# The Topology of Networks and Cortical Synchrony

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#### Abstract

6 In cortex, there are several electrically coupled inhibitory interneuronal 7 networks which are thought to be critical to temporal coordination of 8 cortical and hippocampal oscillations seen in EEG. This is because gap-9 junction mediated networks have many properties, such as speed and 10 bidirectionality, desirable for neural synchronization. Gap junctions exclusively connect GABAergic neurons of the same type, implying distinct 11 12 functional roles for each type of inhibitory network. Using BRIAN, we built 13 a model simulating Layer IV excitatory neurons, which receive thalamic input and synapse onto gap-junction coupled interlaminar inhibitory 14 15 neurons, which in turn inhibit Layer VI excitatory neurons. The electrical coupling of the inhibitory layer drives synchronization of neuronal firing in 16 Laver VI which is dependent on the topology the electrically connected 17 18 inhibitory network. We investigated how lattice (nearest neighbor), random, 19 and small world topologies effect synchronization. Small world networks 20 occur when a percent of connections in a lattice network are rewired 21 randomly, resulting in the path length L between any two neurons scaling 22 with the logarithm of N. Small world networks are less likely to exist in 23 systems where links arise mainly from spatial or temporal proximity. We 24 found that small-world network topology for the gap-junction connected 25 inhibitory network results in the highest correlation between spiking of 26 neurons in the inhibited layer.

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## 28 1 Introduction

29 The neocortex is the outermost layer of the human brain, containing 6 morphologically and 30 functionally distinct layers, with layer IV receiving thalamic input and layer VI sending 31 afferents to the thalamus. At rest, or without stimulation, excitatory networks exhibit 32 independent and sparse firing. However, in recent years understanding the neuronal 33 underpinnings of cortical rhythms has attracted significant attention. In the waking brain, 34 small-amplitude EEG signals are largely asynchronous, with weak, intermittent synchrony 35 exhibiting temporal and spatial selectivity ([1]-[2]). Single neurons seem to exhibit Poisson 36 processes ([1]-[2]). Excitatory synchrony is a result of action potentials highly correlated in 37 time, which is key for a variety of important neural mechanisms such as spike timing 38 dependent plasticity, sensory coding, and gain modulation ([3]). Interplay between 39 excitatory and inhibitory neocortical neurons is essential for synchronous activity ([3]-[4]). 40 Synaptic inhibition likely sculpts the temporal activity patterns of cortical activity. In 1999, 41 Gibson et al. found extensive gap junction coupling between inhibitory interneurons of the 42 same type in neocortex. This suggests that these inhibitory networks have distinct, perhaps

input specific, roles in temporally sculpting excitation through quick and bidirectional gapjunction coupling.

45 While these electrically coupled inhibitory networks are likely important for fast cortical 46 oscillations, the general connectivity of these networks is unknown. Cortical oscillations 47 necessitate a threshold level of synchrony; in randomly connected Hodgkin-Huxley models almost 50 synapses per neurons are necessary ([1]-[3]), while in our model this number is 48 49 greatly reduced, presumably due to gap junction coupling. However, cortical networks are 50 likely not randomly connected, and networks that exhibit dense local clustering and sparse 51 long-range connections are more plausible. Thus, our goal in the current analysis was to 52 determine how the topology of an electrically coupled inhibitory network in neocortex 53 receiving input from cortical layer IV could contribute to synchronization of spiking in layer 54 VI.

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## 56 2 Hodgkin-Huxley model

All simulations were done in BRIAN, a python neural network simulator. We simulated 2400 excitatory and 800 inhibitory neurons with membrane potential described by the differential equation:  $\frac{dv}{dt} = \frac{I_m}{C_m} + \frac{\sigma * x_i}{tau}$ , where  $x_i$  is a keyword in BRIAN for Gaussian noise experiencing a standard deviation  $\sigma = 0.4$  and  $\tau = 15$  seconds in our simulation.  $I_m = I_e +$  $I_{Na} + I_K + I_{leak} + I_{gap}$ , where  $I_{gap} = w * (v_{pre} - v_{post})$  in inhibitory neurons, and =0otherwise. We also modeled the opening and closing of ionic channels and their respective differential equations (see supplementary materials).

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Figure 1: Cortical model

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# 67 **3** Cortical model

68 Our model is intended to simulate connectivity between three cortical layers: layer IV, layer 69 VI, and an inhibitory interneuronal layer that connects the two. Layer IV and layer VI 70 consisted of 1200 neurons each, whereas the inhibitory layer consisted of 800 neurons. Layer 71 IV excitatory neurons received 2  $\mu$ A of excitatory input to model thalamocortical neuronal 72 input. Layer IV was connected to the inhibitory network with 40% sparseness. These 73 inhibitory neurons were then connected to the layer VI with a 10% sparseness. Our 74 conceptual model is outlined in Figure 1.

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#### 76 4 Inhibitory connectivity

77 Three topologies were investigated among the 800 neuron 78 inhibitory network. First, we investigated a regular lattice 79 network of local neighbor-to-neighbor connections (Fig 80 In this network, each of the 800 neurons was 2A). 81 connected to nine neighboring neurons. Second, we 82 constructed a network of random connections (Fig 2B) 83 with a sparseness of 2%. Lastly, a small-world network was created following the Newman-Watts methodology 84 85 ([6]), (Fig 2C). This network was derived from the 86 network of regularly connected neighbors, and additional nonlocal connections were added with a specified probability of 0.5 for each neuron. The three networks 87 88 89 were constrained to have a total number of connections 90 varying by no more than 6%. All networks were defined with symmetric connection matrices to reflect the 91 92 bidirectionality of electrical synapses. It was found that 93 the weight of inhibitory connections had an effect on the 94 coefficient of variation, the ratio of the standard deviation 95 over the mean of spike timing for a particular neuron, for 96 layer VI neurons. Example neighbor-to-neighbor, random, 97 and small world networks (respectively) are shown to the 98 right in Figure 2, and network characteristics are in the 99 supplementary information.

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#### 101 **5 Results**

102 Figures 3, 4, and 5 show BRIAN plots of our cortical 103 model with inhibitory networks of 'regular', 'random', and 104 'small world' topologies respectively. For each figure, the 105 top three subplots are raster plots showing the temporal 106 location of individual action potentials for every neuron in 107 the designated layer. A single point on the graph represents an action potential, with the y-axis designating 108 109 the individual neuron (labeled 1-1200, or 1-800 for the 110 inhibitory layer), and the x-axis designating the time at which the action potential occurs. The bottom subplots of 111 112 each figure show voltage traces of a single, representative 113 neuron from each layer.

114 For each topology, spontaneous and random firing can be 115 seen in Layer VI in the absence of inhibitory connections 116 (Figures 3A, 4A, 5A). As mentioned in the description of 117 our model, this spontaneous firing was achieved using a 118 Gaussian noise current. In these figures, one can also 119 observe a perceptibly denser firing pattern in layer IV that, 120 in addition to the same Gaussian noise current, also 121 includes an external simulation of 2  $\mu$ A to simulate 122 thalamic input. As expected, action potentials are tightly





temporally coordinated in the inhibitory layers, a result of the fast, bidirectional electrical coupling via gap junctions.

When the inhibitory layer is connected to Layer VI, tight, oscillatory synchronization is clearly observed in temporal coordination with the firing pattern of the inhibitory layers (Figures 3B, 4B, 5B). Visually, the extent of Layer VI synchronization is not perceptibly different between the tested inhibitory network topologies. However, when quantitatively investigated we found differences between the degree of synchronization across the inhibitory network topological types.





Figure 3: Regular topology, with and without inhibitory connections to Layer VI





Figure 4: Random topology, with and without inhibitory connections to Layer VI





Figure 5: Small world topology, with and without inhibitory connections to Layer VI

134 The synchrony of firing in the inhibited layer VI excited neurons was evaluated using cross-135 correlation tools in BRIAN. Correlograms, shown in Figure 6, were computed by comparing a single test neuron to all other neurons in the layer. The spikes were compared in 1 ms bins 136 137 and compared within 100 ms before and after the initial spike. Figure X shows the same test 138 neuron from layer VI and it's cross-correlation with all other layer VI excitatory neurons, 139 plotted separately for inhibition by regularly, randomly, and small-world connected 140 inhibitory networks. While all inhibitory network topologies effectively synchronize layer 141 VI, and clearly show the highest correlation value for zero time shift, the values of the 142 correlation differ, the highest values of correlation are displayed by the small-world network 143 (note the color scales in Figure 6).



144 Figure 6: Layer VI correlograms for regular, random, and small world inhibitory networks

Since the small world network exhibited the greatest degree of synchrony, we then investigated how the degree of gap junction coupling affected synchrony using the coefficient of variation (standard deviation/mean), a measure of spike-noise at the level of the individual neuron. We simulated the network 5 times for each value of gap junction conductance investigated between 0-0.85 millisiemens. These values are shown in Figure 7. There is a general trend toward a higher coefficient of variation for higher values of gap junction conductance.

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## 153 6 Discussion and future directions

These results demonstrate how the synchronous firing of large populations of neurons can be driven by an inhibitory interneuronal network coupled via gap junctions. In particular, we have demonstrated how the network topologies of an electrically connected inhibitory layer impacts the degree of synchronization in the inhibited layer, and demonstrated the value of the low path length and high clustering of the small world network.

We would like to further investigate complex topologies and their effects on synchronization, such as scale free network models. Importantly, we would like to achieve biophysical specificity in neuronal subtypes across the layers, which were not implemented in this model. We could then investigate how different inhibitory cell types, such as the well-known fast spiking and low threshold spiking interneuron types, may interact with coupling topologies. Furthermore, we are working on an expanded cortical model including the inter-layer processing that occurs in layer II/III before thalamic input reaches layer VI.



$$\frac{dn}{dt} = \propto_n * (1-n) - \beta_n * n$$





Figure 8: The average length of any two neurons in the simulated networks



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Figure 9: The probability that if neuron X is connected to Y and Y is connected to Z such that X is 183 also connected to Z





Figure 12: Small world network with 0.8 mS conductance

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#### 222 References

- 223 [1] Destexhe et al., Spatiotemporal analysis of LFP, J neuro 1999
- 224 [2] Maldonado P et al. Dynamics of striate cortical activity. Cereb Cortex 2000
- 225 [3] Shadlen MN, Newsome WT. Noise, neural codes and cortical organization. Curr Opin Neurobiol 4: 226 569-579, 1994.
- 227 [4] Softky WR, Koch C. The highly irregular firing of cortical cells is inconsistent with temporal 228 integration of random EPSPs. J Neurosci 13: 334-350, 1993.
- 229 [5] Wang XJ. Neurophysiological and Computational Principles, Physiol. Rev.2010
- 230 [6] Newman MEJ. The structure and function of complex networks. SIAM Review 45(2), 167-256, 231 2003.
- 232 [7] Freeman WJ. Mass Action in the Nervous System. New York: Academic, 1975.
- 233 [8] Wang XJ, Buzsáki G. Gamma oscillation by synaptic inhibition in a hippocampal interneuronal 234 network model. J Neurosci 16:6402-6413, 1996.
- 235 [9] Borhegyi Z, Varga V, Szilgyi N, Fabo D, Freund T. Phase segregation of medial septal 236 GABAergic neurons during hippocampal theta activity. J Neurosci 24: 8470-8479, 2004.
- 237 [10] Shadlen MN, Newsome WT. Noise, neural codes and cortical organization. Current Opinions 238 Neurobiology 4: 569-579, 1994.
- 239 [11] Wang XJ, Golomb D, Rinzel J. Emergent spindle oscillations and intermittent burst firing in a 240 thalamic model: specific neuronal mechanisms. Proc Natl Acad Sci USA 92: 5577-5581, 1995.
- 241 [12] Andersen P, Eccles J. Inhibitory phasing of neuronal discharge. Nature 196: 645–647, 1962.