Neural Correlates of Decision Making using Oscillatory Networks and Feedback Loops

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Abstract: We present a simple model of how binary decisions can be made at the neuronal level using an oscillating circuit that encodes information about the choice to be made and a decision-making circuit that influences the strength of coherence, and thus robust information transfer, of upstream oscillating networks. Additionally, three mechanisms leading to network coherence are investigated. The first involves delayed excitations from a single oscillator (DE model), the second includes propagating pulses in a excitable network (PP model), and the third employs a small network of phase locked, weakly coupled oscillators (WCO model). Our results show that the DE and PP models eventually achieve 100% accuracy in performance on the decision making task while the WCO model never reaches 100%. Additionally, the DE model adapts most quickly to the task while the PP model requires more learning trials than the DE model. Finally, the WCO model does adapt to the task however its output decreases in amplitude over multiple trials.

Introduction

Four- to 12- Hz theta oscillations have been shown to be involved in complex decision-making behaviors such as spatial navigation in rodents[7] and working memory and learning in primates[5]. Additionally, Jones and Wilson (2005)[3] revealed that activity in the medial prefrontal cortex (mPFC) is more highly correlated with activity in CA1 hippocampal cells when rodents are engaged in a decision-making task. Furthermore, the cross-correlation between activity in these regions is significantly reduced when an animal makes an incorrect decision indicating that coherence between mPFC and CA1 activity is associated with correct choice production. As a result of these findings we created a simple model of how binary decisions can be made at the neuronal level using an oscillating circuit that encodes information about the choice to be made and a decision-making circuit that influences the strength of coherence, and thus robust information transfer, of upstream oscillating networks.

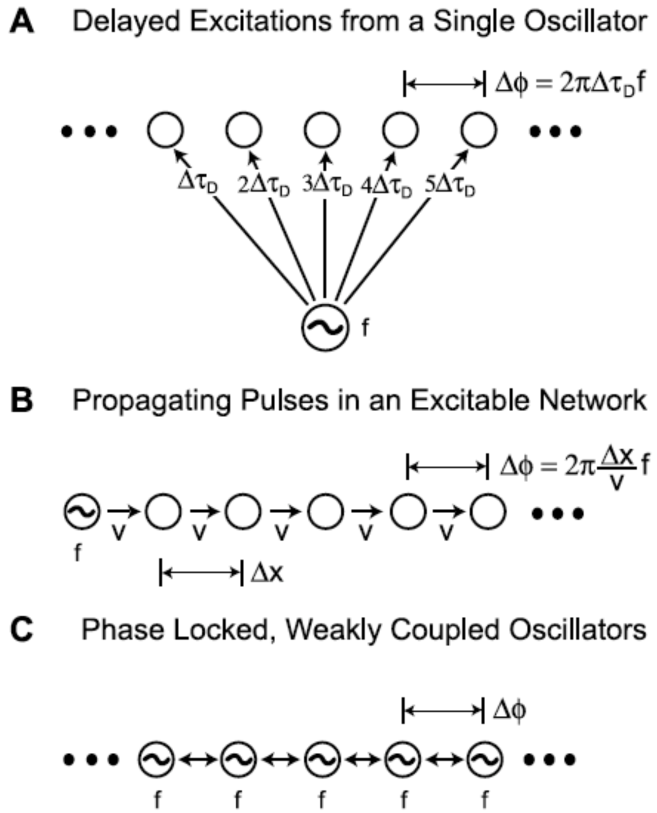
Experimental

We propose a model for decision-making in which synchronization of cortical waves affects a downstream circuit whose output represents a choice. Feedback from the decision-making (DM) circuit to the lower-order oscillating (LOO) region influences the strength of wave coherence such that a correct choice enhances coherence and an incorrect choice decreases it. Thus, the model can adjust its output behavior to maximize the probability of making a correct choice. We investigate how alternate mechanisms for production of synchronized cortical waves can affect both the accuracy and adaptability of down-stream DM circuits.

We inject a current into the LOO region, which oscillates at a baseline level, and the downstream DM circuit must decide whether or not the current amplitude is above a certain threshold. The DM circuit indicates an affirmative response choice by firing and a negative response choice by remaining silent. Because the DM circuit has no prior knowledge as to what the threshold current amplitude is, it initially generates a random output function. However through feedback, correct responses strengthen coherence of activity in the upstream LOO region, and enhanced coherence produces a stronger signal that is more likely to induce a correct choice from the DM circuit.

Three models of oscillation coherence, that were originally proposed by Prechtl et al (1999)[6], are investigated to determine how upstream oscillatory current sources influence a DM circuit. As show in figure 1A, a Delayed Excitations (DE) model consists of a single oscillating cell that propagates its signal to down-stream neurons through multiple delay lines. Figure 1B shows a Propagating Pulse (PP) model in which transmission of pulses along a network produces wave motion. Finally, as shown in figure 1C, a Weakly Coupled Oscillators (WCO) model consists of a network of oscillators interacting through many weak connections.

Figure 1. Proposed Mechanisms for Generation of Wave Coherence



(Prechtl et al. 1999)

Enhanced coherence in the first two models involves a strengthening of synaptic connections. Conversely, in the WCO model, enhanced coherence depends on weak interactions between local oscillators that can affect the timing of a second neuron, but cannot distort the form of that neuron's oscillating limit cycle[6].

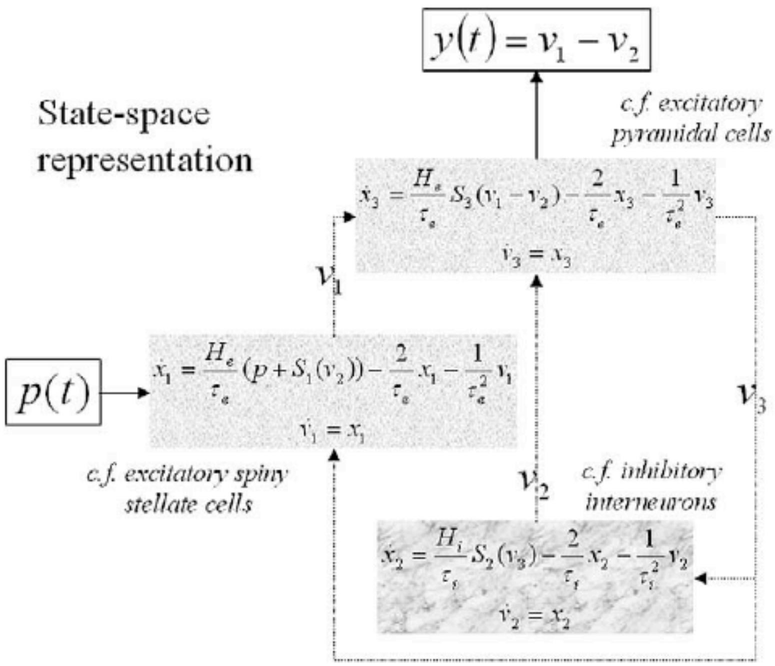
Consequently, we hypothesize that the maximum probability of making a correct choice and the amount of time necessary to attain maximum probability will be differentially affected by the mechanism of oscillation synchronization. We predict that the probability of the DM circuit producing a correct response will be greater when upstream coherence is achieved through a mechanism described by the DE or PP model compared to the WCO model. However, the DM circuit will require less time to achieve its maximum probability of generating a correct response when upstream oscillations are governed by a mechanism described by the DE or PP models compared to the WCO model.

Methods

Modeling the Oscillator

The DE and PP model include propagation of an oscillatory signal to a network of excitatory neurons either in parallel or in series respectively, while the WCO model consists of several oscillators coupled together. Oscillating neurons were generated using Jansen's Model[2] as displayed in figure 2.

Figure 2. Jansen's Model for Oscillating Networks



(David & Friston 2003)

In this model, an excitatory neuron or network of neurons (c.f. excitatory pyramidal cells) oscillate(s) by receiving feedback input from excitatory and inhibitory local interneurons (c.f. excitatory spiny stellate cells, c.f. inhibitory interneurons). External stimulation is represented by a time-dependent pulse density, p(t). The parameters H_e and H_i control synaptic gain by limiting the amplitude of post-synaptic potentials. τ_e and τ_i are the sum of excitatory and inhibitory rate constants of spatially distributed delays in the dendritic arbor. S_k represents a transformation of the average membrane potential of the neuronal population into an average rate of neuronal spikes. The instantaneous transformation is described by the sigmoid fuction:

$$S_k(v) = (c_k^1 e_0) / (1 + \exp(r(v_0 - c_k^2 v)))$$

for the k^{th} subpopulation. The constants c_k^1 and c_k^2 represent the average number of synaptic contacts in the excitatory and inhibitory feedback loops respectively, and v_0, e_0, and r resolve the shape of the nonlinear function.

Modeling Excitatory Neurons

Excitatory neurons of the DE and PP models were programmed to generate an output if input from the presynaptic oscillating neuron produced a voltage change in the postsynaptic neuron greater than a given threshold value. Over time, as the circuit outputs correct responses, the resulting feedback will increase the synaptic connections within the circuit, thus decreasing noise and increasing the success rate.

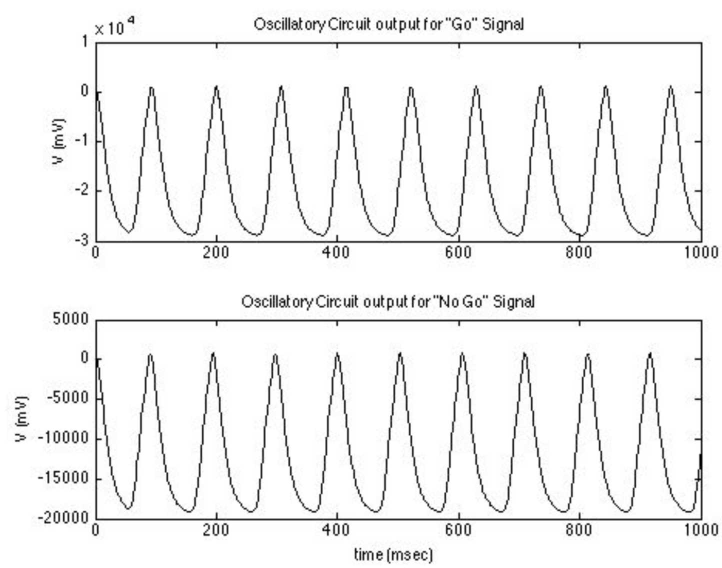
Modeling the Decision Making Neuron

The DM neuron was postsynaptic to excitatory neurons influenced by a single oscillator in the DE and PP models and postsynaptic to several weekly coupled oscillators in the WCO model. The DM neuron was modeled like an excitatory neuron in the first two models except the output of this neuron influenced the activity of the oscillating network (oscillating and excitatory neurons) via a feedback loop onto each lower order neuron.

Results

When applying the different circuit models to the decision paradigm, the results were generally as expected. The difference in signal between the go and no-go trials was largely a matter of amplitude, however a slight phase disparity existed as well. This can be seen in Figure 3.

Figure 3. Go and No-Go Oscillator Signals



Both the DE and PP circuits consisted of one oscillator and four excitatory neurons.

As shown in figure 4, the circuit corresponding to delayed excitations from a single oscillator adapted to the task more quickly, while the propagating pulses were somewhat slower. However, both circuits achieved a final success rate of 100%, which is in contrast to the WCO circuit.

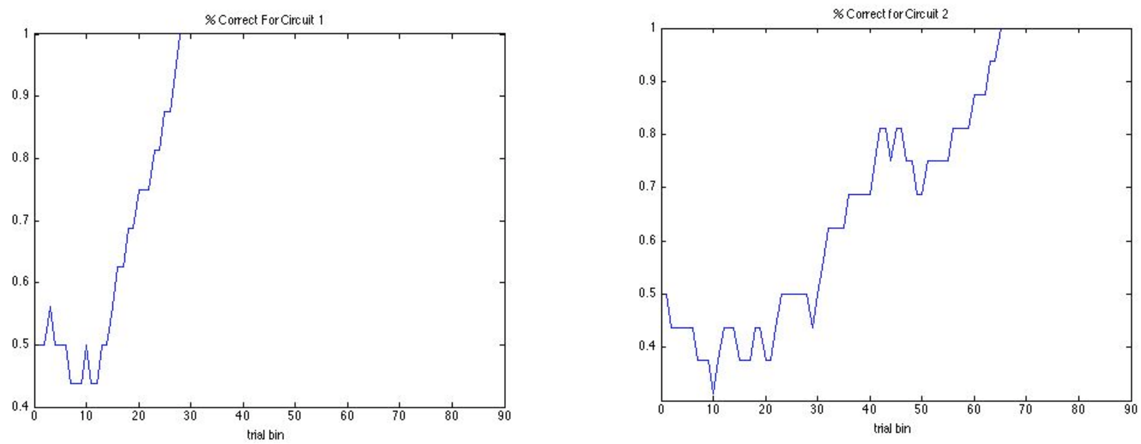
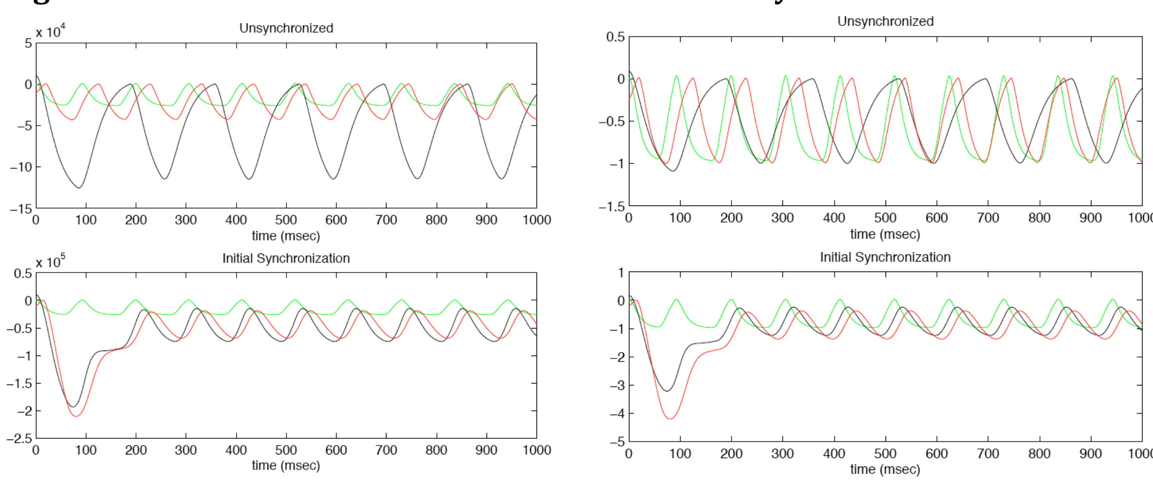


Figure 4. DE and PP Circuit Results

Unlike the DE and PP models, which used a single excitatory network to make decisions, the WCO model used an oscillating network in addition to the upstream oscillating network, to make decisions. Figure 5 shows the resulting difference between the synchronized and unsynchronized activity of three oscillators on both a normalized and unnormalized scale. As the oscillator circuit chooses correctly, the synchronization increases, as has been observed experimentally[3].

Figure 5. Normalized and Unnormalized WCO Activity



Because the DE and PP models used amplitude coding for the decision making process, we originally used the same type of coding for the WCO model. This coding scheme did not supply an appropriate adaptability result that could be compared between the three models because the amplitude of the oscillating circuit waxes and wanes over time (unlike the excitatory circuit, which produces a steady output). The adaptability of the WCO model using amplitude coding is shown in figure 6. However, the WCO model was achieving synchronization over time, which lead us to the conclusion that the oscillating circuit required a different coding scheme. Figure 7 reveals that the network activity before and after the decision task is quite different, both in amplitude and phase.

Figure 6. WCO Circuit Results

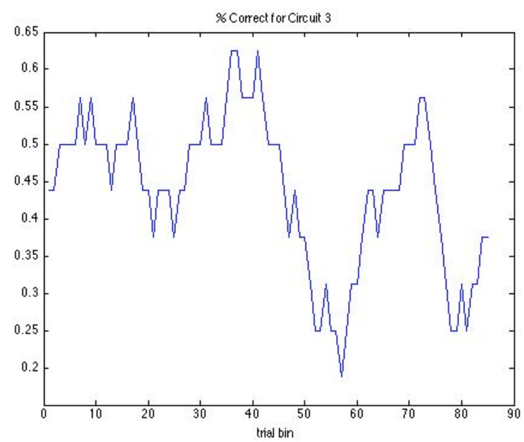
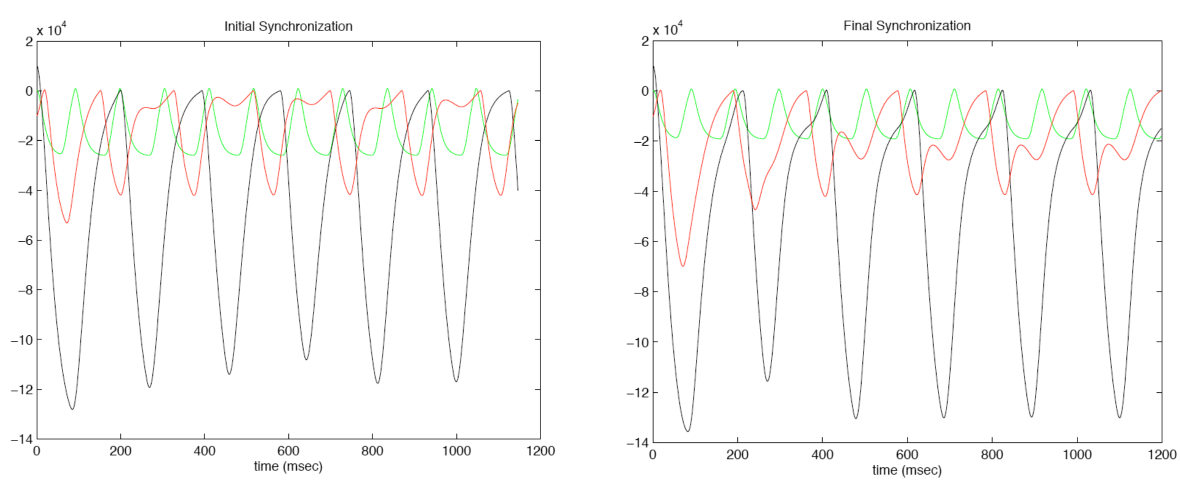
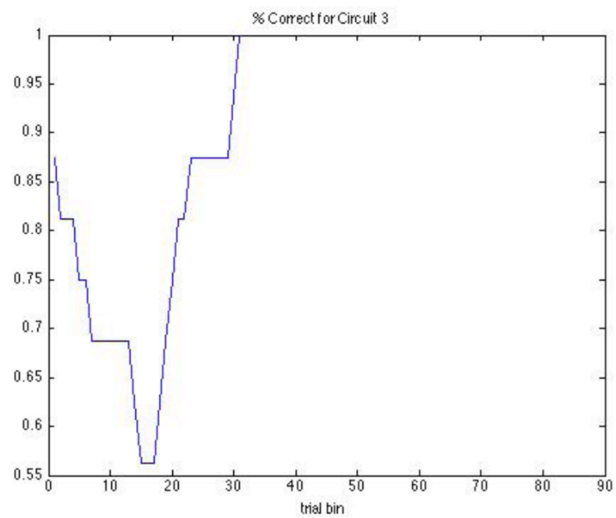


Figure 7. Unnormalized WCO Circuit Before and After Decision Making Trials



Consequently, we tried a phase coding scheme for the oscillating decision-making circuit. Indeed, when the difference in phase between oscillating units, instead of the amplitude of the complete circuit, is used to code which decision the circuit will make, the model adapts to the paradigm as shown in figure 8.

Figure 8. Adaptability of the WCO model using phase coding for decision making Note the difference from amplitude coding as shown in figure 6.



Discussion

The DE and PP circuits worked as expected using amplitude coding in excitatory decision-making circuits. The WCO model failed to adapt to the decision-making paradigm when amplitude coding of the summed circuit activity was used, however, adapted very well when phase coding between oscillating units was used.

In future work, it would be interesting to increase the complexity of the circuits by adding confounding activity between intrinsic units. This may more accurately represent the error rate in experimentation. Additionally, a biological decision making circuit likely receives competing input from multiple upstream networks which should also be included in the three simple models presented here. Investigating the performance of these improved models with respect to competition could also gauge how well these models truly model the neural dynamics of decision making.

References

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