Bayesian decoding of neural spike trains

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Abstract Perception, memory, learning, and decision making are processes carried out in the brain. The performance of such intelligent tasks is made possible by the communication of neurons through sequences of voltage pulses called spike trains. It is of great interest to have methods of extracting information from spike trains in order to learn about their relationship to behavior. In this article, we review a Bayesian approach to this problem based on state-space representations of point processes. We discuss some of the theory and we describe the way these methods are used in decoding
motor cortical activity, in which the hand motion is reconstructed from neural spike trains.

Keywords  Point process · State-space model · Recursive Bayesian filter · Sequential Gaussian approximation · Neural decoding

1 Introduction

The brain receives, processes, and transmits information about the outside world through stereotyped electrical discharges, called action potentials or spikes. External sensory signals are transformed into intricate sequences of these spike events at an early stage of processing within the central nervous system, and all subsequent brain area interactions and computations are carried out using these spike trains. Spike trains are the starting point for virtually all of the processing performed by the brain (Kandel 2000; Dayan and Abbot 2001). It is therefore very important to have good statistical models for spike trains, and methods for examining their relationship to particular stimuli or behavior.

A basic property of action potentials is that they are “all or nothing” events: each time a neuron fires, its voltage wave form is nearly the same, regardless of context. This allows us to reduce spike trains to sequences of event times. On the other hand, while all action potentials remain essentially the same across repeated firing events, the spike sequences generated in response to identical stimuli applied on separate occasions will not be identical; although they may share common statistical features, they exhibit substantial variation. These two fundamental facts suggest that spike train data might be effectively analyzed with the theory of point processes (Snyder 1972; Snyder and Miller 1991; Daley and Vere-Jones 2003). Point processes are used to model physical systems that produce a stochastic set of localized events in time or space. In this case, we use temporal point processes to represent the times of the spiking events and to express the probability distribution of specific sequences of spike times.

While neurons have as immediate inputs the spiking activity of other neurons, these inputs are generally not recorded. Instead, the relationship of spiking activity to a stimulus or behavior becomes the focus of neurophysiological investigation. The prototypical neuron we consider here has inputs from multiple sources and produces a spike train in response. Describing the way a neuron represents information about a stimulus or behavior is the encoding problem. The dual problem of reproducing the stimulus or behavior from neural spike trains is the decoding problem. The ability to reconstruct a signal from observed neural activity provides a way of verifying that explicit information about the external world is represented in particular neural spike trains (Rieke et al. 1997; Dayan and Abbot 2001). Its engineering importance comes from efforts to design brain-machine interface devices, especially neural motor prostheses such as computer cursors, robotic arms, etc (Schwartz 2004). A natural starting point is to take the behavior, such as a hand movement, to follow a dynamic state model and to infer the evolution of states using Bayes’ theorem.