

Research Statement

Youngmin Park

1 Introduction

I develop dimension-reduction methods for neural network models using dynamical systems theory, and in turn, use these findings to understand how biological neural networks function and how they are maintained. I specialize in oscillator coupling theory, numerical bifurcation theory, and often employ general perturbation methods. My research includes two complementary directions. The first involves generalizing oscillator theory from weak coupling to strong coupling, and the second involves reducing the dimension of molecular motor transport problems.

Details of my work in coupled oscillator theory are in Section 2. In summary, I introduced a generalization of coupled oscillator theory, allowing mathematicians to include subtle but important details in reduced phase models that are often neglected by idealized models. This work opens the way for a thorough re-examination of decades of existing oscillator theory that assume either idealized oscillators with strong coupling or general oscillators with weak coupling.

Details of my work in the dimension-reduction of molecular motor transport problems are in Section 3. In summary, I reduced the dimension of a vesicle transport model in confined spaces and analyzed its bifurcations. The model behavior was consistent with experimental observations, suggesting that fluid dynamics forces, molecular motor forces, and the shape of the confinement play significant factors in neural maintenance. This work opens the way for detailed, tractable studies on neural maintenance and how defects in maintenance affect brain function.

2 Neural Oscillations

My work on neural oscillations falls within the broader work of oscillator theories oriented towards understanding pathological neural behavior such as Parkinsonian tremors, epilepsy, and cardiac alternans. Overall theoretical work in these directions has been promising, but tend to use one of three starting points: mathematically tractable but very abstract models [10], particular forms of symmetry [4], and the *weak coupling* assumption, or more generally, the *linear* approximation [3]. The weak coupling assumption has long been an invaluable theoretical tool to understand neural behavior consisting of only small deviations from a known behavior such as quiescence or oscillatory activity. Indeed, the weak coupling assumption has driven much of my work [12, 13, 14].

While these assumptions facilitate theorists to a potent degree and were perhaps close to experimental conditions some decades ago, they are now far from modern experimental conditions. Modern experiments are often done *in vivo*, where neurons are often strongly coupled, heterogeneous, and interact nonlinearly. These properties hold in both normal and pathological neural function, so it follows that pathologies can not

always be understood using abstraction, symmetry, or linearity. Therefore, my field must develop theories that directly address *strongly coupled* networks of *heterogeneous* neurons with *nonlinear* interactions at multiple scales. We must understand the brain as it is.

To this end, *I have formulated a theory of strongly coupled oscillators* [16]. Consider the coupled system of N ODEs,

$$\dot{X}_i = F(X_i) + \varepsilon \sum_{j=1}^N a_{ij} G(X_i, X_j), \quad i = 1, \dots, N, \quad (1)$$

where each system admits a T -periodic limit cycle $Y(t)$ when $\varepsilon = 0$. We allow $\varepsilon > 0$ not necessarily small and assume general smooth vector fields $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ and a smooth coupling function $G : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}^n$. The scalars a_{ij} modulate the strength of coupling between pairs of oscillators, whereas ε modulates the overall coupling strength of the network.

Let θ_i be the phase of limit cycle Y_i and define the phase difference $\phi_i = \theta_i - \theta_1$ for $i = 2, \dots, N$. Under general conditions, it is possible to derive a phase reduction of $N - 1$ equations,

$$\begin{aligned} \dot{\phi}_i = & \varepsilon \sum_{j=1}^N a_{ij} \mathcal{H}(-\phi_i, \phi_2 - \phi_i, \dots, \phi_N - \phi_i, \phi_j - \phi_i) \\ & - \varepsilon \sum_{j=1}^N a_{ij} \mathcal{H}(0, \phi_2, \dots, \phi_N, \phi_j), \quad i = 2, \dots, N, \end{aligned}$$

where

$$\mathcal{H}(\eta_1, \dots, \eta_N, \xi) = \frac{1}{T} \int_0^T \mathcal{Z}(\eta_1 + s, \dots, \eta_N + s) \cdot G(s, \xi + s) ds,$$

and \mathcal{Z} is the higher-order phase response curve from [19]. My theory produces Taylor truncations of the function \mathcal{H} . The higher the truncated order, the more accurately my theory reproduces phase-locked states of N oscillators.

As a first step, I verified my theory using the mathematically tractable complex Ginzburg-Landau (CGL) model with diffusive coupling. The coupling function has two parameters: ε for the coupling strength, and d for the degree to which opposing species affect coupling. Both parameters significantly affect the phase-locking properties of the coupled CGL models. I show the accuracy of the theory in the left panel of Fig. 1, where the strong coupling theory (green, tenth-order) coincides strongly with the ground-truth (black) relative to existing coupling theory (purple, second-order) [20].

Next, I tested this theory using a realistic four-dimensional model of a thalamic neuron. Figure 2 shows how my theory predicts phase differences in two thalamic oscillators for different coupling strengths (higher order corresponds to greater accuracy). The right-hand side of the reduced ODE (labeled $-2\mathcal{H}_{\text{odd}}$) is shown in the top row. Roots and slopes correspond to existence and stability of phase-locked states. Phase differences

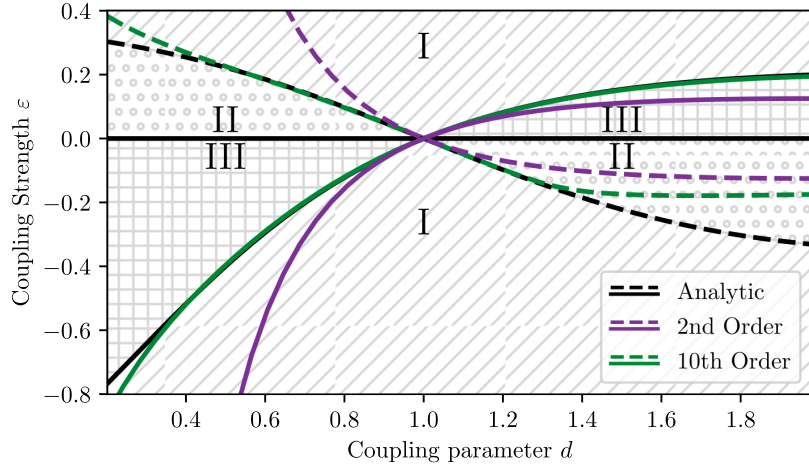


Figure 1: Validation of strong coupling theory using diffusively coupled complex Ginzburg-Landau (CGL) models. The plot is a two-parameter bifurcation diagram in coupling parameters ε and d . Synchrony is only stable in regions I and II, whereas antiphase is only stable in regions I and III. Black solid lines denote boundaries where the system switches between stable and unstable synchrony (ε_s). Black dashed lines denote boundaries where the system switches between stable and unstable antiphase (ε_a). Purple solid, dashed: bifurcations detected using 2nd order interaction functions from [20]. Green solid, dashed: bifurcations detected using 10th order interaction functions. **This result shows that my strong coupling theory substantially outperforms existing coupling theory.**

of the full model is shown in the bottom row for 20 difference initial conditions. Coupling strength increases from weak ($g_{\text{syn}} = 0.02$, left column) to strong ($g_{\text{syn}} = 0.25$, right column). **Roots of the fourth-order reduction coincide with the steady-state phase-locked states of the full system.**

These results demonstrate how my theory is not specific to particular models or coupling functions. Indeed, my theory naturally applies to general coupled oscillator models including those found in physics, biology, and chemistry (the only requirement is that the vector fields of the models are sufficiently smooth).

2.1 Future Work

In the long term, I will further develop mathematical methods to analyze neural networks in several important directions. I will augment my theory to include heterogeneity (including n:m phase-locking), making my theory applicable to far more realistic neural networks. I will augment my theory to include oscillator death to understand interactions between bursting neurons in networks such as subcortical networks and central pattern generators. Finally, I will derive the mean-field equations for neural models (in contrast to existing mean-field theories that use idealized models [10]) to understand

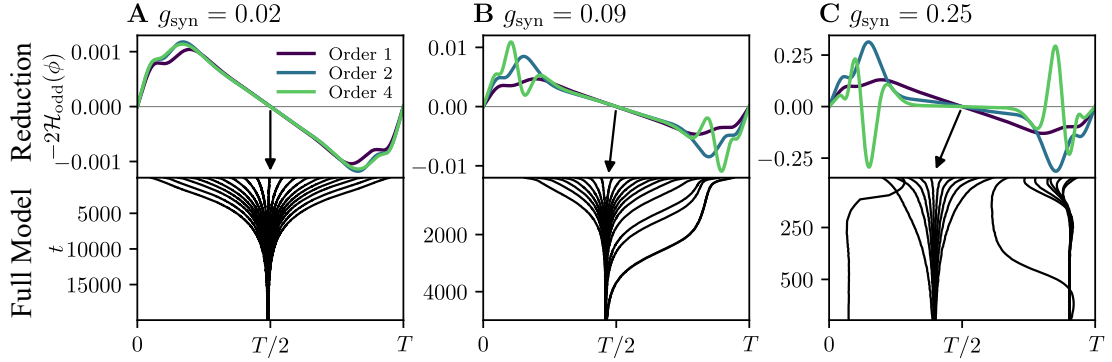


Figure 2: Performance of the strong coupling reduction compared to a full simulation of thalamic neuron models. A: Weak coupling. The right-hand side of the reduction (top) is shown for different orders (higher is more accurate) and coincides with the long-term phase difference of the full model (bottom). B: Moderate coupling. The reduction (top) coincides with the full model (bottom). C: Strong coupling. The reduction (top) only agrees with the full model (bottom) at order 4.

how microscopic neural interactions influence large-scale brain activity.

3 Neural Maintenance: Dendritic Spines

While neural interactions are an important part of understanding how brains function, questions of neural maintenance are equally important. Seemingly minor defects at the nanometer-to-micrometer scale can result in serious disorders at the scale of the whole brain. For example, deficits in molecular motor transport in axons are implicated in neurodegenerative diseases such as Parkinson’s disease [8]. Another example involves pyramidal neurons, the most ubiquitous type of neurons in the mammalian neocortex. They feature tens of thousands of excitatory convergent synaptic inputs, where most incoming synaptic signals terminate on sub-micron bulbs known as dendritic spines [9]. Spines exhibit a significant degree of morphological plasticity [6] with pathological spine formation implicated in disorders such as Autism spectrum disorder and Alzheimer’s disease [17]. How spines function and how they are maintained is therefore an important question.

Dendritic spines receive surface proteins by protein-carrying vesicles that squeeze through the neck of the spine and eventually fuse with the spine head [2]. The motion of such vesicles has been observed to not involve only translocation, where the motion is unidirectional, but includes corking, where the vesicle gets “stuck” in the spine neck, and rejection, where the vesicle initially enters the spine but eventually reverses direction and exits [11]. **How molecular motors affect changes in vesicle direction is the goal of ongoing work.**

Indeed, the importance of this problem has spurred an extensive literature on the

effects of molecular motors on vesicle dynamics, including the computation of the distribution of cargo velocities [7], computing mean first passage times to transport targets on dendritic morphologies [1], and the generation of bidirectional motion despite the assumption of symmetry [18]. *However, these studies often neglect or fix drag forces which could arise from constriction effects in the unique bulbous shape of dendritic spines.*

To this end, I have reduced a fluid dynamics model of dendritic spine transport into a tractable fast-slow system:

$$\begin{aligned}\frac{dZ}{dt} &= U, \\ \varepsilon \frac{dU}{dt} &= F(U) - \zeta(Z)U.\end{aligned}\tag{2}$$

F is the net motor force, U is the vesicle velocity, Z is the vesicle center of mass, and ζ is the function that captures information about the constriction geometry at position Z .

Standard dynamical systems theorems (Fenichel theory) allows us to view the equivalent system in the limit $\varepsilon \rightarrow 0$,

$$\frac{dU}{ds} = F(U) - \zeta U,$$

where ζ is a parameter and $s = t/\varepsilon$. Using this reduced system, I proved the unique existence of unidirectional motion for sufficiently close vesicle-to-spine diameter ratios. The two-parameter diagram in the confinement factor ζ and the ratio of up- and down-motors ϕ is shown in Figure 3. In summary, the two-parameter diagram (panel D) predicts that smaller ζ (wider constrictions) tend to show bidirectional motion, whereas larger ζ (tighter constrictions) predict unidirectional motion.

This result is consistent with experimental observations of vesicle trajectories in the literature [15]. Experimentally-observed vesicles traveling into thin spines with tight constrictions tend to exhibit unidirectional motion, whereas vesicles traveling into wider, stubby spines tend to exhibit bidirectional motion. The consistency suggests that fluid flow in dendritic spines combined with molecular motor forces contribute significantly to bidirectional vesicle motion. Neurons may modify spines to become wider or thinner depending on the needs of the synapse.

3.1 Future Work

While mean-field models are useful with large numbers of agents, sub-micron spines only contain a few dozen myosin motors. *The effects of noise are prominent, and we can not rely on mean-field models to fully understand how spines function.* Thus I will shift my attention to understanding how finite numbers of stochastic motors affect the probability of translocation.

Before turning to the probability of vesicle translocation, I will focus on the specific question of the mean first passage time (MFPT) to switch the direction of vesicle motion. This switching is a well-known “tug-of-war” effect [5] that has not been studied using

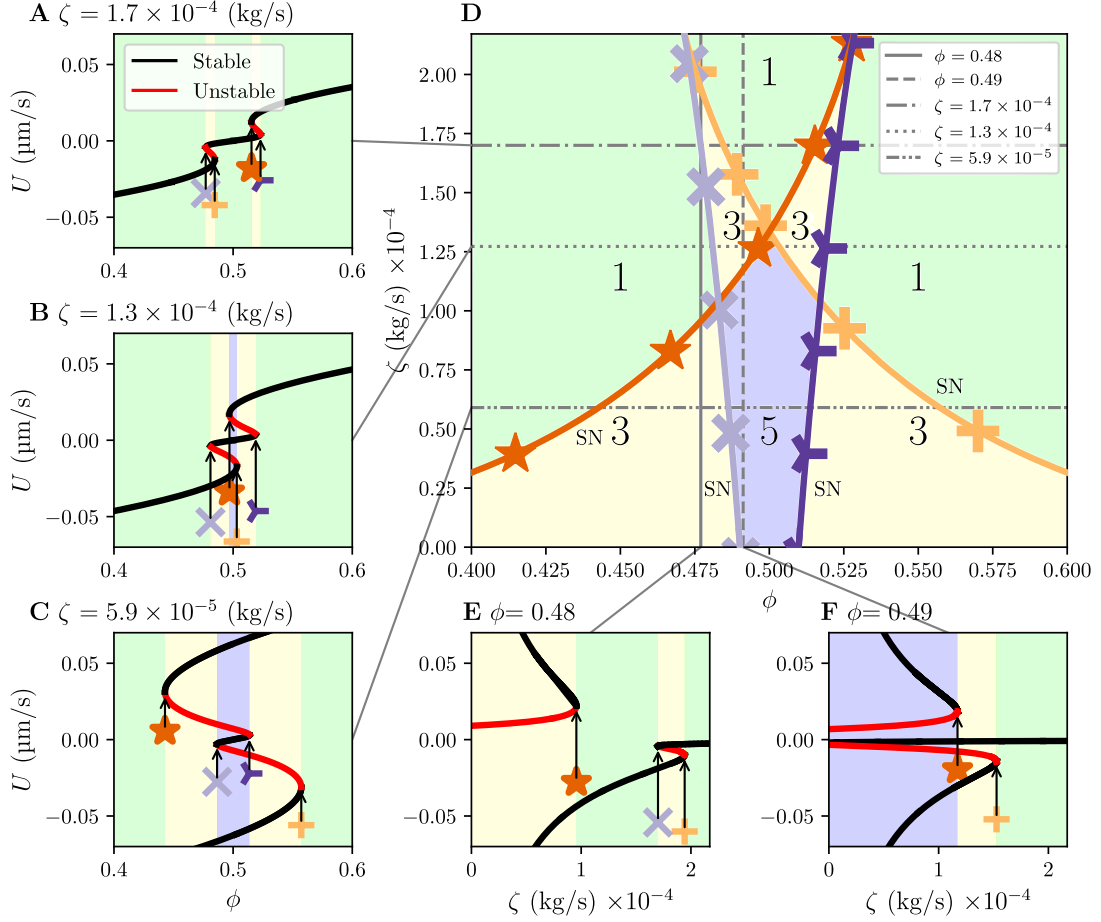


Figure 3: Two parameter bifurcation diagram in ϕ and ζ . Saddle-node (SN) bifurcations are shown in (D) as colored branches with a unique color and symbol. Numbers in (D) indicate the total number of fixed points in the corresponding region of parameter space. Subplots A, B, C, E, F, show one-parameter slices of the two-parameter diagram. Saddle-nodes are labeled with the corresponding branch color and symbol. The critical vesicle-to-spine diameter ratio at the cusps is roughly $2 \mu\text{m}/3 \mu\text{m}$.

myosin motors or with constrictions. I have developed an agent-based simulation where individual myosin motors attach and detach with position-dependent rates in order to compute MFPTs. However, agent-based simulations are computationally expensive: to obtain mean first passage times (MFPT), roughly 5-10 trials must be run in parallel over 50-100 time units with time steps on the order of $1\text{e-}6$. These requirements mean dozens of hours per simulation. I will overcome the problem of long simulation times through the use of a master equation approximation.

Diversity Statement

Youngmin Park

I am a native South Korean who has lived as a minority for most of his life. I grew up with wealth in poverty-stricken countries such as Swaziland and the Philippines, and spent the latter part of my youth in wealthy nations such as Korea and the United States, while still in poverty. My experiences with poverty and the struggles of low-income peoples has profoundly influenced my conduct in social contexts. In all social situations, ranging from casual to professional, I am intensely aware of how my interactions affect (and do not affect) other people. *I strongly support The Cooper Union's commitment to diversity.*

In the professional setting, my conscious efforts at equity, diversity, and inclusion primarily occurred during teaching. In my four years of teaching, I had the pleasure of teaching hundreds of students, where classrooms often consisted of a large variety of socio-economic and educational backgrounds. My goal, first and foremost, was to maintain that *I will give equal attention and care to all students.* To this end, I worked hard to keeping my speech patterns and mannerisms consistent between all students. This conscious effort is of great personal importance, because my experiences with racism revealed the demeaning and demoralizing effect of differing or preferential treatment.

As part of my goal for equity, diversity, and inclusion, I always assisted students with additional needs. One student required larger font (13 points at least) due to problems with his vision, so for each exam, I created an additional version with an augmented font size. He, as well as many other students, brought notes from a staff psychiatrist confirming their need for additional testing time, and that their tests be administered outside the classroom at a special testing facility on campus. For each student and for each exam, I emailed this external testing facility the exam with additional details such as the additional time required, and allowed materials such as calculators and notes. In all cases, I allowed myself to be available by phone so that they could ask questions during the exam.

Racism causes results in preconceived notions formed by exaggerated circumstances such as those that occur in popular media. Every day I work to understand that each individual I meet is no more than my interactions with them, and that I should form my own opinions based on our mutual experiences. This philosophy naturally transfers to my teaching, where I evaluate a student's needs based directly on my interactions with them, as opposed to what I have experienced with people of a similar socio-economic status. It is a lifelong challenge that I wholeheartedly accept. Some students require more mentoring, while others recognize patterns very quickly. *By adjusting my teaching based on the individual, I become a maximally effective teacher.* I help all of my students to the best of my abilities regardless of race, gender, background, and disability.

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