Adaptive Sampling of Neural Systems by Information Maximization

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Abstract

The investigation of neural systems often requires a sophisticated choice of stimuli to make best use of limited experimental time. Here we present an iterative algorithm that continuously adjusts a stimulus ensemble online, subject to the data already acquired about the system under study. The algorithm focuses the stimulus ensemble by maximizing the mutual information between stimulus and response. We apply the algorithm to simulated neurophysiological experiments and show that it can potentially extract the ensemble of stimuli that a given neural system "expects" as a result of its natural history.

Summary

The investigation of many neural systems, such as the auditory or visual system, often relies on the presentation of stimuli that reside in high-dimensional spaces. Conventionally, researchers have either sampled only very specific regions of this space, for instance by using sine wave stimuli or optical bars, or sought to sample the complete space by drawing stimuli from some probability distribution $p(x)$, e.g. Gaussian "white noise". While the systematics of the latter approach is highly attractive, it has often suffered from the fact that white noise stimuli were not appropriately focused onto the "relevant" stimulus regime of a given system. Here we present an adaptive algorithm that lets the system itself show the path towards an optimally focused stimulus ensemble. The adaptation procedure seeks to maximize the mutual information between stimulus and response online, i.e., during the course of an experiment.

Say that we have already tested the system with N different stimuli x_i each of which was presented several times while measuring the corresponding responses. Our present knowledge about the system is summarized by the conditional probability $q(y_k|x_i)$ that a response y_k was obtained from the stimulus x_i. These probabilities allow us to re-evaluate the relative importance of the stimuli x_i in terms of their potential contribution to the mutual information. To measure this contribution, we assign a probability or "weight" $q(x_i)$ to every stimulus. Using the Blahut-Arimoto algorithm (Cover and Thomas, "Elements of Information Theory", 1991), the weights $q(x_i)$ can be readjusted to capture the relative frequencies with which the respective stimuli x_i should be drawn to maximize the mutual information. In turn, these weights can be used to adapt the parameters of the stimulus ensemble $p(x)$ so as to match these relative frequencies. The new stimulus distribution can be used to draw new test stimuli, present them to the system and measure the respective responses. After a certain amount of data has been acquired, the parameters of the stimulus distribution can be adapted again. Note that this adaptation should always be done by using the complete history of the data, not only the data obtained with the most recent stimulus ensemble. The resulting iterative algorithm moves the stimulus distribution towards an optimal ensemble.

To demonstrate the computational power of the algorithm, we simulate an experiment using a stochastic Hodgkin-Huxley-type model neuron. Here the stimuli consist of time-varying, statistically stationary currents, and the response consists of the spike times, discretized in time steps of 0.5 ms. For simplicity, we use a Gaussian stimulus ensemble and show that the algorithm is able to shape the power spectrum of this ensemble to optimize the information transfer between input and output. Note that the algorithm does not rely on any assumption (such as linearity) about the stimulus-response relation.

To test the system, we choose an initial distribution with an average $\mu = 0$ μA/cm^2 and a flat power spectrum with standard deviation $\sigma = 10\,\mu A/cm^2$ and cut-off frequency $f_c = 2000$ Hz. For this prior, only 50% of the stimulus values lie above the neuron's firing threshold and the stimuli will rarely lead to high firing rates. Consequently, we do not properly explore the full range of the stimuli-response relation; if, for example, we test the system for 30 minutes with stimulus currents drawn from this initial distribution, the mutual information rate I_{D} does not exceed ≈ 300 bits/sec.

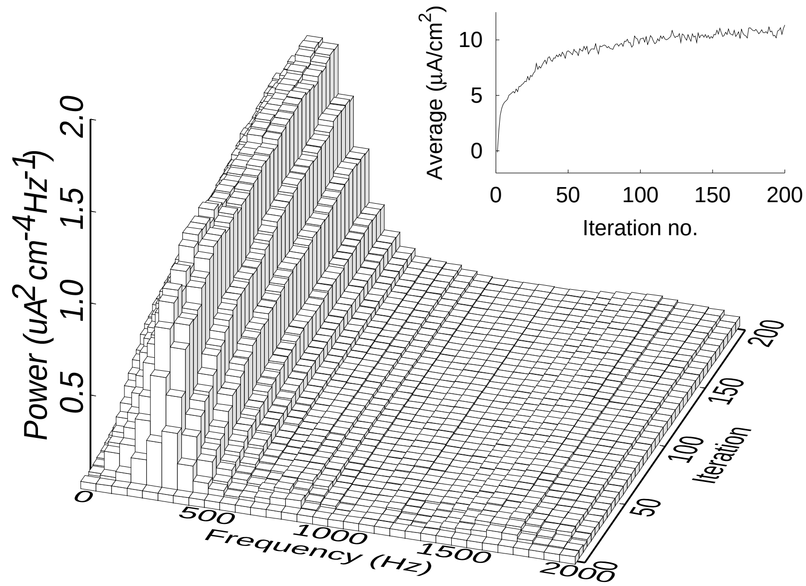

Figure 1: Approaching the optimal stimulus ensemble of a neuron with time-varying stimulus and response. Shown are the evolution of average and power spectrum.

When using the iterative algorithm to adapt the parameters of the stimulus ensemble, on the other hand, the information rate saturates around $\approx$ 670 bits/sec after about 20 minutes. Figure 1 shows how the power spectrum is shaped during these iterations. Only stimulus frequencies below 500 Hz are well suited for the information transfer, the cut-off is roughly determined by the maximum firing rate of the model neuron. The overall increase in power leads to stimulus currents that override the additive noise of the model neuron.

Recent studies indicate that sensory neurons convey large amounts of information if the properties of the stimulus ensembles used match those of natural stimuli. Here we have proposed how to extract a stimulus ensemble that conveys the maximum possible information without any prior knowledge. The proposed method could therefore serve to find the ensemble of stimuli that a given neuron naturally "expects". Note that in contrast to previous online algorithms such as Alopex or Simplex, we are not looking for a single optimal stimulus but rather for a complete ensemble of stimuli.

The optimal stimulus ensemble depends on the chosen criteria about what aspect of the response carries the relevant information. Hence, if a neuron encodes its information in the precise timing of spikes, then the synaptic stimuli should be of a binary nature and either fully excite or fully inhibit the neuron. Measuring the time courses of a neuron's membrane potential thus allows conclusions about the used neural code under optimal conditions.

A more detailed account of the present work is available on the Los Alamos e-print archive (`http://arxiv.org`, *physics/0112070).*