Sungho Hong

Computational Neuroscience Unit
Okinawa Institute of Science and Technology
7542 Onna, Onna-son
Okinawa 904-0411
Japan

Phone: +81-98-966-8714
Email: shhong@oist.jp

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Dear Professor Sheinberg,

I am a postdoctoral researcher in Computational Neuroscience Unit led by Dr. Erik De Schutter at Okinawa Institute of Science and Technology. I would like to be considered as a candidate for a Assistant Professor position in the Department of Neuroscience at Brown University.

During my research career, I have been deeply engaged in studying information processing of single neurons and populations and its underlying biophysical mechanisms. In Dr. Adrienne Fairhall's lab at University of Washington, I showed that multiple intrinsic mechanisms and their nonlinear interactions enable single neurons to adaptively process information in a context-dependent way. In the current lab, also collaborating with Dr. Steven Prescott in University of Pittsburg, I investigated implications of this result at the population level, and showed that such computational capabilities of single neurons can enable correlation-based coding by the population, independently of rate coding. These results were exciting since they suggested novel relationships from intrinsic cellular properties to rich coding strategies of single neurons and neural populations.

I wish to continue to study how biophysical mechanisms at the single neuron and network level impact neural information processing. I plan to investigate how diverse cellular mechanisms, particularly those with long time scales, affect computational capabilities. I will particularly focus on information transmission depending on contexts such as network states, and study how such rich coding strategies of individual neurons manifest in network phenomena. These projects ultimately aim to provide unified understanding about how intrinsic cellular mechanisms enable computational functions of neural circuits in the brain, a concept that has been largely neglected in network studies so far. I am also very interested in developing methods to build computational models based on experimental data, and plan to develop new methods to characterize single neurons and network models based on recent breakthroughs in information theory.

I am excited about this opportunity since I believe that my expertise and research plans about exploring new ways to analyze and build computational models of neural systems can complement the current Neuroscience research programs at Brown University.

I have arranged three letters of recommendation that will be sent to you soon from Drs. Erik De Schutter (Okinawa Institute of Science and Technology), Adrienne Fairhall (University of Washington), and Steven Prescott (University of Pittsburgh). If you have any questions about my application and status, please don't hesitate contacting me. I look forward to hearing from you soon.

Sincerely,

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Japan

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Education

Aug 2004	**University of Pennsylvania** PhD in Physics - Theoretical High Energy Physics. [Advisor: Matthew J. Strassler]	Philadelphia, PA
Aug 1999	**Korea Advanced Institute of Science and Technology** MSc in Physics - Elementary Particle Physics. [Advisor: Kiwoon Choi]	Daejon, Korea
Feb 1995	**Korea Advanced Institute of Science and Technology** BSc in Physics	Daejon, Korea

Academic Positions

Sep 2007 - presently	**Okinawa Institute of Science and Technology** Postdoctoral Researcher in Computational Neuroscience Unit	Okinawa, Japan
Aug 2004 - Aug 2007	**University of Washington** Senior Fellow in Physiology and Biophysics Department	Seattle, WA

Research Interests and Experiences

Computational Neuroscience

2004 - presently

I am interested in studying how biophysical mechanisms at the single neuron and network level impact neural information processing via computational modeling. My research ultimately aims to provide unified understanding about how intrinsic cellular mechanisms enable computational functions of neurons and neural circuits in the brain.

- In Professor Erik De Schutter's lab, I showed how intrinsic cellular properties of individual neurons can determine whether the neural population can use the correlated spiking to convey information, *independently* of their firing rates, via computational modeling and experiments in collaboration with Steven Prescott in University of Pittsburgh.
- I contributed to detailed modeling of the cerebellar Purkinje neuron, focusing on active dynamics in dendrites due to calcium-dependent mechanisms such as Ca^{2+} and KCa channels.
- I have also developed data analysis techniques such as
  1. an efficient method to estimate a phase response curve from small experimental data, based on compressive sensing,
  2. a variant of the multiscale spectral clustering algorithm that helped interpreting *in vitro* multicellular imaging data from the suprachiasmatic nucleus.
- In Professor Adrienne Fairhall's lab, I studied statistical modeling of neural coding applied to single neurons and its biophysical interpretation. Our works have shown that, even at the very basic level, neurons can have mechanisms for processing information adaptively to the context of their inputs.

Theoretical High Energy Physics

2000 - 2004

I worked on the string theory-based frameworks to investigate the strongly bound states similar to nucleons/hadrons. In addition to studying formation of the hadronic states, I demonstrated how to calculate their form factors and couplings, which led to novel proposed solutions to some longstanding puzzles in nuclear physics such as the ϱ meson-universality problem.

Research Talks

Conferences and Workshops

Dec 2011	APCTP-KAIST Young Computational Neuroscientist Workshop	Daejon, Korea
Jul 2009	Computational Neuroscience Meeting 2009	Berlin, Germany

Invited Talks

Oct 2009	Department of Physics, Kyoto University	Kyoto, Japan
	Graduate School of Biomedical Sciences, Hiroshima University	Hiroshima, Japan
Mar 2008	Department of Neurobiology, Yale School of Medicine	New Haven, CT
Jun 2007	Center for Brain Science, Harvard University	Cambridge, MA
Jun 2006	Department of Bio and Brain Engineering, KAIST	Daejon, Korea
Oct 2003	Physics Department, University of Washington	Seattle, WA

Other Professional Services and Experiences

- I have reviewed the submissions for Journal of Physics A, Physical Review Letters, Neural Computation, PLoS Computational Biology, and Computational Neuroscience Meeting.
- I have been reviewing the applications for the Okinawa Computational Neuroscience Course since 2008.
- I have served in Korean Army (mandatory, May 1995 - November 1996).

Publications

Journals papers

Myung J, **Hong S**, Hatanaka F, Nakajima Y, De Schutter E, et al. (2012) Period coding of *Bmal1* oscillators in the suprachiasmatic nucleus, J Neurosci, in revision.

Hong S, Robberechts Q, De Schutter E (2012) Efficient estimation of Phase Response Curves via Compressive Sensing. J Neurophys, in revision.

Hong S, Ratté S, Prescott SA, De Schutter E (2012) Single neuron firing properties impact correlation-based population coding. J Neurosci 32: 1413–1428.

Anwar H, **Hong S**, De Schutter E (2010) Controlling Ca^{2+}-Activated K^{+} Channels with Models of Ca2+ Buffering in Purkinje Cells. Cerebellum 1–13 (online).

Hong S, De Schutter E (2008) Purkinje neurons: What is the signal for complex spikes? Curr Biol 18: R969–R971.

Hong S, Lundstrom BN, Fairhall AL (2008) Intrinsic gain modulation and adaptive neural coding. PLoS Comput Biol 4: e1000119.

Lundstrom BN, **Hong S**, Higgs MH, Fairhall AL (2008) Two computational regimes of a single-compartment neuron separated by a planar boundary in conductance space. Neural Comput 20: 1239–1260.

Hong S, Agüera y Arcas B, Fairhall AL (2007) Single neuron computation: from dynamical system to feature detector. Neural Comput 19: 3133–3172.

Hong S, Yoon S, Strassler MJ (2006) Adjoint Trapping: A New Phenomenon at Strong 't Hooft Coupling. J High Energy Phys 03: 012.

Hong S, Yoon S, Strassler MJ (2006) On the Couplings of Vector Mesons in AdS/QCD. J High Energy Phys 04: 003.

Hong S, Yoon S, Strassler MJ (2004) Quarkonium from the Fifth Dimension. J High Energy Phys 04: 046.

Erlich J, **Hong S**, Unsal M (2004) Matrix Models, Monopoles and Modified Moduli. J High Energy Phys 09: 024.

Conference proceedings and abstracts

Hong S, De Schutter E (2011) Efficient estimation of phase response curves via compressive sensing. BMC Neuroscience 12(Suppl 1): 61.

Anwar H, **Hong S**, De Schutter E (2010) Generating dendritic Ca2+ spikes with different models of Ca2+ buffering in cerebellar Purkinje cells. BMC Neuroscience 11(Suppl 1): 154.

Negrello M, **Hong S**, De Schutter E (2010) What was the Purkinje doing while the monkey slept? BMC Neuroscience 11(Suppl 1): 9.

Anwar H, **Hong S**, De Schutter E (2009) Modeling the excitability of the cerebellar Purkinje cell with detailed calcium dynamics. BMC Neuroscience 10(Suppl 1): 34.

Hong S, De Schutter E (2009) Rich single neuron computation implies a rich structure in noise correlation and population coding. BMC Neuroscience 10(Suppl 1): 05.

Hong S, De Schutter E (2008) Correlation susceptibility and single neuron computation. BMC Neuroscience 9(Suppl 1): 141.

PhD thesis

Hong S (2004) Hadron Form Factors and Interactions: Comparing AdS/CFT and QCD. University of Pennsylvania (Philadelphia, PA).

Teaching Experiences

Jun 2008	I tutored four graduate students participating in the Okinawa Computational Neuroscience Course about computational modeling of neural systems by using modeling tools such as NEURON, Python, etc.
Jul 2000	As a lab instructor of the Penn Summer Science Academy 2000, I helped the high school students carry out basic Physics experiments and understand the underlying concepts.
1999-2001	As a Teaching Assistant in Physics and Astronomy Dept., University of Pennsylvania, I taught the lab experiments sections of the introductory Physics courses (51-2/101-2/150-1).
1996	I taught the problem solving classes for the introductory Physics courses as a Teaching Assistant in Dept. of Physics, KAIST

References

Erik De Schutter
Computational Neuroscience Unit
Okinawa Institute of Science and Technology
Email: erik@oist.jp

Adrienne L. Fairhall
Physiology and Biophysics Department
University of Washington
Email: fairhall@u.washington.edu

Steven A. Prescott
Department of Neurobiology
University of Pittsburgh
Email: sprescot@pitt.edu

Research Plans

I am interested in studying neural systems via computational modeling and in developing new techniques for such modeling. In particular, I am deeply interested in using information theory to identify low dimensional signals from high dimensional data. This is especially challenging when data sets are small and noisy. Interestingly, this is the exactly same challenge faced everyday by the brain. I plan to investigate how biophysical mechanisms in single neurons and neural circuits enable such complex information processing with high precision.

Development of techniques for modeling neural systems

Nowadays, computational modeling is a widely used approach to study neural systems ranging from single neurons to large-scale neural networks. In model building, it is important to infer model parameters reliably from experimental data. Recently developed methods based on statistical learning theory have facilitated this process [1]. However, these estimation algorithms typically assume that the data set is very large, if not infinite, and that experimental conditions are perfectly stationary. In real experiments, there are numerous limitations since the duration of sufficient stationarity can be short, a large amount of "noise" can make the information per data point small, the number of parameters to be determined simply exceeds the size of data, etc.

A possible solution that I am actively pursuing stems from a recent breakthrough in information theory called *compressive sensing* [2]. Compressive sensing aims to provide efficient algorithms for recovering a signal from severely undersampled data when the signal is sparse, which means that it has significantly lower dimensionality than the data. It is a rapidly growing field with many novel applications and I plan to investigate how it can be used to analyze neural data. There are two specific projects, one focusing on single neurons and the other on neural circuits.

The first project aims to develop a compressive sensing-based method to estimate the phase response curve (PRC) of single neurons. The PRC describes how the phase of an oscillator is perturbed by external input and is one of the most important tools for studying collective dynamics of biological oscillators such as synchronization in neural networks [3]. Our prototype of a compressive sensing-based method has shown impressive performance with simulation and *in vitro* data [4] compared with currently existing methods when the data set is small. My goal of this study is to improve it so that it can work with *in vivo* intracellular recording data, and I plan to collaborate with Dr. Michele Giugliano's group in the University of Antwerp, which is carrying out *in vivo* patch-clamp experiments on the cerebellar neurons.

The second project is to construct network models based on imaging data of many neurons. My collaborator, Dr. Toru Takumi's group in Hiroshima University, has recorded oscillatory expression patterns of *Bmal1* gene from ~900 neurons in the suprachiasmatic nucleus (SCN) simultaneously. Here the *prima facie* number of parameters for modeling the network is about ~10^6, which cannot be fully determined with our data size. Our current hypothesis is that significant synaptic couplings are sparsely distributed, which renders the problem ideally suited for investigation using compressive sensing. It is hotly debated how synaptic couplings contribute to the function of the SCN as a master controller of circadian rhythms [5,6] and the aim is to build a functional model capturing the key aspects of the imaging data, which will help us understand how the SCN can retain and encode the circadian information.

Adaptive and context-dependent neural information processing

Information processing by neural systems depends on the context in which the system operates. A well-known example is optimization of information processing by adaptation in single neurons [7-9] and in neural populations [10]. Also, the type of excitability of single neurons can change depending on the level of background synaptic activity [11]. Furthermore, the impact of gap junction on network function can invert depending on how much input is received [12]. I plan to develop computational models to help understand what biophysical mechanisms are responsible and how neural systems can use those mechanisms to optimize information processing.

In Dr. Adrienne Fairhall's lab at University of Washington, I investigated the biophysical mechanisms underlying components of functional models. By using single compartment, conductance-based neuron models, I identified interesting relationships between ion channel dynamics and the functional model that describes the neuron as a *feature detector* [13]. Surprisingly, we found that even at the level of a single neuron, the nonlinear interactions between multiple features, supported by the inward and outward currents, can modify the apparent response property of the neuron in a context-dependent way [13-15]. However, this work has a significant caveat in that it dealt only with mechanisms with time scales faster than the typical interspike interval. An important yet unanswered question is how slower neural mechanisms contribute to processing at longer time scales. Understanding these issues will provide valuable insight into another challenging question: how is the computational function of individual neurons in a neural network affected by the network state? In particular, cortical networks *in vivo* are known to operate in a regime of balanced excitatory and inhibitory synaptic activity, but other parameters such as total synaptic activity and, importantly, the level of fluctuations can vary. In many studies, the effects of those parameter changes are modeled using a network comprising leaky integrate-and-fire neuron models that lack nonlinearly interacting inward and outward currents [16]. In real cortical neurons, balanced input tends to amplify the effects of adaptation mechanisms and to encourage cooperation between the intrinsic inward and outward currents [11]. Therefore, using neuron models that are sufficiently realistic to exhibit context-sensitive operation is critical for developing better network models with which to investigate information processing by cortical networks. I intend to build and explore such models using compressive sensing and other information-theory based methods.

Impact of single neuron computation on network coding

Surprisingly, the impact of intrinsic cell-level properties on network-level information processing s has not been extensively studied. For example, efficient information processing by individual neurons does not necessarily imply that the network will perform likewise. I have been investigating this question with focus on noise correlation, which has been observed in many neural systems and whose role in population coding is vigorously debated.

In Dr. Erik De Schutter's lab at OIST and in collaboration with Dr. Steven Prescott at University of Pittsburgh, I have studied how noise correlation is affected by the intrinsic properties of individual neurons. Previous work made a very strong claim that correlated spiking is mechanistically intertwined with firing rates and excluded any possibility of correlation-based population coding operating independently of rate coding [17]. However, we have shown that this only applies to "integrator" neurons with a single feature and that therefore can only use rate-comodulation for generating correlated spiking. If the neurons operate as "coincidence detectors" with multiple features, correlated spiking can be generated not only by rate-comodulation but also by precise spike-time synchronization, where the latter is largely independent of firing rates. Furthermore, whether the neuron behaves as an integrator or coincidence detector is context-dependent insofar as the operating mode can be dynamically modulated by input statistics [18].

I am interested in extending the scope of this study in various ways. First, recent studies have used the local field potential (LFP) as the common input given to the neuron in a local circuit that drives their correlated firings [19]. This approach opens up a new exciting opportunity to study how the activity of each neurons is associated with the network dynamics in terms of the neuronal input specificity and its dynamical modulation. Secondly, I also plan to put the framework in the context of large network models with balanced excitation and inhibition. Recent studies have begun to explore this area [20], but they again relied on leaky integrate-and-fire models subject to the limitations outlined above. Adaptation, which encourages context-dependent neuronal functions, is expected to have significant and interesting population effects and will help us better understand how cortical networks function.

Mechanisms underlying reliable signaling in small domains

Neural systems typically operate with significant intrinsic and external noise, and it is thus critical to explain how a given system can operate reliably despite noise. One possible way to increase reliability is having redundancy within the system. For example, redundancy in the form of correlated excitation and inhibition has been observed in neural systems (e.g. [21]). Therefore, correlated spiking might increase the reliability of operation in small neuronal domains such as thin dendrites and axons, where noise due to channel stochasticity is significant. Interestingly, ion channels are often clustered and/or colocalized in those structures, suggesting that spatial distribution contributes to redundant but reliable signaling.

In Dr. Erik De Schutter's lab, I constructed a biophysically detailed model of active dendrites of the cerebellar Purkinje neuron. A major component of this model is the calcium (Ca^{2+}) and calcium-activated potassium (KCa) channels [22]. Interestingly, in many systems, KCa channels are colocalized with Ca^{2+} channels [23,24]. Importantly, BK and IK channel typically have a unit conductance $\gg$10 pS, which is much larger than other types of channels, and can thus significantly contribute to generating channel noise. Therefore, understanding if and how cerebellar Purkinje cell dendrites can reliably process information under these noisy conditions, and whether the Ca^{2+}-KCa channel complex increases reliability by introducing redundancy, are important questions.

Recently, stochastic simulation environments such as STEPS [25] have been developed. These are specialized for stochastic simulations in a realistic geometry by using sophisticated simulation algorithms, and make ideal platforms to simulate stochastically gating ion channels that are colocalization within a small space. The ultimate goal is to show what, if any, advantages channel complexes confer to the information processing capabilities of individual neurons and their subcellular compartments.

Summary

My future research will build upon the projects outlined here. Continuing to collaborate closely with experimentalists, I will capitalize on my expertise in computational modeling and information theory to develop novel methods and to apply those methods in order to decipher how computationally important processes are robustly implemented by biological components. Although those individual components are imperfect, they interact in ways that enable the brain, as a whole, to process information with astounding performance. I hope to uncover precisely how that performance is achieved.

References

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2. Baraniuk RG (2007) Compressive sensing. IEEE Signal Processing Magazine 24: 118–124.
3. Izhikevich EM (2010) Dynamical Systems in Neuroscience: The Geometry of Excitability and Bursting (Computational Neuroscience). The MIT Press. Cambridge, MA: The MIT Press.
4. Hong S, Robberechts Q, De Schutter E (2012) Efficient estimation of Phase Response Curves via Compressive Sensing. J Neurophys, in revision.
5. Mohawk JA, Takahashi JS (2011) Cell autonomy and synchrony of suprachiasmatic nucleus circadian oscillators. Trends Neurosci: 1–10.
6. Myung J, Hong S, Hatanaka F, Nakajima Y, De Schutter E, et al. (2012) Period coding of *Bmal1* oscillators in the suprachiasmatic nucleus. submitted.
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13. Hong S, Agüera y Arcas B, Fairhall AL (2007) Single neuron computation: from dynamical system to feature detector. Neural Comput 19: 3133–3172.

14. Lundstrom BN, Hong S, Higgs MH, Fairhall AL (2008) Two computational regimes of a single-compartment neuron separated by a planar boundary in conductance space. Neural Comput 20: 1239–1260.

15. Hong S, Lundstrom BN, Fairhall AL (2008) Intrinsic gain modulation and adaptive neural coding. PLoS Comput Biol 4: e1000119.

16. Rossant C, Leijon S, Magnusson AK, Brette R (2011) Sensitivity of Noisy Neurons to Coincident Inputs. J Neurosci 31: 17193–17206.

17. de la Rocha J, Doiron B, Shea-Brown E, Josic K, Reyes AD (2007) Correlation between neural spike trains increases with firing rate. Nature 448: 802–806.

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20. Litwin-Kumar A, Oswald A-MM, Urban NN, Doiron B (2011) Balanced synaptic input shapes the correlation between neural spike trains. PLoS Comput Biol 7: e1002305.

21. Cafaro J, Rieke F (2010) Noise correlations improve response fidelity and stimulus encoding. Nature 468: 964–967.

22. Anwar H, Hong S, De Schutter E (2010) Controlling Ca2+-Activated K+ Channels with Models of Ca2+ Buffering in Purkinje Cells. Cerebellum: 1–13.

23. Berkefeld H, Sailer CA, Bildl W, Rohde V, Thumfart J-O, et al. (2006) BKCa-Cav channel complexes mediate rapid and localized Ca2+-activated K+ signaling. Science 314: 615–620.

24. Fakler B, Adelman JP (2008) Control of K(Ca) channels by calcium nano/microdomains. Neuron 59: 873–881.

25. Hepburn I, Chen W, Wils S, De Schutter E (2012) STEPS: Efficient simulation of stochastic reaction-diffusion models in realistic morphologies. submitted.

Teaching Statement

Neuroscience is a rapidly developing field and teaching neuroscience topics poses a challenge to give students not only a broad perspective of the field but also to provide them with sufficient depth of under-standing that they can begin to develop and contribute their own ideas. In my future teaching, I hope to demonstrate importance of the analytic approach based on biophysics and use of computer simulations to help us understand how neural systems work.

Teaching experiences

I have taught students with various backgrounds and in various settings:

From 1995 to 1996, I taught problem solving classes for introductory physics courses as a Teaching Assistant in the Korea Advanced Institute of Science. In the traditional classroom setting, I have helped students solve the homework/test problems.

From 1999 to 2001, I led experimental laboratory classes for introductory physics courses as a Teaching Assistant in University of Pennsylvania. My primary role was explaining to the students how the experiments are planned and what are the underlying concepts that they need to learn, and grading the reports.

In the summer of 2001, I worked in a similar capacity as a lab instructor for high school students participating in Penn Science Summer Academy.

In 2006, I served as a tutor for Okinawa Computational Neuroscience Course. I worked with four participating graduate students, who were interested in computational modeling of single neurons and neural networks. I helped them define their proposed projects so that they could carry them out within the three week term of the Course, introduced to them the relevant simulation tools such as NEURON, and helped them overcome technical difficulties.

Teaching plans

The Biological Physics course that I took at the University of Pennsylvania has had the most profound impact on my philosophy on teaching interdisciplinary topics. The course was taught by Dr. Philip Nelson, and the course material was later published as a textbook, *Biological Physics: Energy, Information, Life* (W. H. Freeman and Co.: New York, 2004). In the course, Dr. Nelson emphasized the power of the analytic approach and elegantly demonstrated how abstract physics concepts such as entropy and the fluctuation-dissipation relation can give insight into biological phenomena at the cellular level.

As neuroscience is one of the most quantitative fields in biology, I believe that it is important for students to become comfortable using quantitative and analytic principles to conceptualize and explore biological phenomena in a rigorous way. As I have experienced in the Biological Physics course, this will also pro-vide a very good starting point particularly for the science/engineering students who had no significant experience in biology.

However, I have also noticed that strong emphasis on analytic problem solving in assignments and tests has a downside insofar as students with biological backgrounds may have difficulty following with the course material. I believe that this is a general problem of focusing purely on the theoretical knowledge. The same concepts can be better understood via the laboratory classes that provide hands-on experience rather than just problem solving classes. Therefore, ideally the experimental experience should be provided for every concept to be taught. However, if it is not practical, I suggest that computer simulations can be good alternatives.

Teaching via computer simulations has several other advantages: first of all, students can learn how to use the modeling tools that can still be used when they carry out their own research projects. Secondly, while analytic methods are mostly useful for giving the answers to specific questions, students can “play with” the computer simulations for an extended period of time: they can explore the models with changing parameters, modify the models to match real experimental data, try to find the simplifications of complex models that can give us better understanding about the phenomenon, etc. Therefore, as far as I have observed, computer simulations make it easier to design project-based classes where the major activities are motivated by the students themselves rather than given top-down from the teacher. For example, in Okinawa Computational Neuroscience Course, which I served as a tutor in 2008, student projects based on computational modeling and simulations work has been one of a major component of the Course and has been exceptionally well received by the students.

In summary, I intend to focus my future teaching efforts on analytic and quantitative methods relevant for understanding the biophysical basis of neural activity, and I hope to do this by engaging students in student-motivated projects based on computational modeling and simulations.