State Estimation and Prediction Based on Dynamic Spike Train Decoding: Noise, Adaptation, and Multisensory Integration

Omer Bobrowski, Ron Meir and Yonina C. Eldar
Department of Electrical Engineering
Technion, Haifa 32000, Israel

April 18, 2008

A key requirement facing organisms, or agents in general, acting in uncertain dynamic environments is the real-time estimation and prediction of environmental states, based upon which effective actions can be selected. In this work we show how an agent may use a simple real time neural network, receiving noisy multisensory input signals, to solve these tasks effectively.

Consider an agent observing the environment through a set of noisy (possibly multi-modal) sensory neurons. Based on these observations it needs to estimate the state of the environment (more generally, the state distribution) with the highest accuracy possible. It is well known that if the stochastic dynamics of the environment and the observation process are fully known, then the state distribution can be optimally recovered through the so-called *Bayes filter* based on an exact calculation of the posterior state distribution. For example, if both the environmental and observational processes are linear, and are corrupted by Gaussian noise, the optimal filter reduces to the classic Kalman filter, which can be computed recursively. In a biological setting, the agent observes the environment through a set of sensory neurons, each of which emits spikes at a rate which depends (stochastically) on the current state of the environment according to the neuron's response function (a.k.a. tuning curve). For the state estimation procedure to be effective in a biological context, it must be possible to implement it robustly in real time by a neural network.

The problem of hidden state estimation based on multiple noisy spike trains has been receiving increasing attention over the past few years. Much emphasis has been laid on Bayesian approaches, which facilitate the natural incorporation of prior information, and which can often be guaranteed to yield optimal solutions. While many naturally occurring problems are dynamic in nature, a large fraction of the work to-date has focused on static stimuli. More recently attention has shifted to dynamic phenomena and online estimation. Our work is formulated within the rigorous theory of real-time nonlinear filtering[1], and applied to dynamic spike train decoding. A consequence of this analysis is the demonstration that optimal real-time state estimation based on point process observations is achievable by relatively simple neural architectures. An advantage of the proposed formulation, is that there is no need for time discretization and input process smoothing. These results provide a solid theoretical foundation for dynamic neural decoding and computation, and recover many previous results in appropriate limits. The static limit of our formulation leads to some well known results (some of which have been experimentally verified), and provides useful extensions even in that limit. However, the main advantage of the general framework is in setting the stage for mathematically precise, yet experimentally verifiable, predictions for future experiments dealing directly with dynamic phenomena.

We briefly summarize the main results of our formulation. First, we note that environmental noise (in addition to neural noise) plays an important component of real world situations. We incorporate such noise into the general filtering framework, and derive several consequences from this. For example, we establish the existence of an optimal width for the tuning function of the sensory cells. This width depends on the noise level, suggesting that for optimal performance the system must adapt to the specific environmental conditions. Second, we observe that organisms, or artificial agents, often require multisensory processing in order to reach reliable and robust state estimation. We show how the framework can easily be extended to this situation. Our results provide novel predictions in the dynamic setting, and recover previous results in the static limit. We demonstrate clearly why multisensory information is effective, when comparing to unisensory information arising from the same number of sensory cells. In the process, we provide a clear mechanistic explanation for the experimentally observed phenomena of enhanced response and inverse effectiveness. Third, we develop a framework for history dependent spike trains, and consider the effect of adaptation on system performance. Interestingly, we can show that adaptation can benefit neural computation. More specifically, when the system is subjected to energy constraints (e.g., limits on the overall number of spikes fired per unit time), adaptation leads to near optimal performance. Finally, we extend the setup to prediction (rather than estimation), an essential component of closed loop situations where state prediction combines with action selection in order to generate appropriate actions.

[1] P. Brémaud, Point Processes and Queues: Martingale Dynamics, Springer 1981