291. Feedback-Directed State Transition for Recursive Bayesian Estimation of Goal-Directed Trajectories

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We consider the problem of decoding time-evolving physical parameters, such as hand position, from neural data when there is prior information available about the desired final state, such as reach endpoint. For reach trajectories, it has been shown that the desired reach endpoint can be reliably decoded from neural activity that occurs before the reach begins. In this work, we incorporate this goal information into a recursive Bayesian framework to improve average estimation error across the entire trajectory. While most recursive Bayesian estimators to date have modeled the state evolution as a random walk defined by a static covariance matrix, we show how to use this goal information to transform the state evolution into a directed random walk defined by a dynamically adapting covariance matrix. We applied this technique to decoding hand trajectories from neural recordings in monkey pre-motor cortex and found that using an adaptive random walk model gave 45.5% lower estimation error than using a static random walk model. This result indicates that goal-directed trajectory estimation can be significantly improved if prior information about the intended goal location is available and is incorporated into the estimator.

Recursive Bayesian techniques represent a class of state-of-the-art methods for decoding time-evolving physical parameters from neural data. These methods include the Kalman filter , the switching Kalman filter, and the particle filter, which have all been used to decode hand trajectory. Another such method is a point process-driven Bayes' filter which has been used to decode the position of a freely foraging rat.

There are two major advantages of using recursive Bayesian techniques. First, Bayesian estimation requires formal statistical models for the generation of neuronal spike trains or spike counts (the observation model) and for the time-evolution of the relevant physical parameters (the state model). If the modeling assumptions are satisfied, then Bayesian estimation makes optimal use of the observed data. Second, recursive algorithms provide estimates as the observed data stream in, as opposed to batch algorithms which wait for all data to arrive before outputing the first estimate. This sequence of predictions is critical for real-time decoding applications, such as neural prosthetics. Furthermore, recursive algorithms have smaller storage requirements and can be designed to track adaptively varying model parameters.

In previous work (Brockwell et al. J Neurophysiol, 2004; Brown et al. J Neurosci, 1998), the state model is defined to be a zero-mean Gaussian random walk, which refers to the time-evolution of the physical parameters contained in the state vector (such as position, velocity, or acceleration). The random walk is typically described by a static covariance matrix, which is fit to the training data and remains unchanged across all time steps. Using a static covariance matrix is a logical approach for decoding an arbitrary trajectory through state space when there is no additional knowledge about the trajectory being estimated beyond what is contained in the training data.

However, for goal-directed trajectories, there is usually an additional piece of information: the intended trajectory endpoint. Examples of goal-directed trajectories include a hand reaching for an object or a rat running towards a food source. For reaching trajectories, it has been shown that the desired reach endpoint can be reliably decoded from neural activity in the pre-motor and parietal cortices before the reach begins. We asked how this prior goal information can be used to improve the average estimation error across the entire impending trajectory.

The recursive Bayesian paradigm provides a natural framework for incorporating this goal information. Instead of using a static random walk covariance matrix, we can dynamically adapt this covariance matrix at each time step based on the error vector between the current state estimate and the goal. We propose such a technique that adapts the random walk covariance matrix based on the current state estimate and its uncertainty. We then applied this technique to decoding hand reach trajectories from neural data recorded in monkey pre-motor cortex (96-electrode array). The monkey performed a 'delayed-reach' center-out task wherein a random delay period (750 or 1000 ms) was inserted between the appearance and eye fixation of a reach target and the appearance of an arm-movement initiation 'go' cue. We decoded reach trajectories using peri-movement neural activity and showed that, when taking into account goal information decoded from the delay activity (last 700 or 950 ms of delay period), average trial-by-trial RMS error decreased by 45.5% (Wilcoxon paired-sample test, $p < 10^{-72}$). This result indicates that goal-directed trajectory estimation can be significantly improved by using goal information when it is available.

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