Graduate Project Report

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I. INTRODUCTION OF NEURAL AVALANCHE

Neural avalanche (NA) is a cascade of bursts of activity in neuronal networks whose size distribution can be approximated by a power law, which is the self-organization behavior in neural systems [1], generally showing a power-law spatial and temporal distribution in different time scales.

$$P(S) \sim S^{-\tau}, P(T) \sim T^{-\alpha}, \langle S \rangle \sim T^{\gamma},$$

$$\gamma = \frac{\alpha - 1}{\tau - 1}$$

Here the $\tau, \alpha,$ and γ are called critical exponents.

The dynamics behind NA remain controversial, and different mathematical model has been considered, such as self-organized criticality (SOC) [2] and self-organized bistability (SOB) [3]. And neural field theory has also been explored to study NA [7].

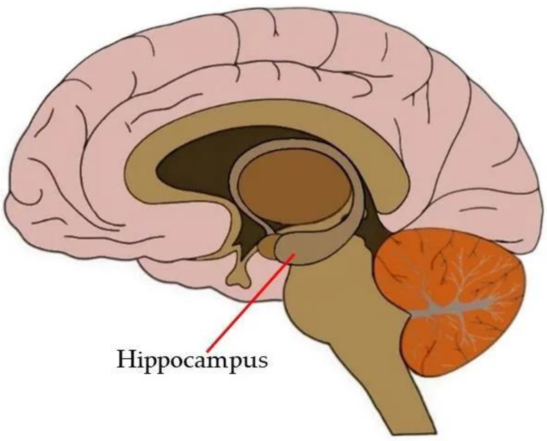

FIGURE 1 FROM NEUROSCIENTIFICALLYCHALLENGED.COM, THE POSITION OF HIPPOCAMPUS IN THE BRAIN

NAs were first observed in cultured and acute cortical slices by Beggs and Plenz [1], and till now this emergence has been found both in vivo [4] and in vitro [5], even in living humans' brains [6].

In this project, we will study the neural avalanche behavior in different parts of the hippocampus structure. We mainly studied the CA1, CA3 and hypothalamus systems.

II. THE AVALANCHE DATA

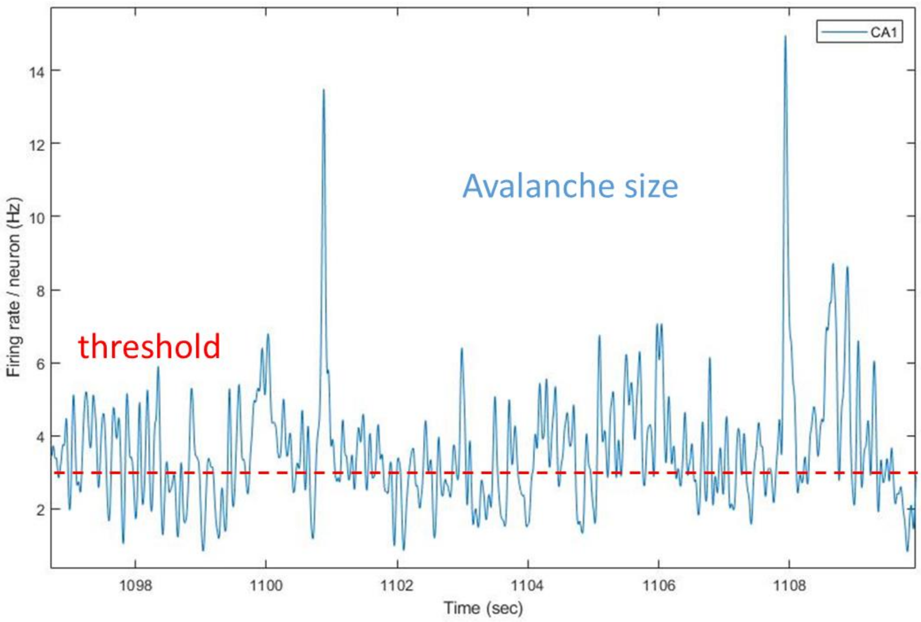

FIGURE 2. THIS FIGURE SHOWS THE ELECTRIC SIGNAL GOTTEN IN THE EXPERIMENTS.

We define the size of an avalanche as the total number of spikes, that is, the integral of the rates over the avalanche durations (the area enclosed by the spiking signal) This method has been used in some previous works [8].

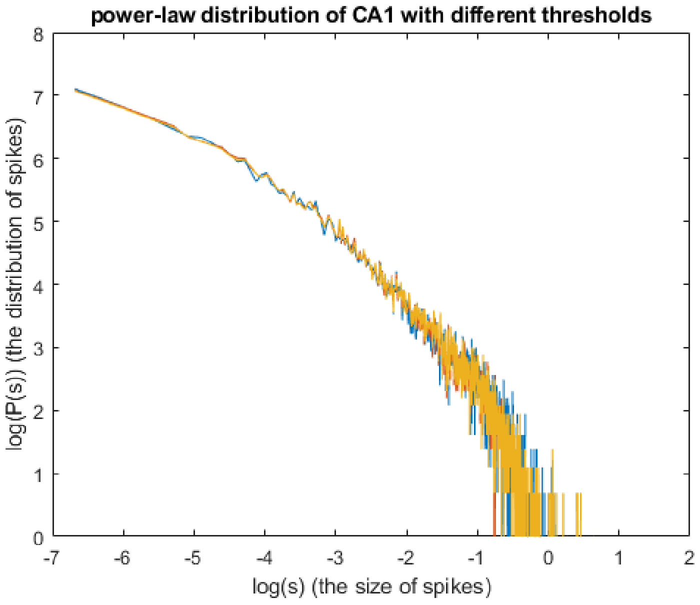

FIGURE 3. THIS FIGURE SHOWS THE ROBUSTNESS OF DIFFERENT THRESHOLDS

The threshold was set manually, but this makes no difference for the data. The figure 3. shows the power-law distribution with different settings of the threshold. The threshold of orange, blue, and red lines are separately 3,4, and 5. The Characteristics of data are independent of the threshold, excluding the errors caused by the manually setting of the threshold. The avalanche data of CA1 is displayed here as an example, this robustness also consists in the data of CA3 and hypothalamus.

Our data also shows the robustness of time scale,

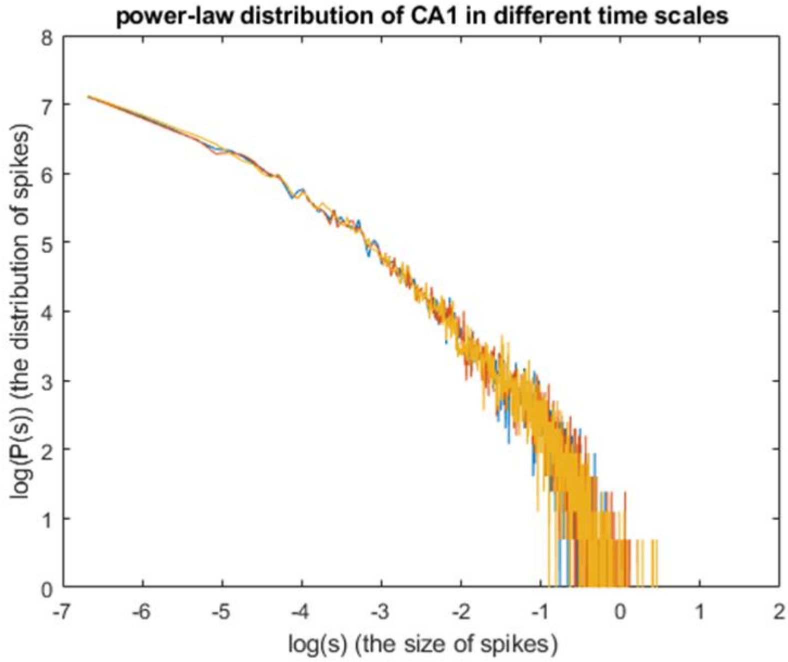

FIGURE 4. THIS FIGURE UNIVERSALITY IN DIFFERENT TIME SCALES

The figure 4. shows the distribution of spiking data of CA1 in different time scales, the orange, blue, and red lines separately represent the log-log distribution in “1-2000ms”, “1-5000ms” and “1-10000ms”.

The data picked in different time scales show the same distribution, indicating a scaling invariance property, which proves the power-law distribution. The data in CA3 and hypothalamus shows the same scaling-free behavior.

The previous analyses show the robustness; however, the region of brain dose effect the data shape.

The figure 5. shows the different power-law distributions in CA1 (blue), CA3 (orange), and the hypothalamus (red). The variance of the slope shows illustrating different critical exponents, which probably means different underlying dynamics. This exponent is related to the connection between neurons and the topological structure of the network.

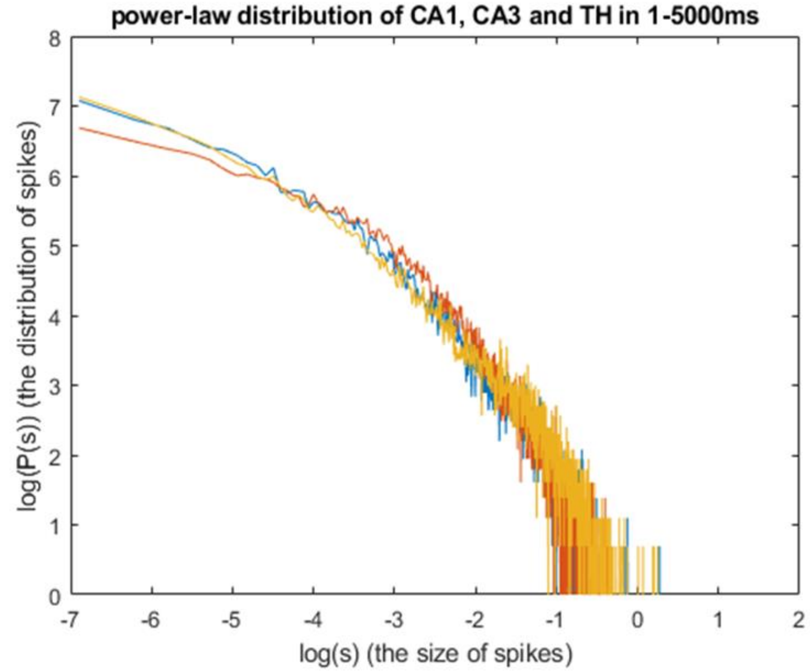

FIGURE 5. POWER LAW DISTRIBUTION OF DIFFERENT REGIONS OF THE BRAIN

III. CRITICAL EXPONENTS

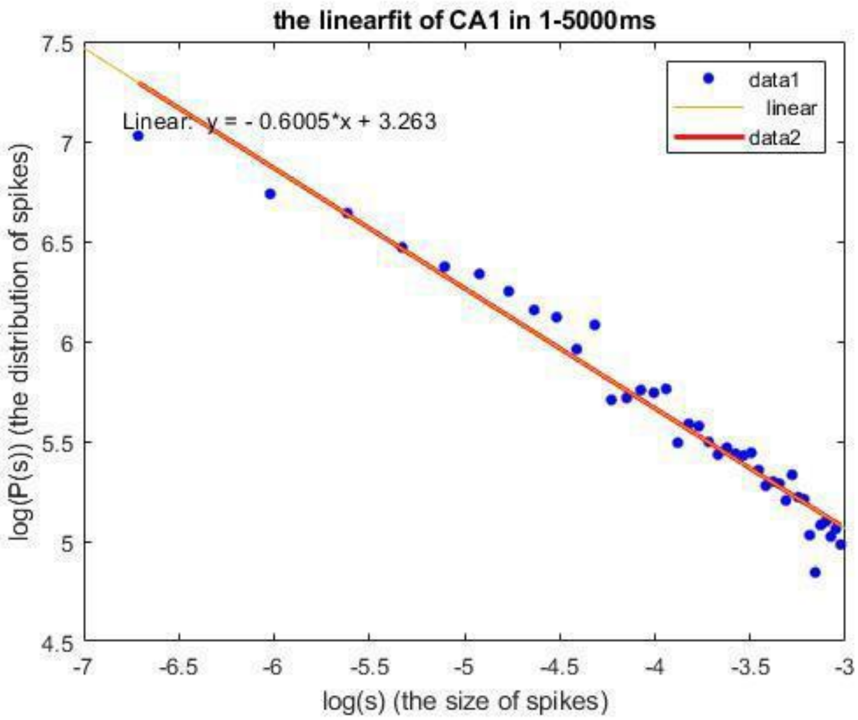

FIGURE 6. THE LINEAR FIT OF THE LOG-LOG FIGURE OF SIZE DISTRIBUTION.

We find out the power exponent of the avalanche size α different parts of the brain, listed as below:

Brain region	CA1	MB	CA3	APN	LP	TH	VPM
Exponents α	0.6	0.68	0.45	1.5	1.33	0.64	1.33

We linear fit the log-log figures in different parts of the brain. The cutoff point of every part is uniformly set to be 3. And the slope of every fitting line represents the critical exponents. We can find out that the exponent of CA1 and hypothalamus (TH) are almost the same, but the exponent of CA3 shows an obvious difference.

We also tested the relationship of time and size distributions and got the parameters γ and τ for different brain regions. The order parameters of LP and VPM are almost the same, might indicating similar dynamics.

	CA1	TH	CA3	APN	LP	VPM	MB
Exponents γ	0.705	0.847	0.750	0.903	0.892	0.844	0.832
Exponents τ	0.282	0.305	0.412	0.451	0.298	0.294	0.266

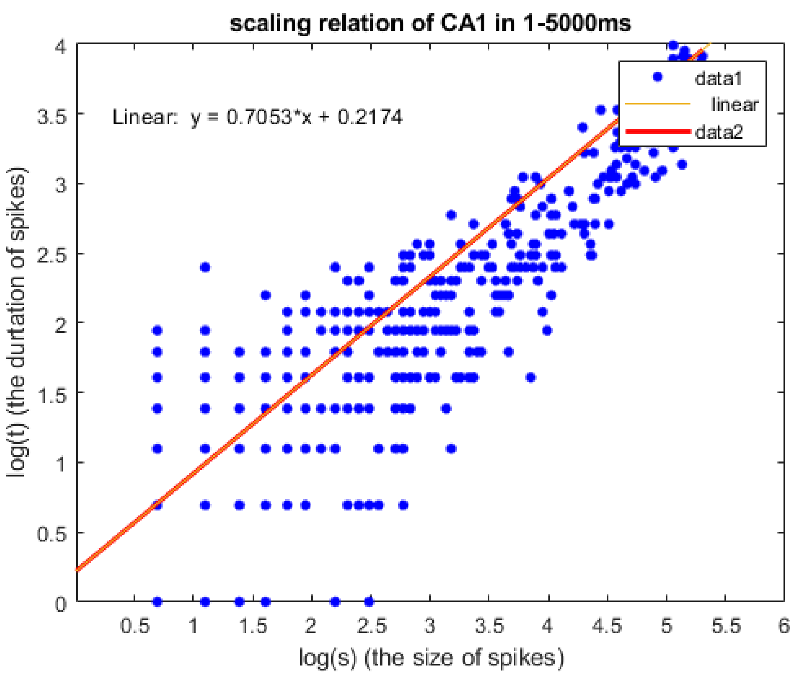

FIGURE 7. THE LOG-LOG FITTING OF TIME DISTRIBUTION

We found out the α and τ and calculated γ.

IV. INHIBITORY AND EXCITATORY SIGNALS

All the data used in previous slides are the excitatory spiking data, now we move to the inhibitory spiking data. Inhibitory data also exhibits all the universality properties above.

The inhibitory data also shows the scale free behavior and threshold is not related to the data shape.

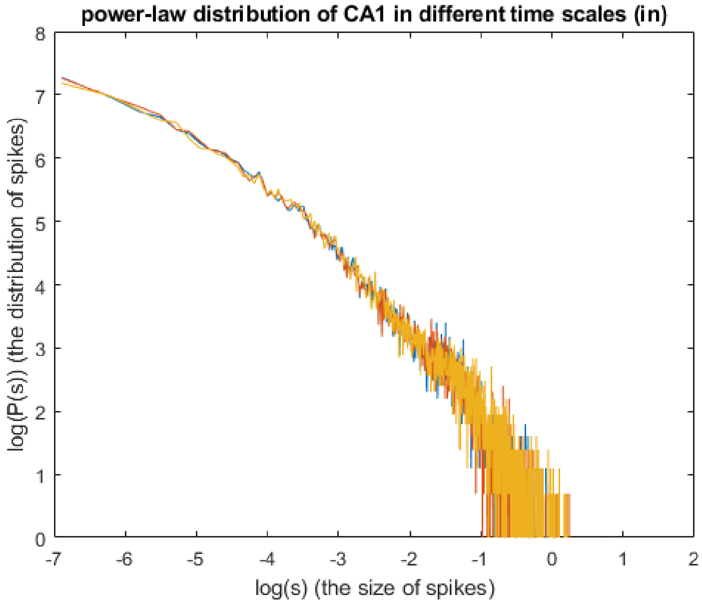

FIGURE 8. TIME INVARIANCE OF THE DATA OF INHIBITORY DATA.

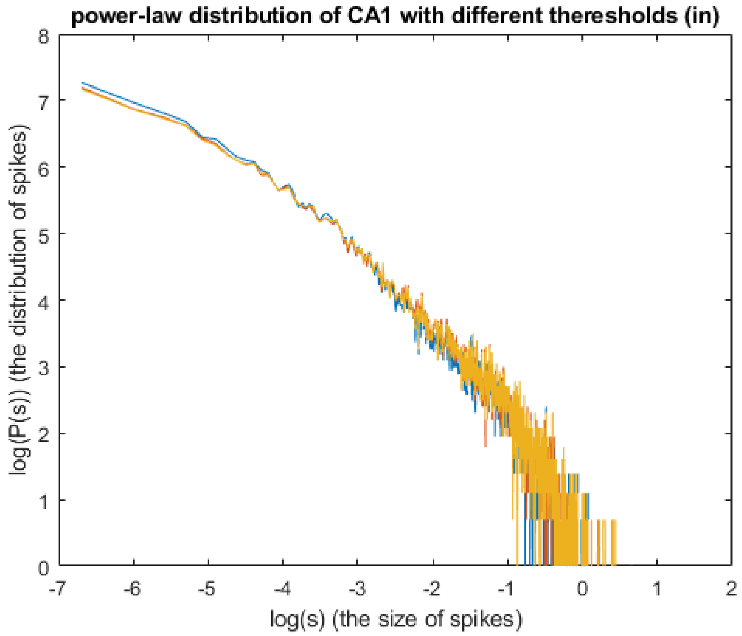

FIGURE 9. THE THRESHOLD IS NOT RELATED TO THE SHAPE OF INHIBITORY SIGNAL

In comparison with the excitatory signals, the excitatory and inhibitory data overlap in CA1 and Th, but the linear part of the distribution in CA3 is slightly different.

The new exponents τ , γ and α for inhibitory CA3 spiking signals are respectively 0.52, 0.69, and 0.67.

V. DISCUSSION

The nonlinear parts of the log-log plots seem too long, does that mean this model is not power law? The nonlinearity might be caused by the feedback mechanism in the recurrent network

The robustness of our data is solid evidence of a power law distribution Different underlying dynamics (such as SOC SOB) can uniformly lead to the power law behavior as long as it runs near the critical point.

In other words, this distribution is one intrinsic property of criticality Almost all the previous works show a power law distribution.

However, the feedback between neurons has not been considered yet, maybe a new model can be raised if we consider the loop in the neural systems. This can be a future goal of this project.

VI. REFERENCE

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