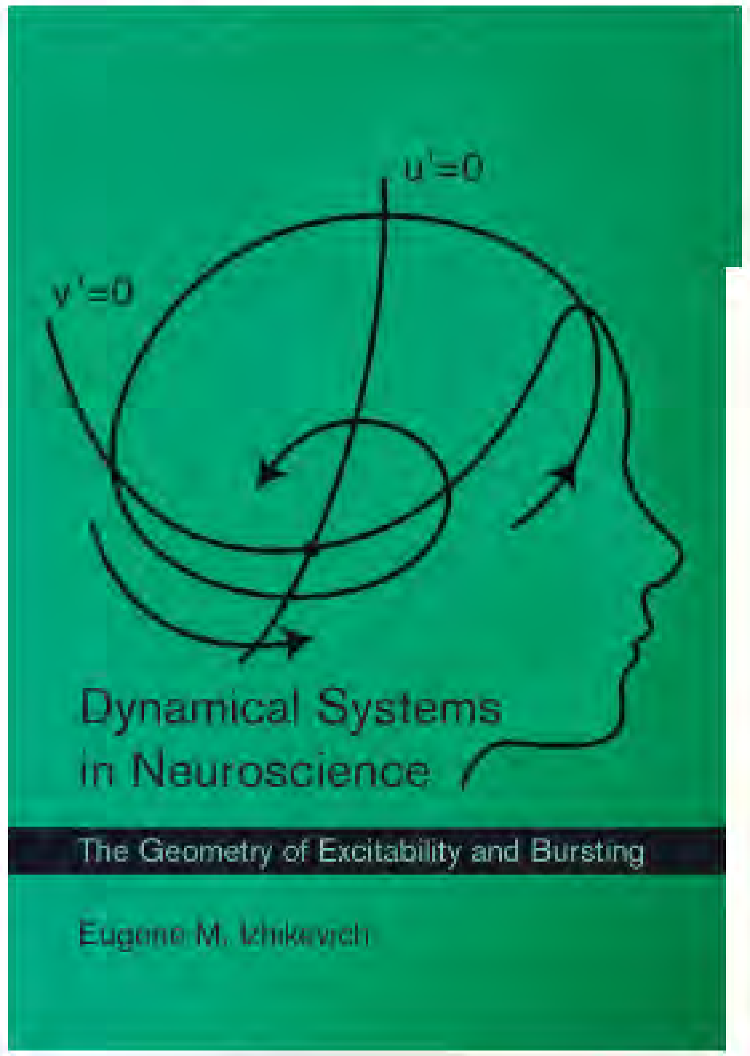


Figure 9.6: Four major classes of bursting models are defined by the slow resonant gating variables that modulate spiking activity.

Transient oscillation dynamics: bursting systems



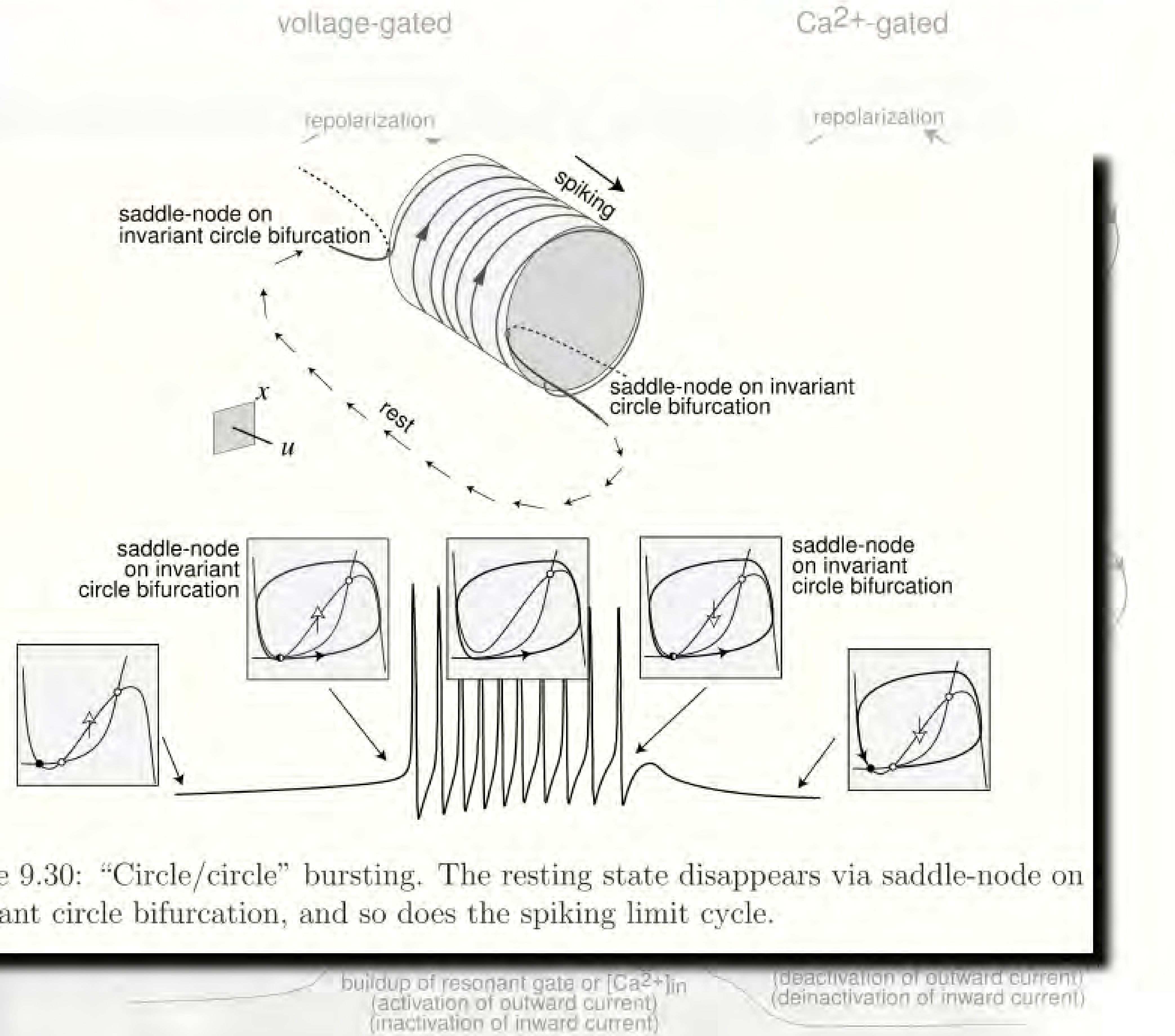
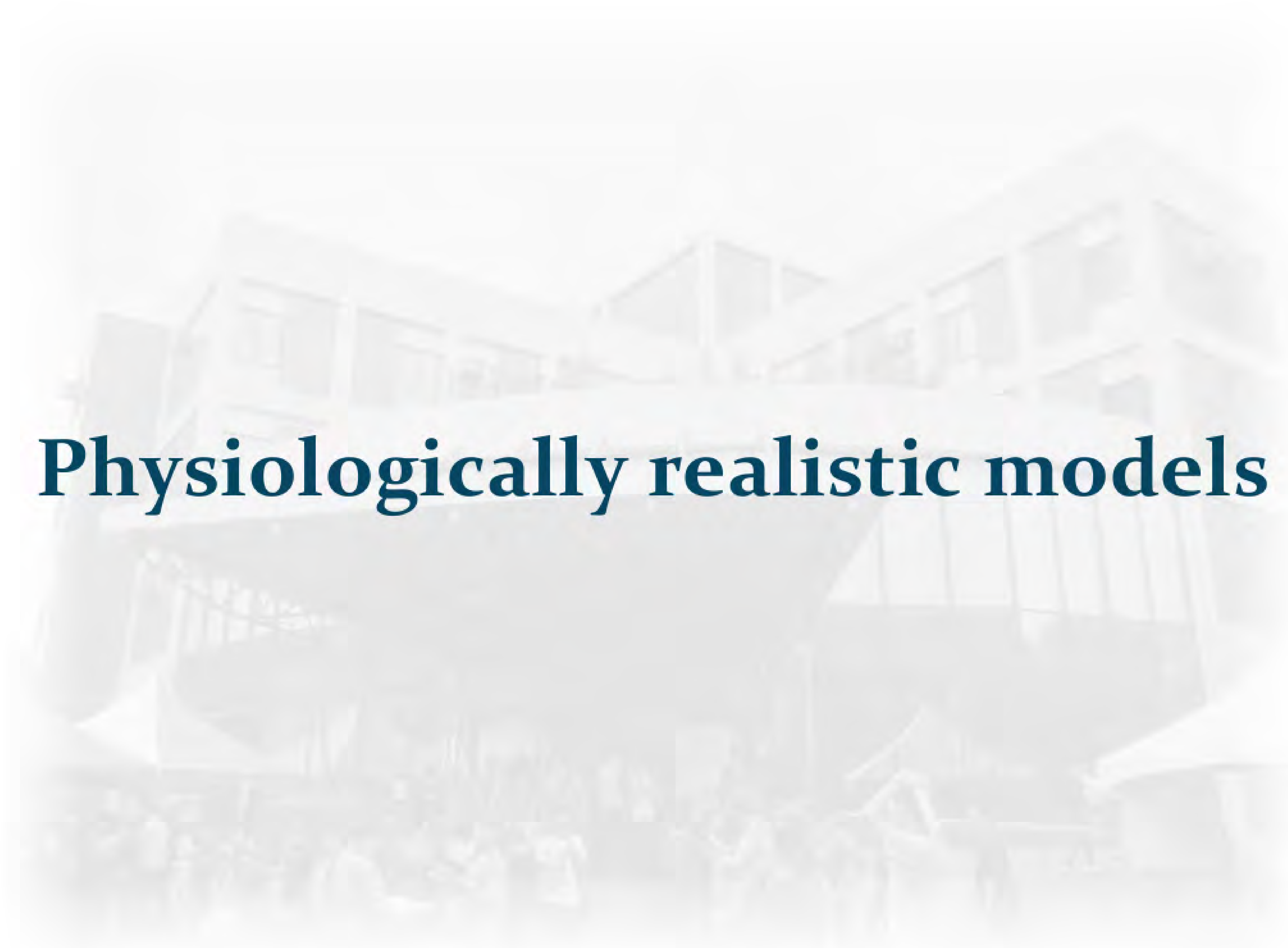


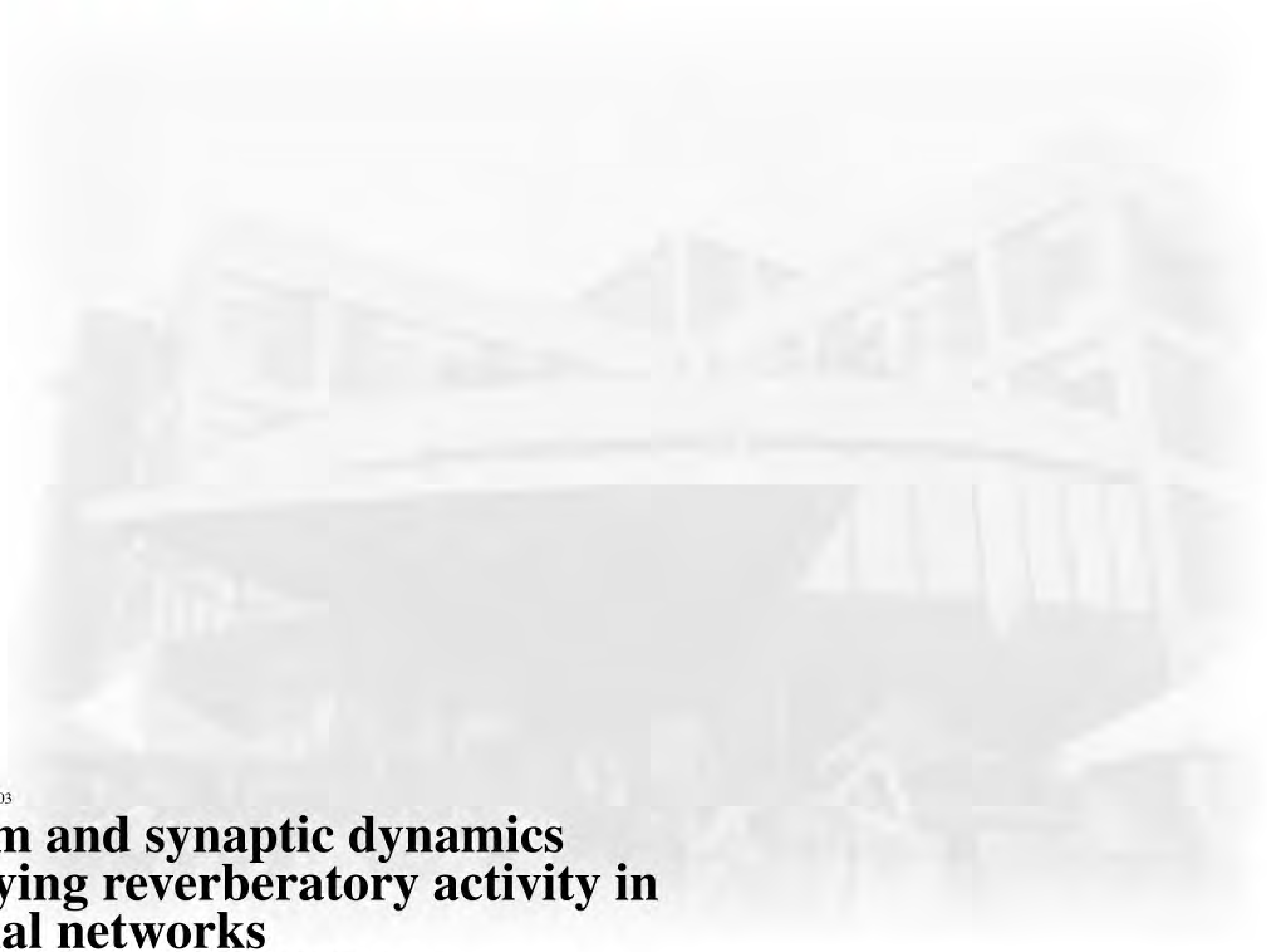
Figure 9.30: "Circle/circle" bursting. The resting state disappears via saddle-node on invariant circle bifurcation, and so does the spiking limit cycle.

Figure 9.6: Four major classes of bursting models are defined by the slow resonant gating variables that modulate spiking activity.



Physiologically realistic models

In silico neuronal networks



Phys. Biol. **4** (2007) 91–103

Calcium and synaptic dynamics underlying reverberatory activity in neuronal networks

Vladislav Volman[1,2,3], Richard C Gerkin[4,5], Pak-Ming Lau[4],
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In silico neuronal networks

Morris-Lecar neurons

$$C\frac{dV}{dt} = -I_{\text{ion}} + G(V_r - V) + I_{\text{bg}}$$

$$\frac{dW}{dt} = \theta\frac{W_\infty - W}{\tau_W}$$

$$I_{\text{ion}} = g_{\text{Ca}} m_\infty (V - V_{\text{Ca}}) + g_{\text{K}} W(V - V_{\text{K}}) + g_{\text{L}}(V - V_{\text{L}})$$

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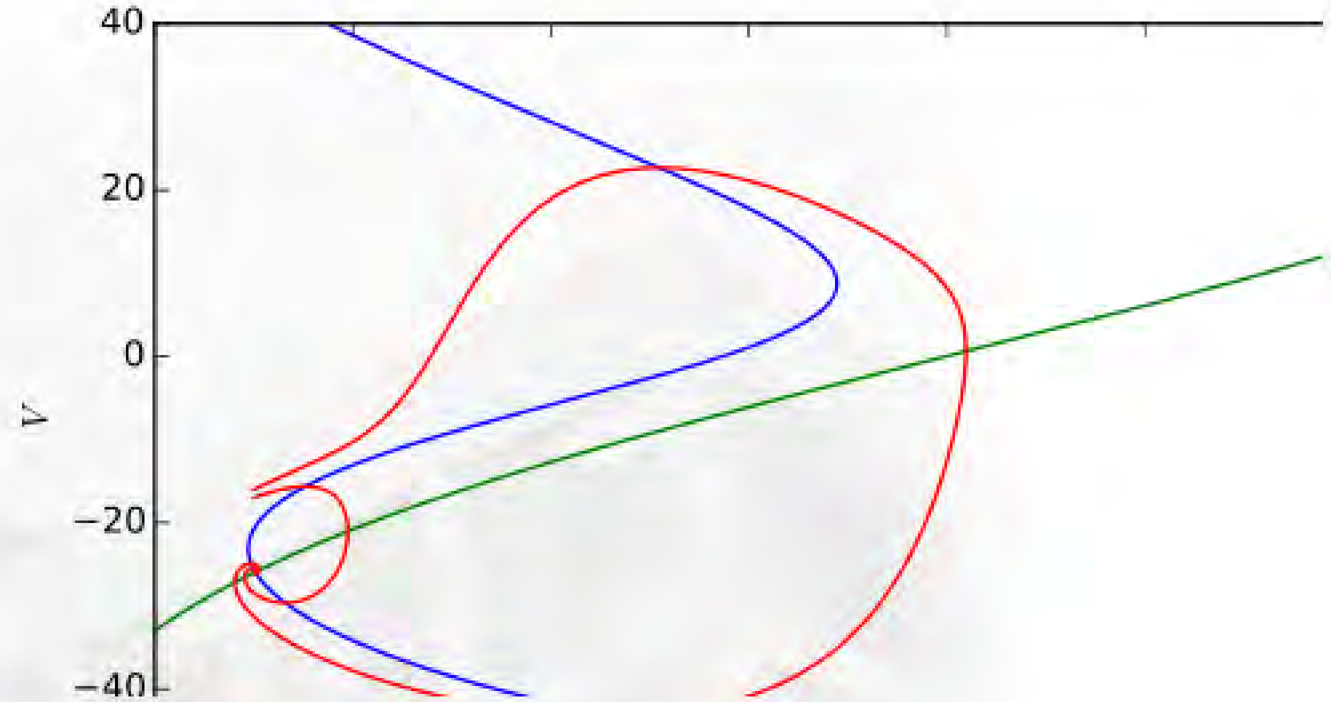

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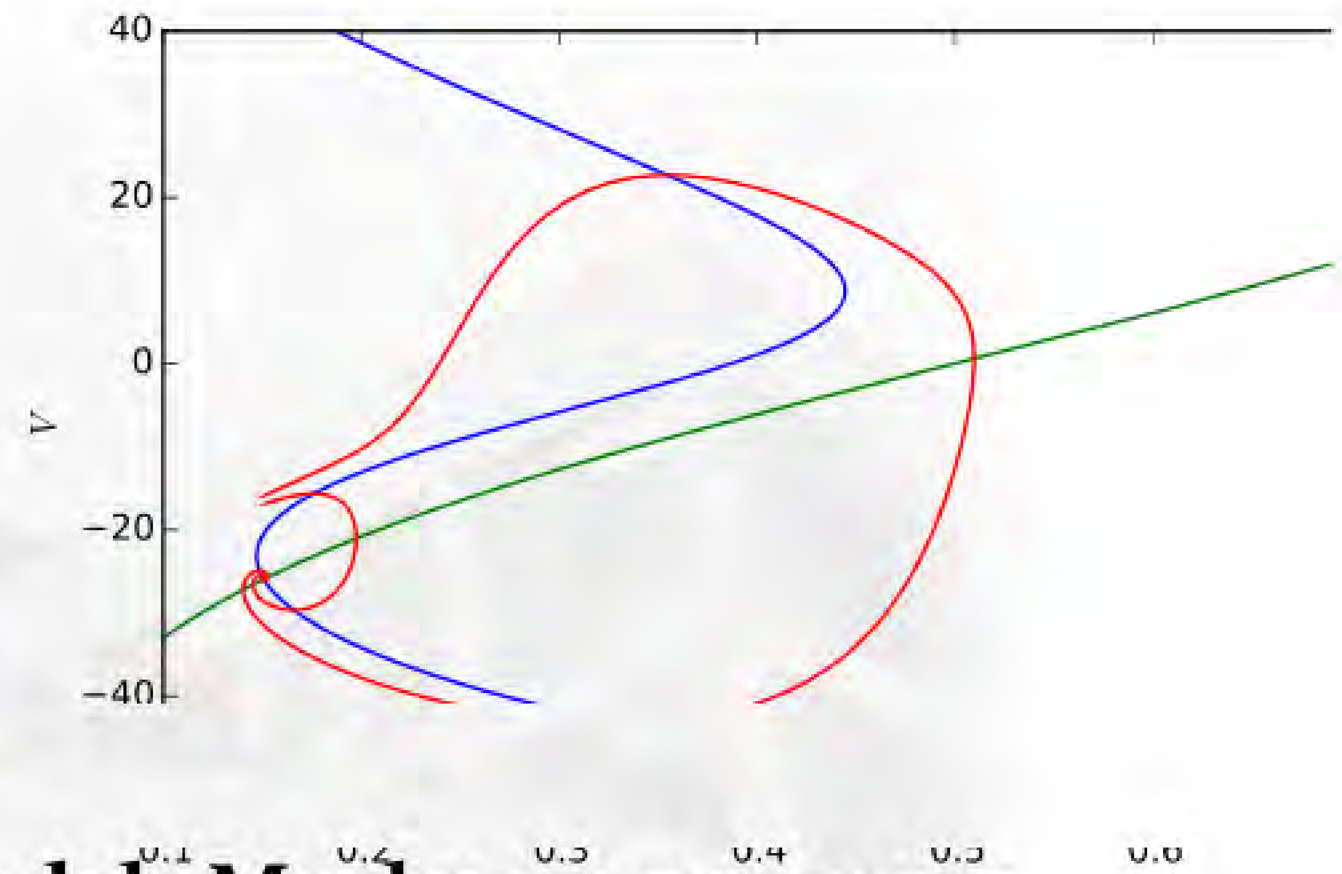

Tsodyk-Markram synapses

$$\frac{dX}{dt} = \frac{Q}{\tau_s} + \frac{Z}{\tau_r} - uXS - X\xi$$

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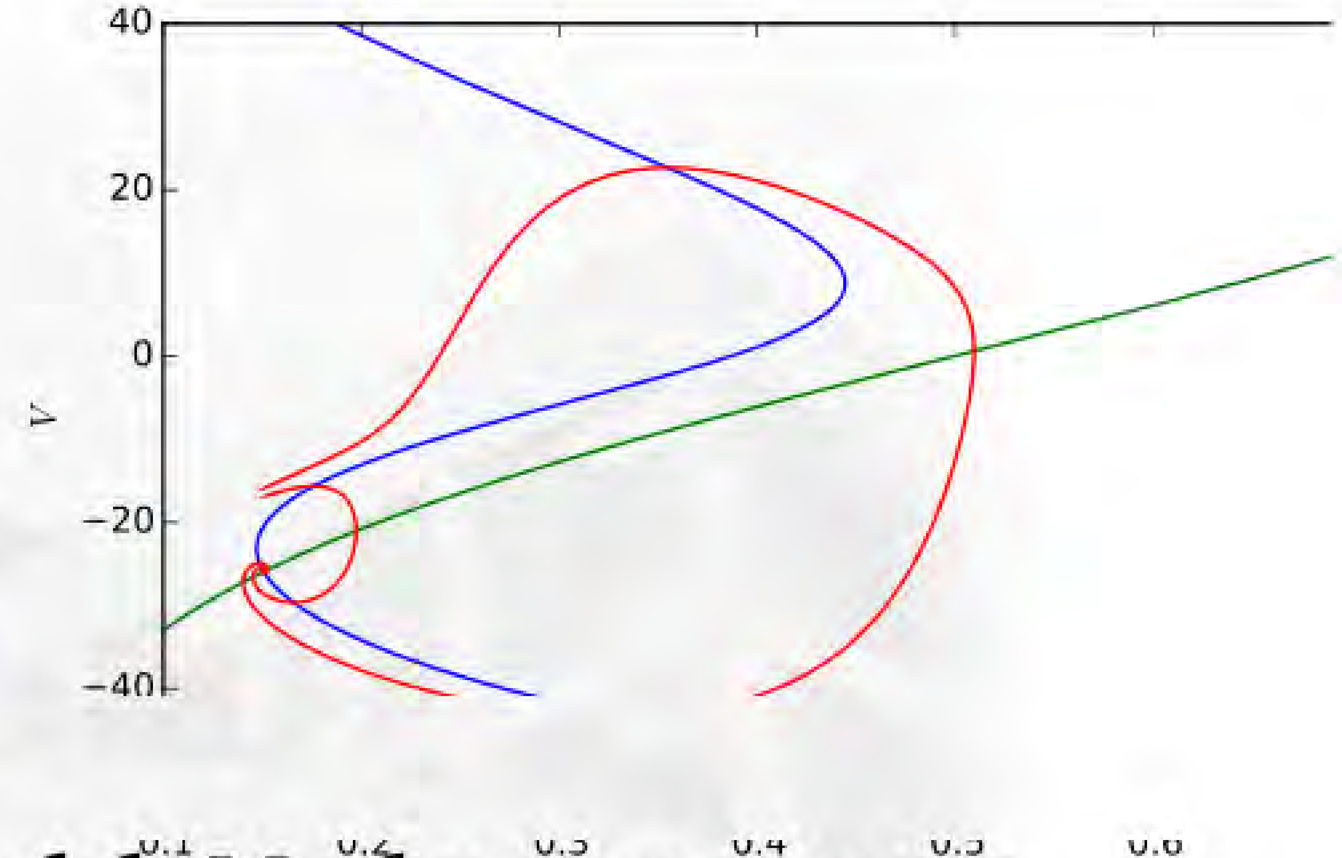

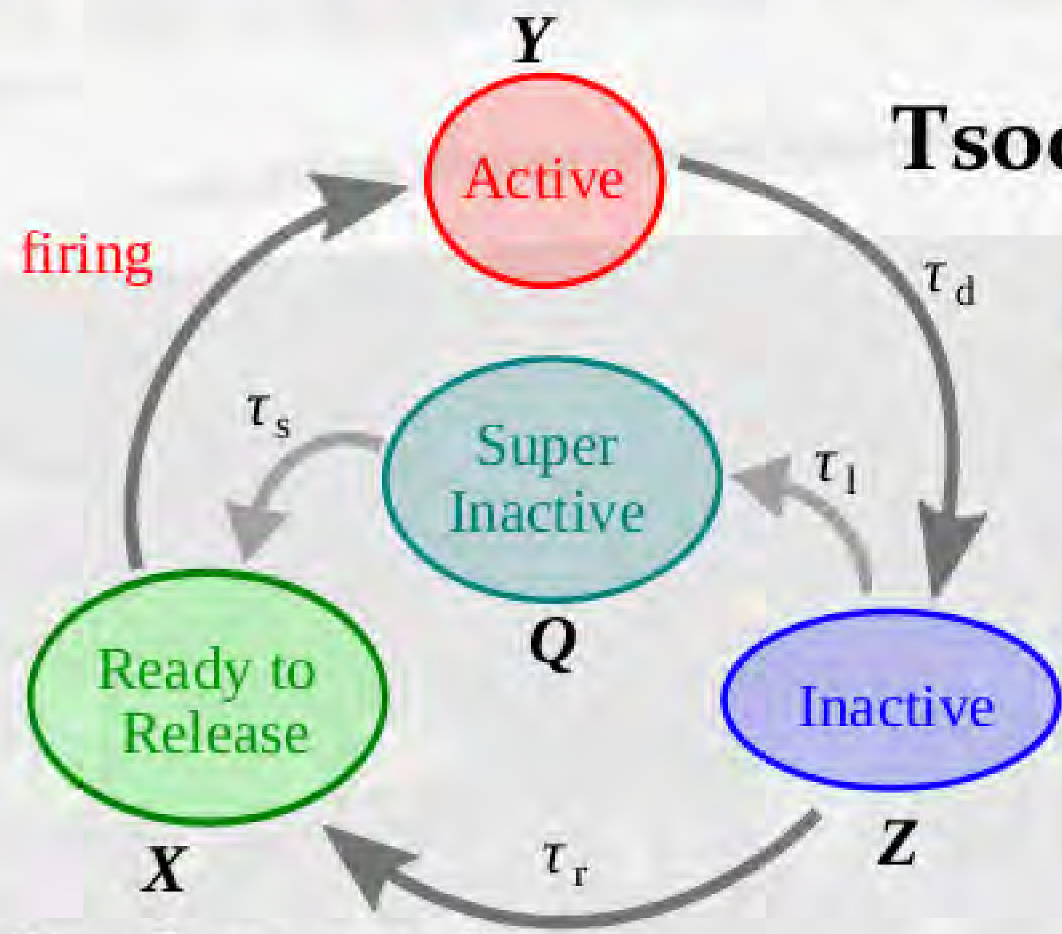

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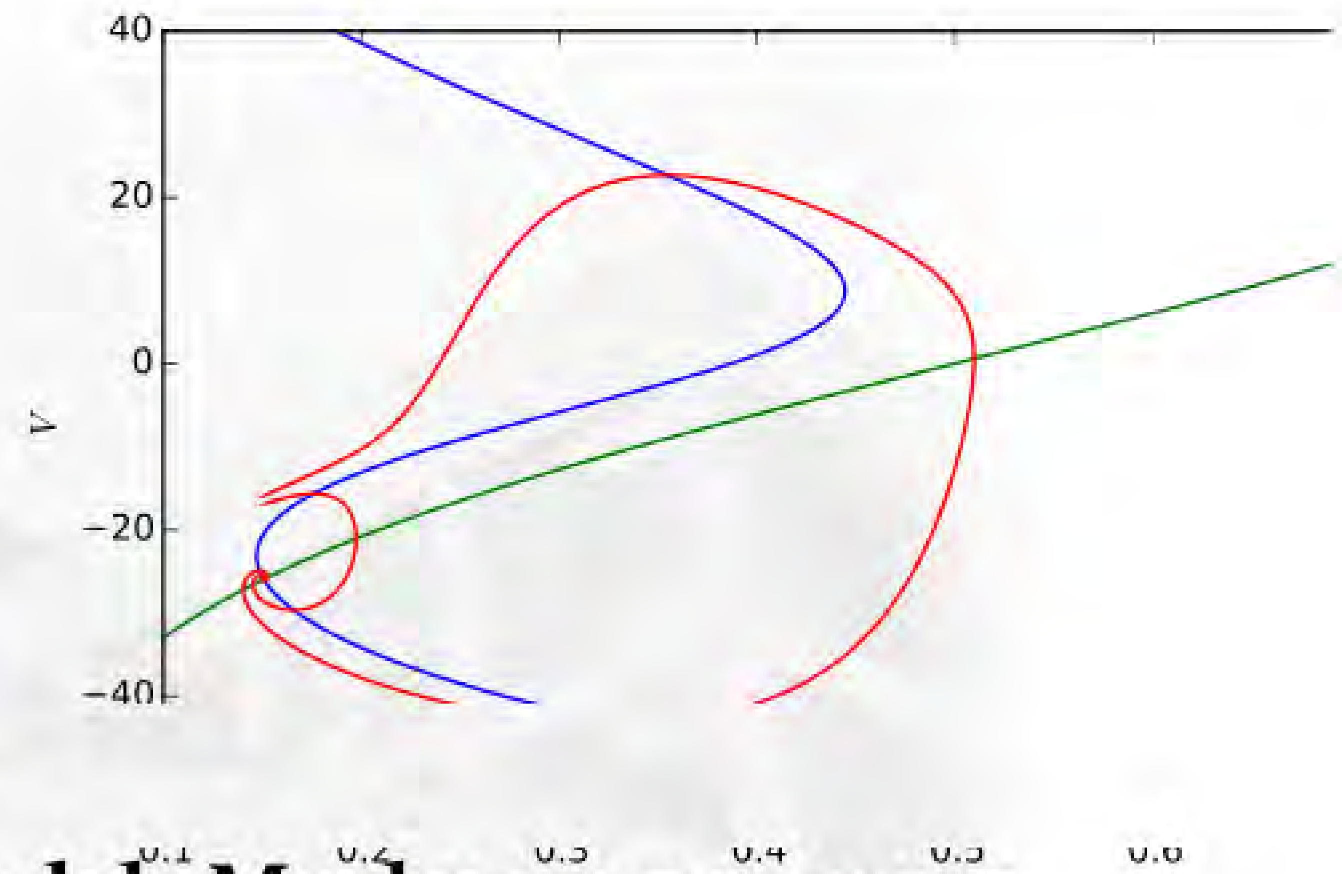
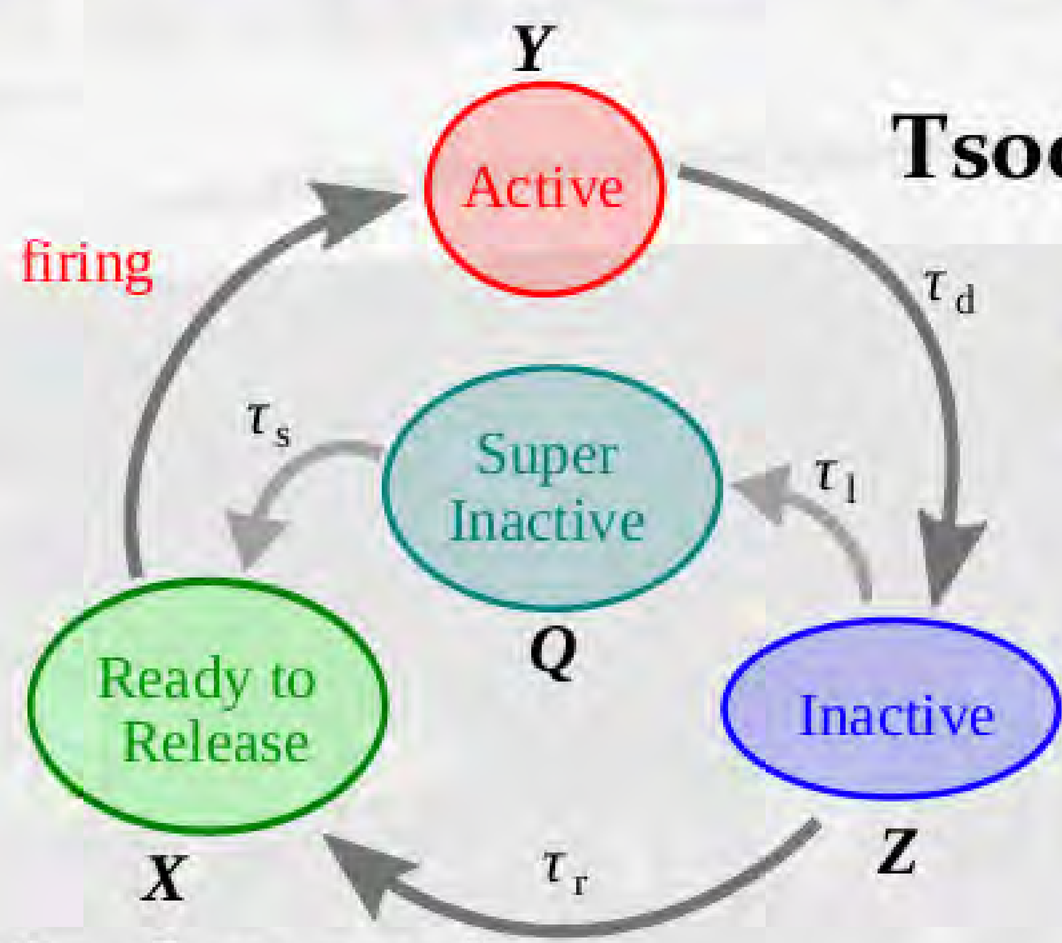


Multiple time scales including additional slow recovery from super inactive state Q.



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Phys. Biol. 4 (2007) 91–103

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Stochastic, asynchronous release

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Residual calcium dynamics

$$C \frac{d}{dt} R_{\mathrm{Ca}} = \frac{-\beta R_{\mathrm{Ca}}^n}{k_R^n + R_{\mathrm{Ca}}^n} + I_P + S\gamma \log \frac{R_{\mathrm{Ca}}^0}{R_{\mathrm{Ca}}}$$

$$\eta = \eta_{\mathrm{max}} \frac{R_{\mathrm{Ca}}^m}{k_a^m + R_{\mathrm{Ca}}^m}$$

η is the Poisson rate of asynchronous release events.

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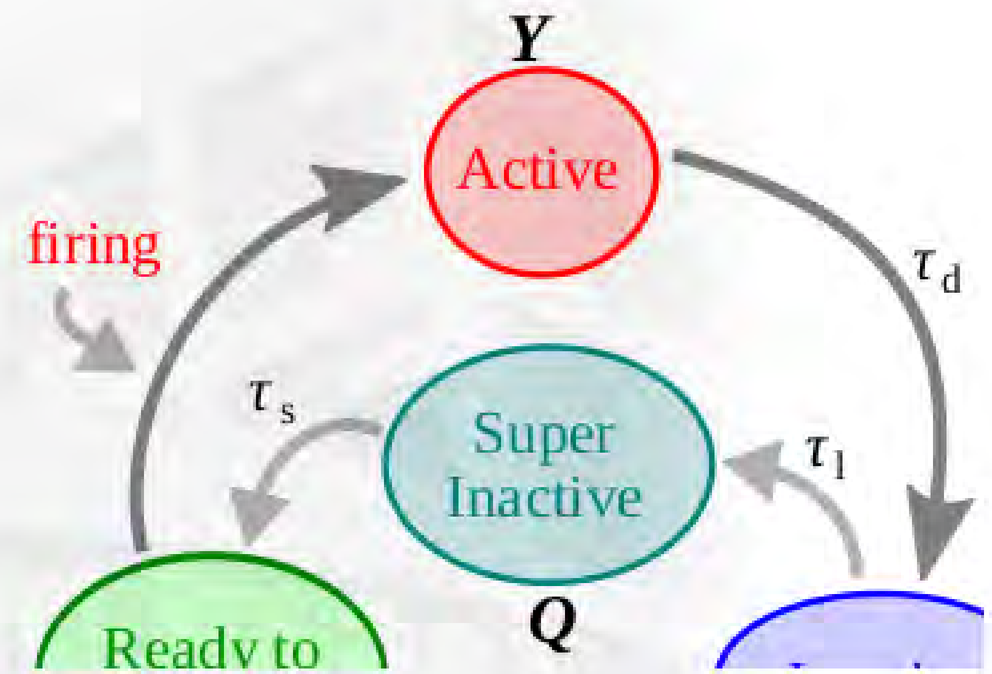

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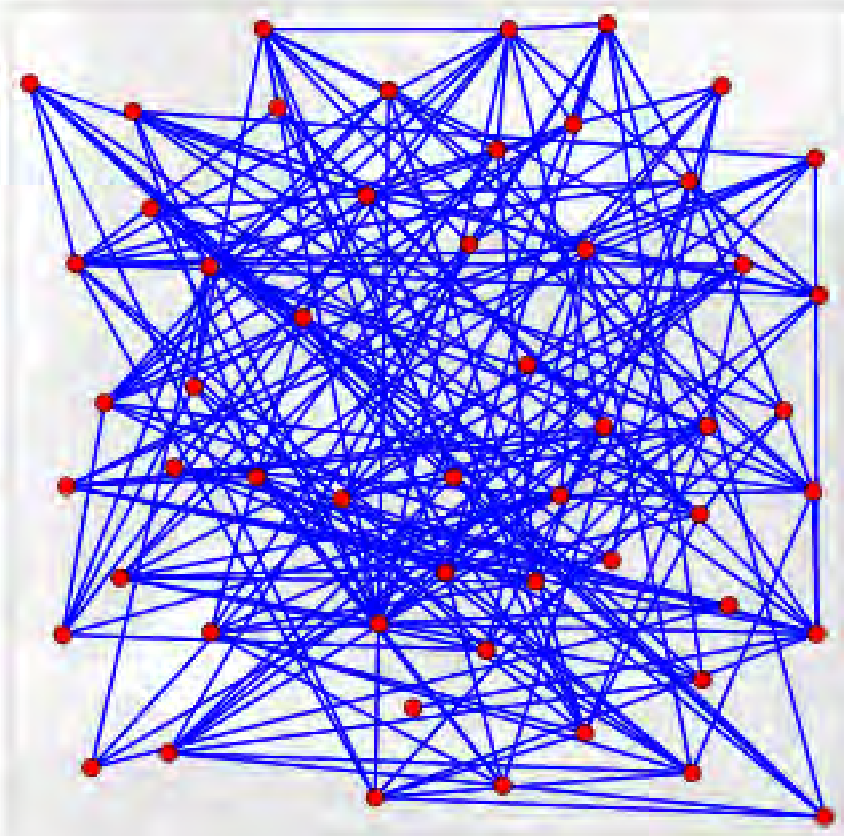

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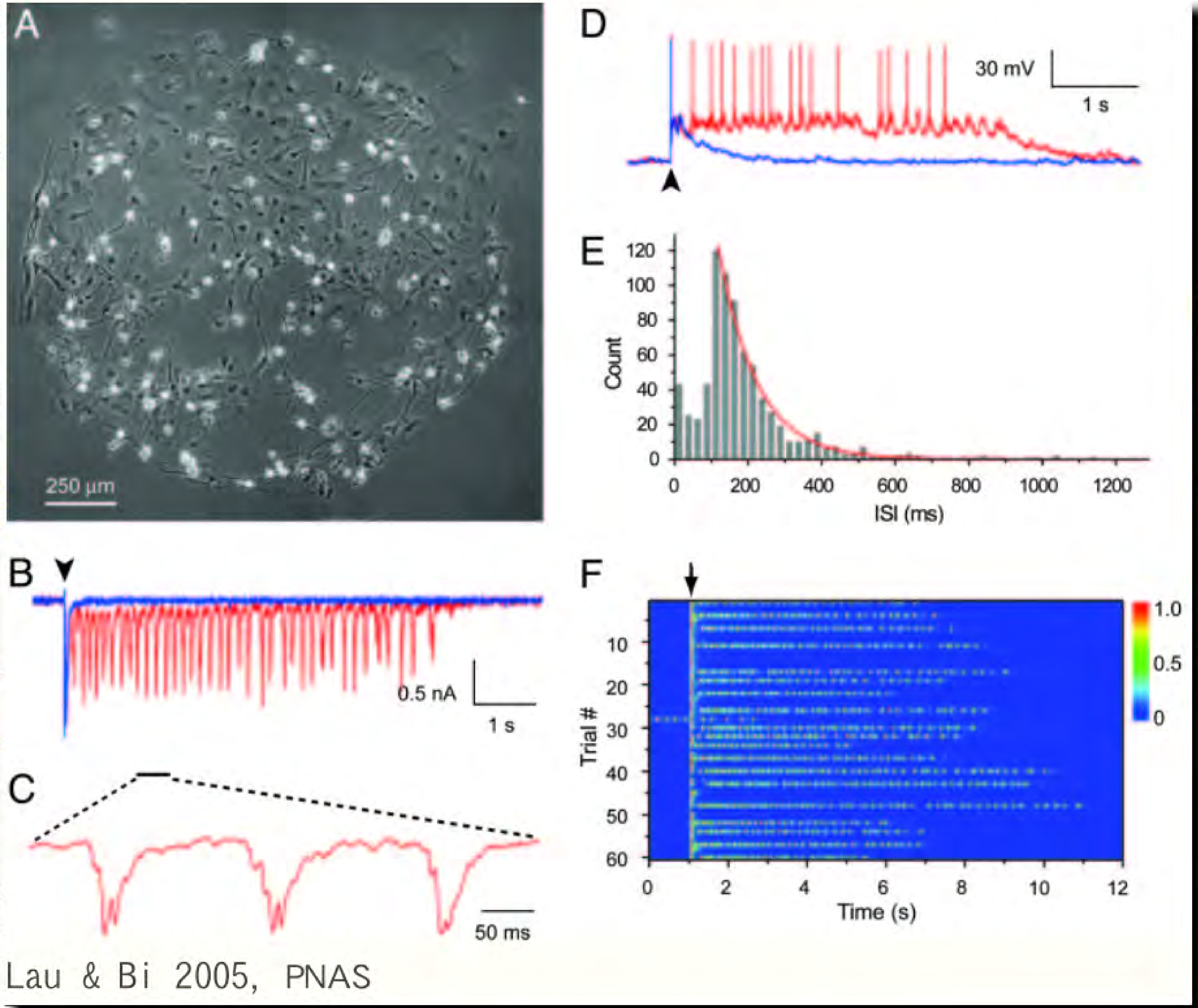
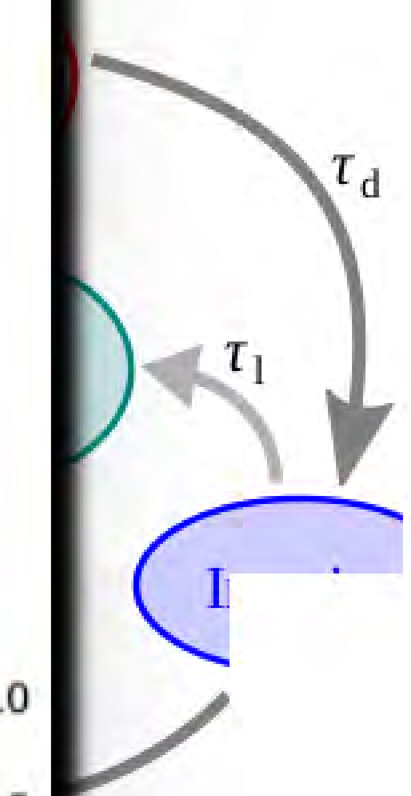


Lau & Bi 2005, PNAS



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Calcium
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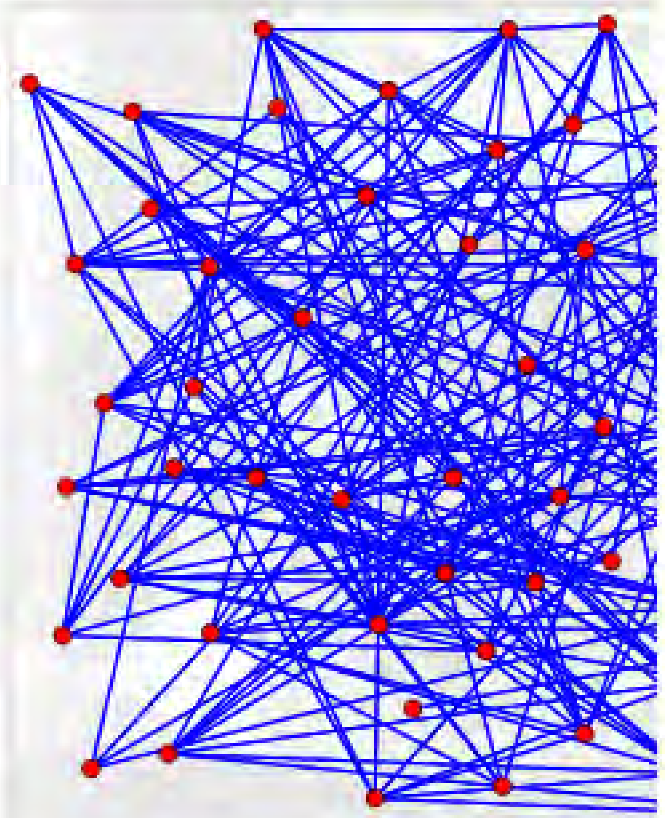
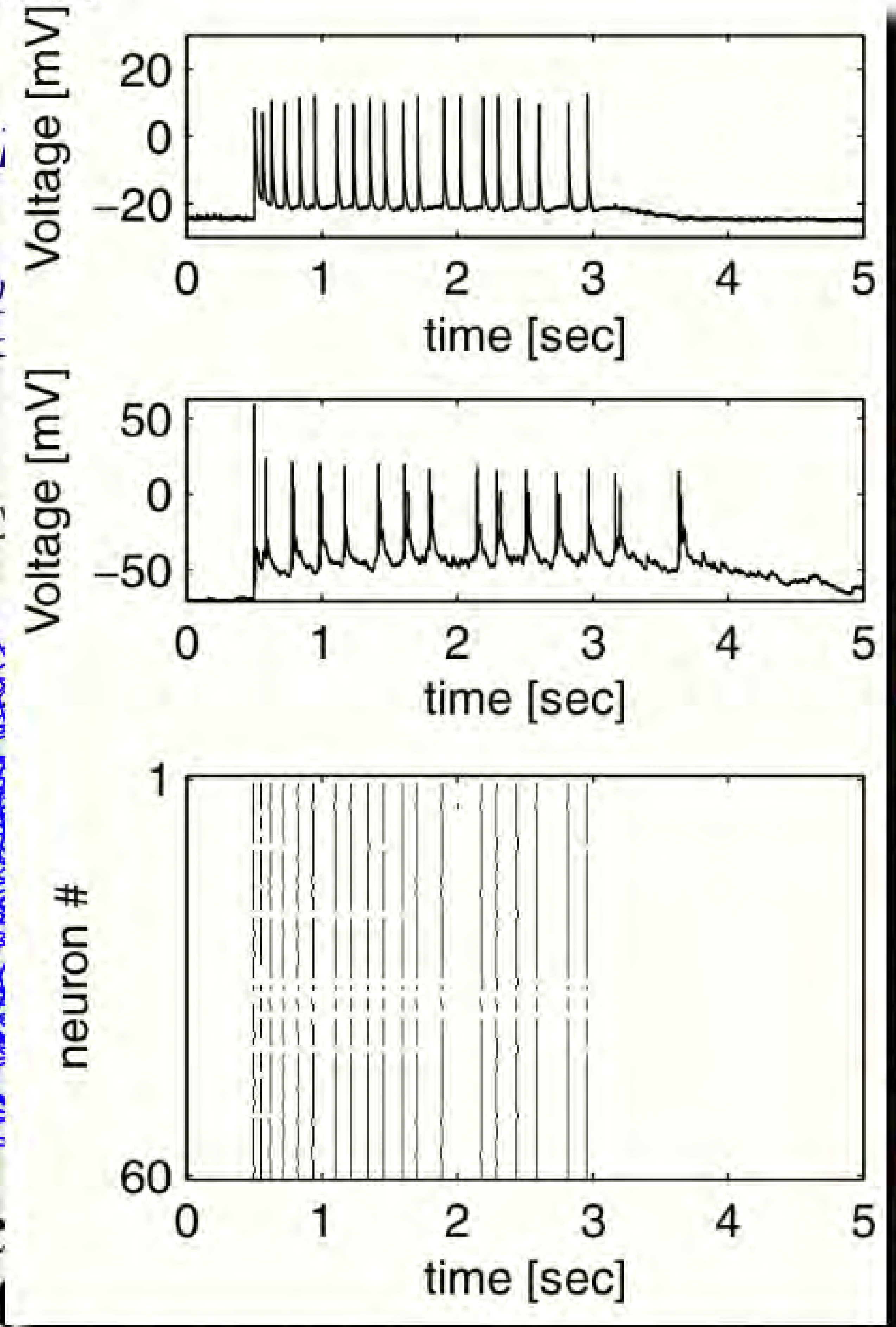
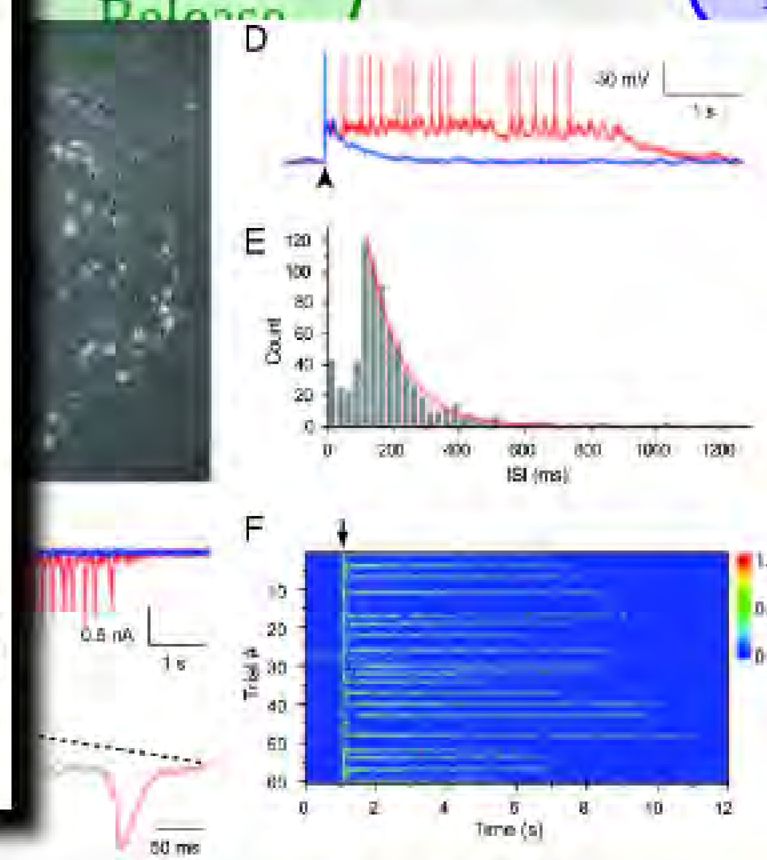
η is the Poisson rate of as… events.







Phys. Biol. 4 (2007) 91–103

Calcium and synaptic underlying reverberat neuronal networks

Vladislav Volman[1,2,3], Richard C Gerkin[4,5], Pak-Ming Lau[4], Eshel Ben-Jacob[1,2] and Guo-Qiang Bi[4,5]

Lau & Bi 2005, PNAS

Culture on high-density MEA

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- Wistar rat E17 cortical cells
- Planting Density: 1500~2000 cells/mm^2
- Coating : PDL + Laminin (0.1mg/ml)
- Medium : NB + B27 + Glutamax
- Incubator : 37° and 5% CO_2

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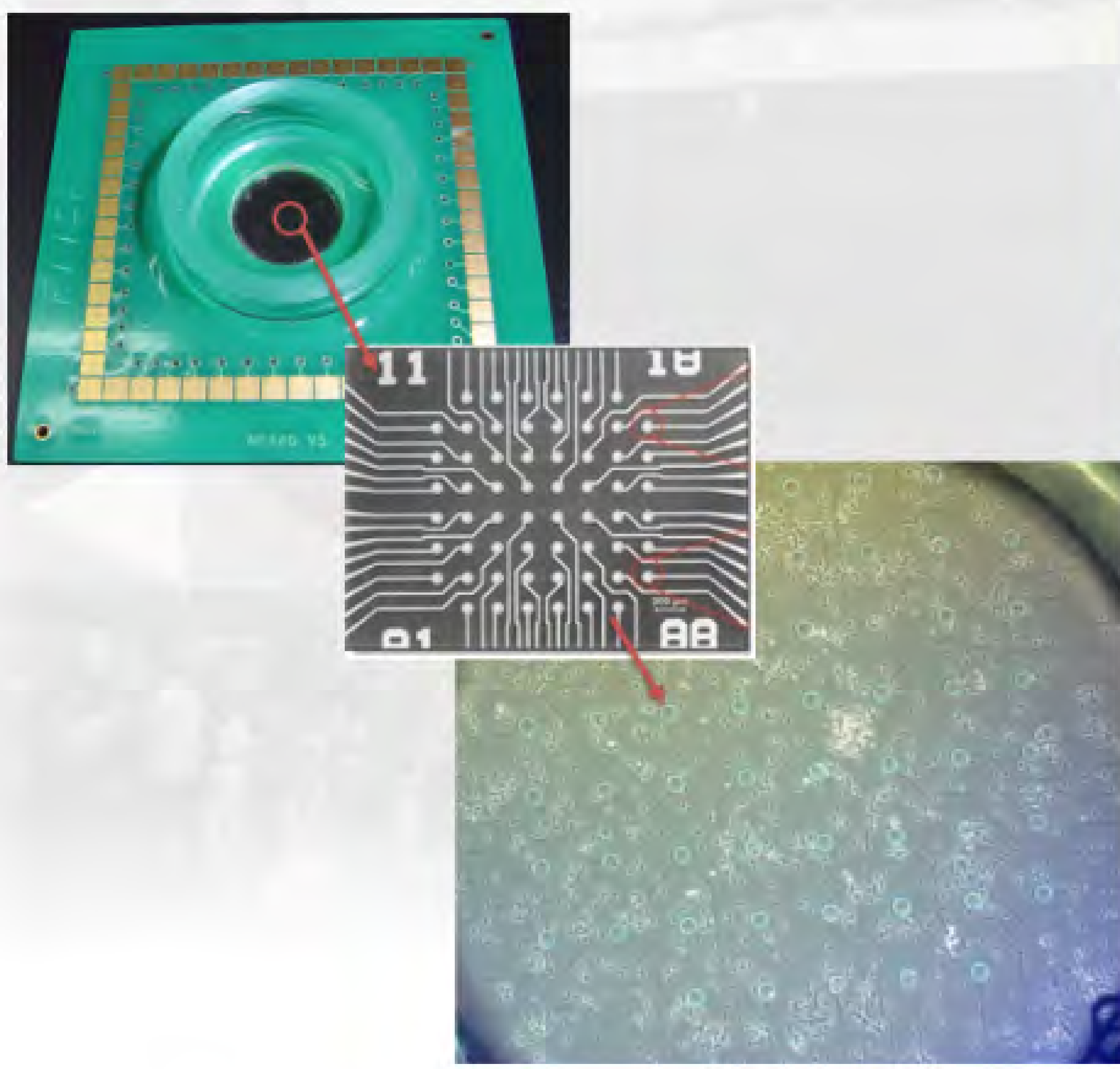

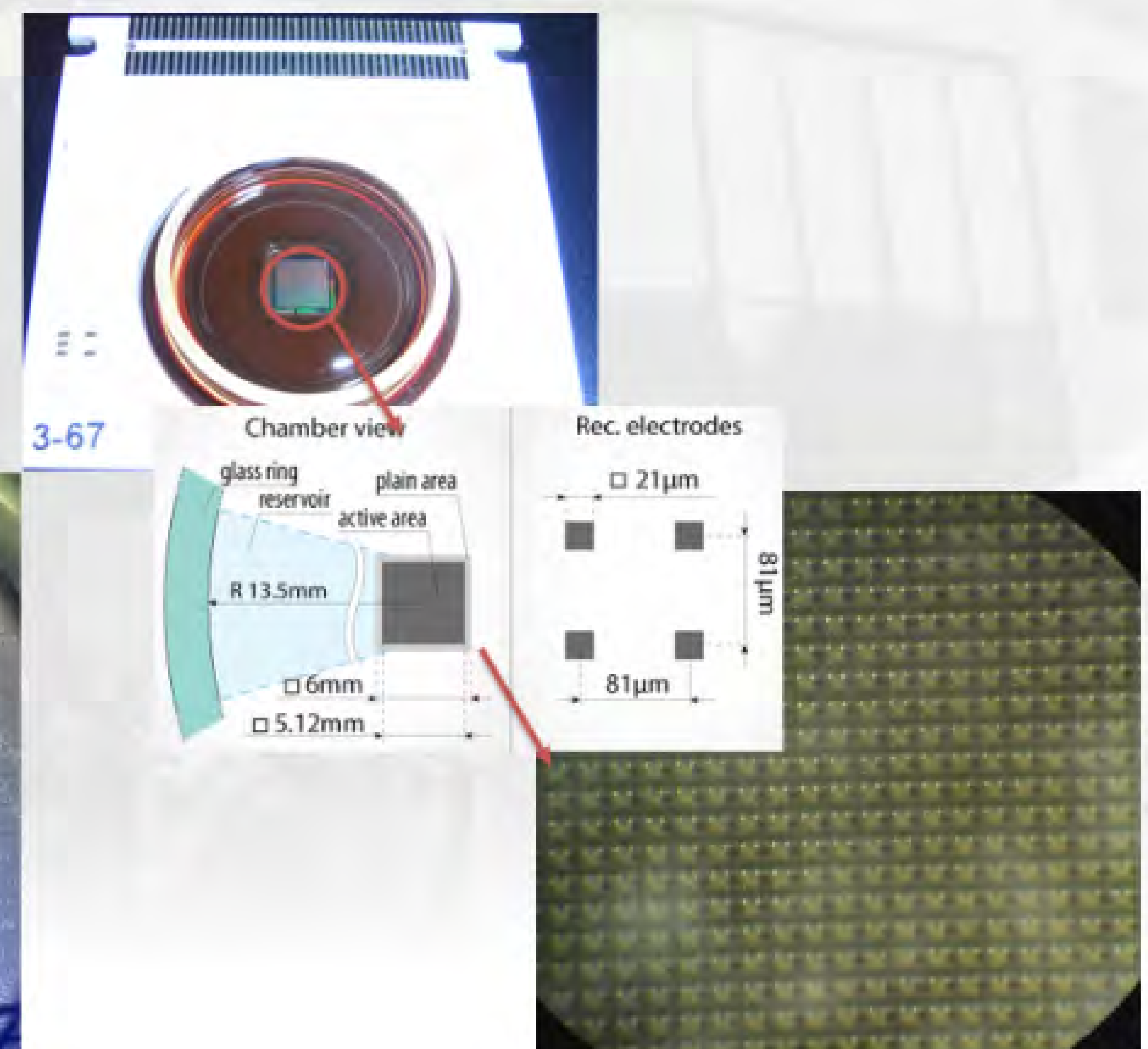

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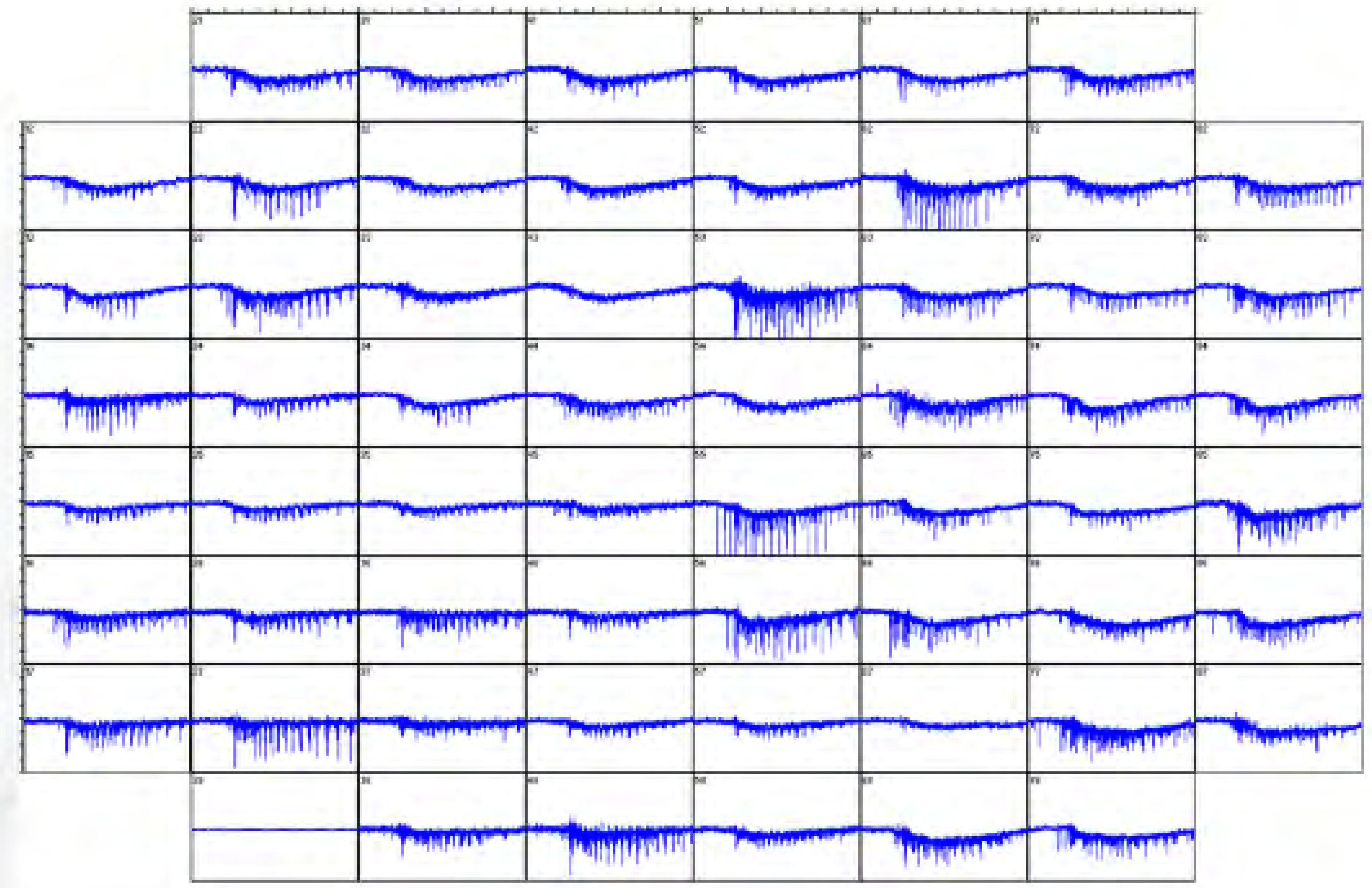
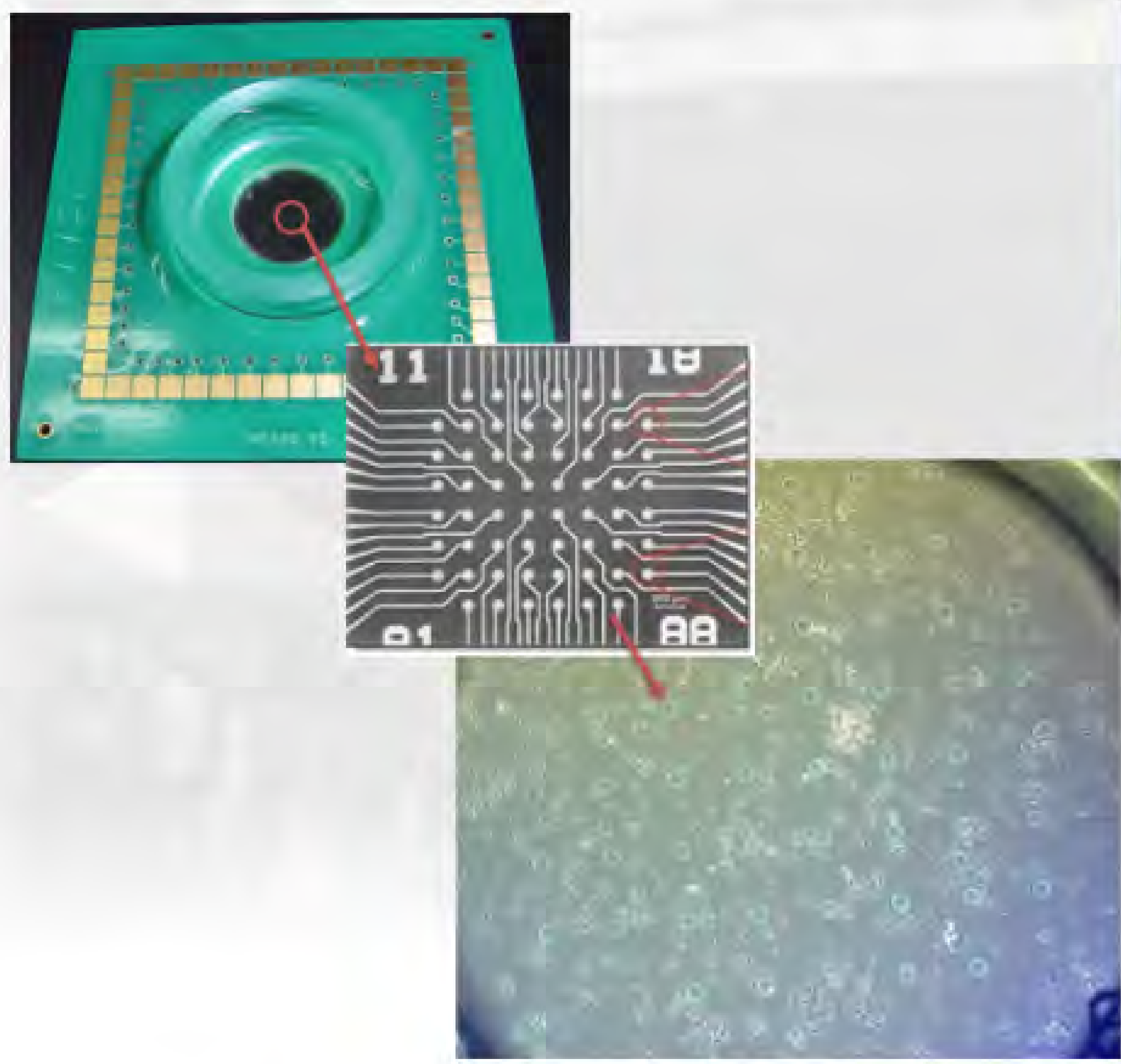
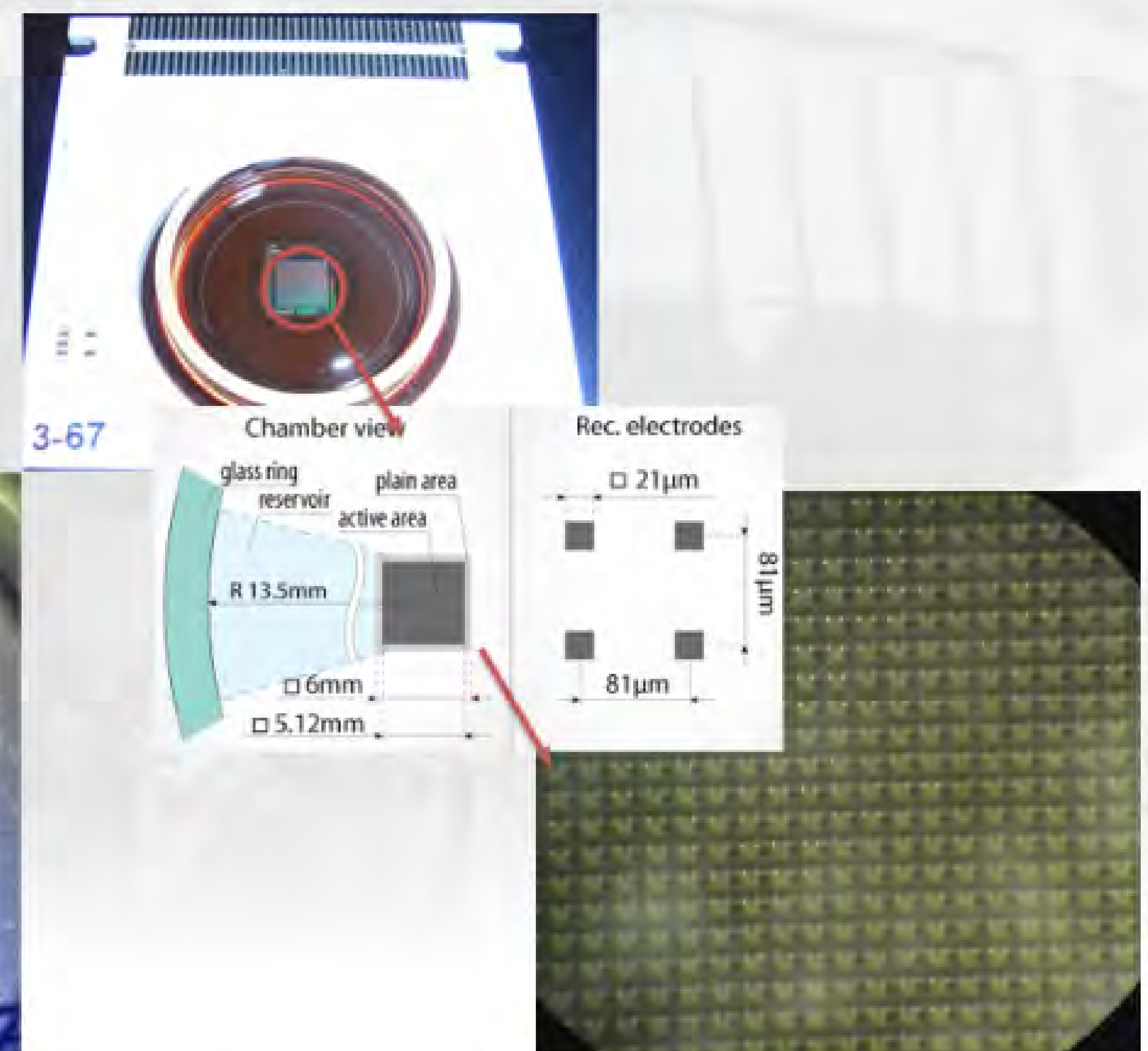
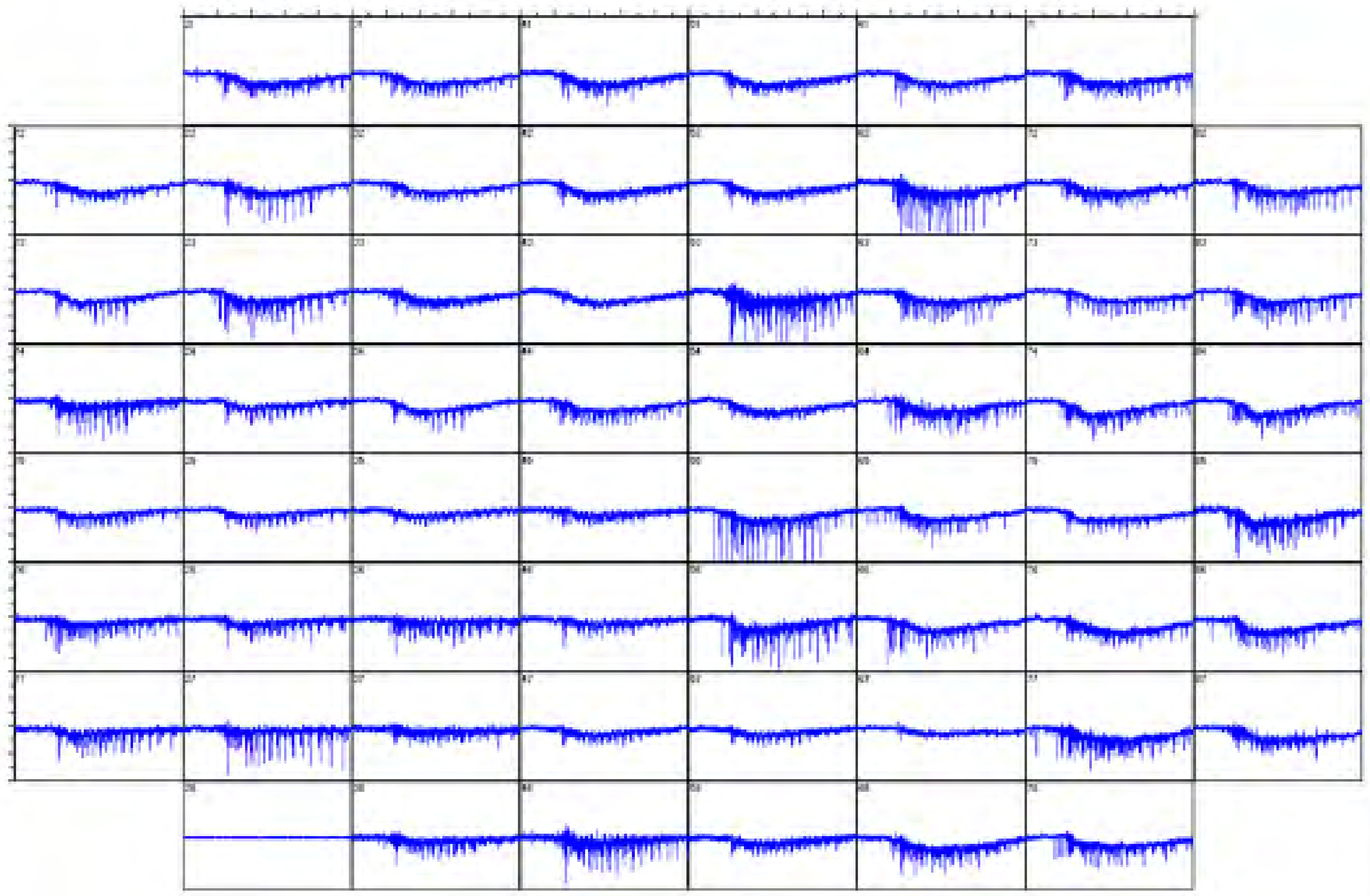






MEA results and analysis



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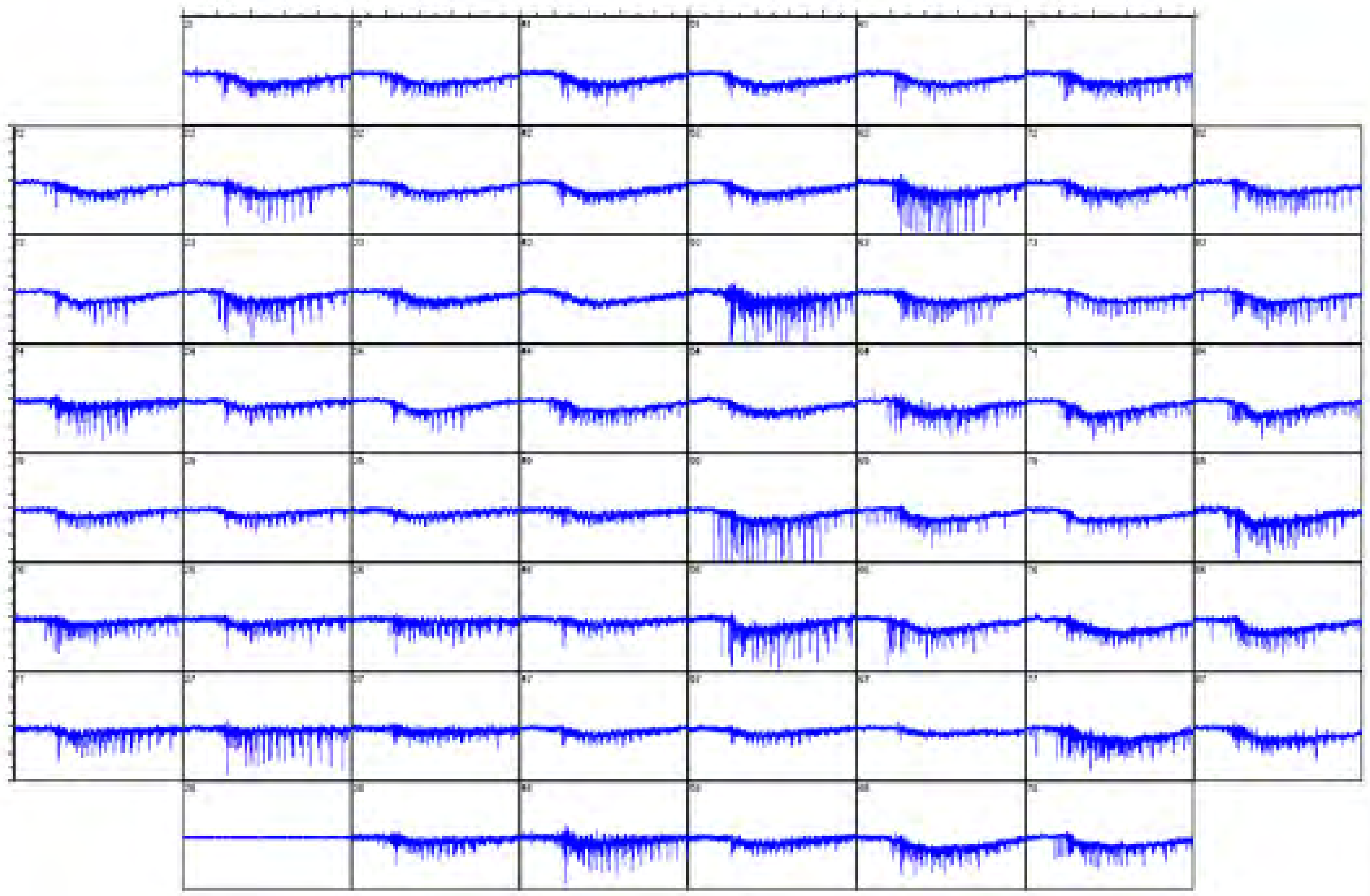

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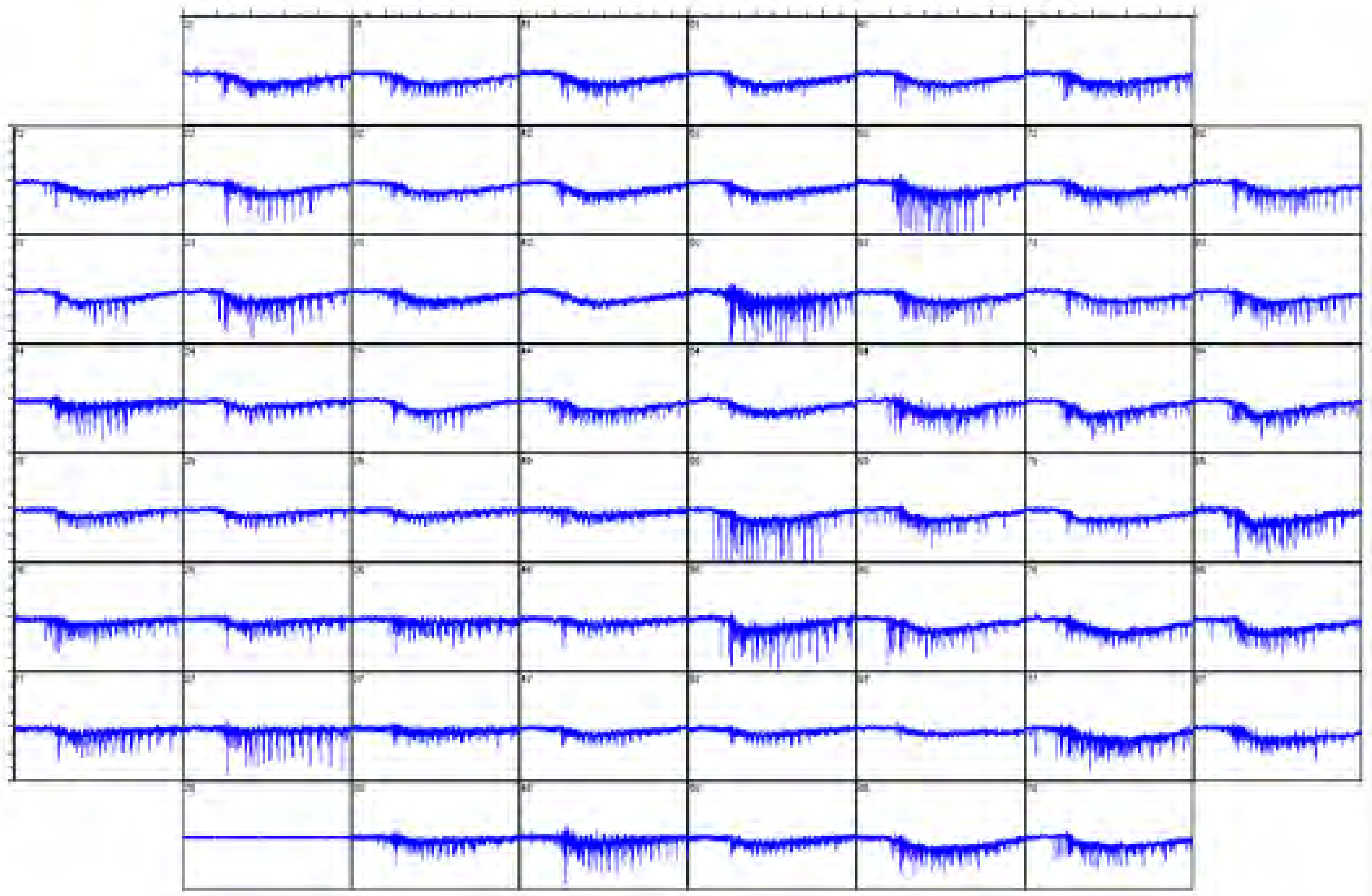

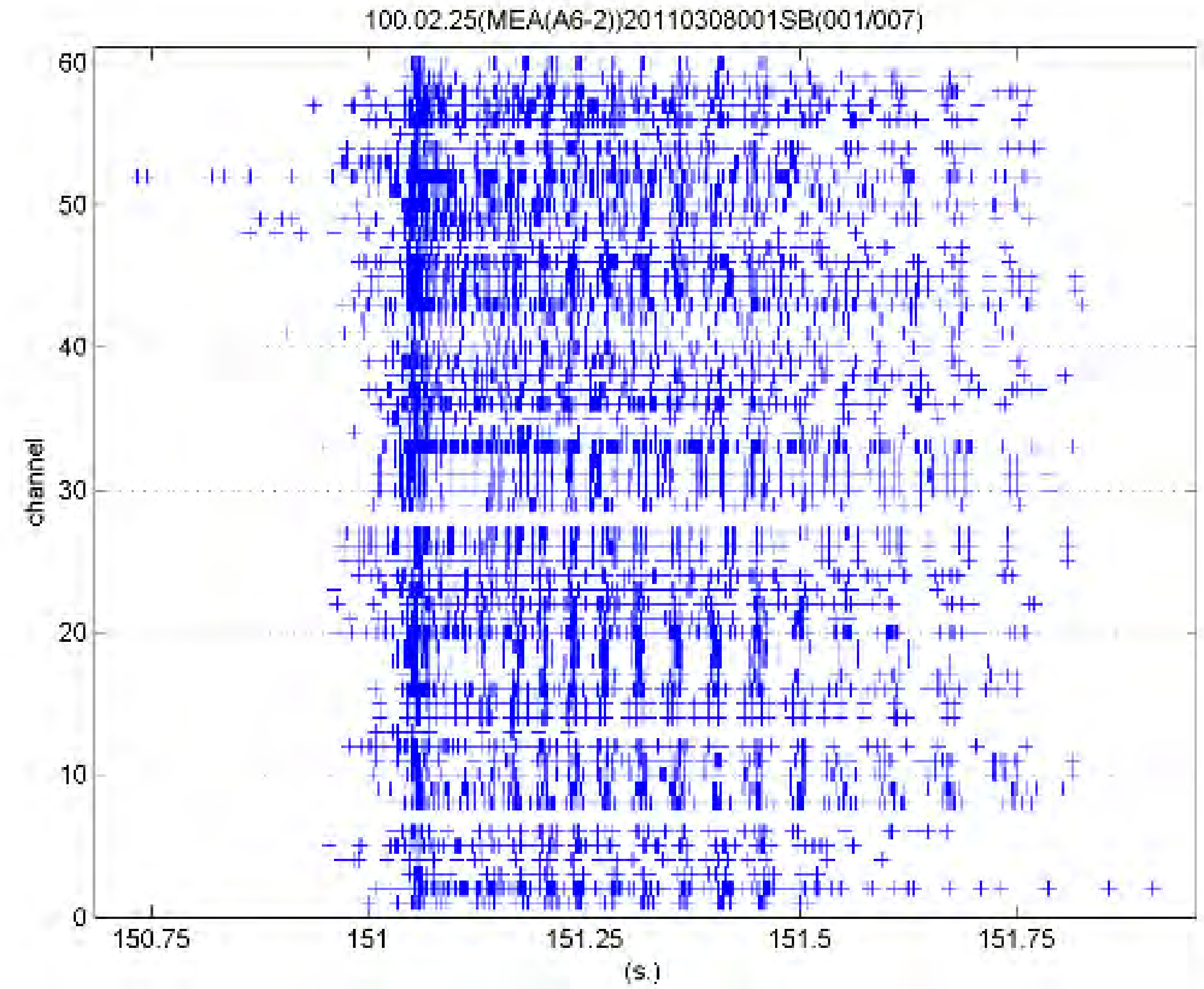

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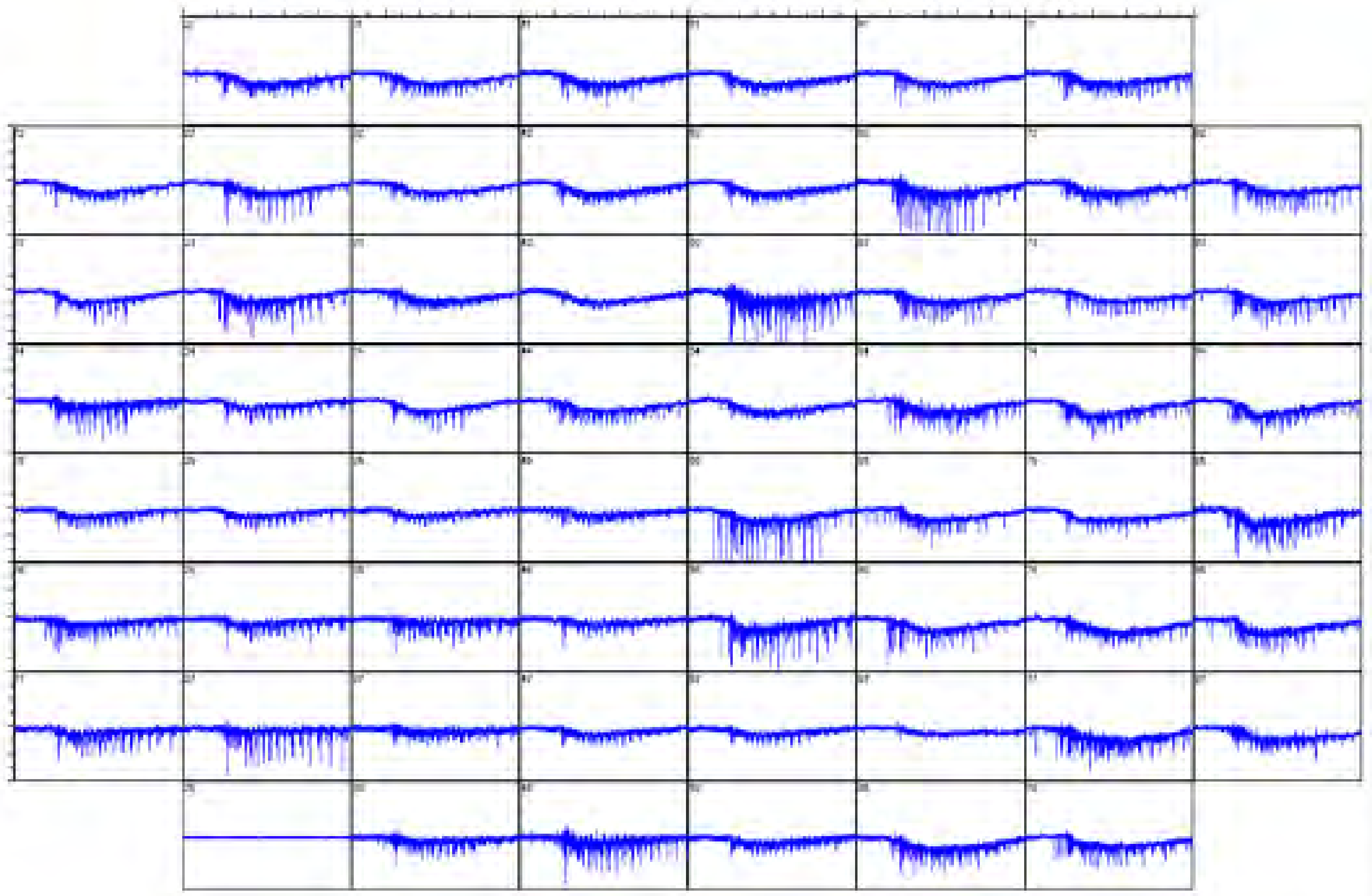
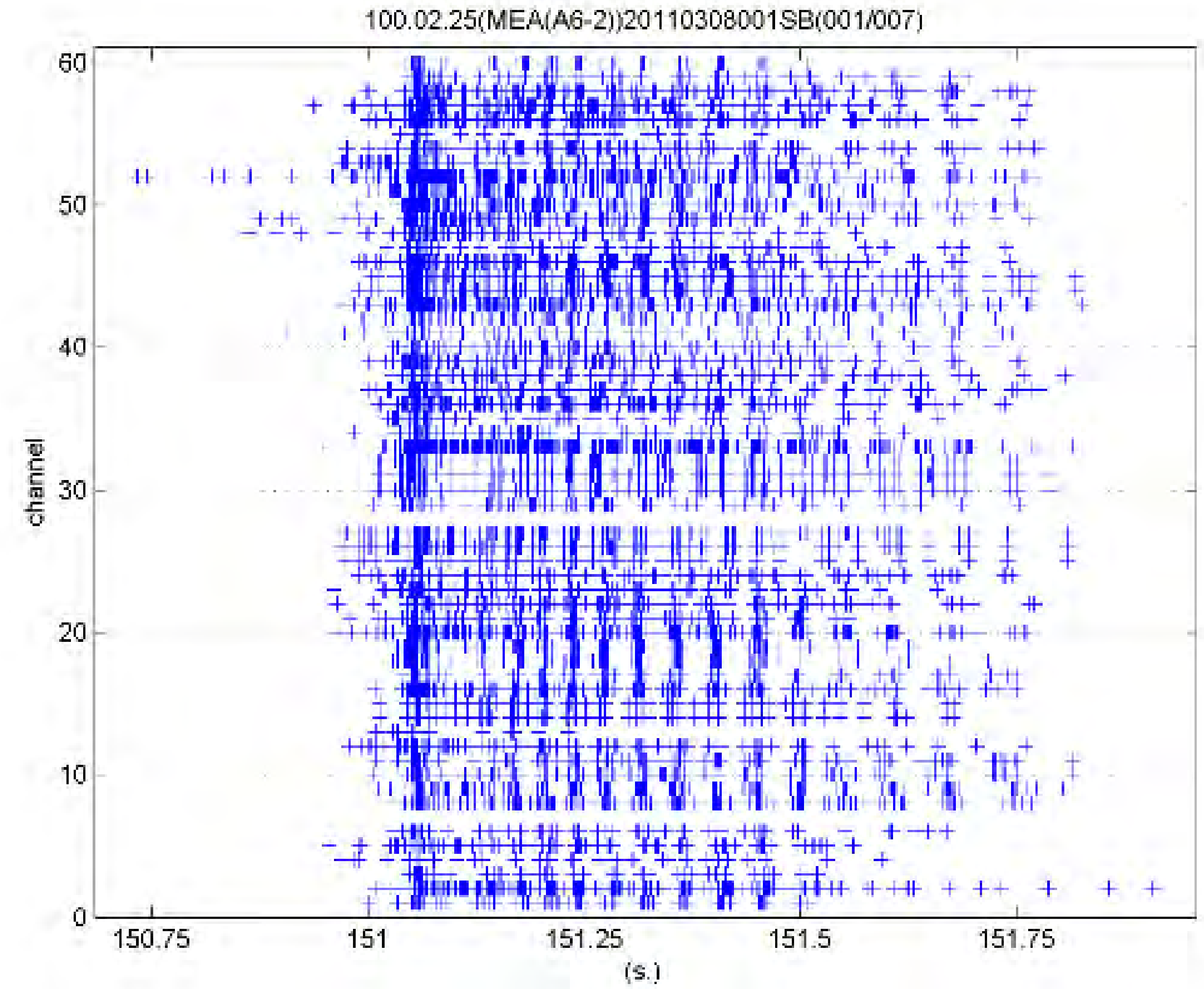
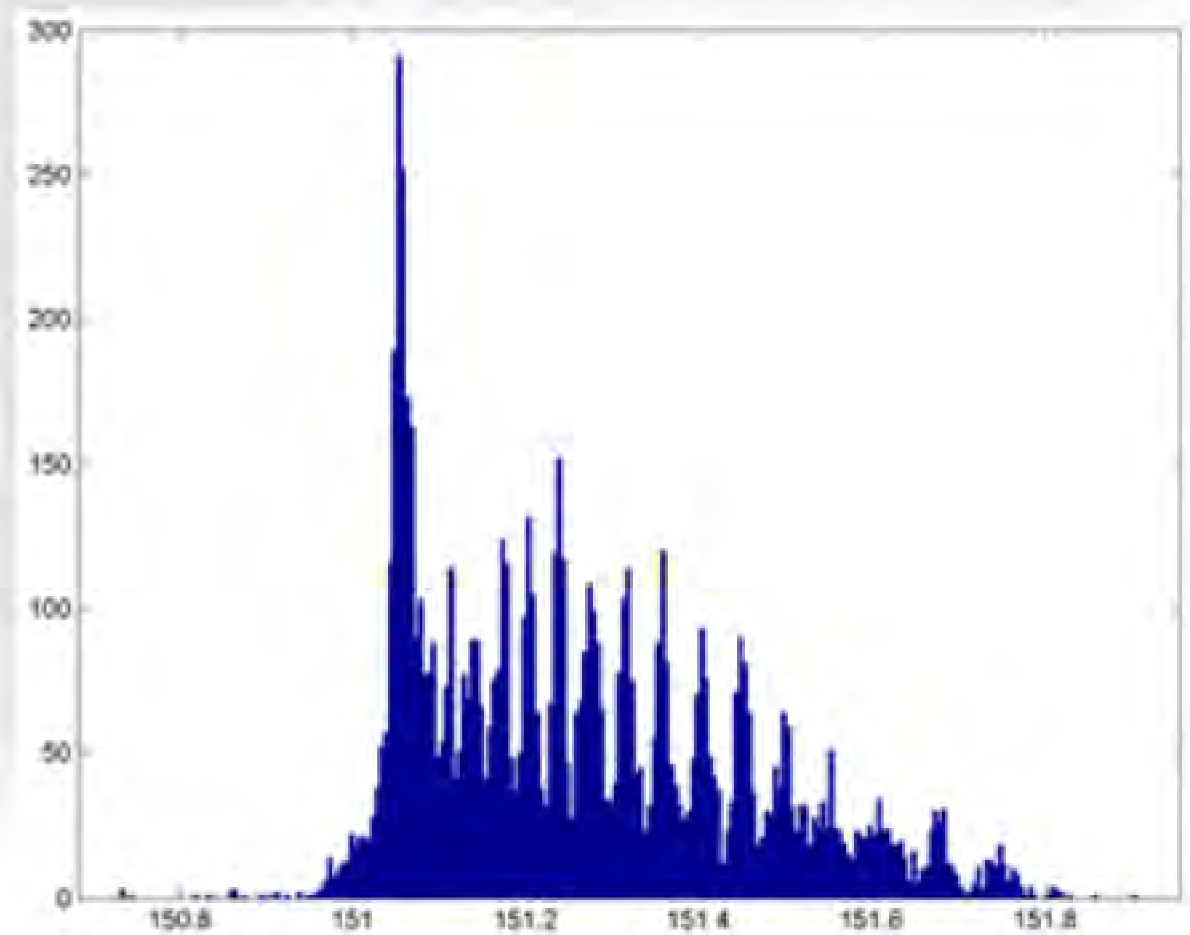
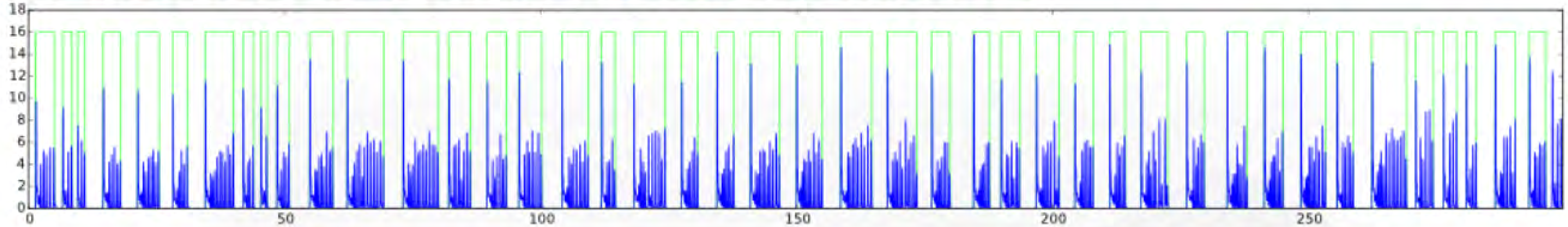






Reverberatory bursts (superbursts) 1



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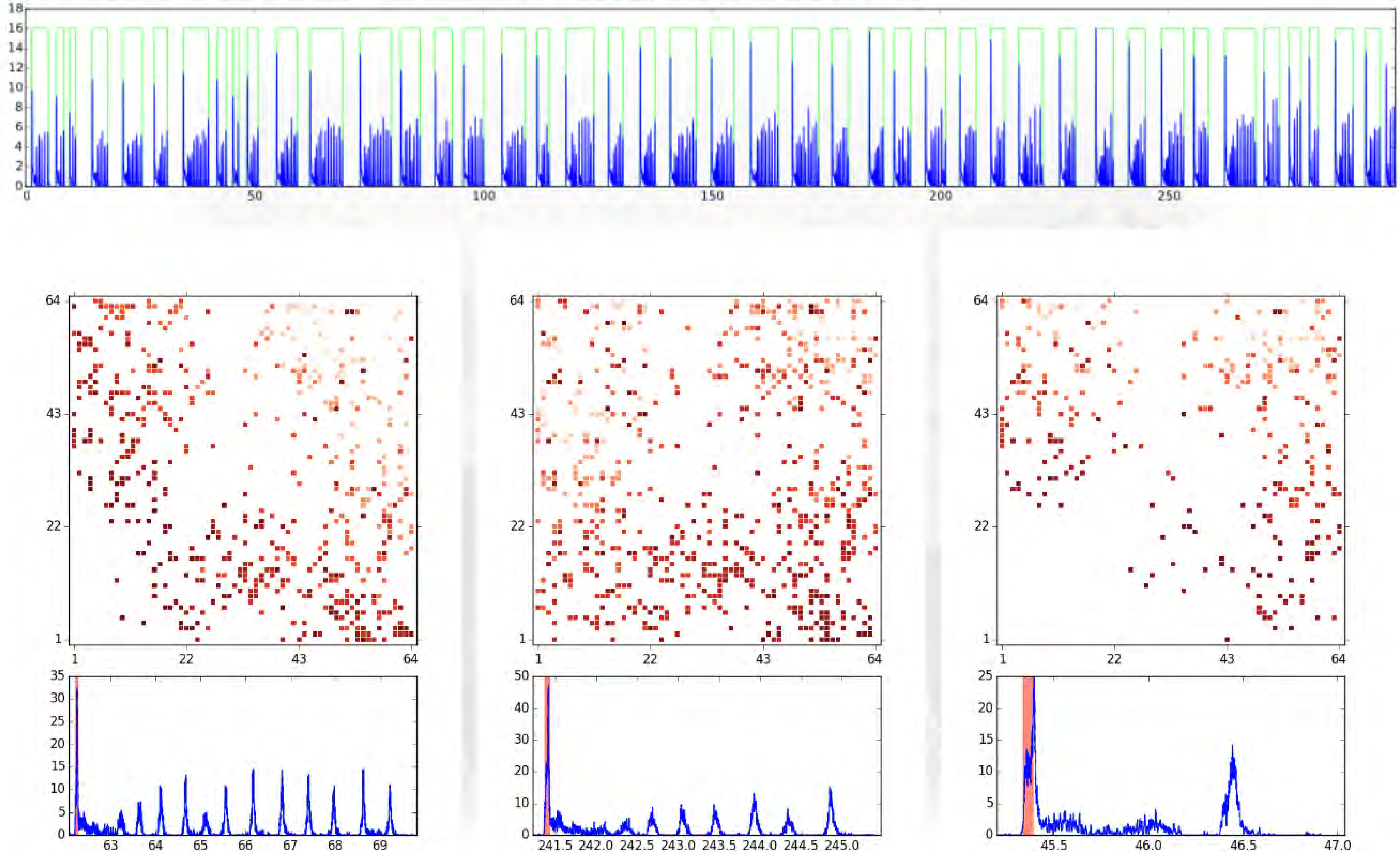
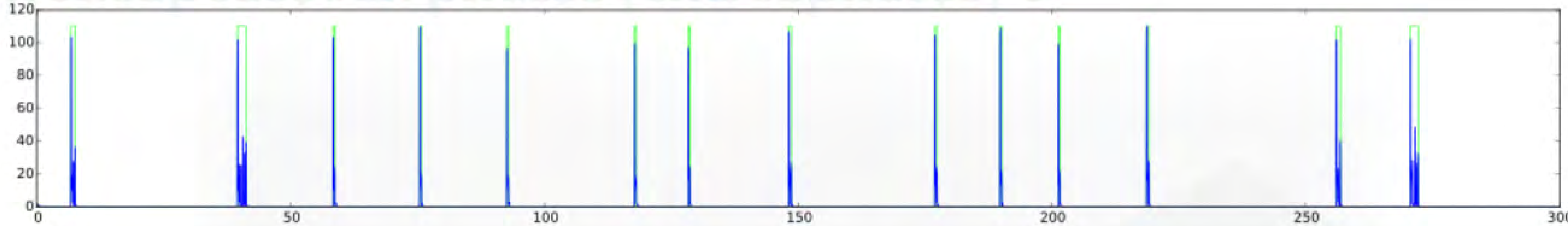


Reverberatory bursts (superbursts) 2



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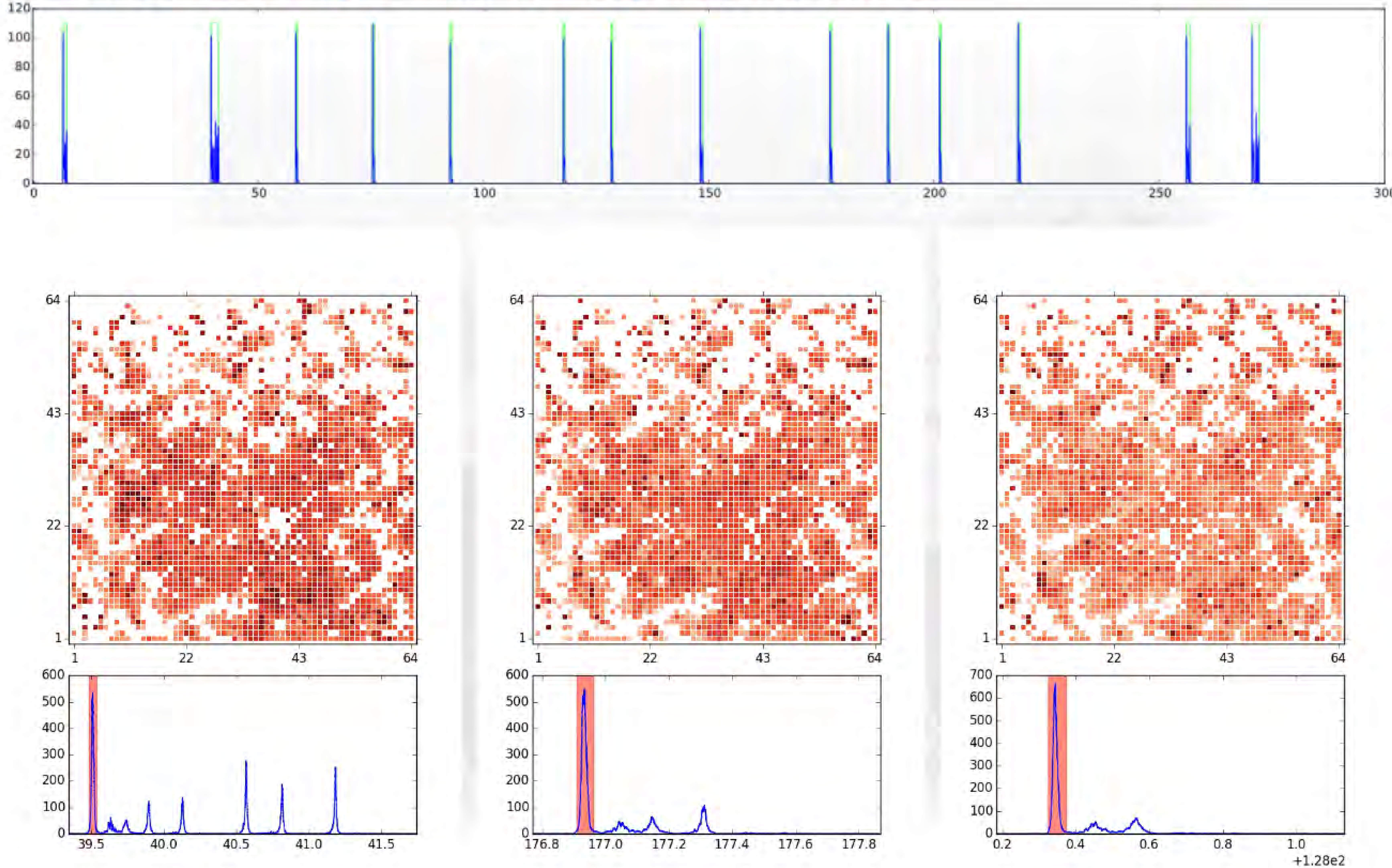
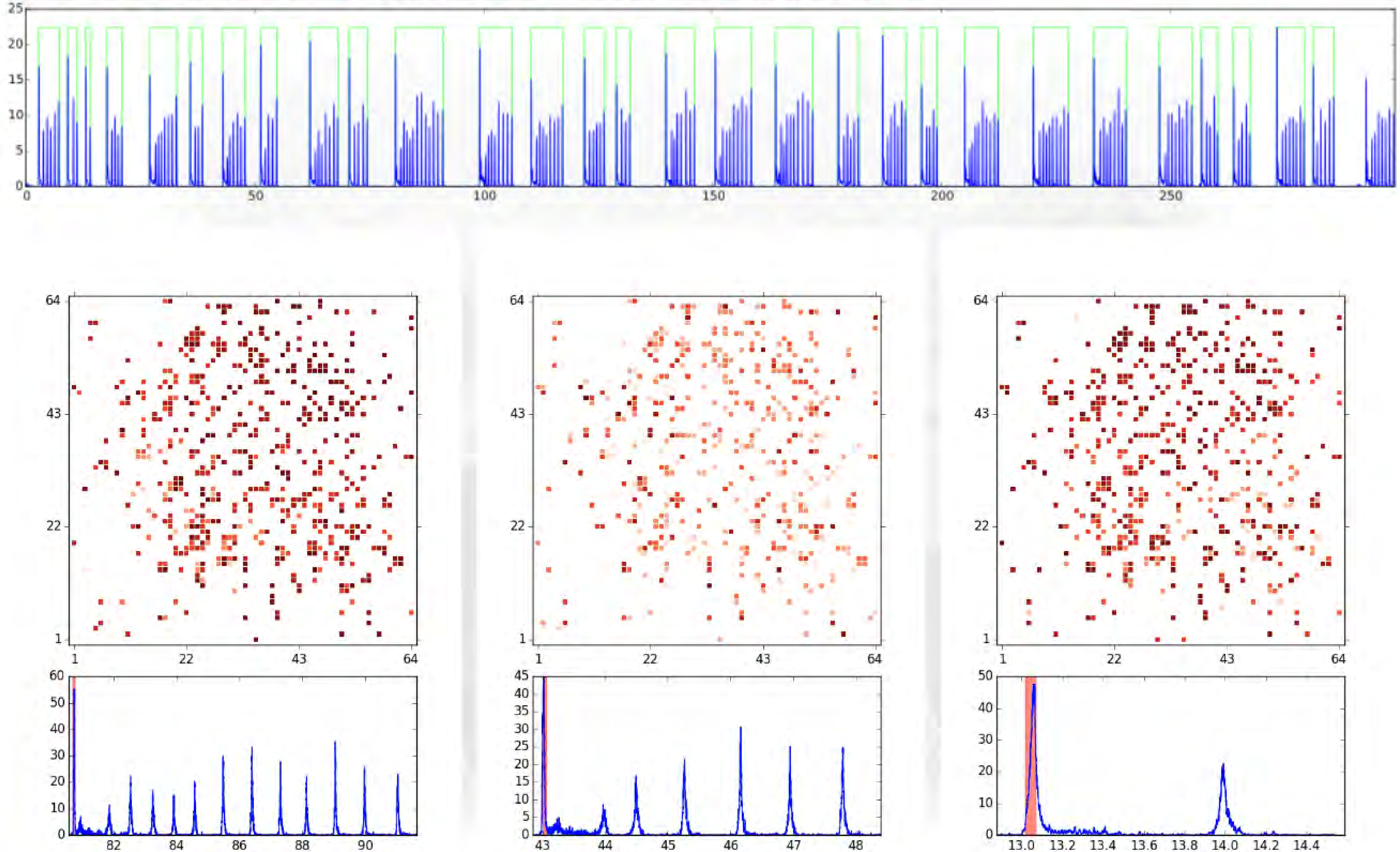


Reverberatory bursts (superbursts) 3



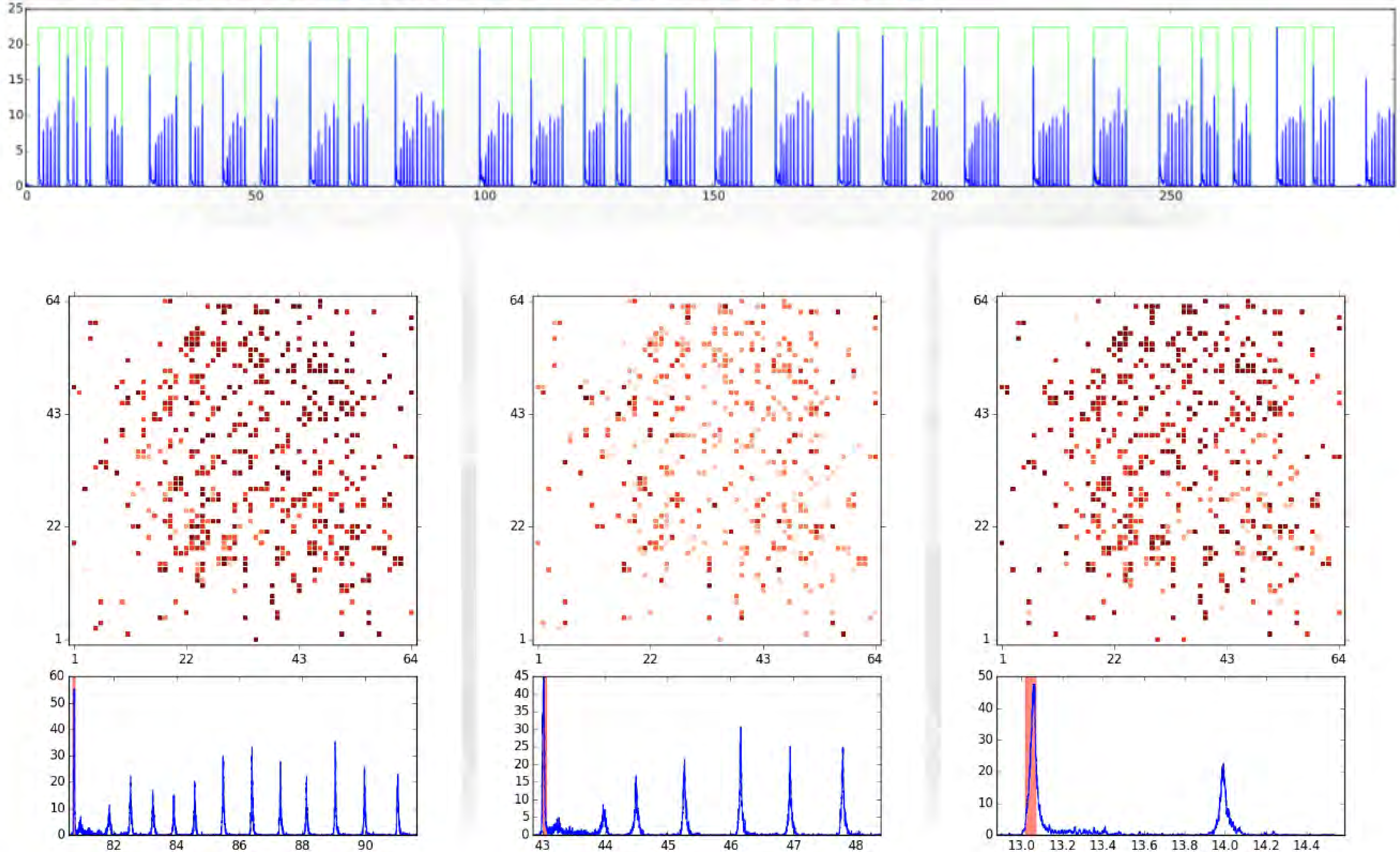
Quantify increase of synchrony

Quantify increase of synchrony

Effective duration of reverberation (sub-burst):

$$\tau_{\text{eff}} \equiv \frac{\text{spike count}}{\text{peak height}}$$

Reverberatory bursts (superbursts) 3



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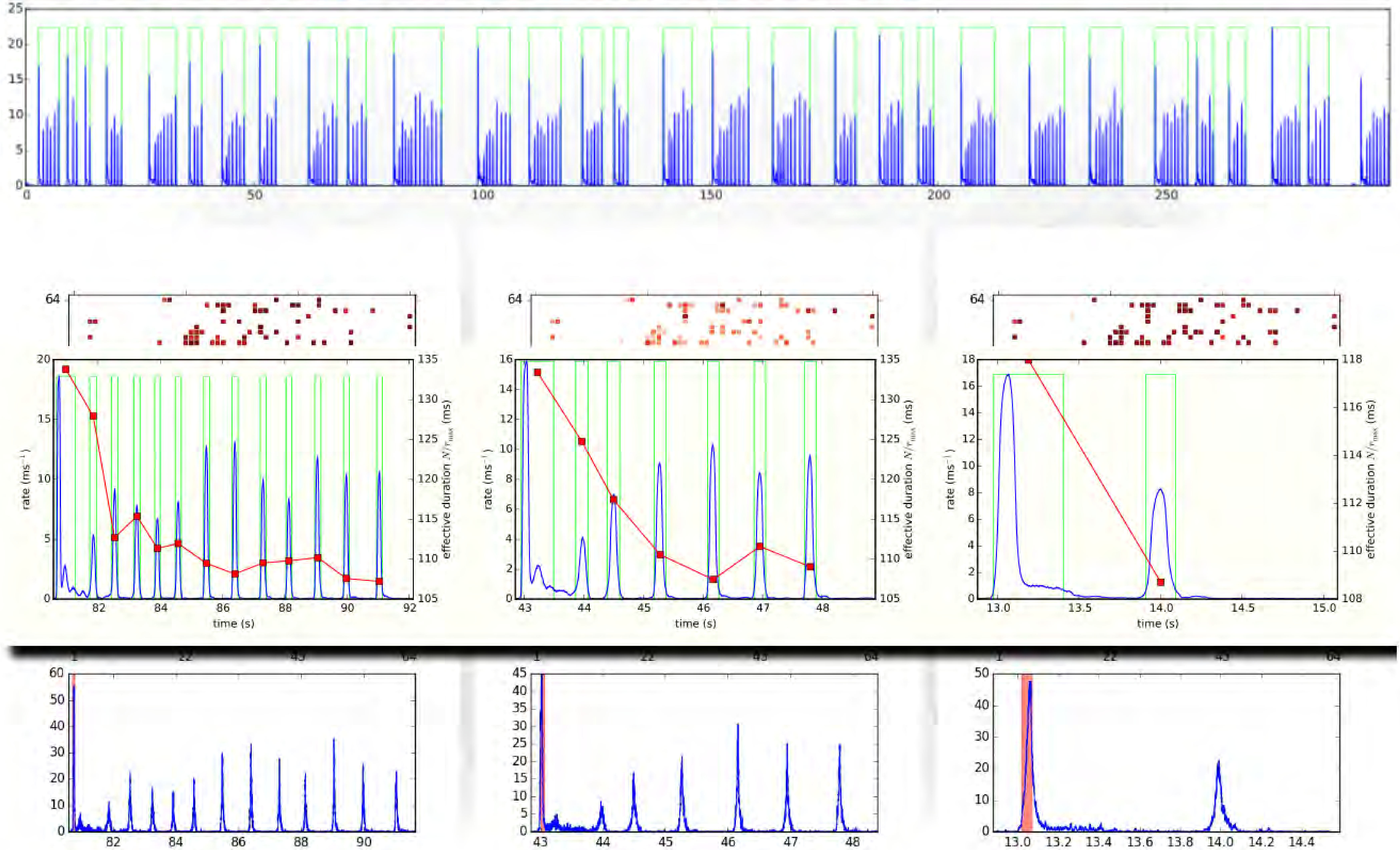

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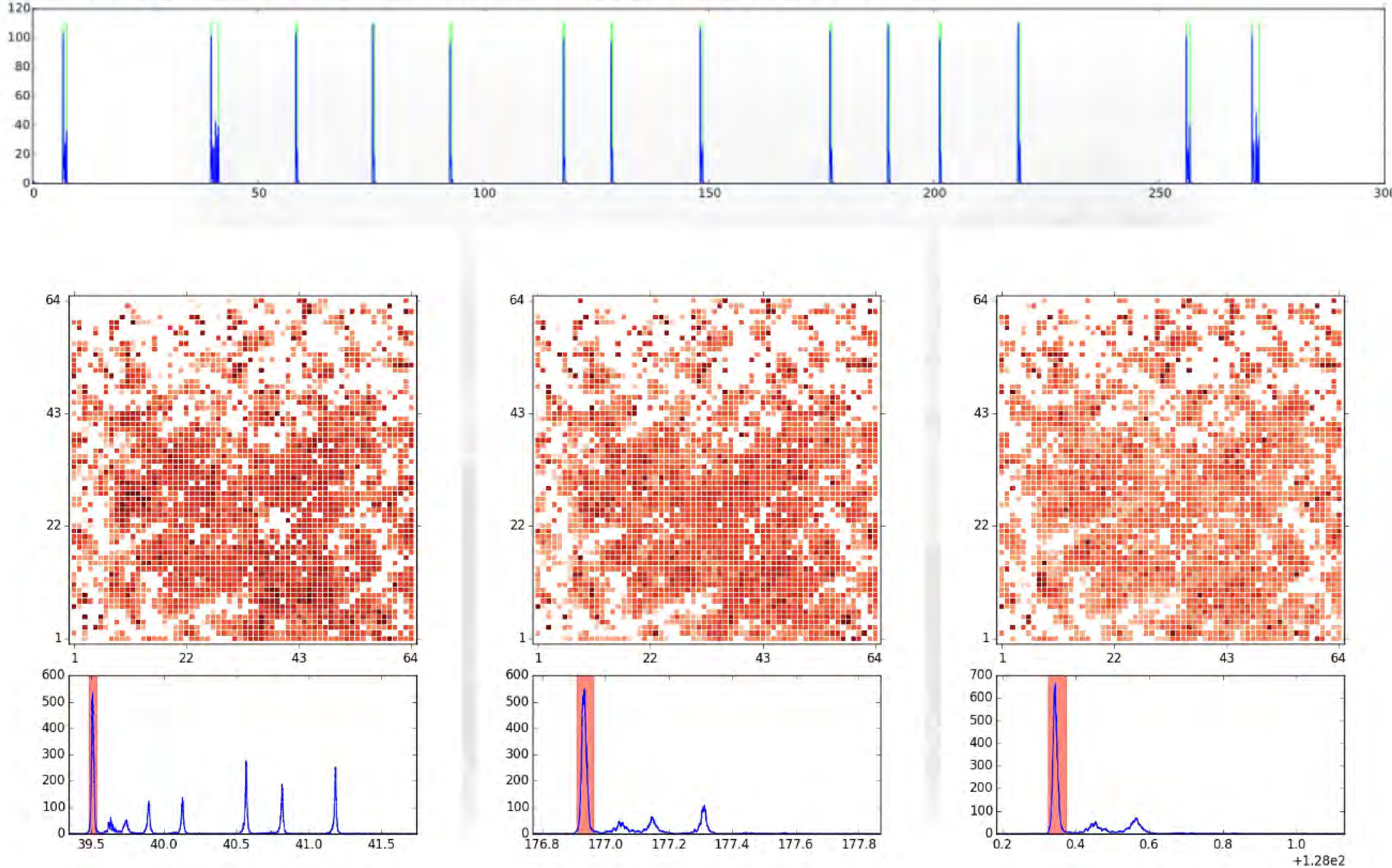

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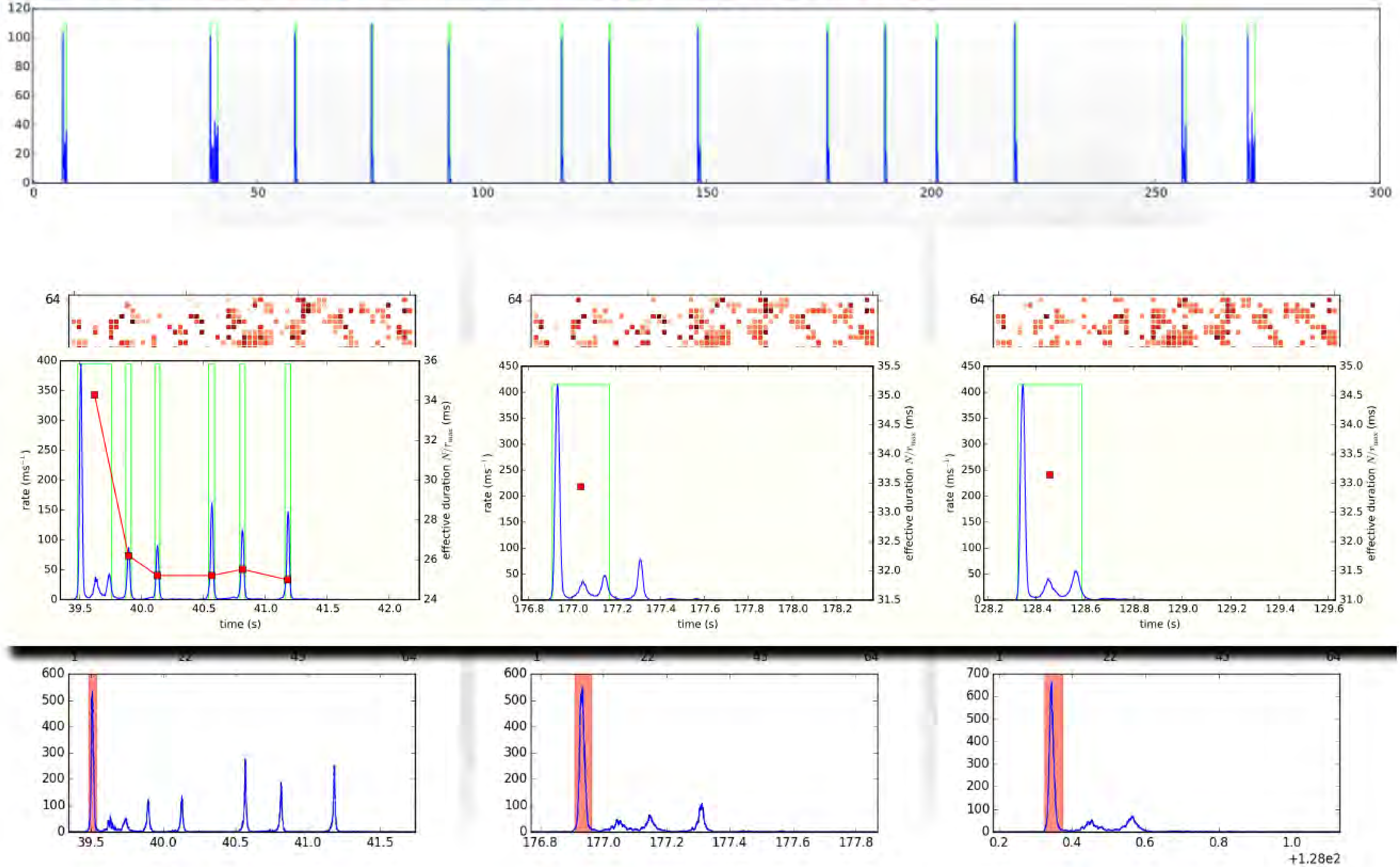

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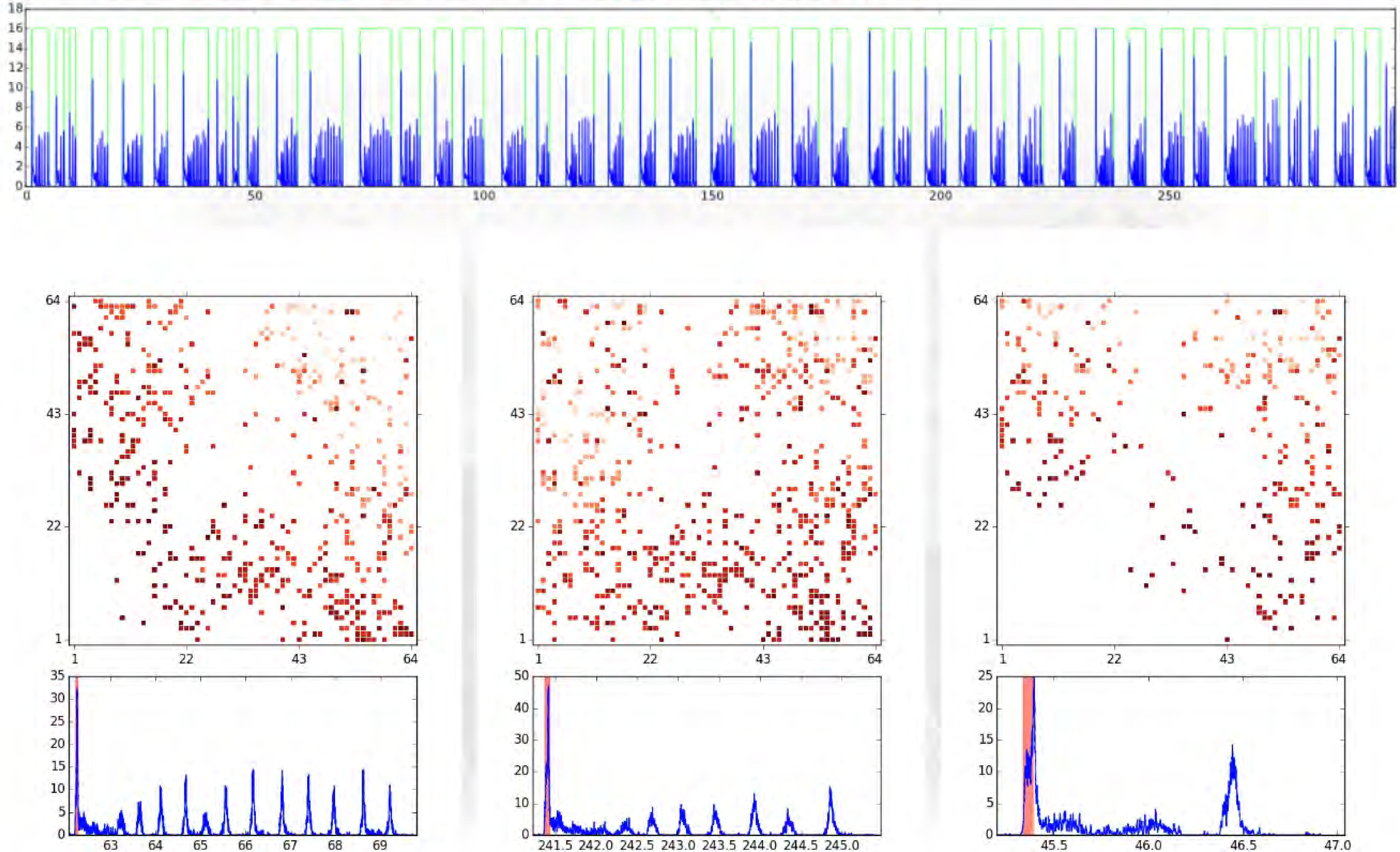

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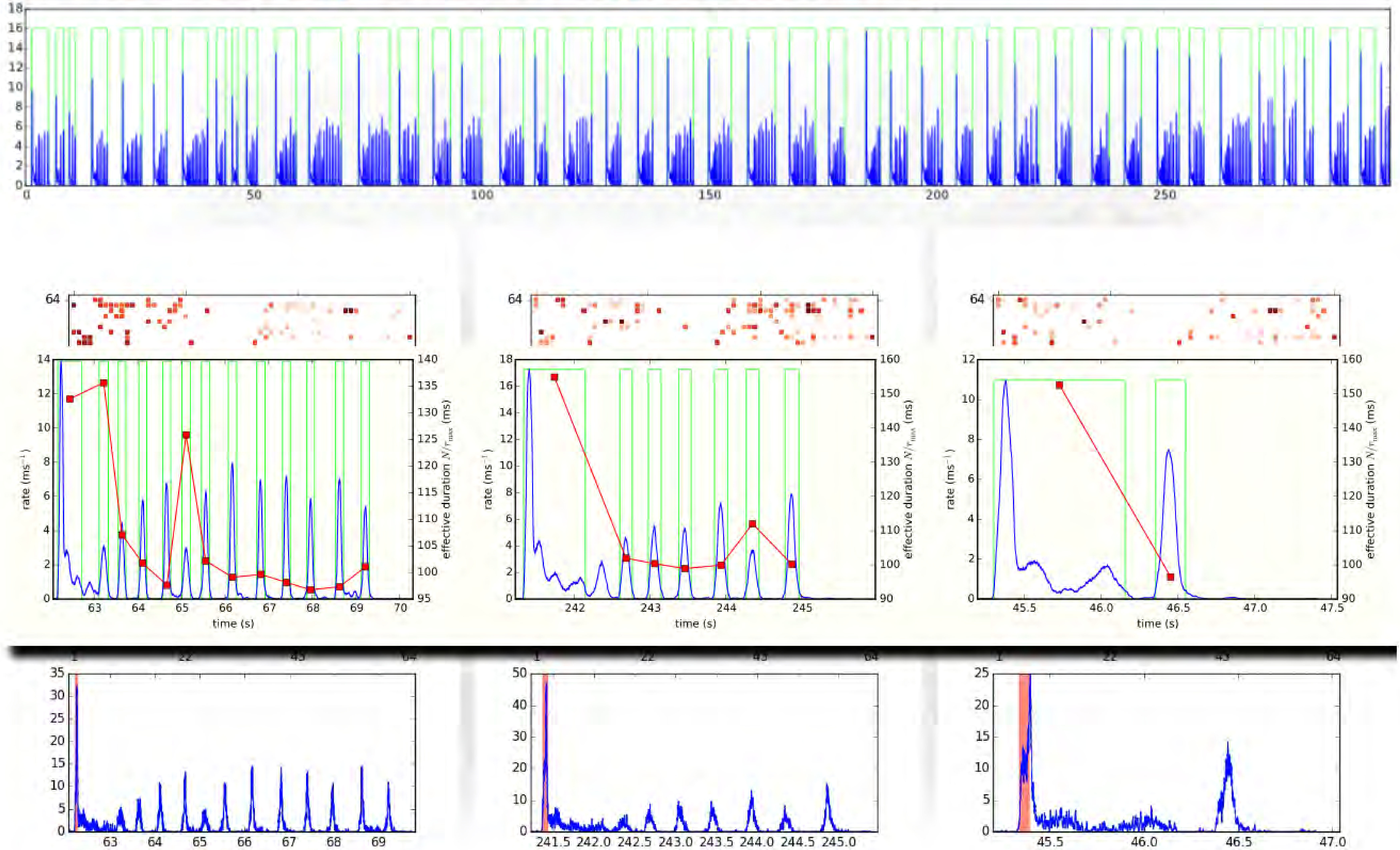

Modeling with geometrical constraint (on 2D networks)

Geometrically constrained (2D) networks

Random placement with minimal distance constraint.

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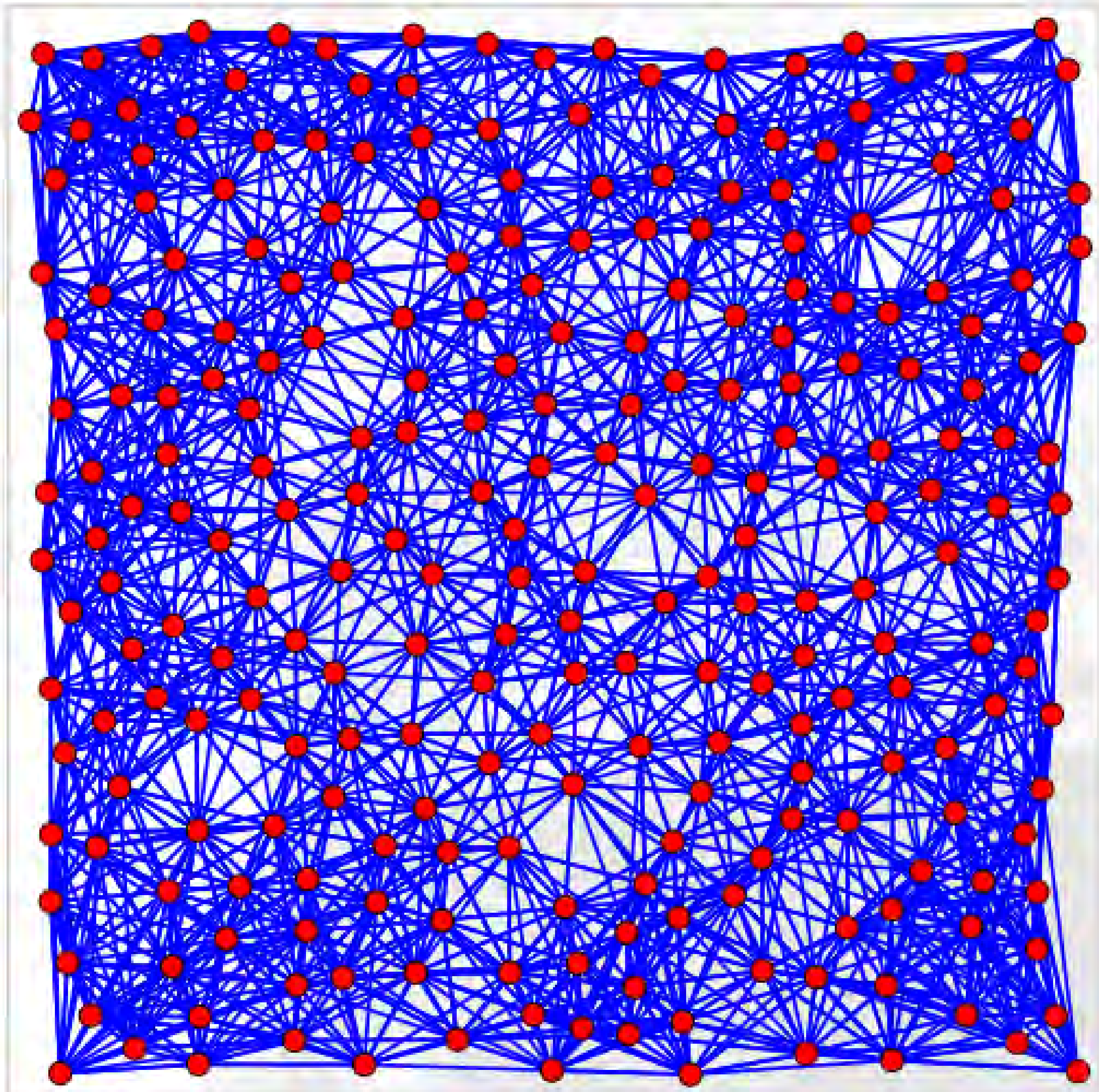

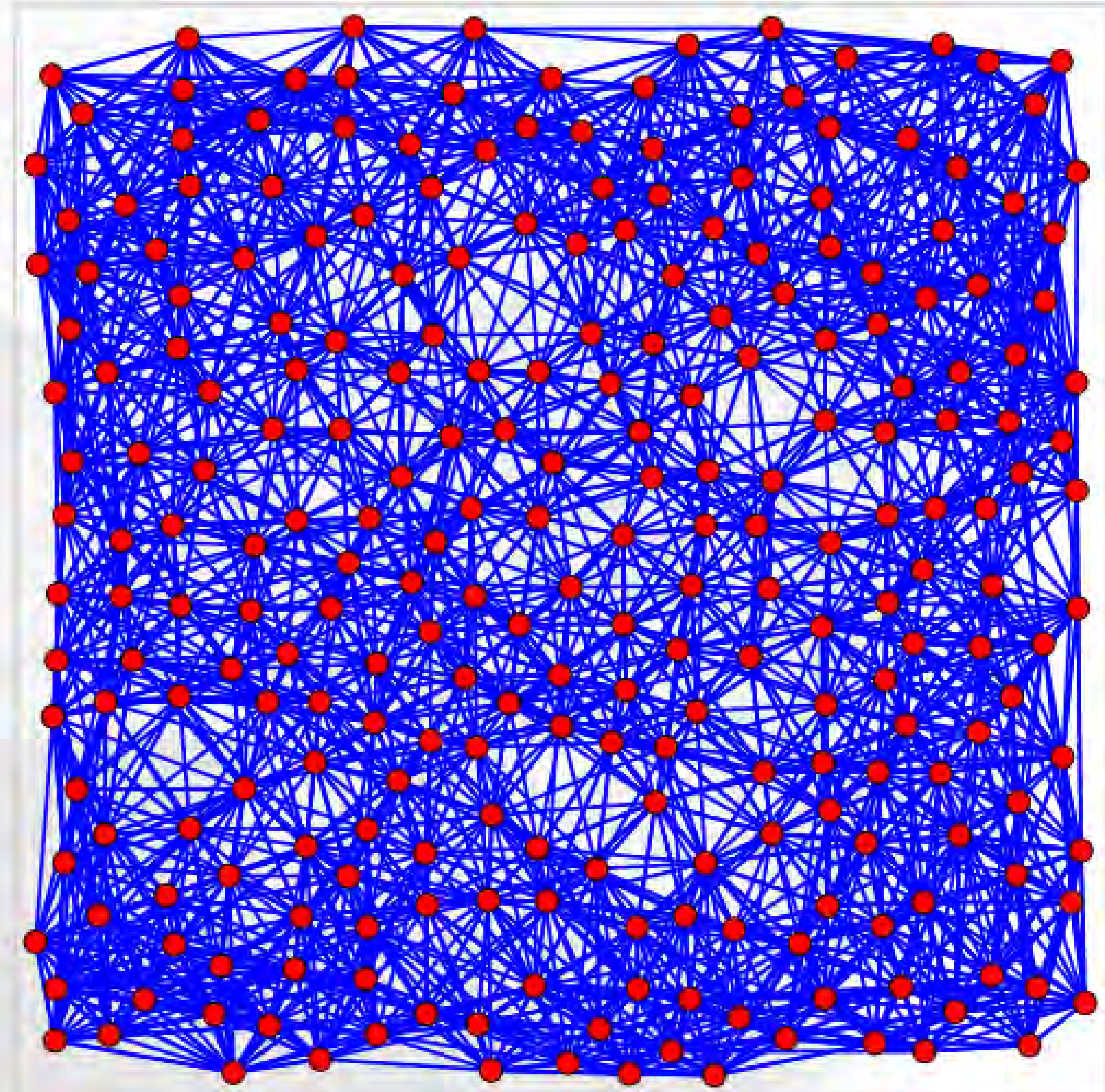

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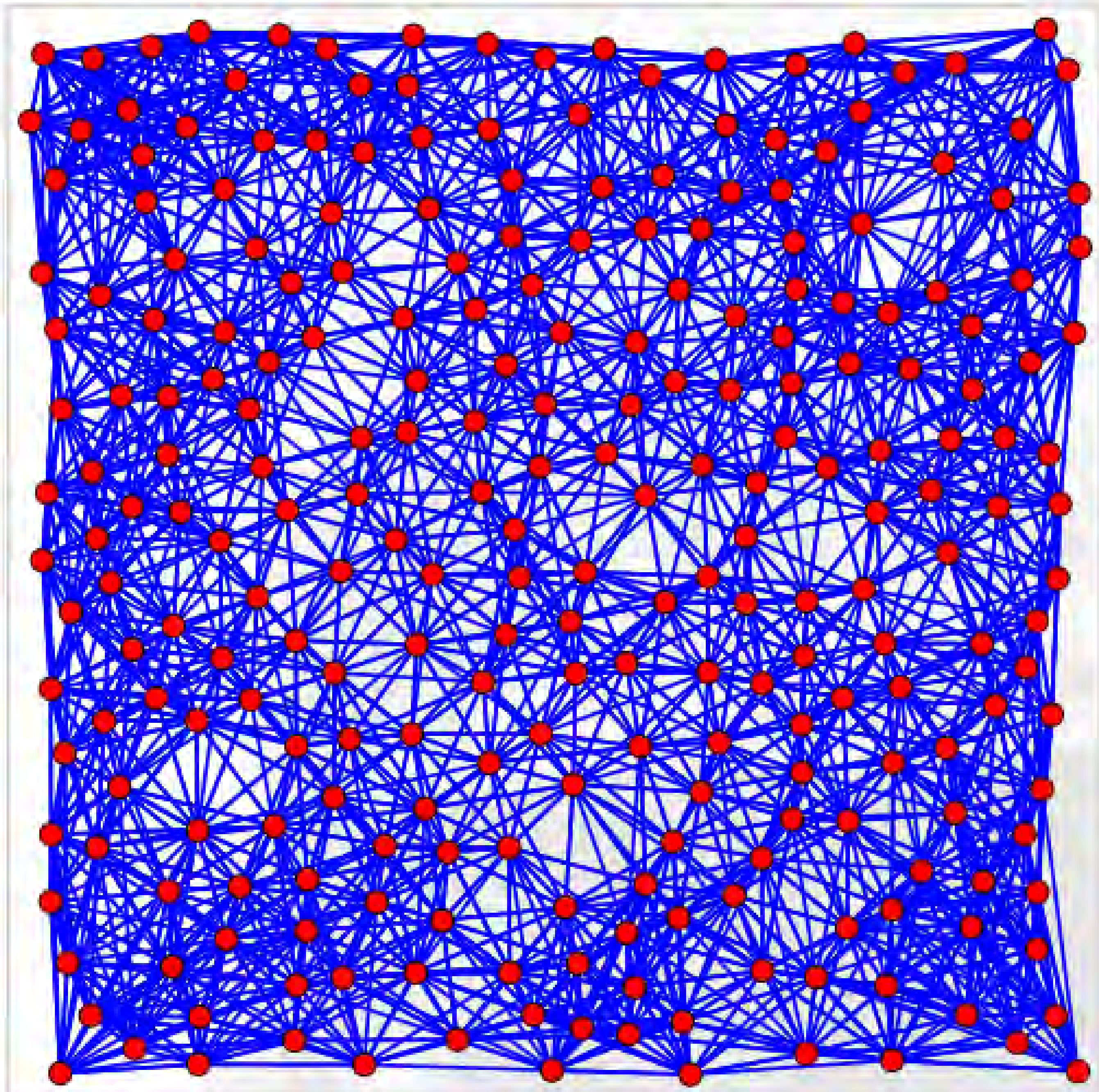

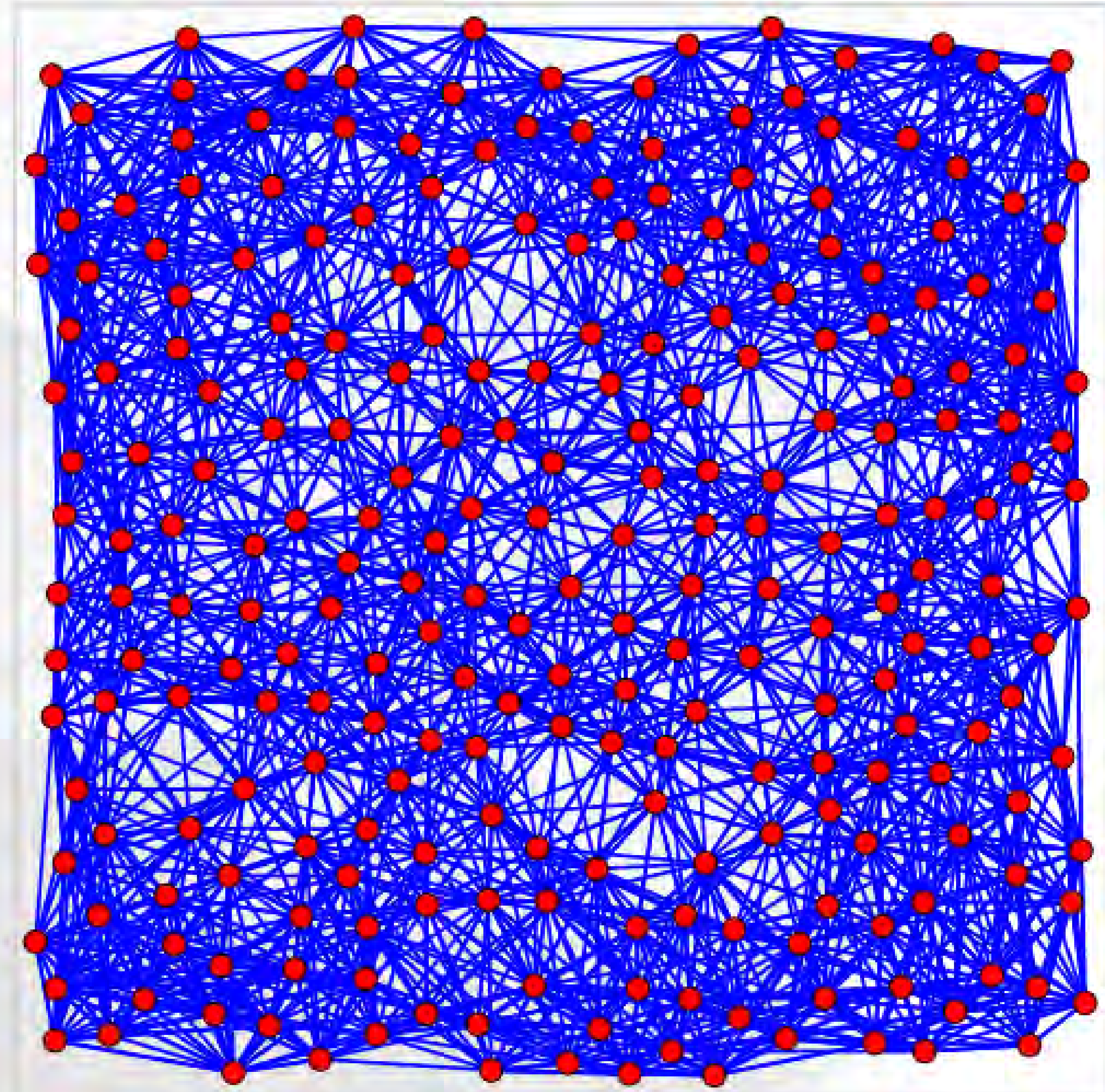

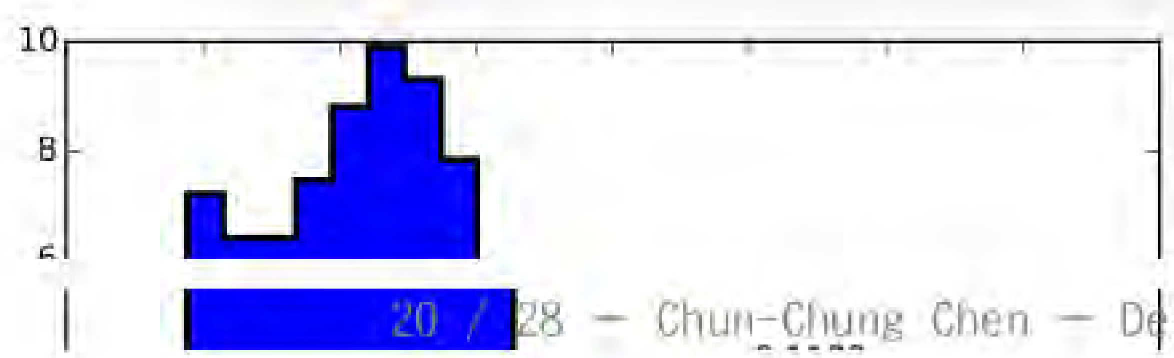

Interactive search for working parameter sets... Possible?

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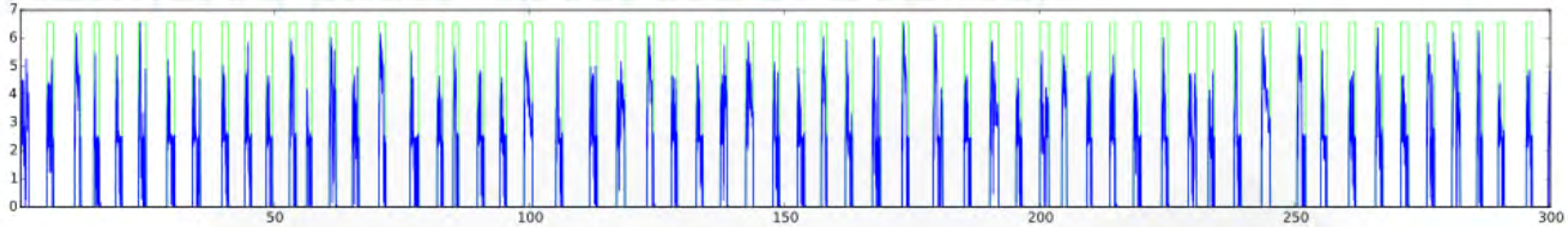
Impractical without physiological insights!

Simulated burst, short range network



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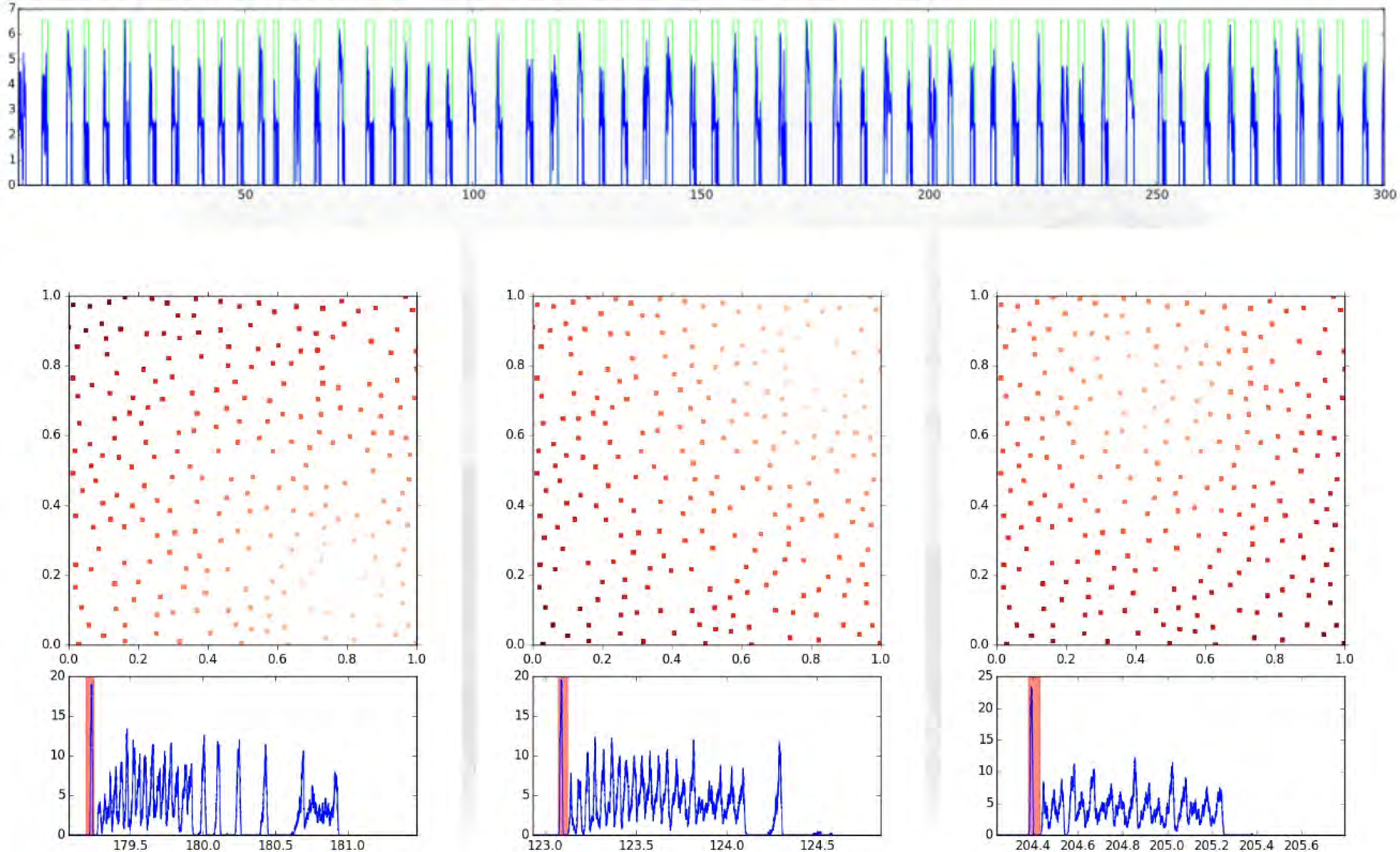

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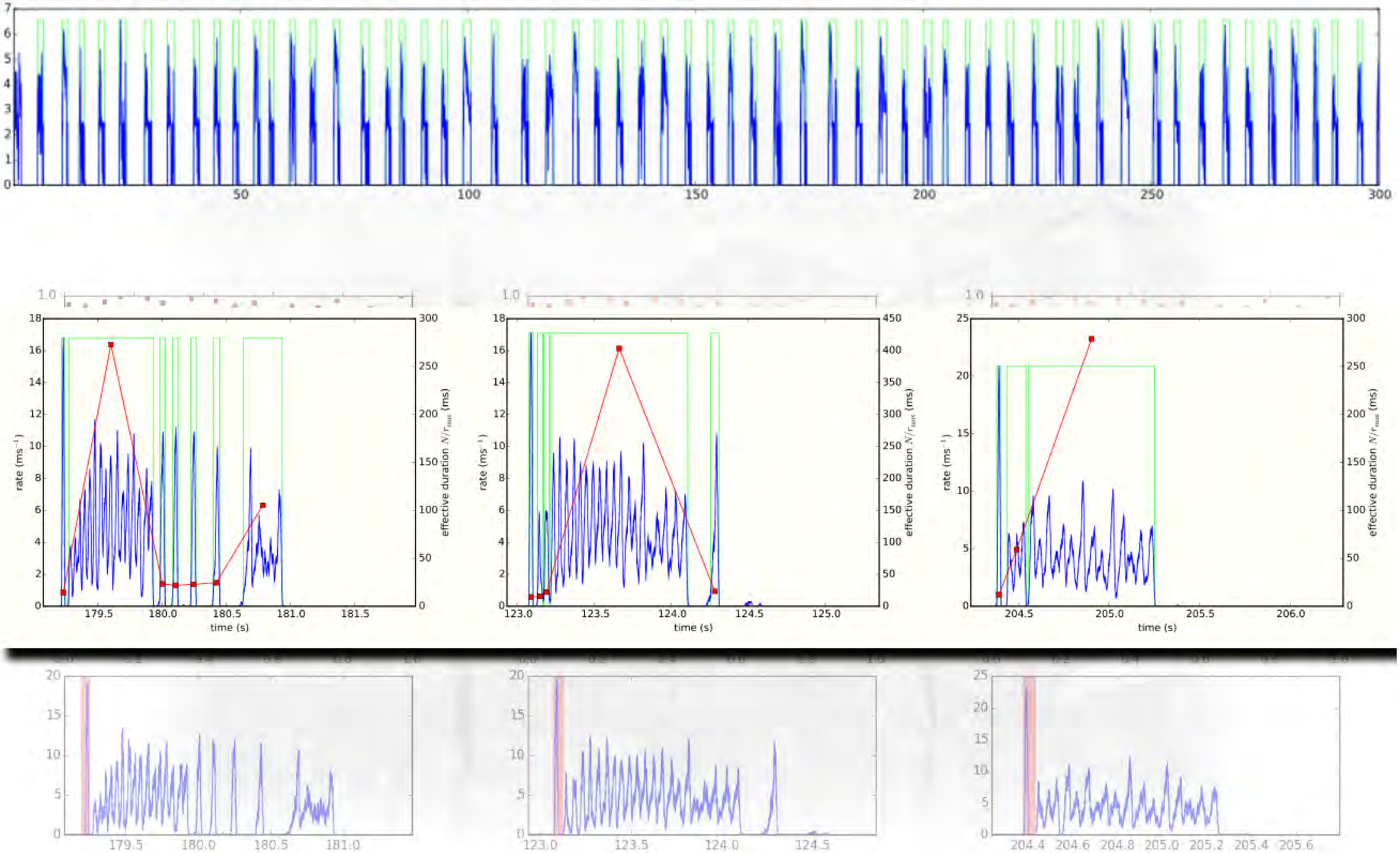
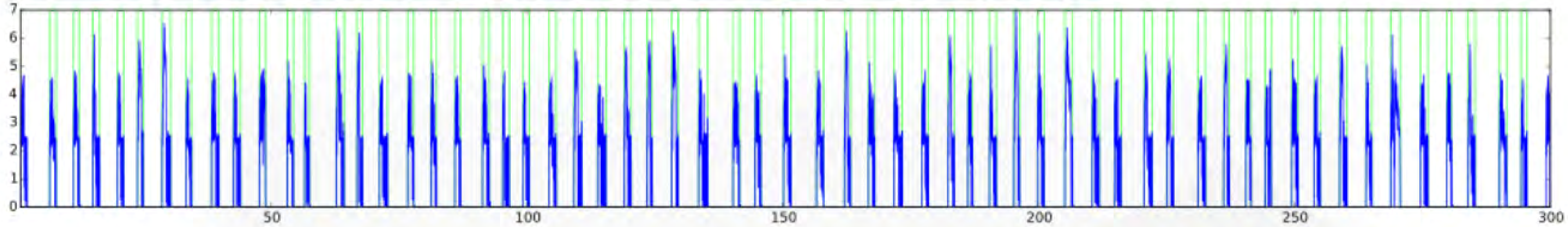


Simulated burst, longer range network



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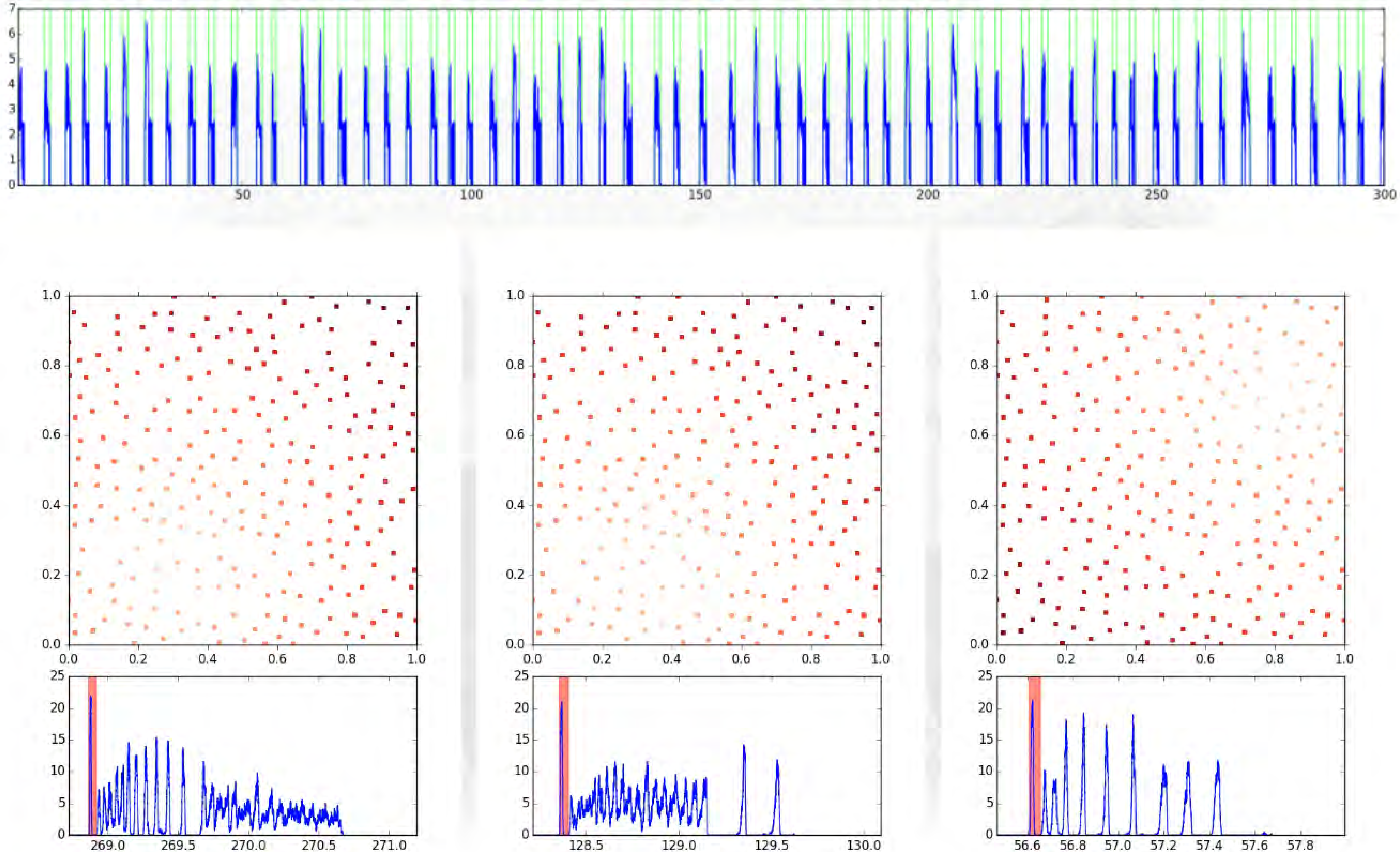

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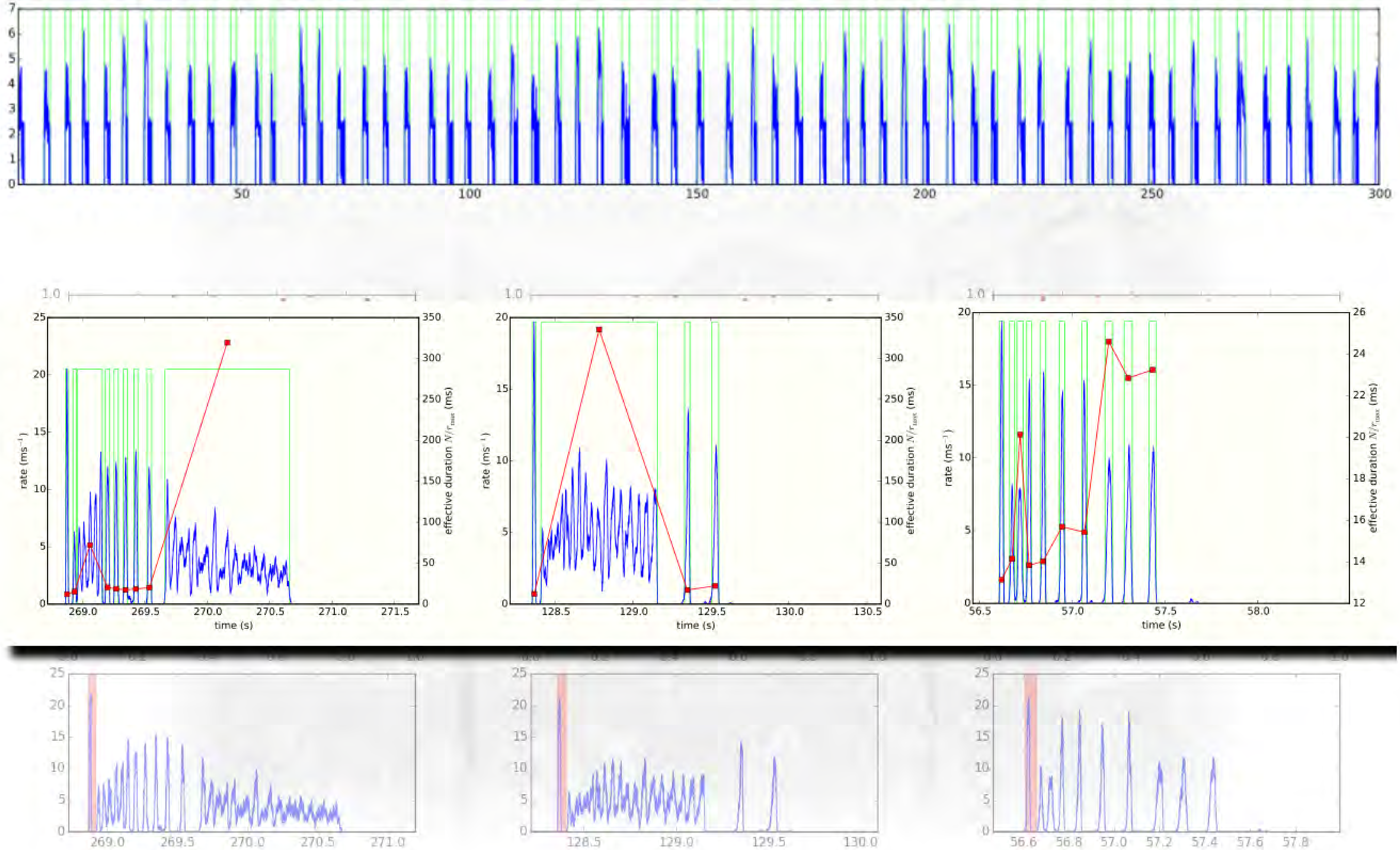

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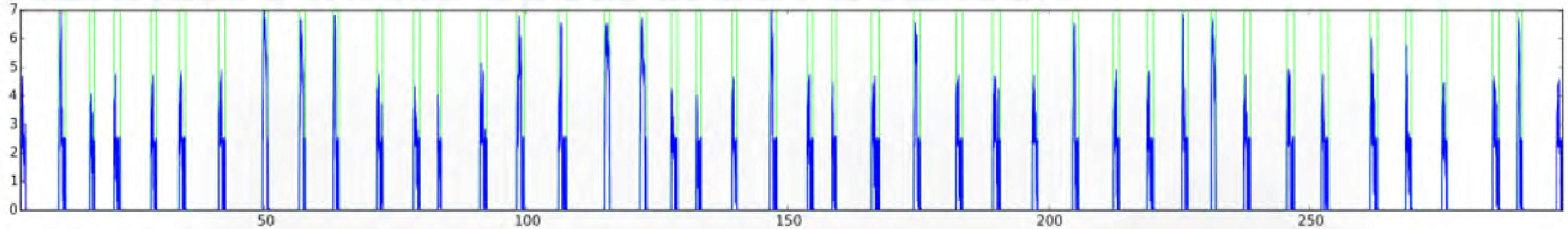

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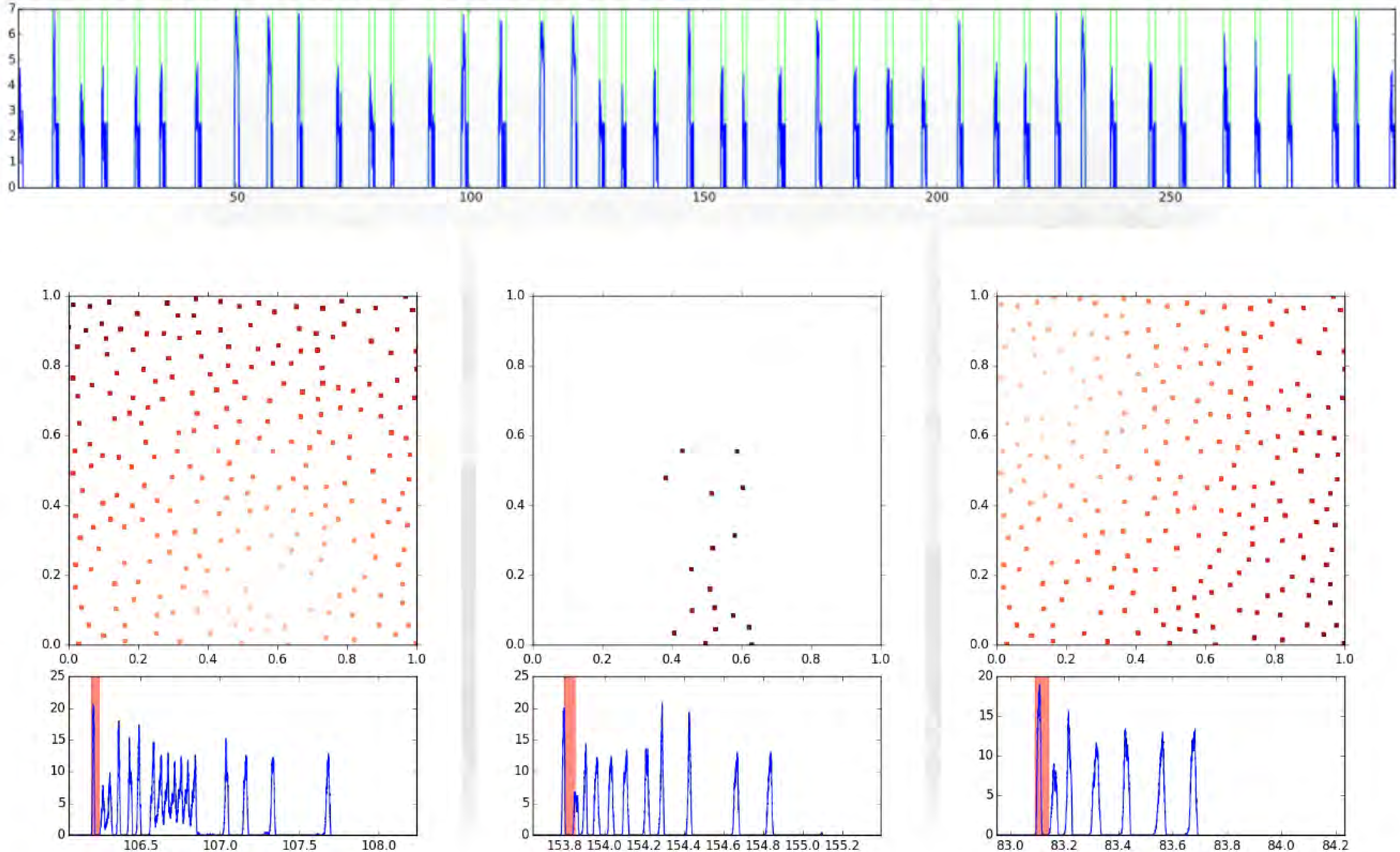

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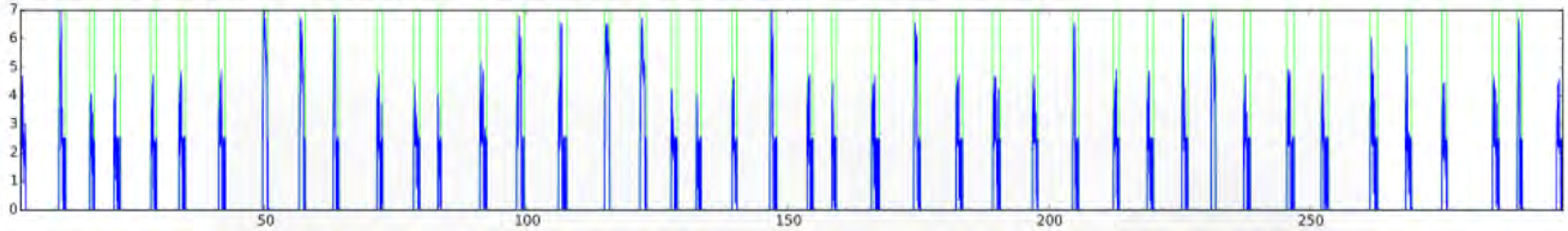

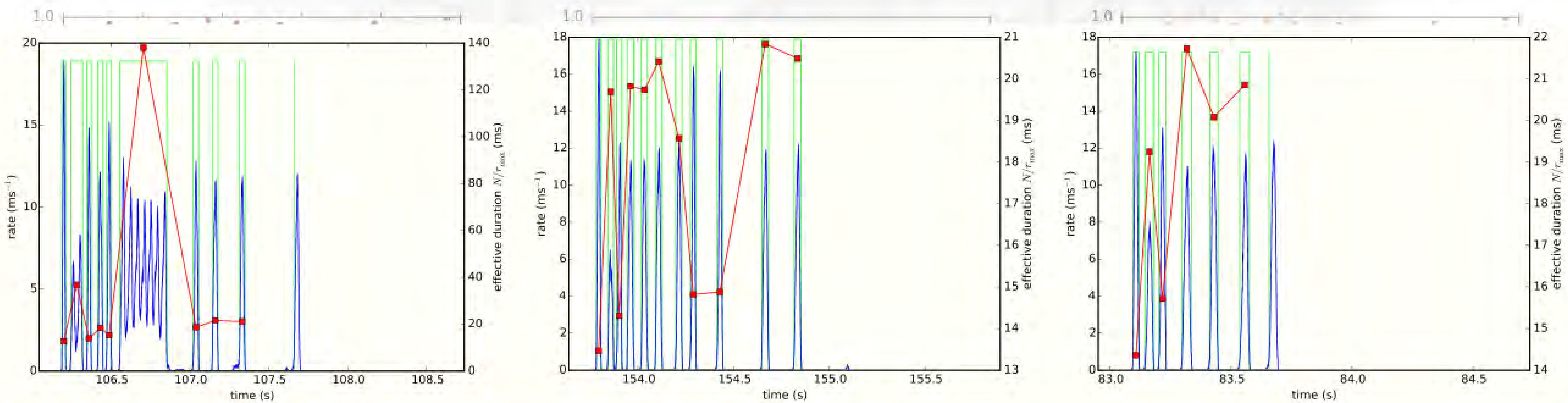

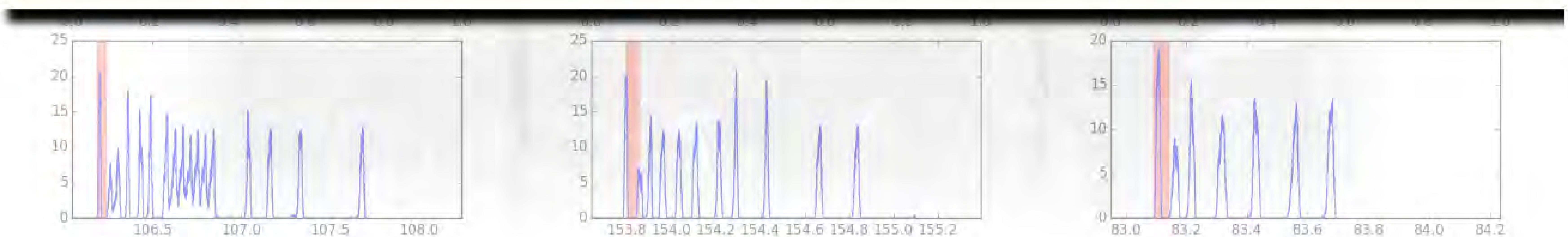

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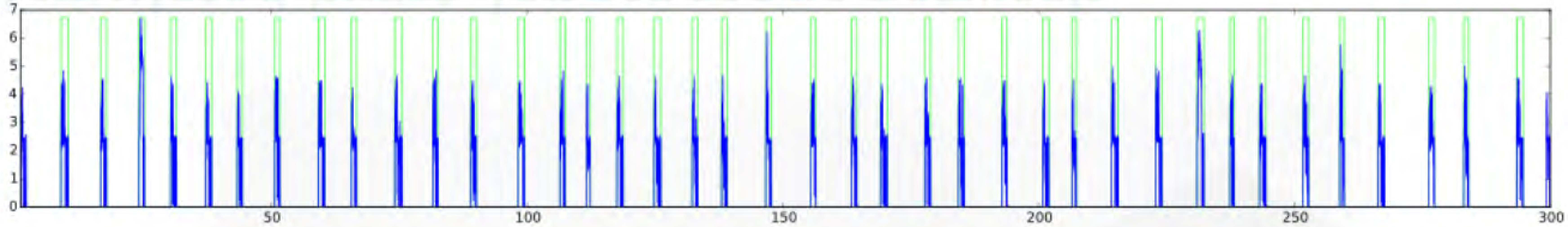

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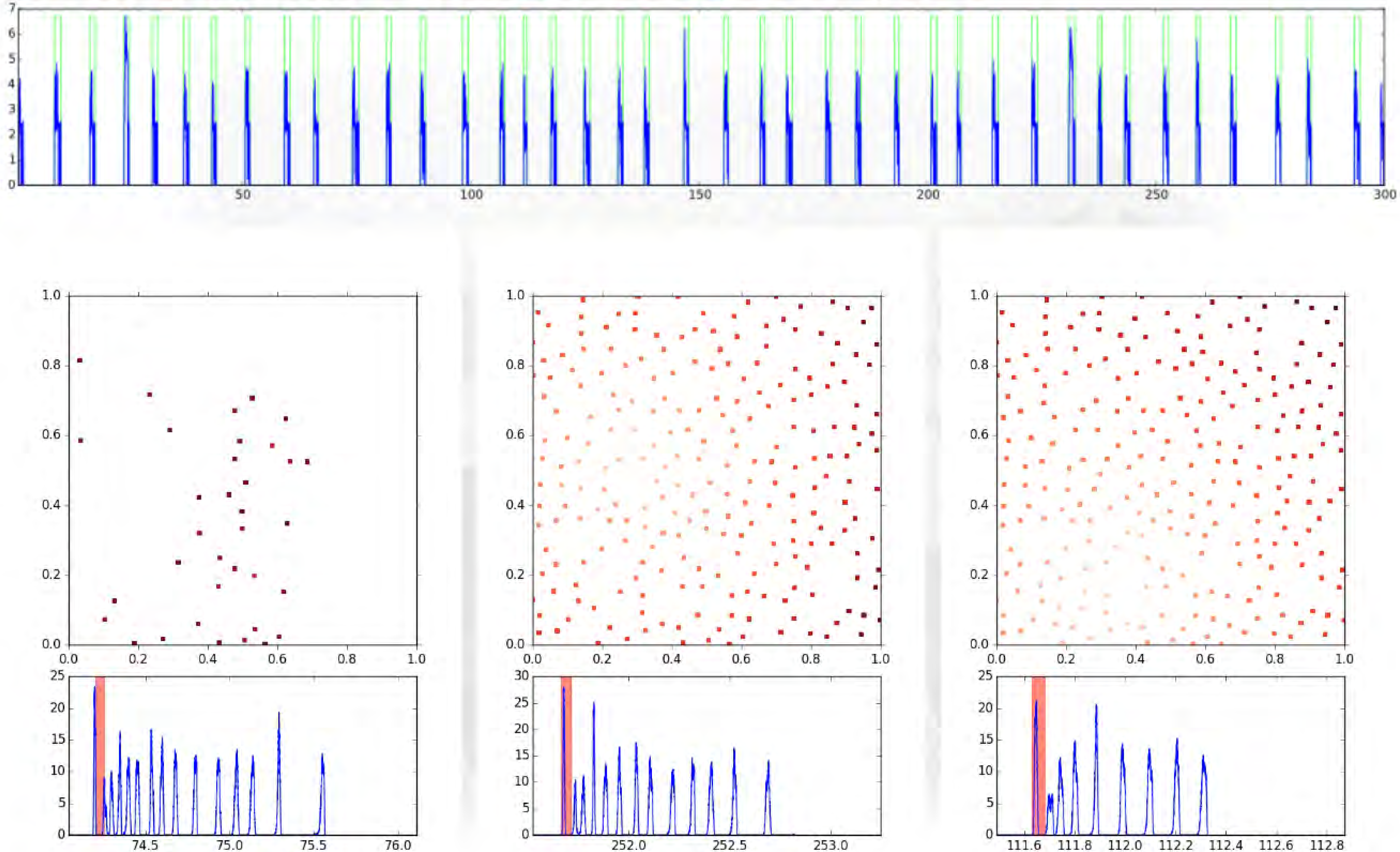

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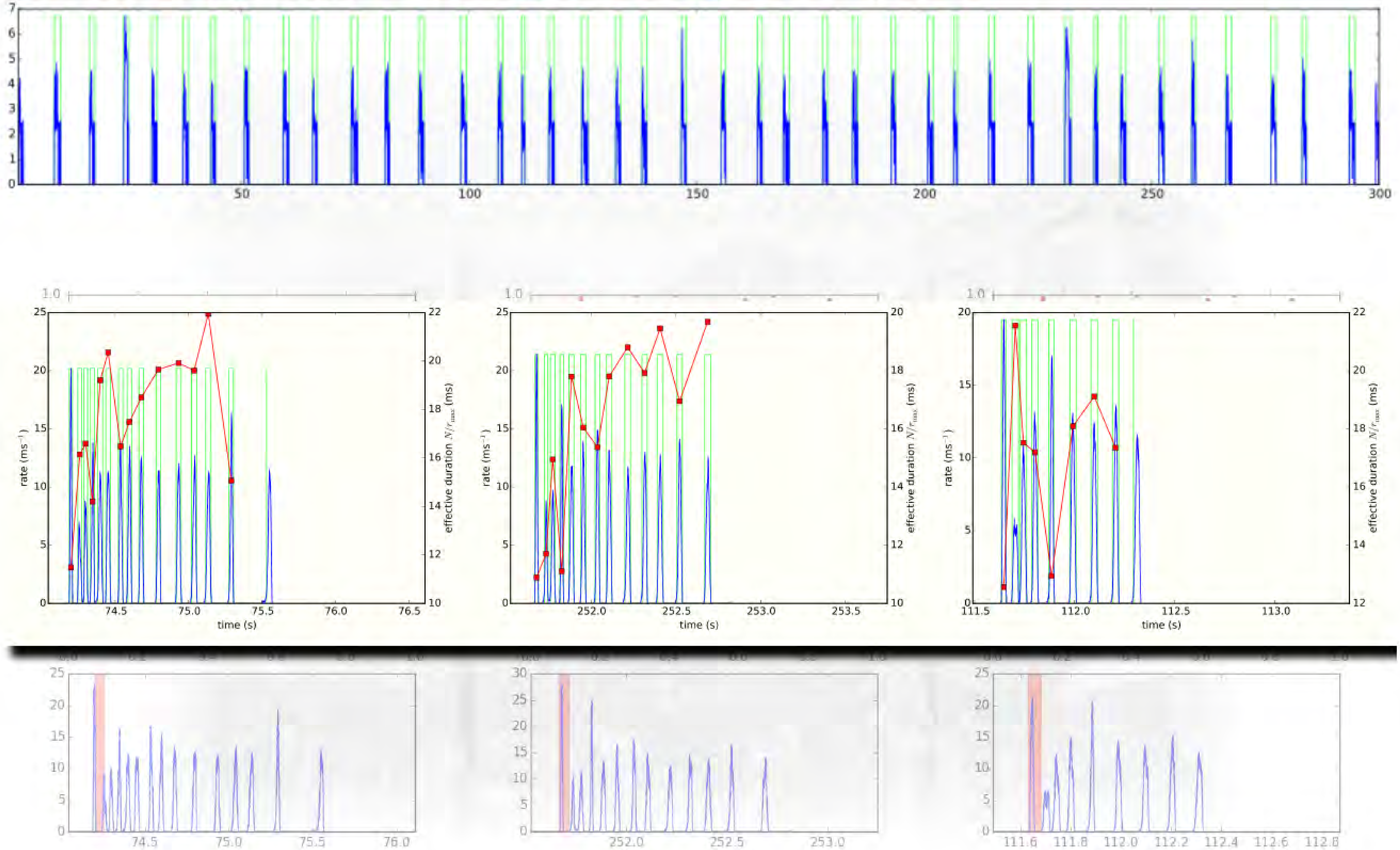

Towards a forensic theory on the cause and propagation of reverberatory bursts.

Summary

- Multiple time scales are involved in reverberatory network bursts. (superbusrts)
- The bursts are typically initiated by propagating waves sweeping across the system.
- Uncoordinated firings rise following initial activity peak and subsequent refractory period, likely activated by noise.
- Due to depletion of synaptic resources, capability for noise to fire up neurons can diminish over time.
- Synaptic input plays an increasingly important role, leading increase in synchrony of reverberation activity. (inverted superbursts)

Further study

- What are the roles played by the network and its topology.
- What does the calcium do?
  - Controls the rate of asynchronous release.
  - Determines fraction of synchronous release.
  - Changes the firing threshold of neurons.
- What is the termination mechanism of network bursts.
  - Super inactive state.
  - Inhibition.

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Thank you for your attention!