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Systems-Theoretic Analysis and Optimization of Biophysical Neuronal Networks

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WASHINGTON UNIVERSITY THE

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Final Report

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14. ABSTRACT
The overall goal of grant FA9550-15-1-0199 was to investigate the link between biophysical neural dynamics and function (e.g., information processing, computation). This goal is motivated by the fact that despite the exquisite range of dynamics present in actual neural circuits, most artificial neural network constructs rely on high level architectural abstractions devoid of temporal dynamics. Thus, an improved understanding of the functional role of neural biophysics could ultimately lead to new machine intelligence schemes. The major activities were organized into two objectives, involving both analysis and synthesis of biophysical neural dynamics. This final report document details the research outcomes and products.

15. SUBJECT TERMS
Neural computing, Computational Cognition, Spike Timing

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1. FINAL Performance Report

AFOSR Grant: FA9550-15-1-0199

Systems-Theoretic Analysis and Optimization of Biophysical Neuronal Networks

Submitted to: Dr. James Lawton

5/1/2015-4/30/2019

PI: ShiNung Ching

Electrical and Systems Engineering
Washington University in St. Louis

2. Objectives

The objectives of this research were to:

i. Elucidate how the biophysical dynamics of neuronal networks mediate their responses to (time-varying) afferent inputs.
ii. Optimize these temporal dynamics in synthesized networks toward processing of dynamic stimuli

3. Summary and Status of effort

This report summarizes the outcomes and accomplishments achieved under grant FA9550-15-1-0199. This project had two objectives, noted above. These objectives are synergistic and related to the understanding and eventual design of biophysically-inspired neural network constructs. Succinctly, the goal was to reveal general principles that underlie brain-like computation, which could then be leveraged in the synthesis of new machine intelligence schemes. This in turn can enable computational methods for engaging cognitive tasks, as consistent with the goals of the AFOSR Computational Cognition and Machine Intelligence program.

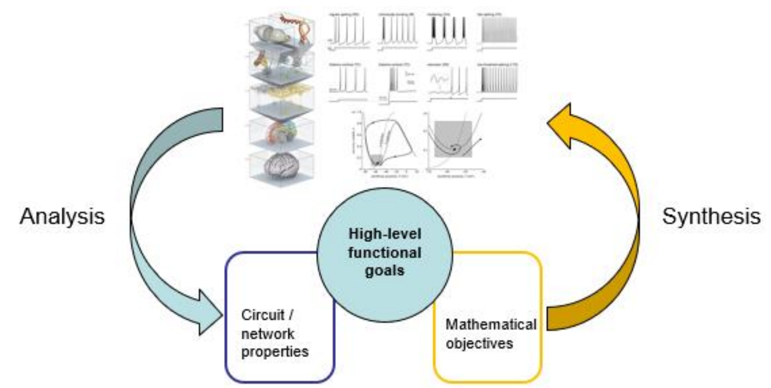

Figure 1. Objective one seeks to take known biophysics toward revealing fundamental circuit and network properties associated with high-level functional goals. Objective two takes the end goals and backward optimized the dynamics and neurons and networks. If successful, the two tracks converge and reveal fundamental principles of neural computation that can be leveraged toward machine intelligence.

Specifically, the first objective pertains to analysis of biophysical, dynamical systems-based neural models, in order to better understand their input-output relationships. In so doing, this analysis reveals the substrate for information processing at the level of individual neurons. The second objective adopts a normative, optimization-based view of neural dynamics. The goal here involved synthesizing neural and network dynamics based on specific functional objectives. A focus was on objectives related to processing time-varying stimuli, toward the construction of general schemes for history-dependent computation. Ideally, the two objectives converge, so that the optimized dynamics are consistent with those modeled from biophysical principles. Figure 1 illustrates this research paradigm.

The research within this proposal spans the domains of systems theory (dynamical systems modeling, analysis, optimization), information theory and computational neuroscience. The broad nature of the project is reflected in its outcomes and products, which appeared in a range of academic venues. In total, the project led to the publication of 10 papers in refereed journals and a further 7 in refereed conferences. Another 3 papers remain under review.

The principal investigator for this effort is Professor ShiNung Ching. Dr. Ching has been assisted by graduate students and a postdoctoral associate. Several additional graduate students not requiring stipend support also contributed to the research effort. The PI and students have disseminated the findings of the project at several national meetings in systems theory, machine intelligence and computational neuroscience.

4. Accomplishments

This section summarizes the key accomplishments and products associated with the project. Portions of this summary are adapted from prior Annual Report documents, while other sections are new and based on results from the last reporting period. Full details regarding these accomplishments are contained in the referenced archival publications. These accomplishments are organized based on the schematic of Figure 1 (Analysis and Synthesis). For each accomplishment, the relevant products from Section 6 are indicated.

4.1. Analysis of biophysical neural dynamics to understand circuit properties

Related to objective (i), we have performed fundamental characterizations of the sensitivity of recurrent networks to time-varying stimuli, in order to understand the ability of such networks to encode time-varying input intensity and orientation. Such analysis can reveal how neural circuits enable history-dependent computations. We have also developed new methods for assessing information propagation in nonlinear dynamical models of neural populations.

4.1.1. Sensitivity of recurrent neural circuits to history, enabling novelty detection

A key question in theoretical neuroscience pertains to how neural circuits produce actionable representations of afferent stimuli or inputs. Such representations (i.e., neural codes) are the substrate for downstream information processing and thus a critical pre-cursor to any neural computation scheme.

We first approached the neural coding problem through the lens of network sensitization, studying how circuits might be particularly apt to propagate certain types of afferent excitation. To this end, we developed a new construct termed the network bispectrum that holistically describes how stimulus energy and tuning trade off against each other towards producing discriminable representations in the network state space. This analysis allowed us to study how neuronal dynamics may endow networks with 'useful' sensitization properties, such as tuning their receptive fields to novel stimuli. This in turn may help us to better leverage these dynamics in the construction of systems for novelty detection and/or detection of rare events.

These results are significant because they show how both the structural and dynamical properties of neural networks intrinsically enable processing capabilities (e.g., sensitivity to stimulus novelty or contrast) that may be advantageous for higher-level information extraction and processing.

Relevant products: [6.a.v],[6.a.vii],[6.a.viii], [6.b.vi]

4.1.2. Neural plasticity and its effects on input-to-output circuit lability

Building on our initial results, we focused on the question of how neural circuits accentuate stimulus novelty over time via mechanisms of neural plasticity. The motivation here was specifically to understand how the prior history of a time-varying input modifies the sensitivity of the network itself. That is, whereas our initial results above focused on a static network, these analyses treated the case where the neural dynamics themselves adapted over time.

We performed this analysis in small, canonical biophysical network motifs. Our key finding was that such motifs, which tend to be overrepresented in early sensory processing pathways, indeed tend to accentuate stimulus contrast over time, thus facilitating even greater detection of novel inputs (versus the case of a static network). These results are significant because they ascribe a functional role to neural plasticity in the context of neural coding, e.g., producing favorable sensory 'tuning curves.'
Relevant products: [6.a.iv]

4.1.3. *Input propagation in the spiking domain*

We also performed analysis of input-to-output properties for neurons with explicit spiking dynamics. Specifically, we examined the use of Integrate-and-Fire-type (IF) neurons in networks that can perform functions including input coding, dynamical-systems approximation and control. A particular focus was on analyzing the extent to which such neurons can produce dissociable spiking patterns. The idea here is thus: consider a network that receives *n* distinct afferent inputs. Will this network produce *n* distinct spiking outputs (i.e., that can be associated distinctly to each input), or will they compress the inputs to a single spiking representation? What sorts of dynamics and/or network configurations promote either situation?

To this end, we provided a complete, fundamental characterization regarding the 'pattern sensitivity' of IF neurons. The analysis is important as it provides a lower-bound on achievable spike timing in networks impinged upon by extrinsic stimuli, thus impacting the use of such networks to process the stimuli in question. We subsequently parameterized networks of IF neurons in order to produce desired spiking profile. Our synthesis procedure will be further discussed in Section 4.2.
Relevant products: [6.a.ix], [6.b.vii]

4.1.4. *Information-theoretic stimulus encoding and noise rejection*

On the question of stimulus encoding, we pursued an additional track of research wherein we explicitly integrated information-theoretic frameworks into our problem formulation. In particular, we asked how the dynamics of neurons and of networks (e.g., via synaptic plasticity) might allow information-theoretic objective functions to be maximized. In particular, the Shannon mutual information can be understood as a computational primitive that indicates the extent to which a network mediates encoding and decoding of afferent excitation in a Bayesian sense.

We have made several contributions regarding how Shannon mutual information might be maximized via neuronal dynamics. While much of this work falls into the realm of network synthesis (discussed below in Section 4.2), we performed extensive analysis on how multiple time-scales of plasticity (e.g., short and long-term adaptation) enable networks to learn unsupervised representations. Indeed, using optimization arguments, we showed that neurons with multiple time-scales of adaptation allow for recurrent networks to find efficient stimulus representations through only local (pairwise) interactions between neurons. This result is significant because it shows how

neural dynamics might provide a means for scalable unsupervised learning (and neural coding).
Relevant products: [6.a.x],[6.a.ii],[6.a.iii],[6.b.iv],[6.c.iii]

4.1.5. Empowerment of nonlinear neural mass models

We performed a second information-theoretic analysis, aimed at revealing intricate information processing relationships mediated by nonlinear neural dynamics. Indeed, while we know that actual neurons possess a range of intricate nonlinear biophysics, the informational advantages associated with such nonlinearities are far from clear. Perhaps as a result, artificial neural network constructs rarely leverage such dynamical nonlinearities. As a first step to fill this gap, we attempted to characterize the information-theoretic channel capacity, sometimes known as the 'empowerment,' of a nonlinear neural mass model. Our goal was to ascertain how the information propagation of a population of neurons varied based on its dynamical regime (e.g., the stability of its fixed points). This problem is analytically and computationally challenging for reasons related to the nature of the nonlinear dynamics and their continuous state spaces.

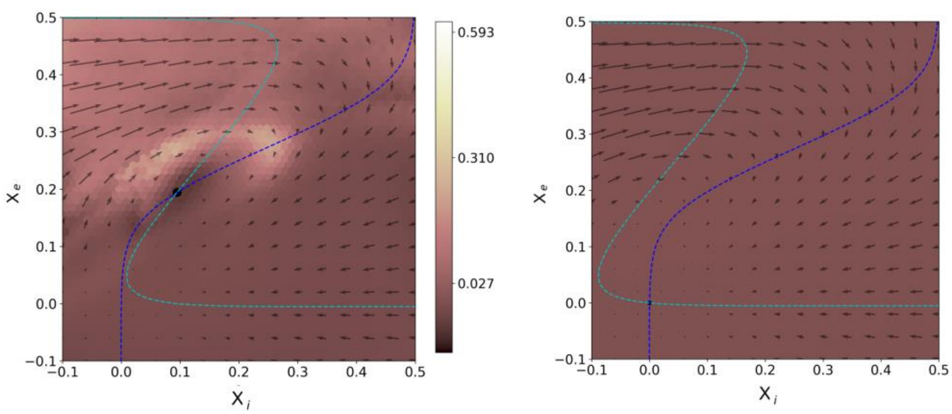

Figure 2. *(left)* Empowerment landscape of a Wilson-Cowan nonlinear neural mass model in an oscillatory regime. We observe that the oscillatory limit cycle forms a locus of high empowerment, implying that afferent activity is well-encoded by the population when received at these states. *(right)* In contrast, when the dynamics exhibit a single stable fixed point (i.e., not oscillatory), empowerment is low across the entire state space.

In the last reporting period, we made progress on developing a method to characterize the empowerment of dynamical neural models. Figure 2 illustrates the type of characterization that our analysis method produces. In particular, our analysis allows us to draw conclusions about the functional advantages of certain nonlinear regimes, including neural oscillations. Such oscillations are observed ubiquitously in actual neural circuits, but are rarely manifest in artificial networks. Thus, this analysis may pave the way for incorporating oscillatory dynamics into such networks in a functionally meaningful way.
Relevant products: [6.b.i],[6.c.i]

4.2. Synthesis of neural dynamics for high-level functional objectives and tasks

Our second aim involves synthesis of neural circuits. Here, rather than starting with known biophysics, we first formulate a functional objective. Our hope is that biophysically interpretable dynamics emerge from the optimization of the objective (i.e., 'building' a neural network model based on a functional specification). The last reporting period focused heavily on this objective and several interesting developments have been achieved. We will focus on the most recent, and potentially most broadly impactful finding. Then we will go on to review earlier products and contributions.

4.2.1. Synthesis of recurrent neural circuit dynamics for monotone inclusion: A substrate for solving complex decision tasks

During the last reporting period, a postdoctoral associate (Dr. Peng Yi) was appointed to the project and worked extensively on normative synthesis of recurrent neural dynamics for 'general purpose' functional objectives. We specifically examined the issue of how networks might, through their dynamics, solve the problem of monotone inclusion. Monotone inclusion is a general mathematical optimization problem that encompasses many key problems in decision and inference. For example, Bayesian inference and Markovian decision-making are both examples of monotone inclusion problems.

We showed that in a recurrent neural circuit/network with Poisson neurons, each neuron's (nonlinear) firing curve can be understood as a proximal operator of a local objective function, while the overall circuit dynamics constitutes an operator-splitting system of ordinary differential equations whose equilibrium point corresponds to the solution of the monotone inclusion problem. Our analysis thus establishes that neural circuits are a 'universal' substrate for solving a broad class of computational tasks. In this regard, we provided an explicit synthesis procedure for building neural circuits for specific MI problems and demonstrated it for the case of Bayesian inference and sparse neural coding (efficiently representing information with just a few neurons within a larger population). This concept has significant potential for generalization to handle an even broader class of computational tasks and thus could represent a new biophysically salient paradigm for 'training' neuromorphic systems without relying on traditional, gradient-based algorithms.

<u>Relevant products</u>: [6.c.iv]

4.2.2. Information-maximization and storage in recurrent neural circuits

A significant arc of research related to objective (ii) involved optimizing spiking networks for generic information-theoretic functional objectives. Whereas in our analysis results we focused on establishing the informational properties of known circuit models, our goal here was the construct neuronal network dynamics based on explicit maximization of these information quantities. We specifically made breakthroughs in the development of local learning strategies for adapting these networks to dynamic stimuli. That is, strategies wherein the connections between any pair of neurons depend only on the activity of those neurons (i.e., without requiring 'global' knowledge about other neurons in the network). The local character of the derived strategy is significant because it enables efficient, scalable learning for high dimensional context- and history-dependent tasks. We have demonstrated this by using the developed method to solve canonical tasks including *n*-back memorization. The key innovation underlying this result leverages our aforementioned analysis of multiple time-scales of synaptic adaptation (analogous to the notion of metaplasticity in physiological synapses). Specifically, we show through our synthesis procedure that such dynamics allow each connection to hold a local estimate of the overall network state at each moment in time.

We subsequently generalized this synthesis procedure in two important ways. First we showed that using the optimized local dynamics, it is possible to create an information-based growth criteria that allows networks to adaptively change their size in response to task needs. This development obviates the problem of parameterizing the size of a network when task conditions are unknown and/or the need for computationally redundant, surplus network complexity. In addition to this growth criteria, it turns out that the principle of information optimization allows for networks to be easily modulated by a secondary, extrinsic cost function, enabling reward or reinforcement-based learning. The overall schema is that of a dynamical network that can fluidly alternate between both unsupervised and supervised modes based on task circumstances.

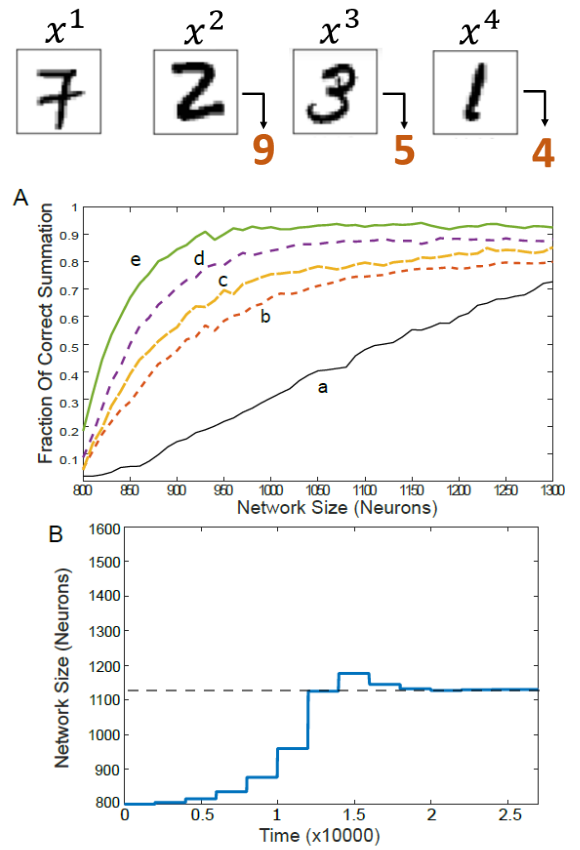

Figure 3. *(A) Our proposed information-optimization architecture (e) can achieve nearly 0.95 fraction correct (cross-validated) in a 1-step temporal summation task (summating handwritten MNIST digits). All learning occurs via local (pairwise) interactions between neurons. Suboptimal parameterizations are reflected in (a-d). (B) The information-optimization scheme yields a growth criteria that results in a network size at the cusp of the performance curve of (A).*

We tested this result on a temporal summation task, wherein the goal is to output the sum of sequentially presented handwritten (MNIST) digits. Figure 3 illustrates the performance of our proposed network in comparison to several competing, suboptimal design schemes. Our growth method, in particular, rapidly converges to the cusp of the performance curve, resulting in a network with just enough neurons to produce maximal performance. It is worth commenting on the computational requirements of this task: first, encoding the raw images, then storing stimulus history and finally enacting the summation operation. The result is encouraging not just because of the performance achieved, but because it

shows that recurrent, dynamical networks can be synthesized based on high-level objectives that can nonetheless engage specific tasks.
Relevant products: [6.c.ii],[6.b.v],[6.a.vi]

4.2.3. Spiking networks as efficient controllers

We have also worked on the synthesis problem in the spiking domain. Here, we pursued a problem formulation based on the idea of predictive neural coding, wherein each spike within a network is linearly decoded into a signal that induces a desired action. Within this framework, we showed how the architecture and dynamics of an integrate-and-fire spiking network can be exactly determined in order to produce desired output trajectories when spikes are used to control an exogenous dynamical system (e.g., as in the problem of pole-balancing and path following, among others). In addition to exhibiting dynamics that bear intriguing biophysical plausibility, the ensuing networks exhibit strong robustness properties, wherein a portion of the network can compensate for the loss/disruption of another.
Relevant products: [6.a.i],[6.b.ii],[6.b.iii]

4.2.4. Empowerment-maximizing neural dynamics

Finally, we returned to the idea of empowerment discussed above in Section 4.1.5. However, instead of simply analyzing the empowerment of a nonlinear neural model, we attempted to synthesize the dynamics to achieve the best possible information processing capacity subject to energetic and other biophysical constraints. In other words, can we synthesize a set of neural dynamics that in a general but mathematically rigorous way, are `usable' toward the completion of computational tasks. We devised a strategy to optimize the dynamics of a system using empowerment over its state space as an objective function. This results in dynamics that are generically conducive to information propagation. For example, the optimized environment would be expected to perform well as an encoder (of afferent input distributions).
Relevant products: [6.b.i],[6.c.i]

5. Personnel Supported

The following personnel worked on research supported by the AFOSR under grant FA9550-15-1-0199:

i. **ShiNung Ching (PI)** was supported for 4 months of effort over the entire project period.
ii. **Delsin Menolascino (Graduate Student, Washington University in St. Louis)** was supported for 40 months of effort over the entire project period. Dr. Menolascino completed his Ph.D. in the Fall of 2019. He is now a research scientist at the Teladyne Corp., working on computational neuroscience and machine learning.
iii. **Sensen Liu (Graduate Student, Washington University in St. Louis)** was supported for 39 months of effort over the entire project period. Dr. Liu completed his Ph.D. in the Summer of 2018. His last reported position was as a consultant and as an entrepreneur.

iv. **Yi Peng (Postdoctoral Associate, Washington University in St. Louis)** was supported for 7 months of effort over the entire project period. Dr. Yi is now an assistant professor of engineering at Tongji University in Shanghai, China.

v. **Vignesh Narayanan (Postdoctoral Associate, Washington University in St. Louis)** was supported for 1.25 months of effort. He assisted Dr. Yi on implementing numerical simulation of recurrent neural networks.

vi. **Gautam Kumar (Postdoctoral Associate)** provided contributions to the project during its first year. Dr. Kumar was supported through an external career development award. He is now Assistant Professor of Engineering at the University of Idaho.

vii. **Elham Ghazizadeh (Graduate Student, Washington University in St. Louis)** was supported for 3 months of effort. She is expected to graduate in 2020.

viii. **Fuqiang Huang (Graduate Student, Washington University in St. Louis)** was supported for 3 months of effort. He is expected to graduate later in 2019.

ix. **Anirban Nandi and MohammadMehdi Kafashan (Graduate Students, Washington University in St. Louis)** provided ancillary contributions to the project. Dr. Nandi is currently a research scientist at the Allen Institute of Brain Science, while Dr. Kafashan is a postdoctoral associate at Harvard University.

6. Publications

a. Published Journal Papers:

i. Huang, F., & Ching, S. (2019). Spiking networks as efficient distributed controllers. *Biological cybernetics*, 113(1-2), 179-190.

ii. Kafashan, M., & Ching, S. (2017). Recurrent networks with soft-thresholding nonlinearities for lightweight coding. *Neural Networks*, *94*, 212-219.

iii. Kafashan, M., Nandi, A., & Ching, S. (2016). Relating observability and compressed sensing of time-varying signals in recurrent linear networks. *Neural Networks*, 83, 11-20.

iv. Kumar, G., & Ching, S. (2016). The Geometry of Plasticity-Induced Sensitization in Isoinhibitory Rate Motifs. *Neural Computation*, 28(9), 1889-1926

v. Kumar, G., Menolascino, D., & Ching, S. (2018). Sensitivity of linear systems to input orientation and novelty. *Automatica*, *93*, 462-468.

vi. Liu, S., & Ching, S. (2017). Recurrent Information Optimization with Local, Metaplastic Synaptic Dynamics. *Neural computation*, 29(9), 2528-2552.

vii. Menolascino, D., & Ching, S. (2017). Bispectral analysis for measuring energy-orientation tradeoffs in the control of linear systems. *Systems & Control Letters*, 102, 68-73.

viii. Menolascino, D., & Ching, S. (2018). Information spectra and optimal background states for dynamical networks. *Scientific reports*, 8(1), 16181.

ix. Nandi, A., Schättler, H., Ritt, J. T., & Ching, S. (2017). Fundamental Limits of Forced Asynchronous Spiking with Integrate and Fire Dynamics. *The Journal of Mathematical Neuroscience*, *7*(1), 11.

x. Yi, P., & Ching, S. (2019). Multiple timescale online learning rules for information maximization with energetic constraints. *Neural computation*, 31(5), 943-979.

b. Refereed Conference Publications/Abstracts:

i. Ghazizadeh, E., & Ching, S., (2019, July). Defining information-based functional objectives for neurostimulation and control. In American Control Conference. 2019

ii. Huang, F., & Ching, S. (2018, June). Dynamical Spiking Networks for Distributed Control of Nonlinear Systems. In 2018 Annual American Control Conference (ACC) (pp. 1190-1195). IEEE.

iii. Huang, F., Riehl, J., & Ching, S. (2017, May). Optimizing the dynamics of spiking networks for decoding and control. In American Control Conference (ACC), 2017 (pp. 2792-2798). IEEE.

iv. Kim, S. A., & Ching, S. (2016, July). Quasilinearization-based controllability analysis of neuronal rate networks. In American Control Conference (ACC), 2016 (pp. 7371-7376). IEEE.

v. Liu, S., & Ching, S., (2018, March). Local, reinforceable and information-optimal learning in growing networks. In Computational and Systems Neuroscience (COSYNE), 2018.

vi. Menolascino, D., & Ching, S. (2016, July). Endpoint-based discriminability of minimum energy inputs. In American Control Conference (ACC), 2016 (pp. 3038-3043). IEEE.

vii. Nandi, A., & Ching, S., (2017, June). Phasic response motifs are optimal for persistent detections. In International Conference on Mathematical Neuroscience. 2018

c. Submitted and Under Review:

i. Ghazizadeh., & Ching, S., (Under Review). Creating usable neural dynamics by maximizing information propagation.

ii. Liu, S., & Ching, S., (Under Review). Reinforcable, local infomax in recurrent growing networks.

iii. Menolascino., & Ching, S., (Under Review). Quantifying noise rejection and stimulus encoding over networks with sigmoidal nonlinearities

iv. Yi, P., & Ching, S., (Under Review). Synthesis of recurrent neural dynamics for monotone inclusion with application to Bayesian inference

7. <u>Interactions</u>

a. Participation Participation/presentations at meetings, conferences, seminars

i. *Conferences:*

1. Sensen Liu presented at the 2016 Computational and Systems Neuroscience conference (Cosyne)
2. ShiNung Ching presented at the 2015 American Control Conference

3. Delsin Menolascino attended the 2015 American Control Conference
4. ShiNung Ching attended the 2016 American Control Conference
5. Delsin Menolascino presented at the 2016 American Control Conference
6. ShiNung Ching and Yi Peng attended the 2017 Neural and Information Processing Systems (NIPS)
7. ShiNung Ching attended the 2017 American Control Conference
8. Sensen Liu presented at the 2017 Computational and Systems Neuroscience Meeting (COSYNE)
9. Anirban Nandi presented at the 2017 International Conference on Mathematical Neuroscience
10. Fuqiang Huang presented at the 2018 American Control Conference
11. Sensen Liu presented at the 2018 American Control Conference
12. ShiNung Ching attended the 2018 BRAIN Initiative Investigators Meeting
13. ShiNung Ching presented at the 2018 Conference on Decision and Control
14. ShiNung Ching presented at the 2019 BRAIN Initiative Investigators Meeting
15. ShiNung Ching presented at the 2019 Midwest Conference on Game Theory

ii. *Invited Talks:*

1. Special Session on Neuroscience and Control Theory, at 2015 American Control Conference, Chicago IL. (7/2015, Ching)
2. University of Michigan, Invited Seminar, Department of Electrical Engineering and Computer Science (9/2015, Ching)
3. Special Session on Neural Dynamics, American Control Conference (7/2016, Ching)
4. Computational Neuroscience Program Review, ONR (7/2016, Ching)
5. Biomedical Engineering Seminar, Washington University in St. Louis (9/2016, Ching)
6. Special Session on Dynamics in Neuroscience, SIAM Conference on Applied Dynamical Systems (5/2017, Ching)
7. Special Session on Analysis and Control of Neural Dynamics, American Control Conference (5/2017, Ching)
8. Workshop on Brain Dynamics and Neurocontrol Engineering (7/2017, Ching)
9. Workshop on Dynamics and Control in Neuroscience, Mathematical Biosciences Institute (9/2017, Ching)
10. Workshop at the Computational and Systems Neuroscience Meeting (COSYNE) (3/2018, Ching)
11. DGIST (South Korea) Invited Colloquium, Daegu, South Korea (9/2018, Ching)
12. Special Session on Analysis of Neural Circuits, American Control Conference (7/2019, Ching)

b. Consultative and advisory functions to other laboratories and agencies
None.
c. Technology Assists, Transitions, and Transfers
None.

8. New discoveries, inventions, or patent disclosures

None.

9. Honors/Awards

ShiNung Ching (PI) received the CAREER award from the National Science Foundation.

ShiNung Ching (PI) promoted to the rank of Associate Professor with tenure at Washington University in St. Louis.