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December 7, 2003

Professor Rob de Ruyter van Steveninck
Biocomplexity Institute, Indiana University
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Dear Professor de Ruyter van Steveninck:

I would like to be considered for the Assistant Professor position in the Department of Physics at Indiana University. After more than three years of postdoctoral research with Professor Sebastian Seung at M.I.T, working on biophysical properties of neural networks and their applications to neurobiological functions, I look forward to establishing a solid research program in theoretical biophysics and teaching physics at all levels at Indiana.

I had a great visit to Indiana this March. I enjoyed interacting with faculty members at both the Physics and the Psychology Departments. With addition of two new faculty members on experimental neurobiology, the Physics Department at Indiana provides me with a great environment for leading a flourishing research program in theoretical neurobiology.

In the past year, I have finished three research papers. One paper, accepted for publication in Physical Review E, shows that a network consisting of a synfire chain of neurons can recognize a specific spatiotemporal sequence of input spikes from sensory neurons. Recently, I have extended this result to cover more general networks of multi-compartmental neurons for processing arbitrary spatiotemporal sequences of input spikes. The other two papers are the results of my collaboration with the experimentalists in Professor Sur's lab at M.I.T. These papers address issues on visual cortex, and currently are in review process.

Enclosed please find my CV, list of publications, list of references, and statement of research interests and plan. I have requested recommendation letters to be sent directly to you from Professor Seung, Professor Sur, and Professor Graybiel of M.I.T, as well as Professor Dubin of University of California at San Diego.

Sincerely yours,

Jin Dezhe

Dezhe Jin

Research Interests and Plan

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My research focuses on the biophysical properties of neural networks and their applications to computational models of brain functions. Consisting of a large number of intricately connected neurons, brain is one of the most sophisticated dynamical systems in nature. Understanding how brain computes is thus a challenging task that needs a multidisciplinary effort. Following John Hopfield, physicists have played an increasingly important role in this effort. My goal is to continue and amplify this trend by establishing a solid research program in a physics department. The program will advance neurobiology with theoretical and computational tools drawn from physics, and train graduate students and postdoctoral researchers with physics background into neuroscientists. The program will also benefit the studies of other biological and physical networks, including genetic networks, heart cells, colonies of flashing fireflies, forest fires, and earthquakes (Mirollo & Strogatz (1990); Herz & Hopfield (1995)).

My research consists of two integrated parts: theoretical analysis of neural networks, and detailed computational modeling of neurobiological functions such as feature selectivity in visual cortex, motor control in basal ganglia, olfaction in insects and mammals, and song generation and recognition in songbirds. The modeling will be done with close collaborations with experimentalists.

Analysis of the biophysical properties of neural networks. The aim of the research is to discover emerging properties of neural networks and elucidate their roles in neurobiological functions. Most previous work on neural networks analyzed rate models (Hopfield (1984)), which ignored the fact that neurons interact with individual spikes[1], and approximate the neuronal interaction as a function of the averaged spike rates of the neurons. My research has focused and will continue to focus on biologically more realistic models – spiking models, which preserve the pulse-coupled nature of the neural interaction.

Fast computation with spike sequence attractors.– My recent works show that, compared to rate models, spiking models have richer and faster dynamics that can be exploited for information processing in brain (Jin & Seung (2002); Jin (2002)). In these works, recurrent neural networks driven by constant external inputs with different values are analytically studied with a novel nonlinear mapping technique. The neurons are modeled as integrate-and-fire neurons, which capture the essence of the biological process of spike generation. For a large class of network structures, the dynamics of the networks quickly converge to dynamical attractors consisting of periodic sequences of spikes with precise timings. These spike sequence attractors are richer in structure compared to the attractors in the rate models, which ignore the order and timing of the spikes (Hopfield (1984)). Moreover, convergence to the spike sequence attractors typically

[1]Spikes are pulses of neuronal membrane potentials that are transmitted to other neurons through their connections.

takes only a few transient spikes, which is much faster than the transient dynamics in the rate models.

Many important issues related to spike sequence attractors need to be explored. How do these attractors depend on the structures of the networks? How many attractors are there for a given set of the external inputs? How are they affected when more biological details are added, including noise and different neuron models, etc.? What roles do these attractors play in information processing in brain? Rate model attractors have inspired many models of various brain functions, including associate memory (Hopfield (1984)), head direction cells (Zhang (1996)), and neural integrators (Seung (1996)). I expect the same for the spike sequence attractors.

Spiking neural networks and finite state machines.- The spike sequence attractors are the results of spiking neural networks driven by constant external inputs. In many cases, however, the external inputs are spatiotemporal spikes. For example, auditory stimuli produce spatiotemporal spiking of neurons in the cochlear ganglion, which in turn drives neural networks in auditory brain stem nuclei and auditory cortical neurons (Trussell (1999)). How do spiking neural networks process such time dependent spike inputs?

To answer this important question, I studied a spike sequence recognizing network in a recent paper (Jin (2003)). The network consists of excitatory neurons that are connected to form a chain structure, and two inhibitory neurons that provide fast feedback inhibition and delayed feedforward inhibition. Driven by spatiotemporal spikes, the excitatory neurons spike selectively to a particular input spike sequence. Such selectivity is useful for tasks like speech recognition. The dynamics of the network can be mapped into that of a finite state machine. Finite state machines are powerful conceptual models that have been applied to understand the computational powers of digital computers (Sipser (1997)) and the structures of natural languages (Jurafsky & Martin (2000)). Is it possible that neural networks driven by spatiotemporal spikes can be understood in terms of finite state machines, even when the network structures are quite general? A positive answer to this question will greatly advance our understanding of the information processing capabilities of spiking neural networks. Future work in this direction will also include the effects of noise, which may turn the neural networks into Markov machines, which are the probabilistic versions of the finite state machines.

Modeling of neurobiological functions. The goal of the research is to construct biologically detailed computational models of neurobiological functions. The modeling will be guided by the theoretical studies of the neural networks; more importantly, it will be shaped by experimental data. Establishing close collaborations with experimental groups will thus be essential. The following projects are either already underway, or have strong potential for applying our results on spiking neural networks. Other projects will be added as the opportunities for collaboration arise.

Orientation selectivity and feature maps in the primary visual cortex.- Neurons in the primary visual cortex spike rigorously when the visual stimuli have their preferred features, which include orientation, spatial frequency, ocular dominance, etc. Across the cortical surface, the preferred features of the neurons change smoothly to form feature maps. How do the feature preferences of neurons arise? Several mechanisms, especially for the case of orientation selectivity, are proposed and debated (Sompolinsky & Shapley (1997)). Modeling will play an important role in clarifying this important issue, especially since there are many detailed experimental results available for constraining the model parameters. Currently, we are collaborating with Professor Sur's lab at M.I.T. to combine experimental and theoretical efforts to tackle various problems related to the feature selectivity in the primary visual cortex. We have already submitted two papers (Jin et al. (2003); Yu et al. (2003)).

Motor control in basal ganglia.- Basal ganglia is a critical structure in brain. It is driven by various areas of cortex, and in turn influences cortical activity through thalamus (Graybiel (2000)). Over the years, experiments have shown that basal ganglia is especially important for motor control and learning. Damages to basal ganglia result in well-known motor control disorders such as the Parkinson's disease. However, exactly how basal ganglia works is poorly understood. Recently, we have established a close collaboration with Professor Graybiel's lab at M.I.T. The goal is to elucidate the functions of basal ganglia by analyzing the experimental data with novel techniques and constructing models based on the data. The work is in progress.

Olfaction in mammals and insects.- Olfaction is a complex pattern recognition problem. A single perceived odor often consists of many chemical components; therefore, the olfactory system must bind the multi-dimensional signal into a unified perception. Odor perception is also largely invariant with the change of the concentration of the odor mixture. How does the olfactory system solve such a complex problem? Recent experiments suggest that the inputs to the olfactory system evoked by the multi-molecular mixtures are transformed into spatiotemporal spike activities of the neurons in the olfactory bulb in mammal or the antennal lobe in insect (Laurent (1999)). Precisely timed spikes are also observed (Stopfer & Laurent (1999)). This is quite similar to the transformation of the external inputs to spike sequence attractors in my recent theoretical works. There are also strong similarities between the olfactory network structures and those studied in the theoretical works. These similarities suggest that there is a good chance of relating the spike sequence attractors to olfaction. I plan to pursue this possibility by constructing biologically detailed models of olfactory systems.

Song generation and recognition in songbirds.- Recent experiments have shown that singing in songbirds is driven by precisely timed spike sequences in the neurons of HVC, a premotor area (Hahnloser et al. (2002)). How are such sequences are generated? Experimental observations suggest that neurons in NIF, another premotor area, are spontaneously active and drive the neurons in HVC. This poses an interesting problem of generating precisely timed spike sequences from noisy external inputs. One possibility is that HVC neurons receive inputs from a large number of NIF neurons, hence averaging out the noise. These averaged inputs in turn generate precisely timed spike sequences through the recurrent networks in HVC, much like the generation of the spike sequence attractors in the neural networks that I have studied theoretically. Details, however, must be filled in with the experiments. Another interesting problem is how the songbirds recognize the songs. Experimentally, neurons that are selective to the bird's own song are found in HVC and other areas (Lewicki & Arthur (1996)). Such selectivity might arise from a network that is quite similar to the one I have studied for spike sequence recognition. I expect to set up a collaboration with Dr. Hahnloser and Dr. Fee at M.I.T. for future work in songbirds.

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