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Smoothing bandwidth selection for response latency estimation

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Abstract

Stimulus response latency is the delay between stimulus onset and the evoked modulation in neural activity. A common technique to estimate latencies involves binning the spike arrival times to form a peri-stimulus histogram. This histogram is smoothed using a fixed bandwidth. The estimated latency is the first time following stimulus onset in which the smoothed histogram exceeds the midpoint between the minimum and maximum of the smoothed histogram. We demonstrate that the choice of smoothing bandwidth is critical to the accuracy of this latency estimation technique. We suggest a bootstrap resampling technique for bandwidth selection which results in a robust latency estimate.

Keywords: Latency; Peri-stimulus histogram; Smoothing bandwidth; Bootstrap

Since neurons have finite transmission velocities and synaptic delays, a lag exists between stimulus onset and the evoked modulation in neural activity. This delay, known as the stimulus response latency, provides information concerning hierarchical processing and functionality (Bullier and Nowak, 1995; Gawne et al., 1996). For example, in the visual system, significant differences in response latencies have been reported for neurons belonging to the parvocellular and magnocellular systems (Nowak et al., 1995), which are believed to play different functional roles in visual processing (e.g. Livingston and Hubel, 1988; Fellman and Van Essen, 1991).

In a typical neural recording session, a stimulus is presented a number of times and the spike arrival times from stimulus onset are binned to form a peri-stimulus histogram. An example of this histogram appears in Fig. 1, which displays data obtained from a single unit recording in the primary visual cortex of an awake, fixating monkey. The response latency is often estimated through analysis of this histogram.

One common nonparametric response latency estimation procedure, known as the 'half-height' technique, involves smoothing the peri-stimulus histogram using a fixed bandwidth. The minimum and maximum values of the smoothed histogram are then determined. As seen in Fig. 2, the first time from stimulus onset in which the smoothed histogram exceeds the average of the minimum and maximum value is the estimated latency (e.g. Mastronarde, 1987; Humphrey and Weller, 1988; Heggelund and Hartveit, 1990; Saul and Humphrey, 1990; Kwan et al., 1991; Lu et al., 1995; Gawne et al., 1996).

In this estimation technique the choice of smoothing bandwidth is critical. The bias-variance tradeoff suggests that using a bandwidth which is too large will result in an estimate which is dominated by bias, whereas using a bandwidth which is too small will result in an estimate which is dominated by variance (Silverman, 1986). To demonstrate the importance of the smoothing bandwidth, we consider simulated vectors containing 100 random variables in which the first 50 component samples are independent and identically distributed (i.i.d.) from a Poisson (1 spike/bin) distribution, representing the spontaneous activity, and the last

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50 components are i.i.d. Poisson (6 spikes/bin), representing the initial response activity. That is, in this simulation, the latency was fixed at the 50th bin. If the bin size under consideration is 1 ms, then this simulation represents the data collected from 100 stimulus presentations to a neuron with a spontaneous activity of 10 spikes/s and an initial response rate of 60 spikes/s. While the Poisson assumption is by no means universally accepted, it is nonetheless a common approach for modeling cortical neural spike trains (see, for instance, Gerstein and Mandelbrot, 1964; Shadlen and Newsome, 1994).

Using a normal smoother of integer bandwidths in the range 1–23 bins, we estimate the latency using the half-height technique. This is repeated 1500 times to obtain an empirical distribution of estimated latencies. As seen in Fig. 3, the smoother with a bandwidth of 13 bins had the minimal root mean squared error of the latency estimation. There is a clear asymmetry in that using a smoother which is larger than 13 bins is less critical than using a bandwidth which is too small. In fact, choosing a smoothing bandwidth 5 bins smaller results in a latency estimate with twice the root mean squared error.

We now suggest a simple bootstrapping procedure (Efron, 1982) for selecting a smoothing bandwidth and obtaining a latency estimate. We sample with replacement from the set of spike arrival times to create a set of replicated spike arrival times (a bootstrap replicate).

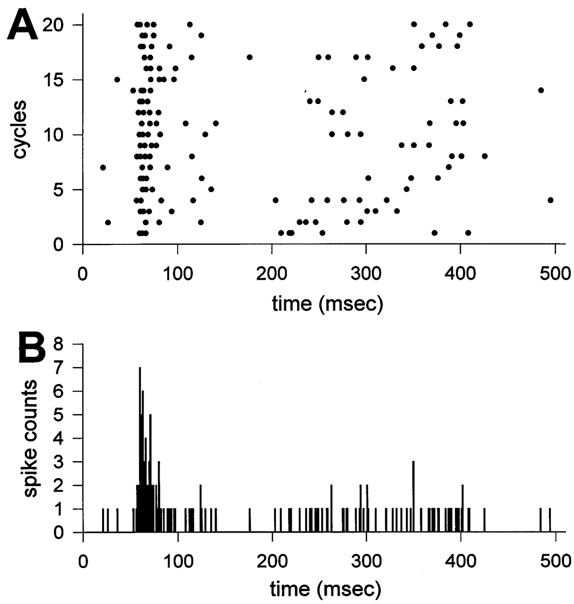

Fig. 1. Peri-stimulus histogram. Spike arrival times of a neuron from area V1 of an awake, fixating monkey for a flashing stimulus (1 Hz) are represented as tick marks in (A). The stimulus was presented for 500 ms, starting at time $t = 0$, for a total of 20 presentations. Using a bin width of 1 ms the histogram of spike arrival times (B), known as the peri-stimulus histogram, clearly demonstrates that there is a burst of activity approximately 60 ms from the time of stimulus onset.

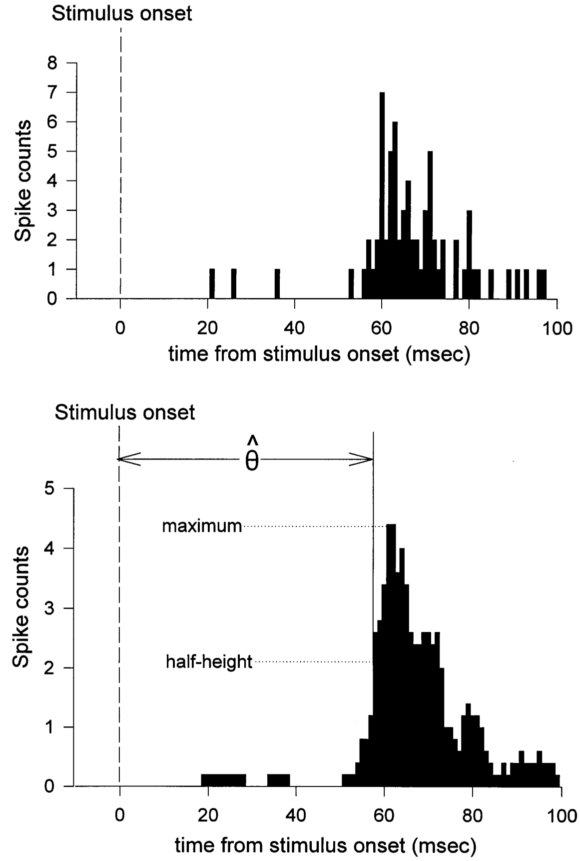

Fig. 2. Half-height estimation. A common nonparametric technique for estimating the latency involves smoothing the peri-stimulus histogram (same as Fig. 1B) to obtain a smoother version of the stimulus evoked neural response (B). Here we have used a 5 bin box smooth. The maximum and minimum values of the smoothed histogram are then determined. The first time from stimulus onset in which the smoothed histogram exceeds the average of the minimum and maximum of the smoothed histogram is the estimated latency.

Next, we smooth the new peri-stimulus histogram with all bandwidths to obtain a second vector of estimated latencies. Repeating for m bootstrap replicates yields a set of m estimated latencies for each smoothing bandwidth. Since the true latency is unknown and hence a bias estimate is unavailable, we suggest selecting the bandwidth which provides the smallest variance of estimated latencies. Using this selected bandwidth, the latency is then estimated from the original data set.

To demonstrate the efficacy of this suggestion, we select one vector from the first simulation and create the corresponding spike arrival times. This now simulates the situation in which the experimenter has obtained a set of spike arrival times from repeated stimulus presentations. We then use $m = 500$ bootstrap replicates to create a distribution of estimated latencies for each smoothing bandwidth. As shown in Fig. 4, the preferred bandwidth is estimated to be 13 bins. This is in agreement with the results from Fig. 3 and demonstrates that the bootstrap technique can be effective in

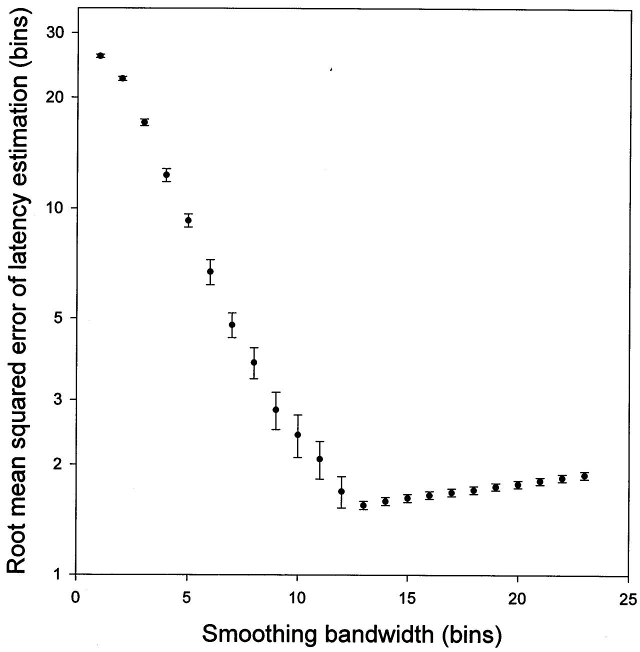

Fig. 3. Simulation results. Using the half-height technique (Fig. 2), the root mean squared error of the latency estimation is minimal at a bandwidth of 13 bins, when the spontaneous activity is 1 spike/bin, the initial response is 6 spikes/bin, and the lengths of the spontaneous and initial response are 50 bins. Choosing a smoothing bandwidth 5 bins smaller results in a latency estimate with twice the root mean squared error. A bootstrap resampling technique is employed to estimated the uncertainty in the root mean squared error.

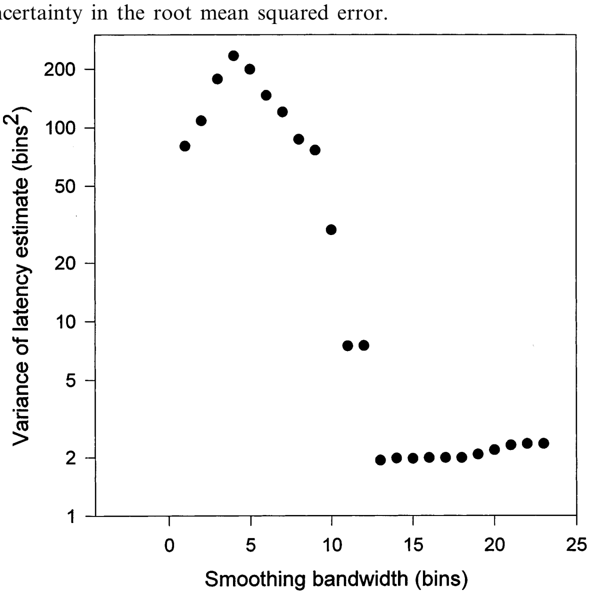

Fig. 4. Bootstrap example. Using the simulated vector in which the spontaneous activity was 1 spike/bin, the initial response was 6 spike/bin, and the length of the spontaneous and initial response was 50 bins, the variance of latency estimation using the bootstrap methodology was minimal at a bandwidth of 13. In the bootstrap method, the experimenter samples with replacement from the set of spike arrival times to create a set of replicated spike arrival times. The peri-stimulus histogram is smoothed using all smoothing bandwidths to obtain a vector of estimated latencies. Repeat this process for m bootstrap replicates yielding a set of m estimated latencies for each smoothing bandwidth (in this case $m = 500$). Select the bandwidth having the minimal variance of estimated latencies. Using this selected bandwidth, the latency is then estimated from the original data set.

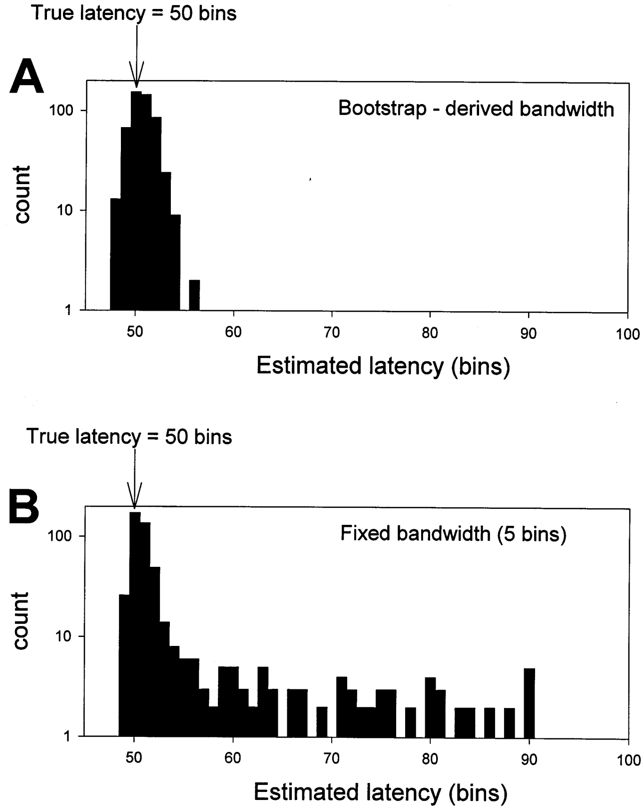

Fig. 5. Bootstrap example. Five hundred vectors were simulated in which the spontaneous activity was 1 spike/bin, the initial response was 6 spikes/bin, and the lengths of the spontaneous and initial response were 50 bins (so that the true latency = 50 bins). For each vector, the latency was estimated using a fixed bandwidth (5 bins) and a bootstrap-derived bandwidth. The distribution of latencies clearly demonstrates that the bootstrap-derived bandwidth (A) provides more accurate and precise (mean of bootstrap-derived bandwidth latencies $= 50.7 \pm 0.06$ bin, mean of fixed bandwidth latencies $= 54.2 \pm 0.4$ bins) latency estimates than the fixed bandwidth estimator (B).

choosing the smoothing bandwidth. Using the selected bandwidth in the original data set resulted in an estimated latency of 51 bins. It should be noted that, in our simulations, we only sampled integer bandwidths, the use of non-integer bandwidths would result in greater improvement in the latency estimation.

The above example illustrates that the bootstrapping technique is a viable method for improving the estimation of response latencies using the half-height technique. In order to demonstrate the statistical superiority of the bootstrapping technique, we select 500 vectors from the first simulation. We estimate the latency using a fixed bandwidth smoother (5 bins as in Gawne et al., 1996) and with the bootstrap-derived bandwidth. The distribution of latencies obtained from this simulation (Fig. 5) clearly demonstrates that the bootstrap-derived bandwidth provides more accurate and precise latency estimates than the fixed bandwidth estimator (mean of bootstrap-derived bandwidth latencies $= 50.7 \pm 0.06$

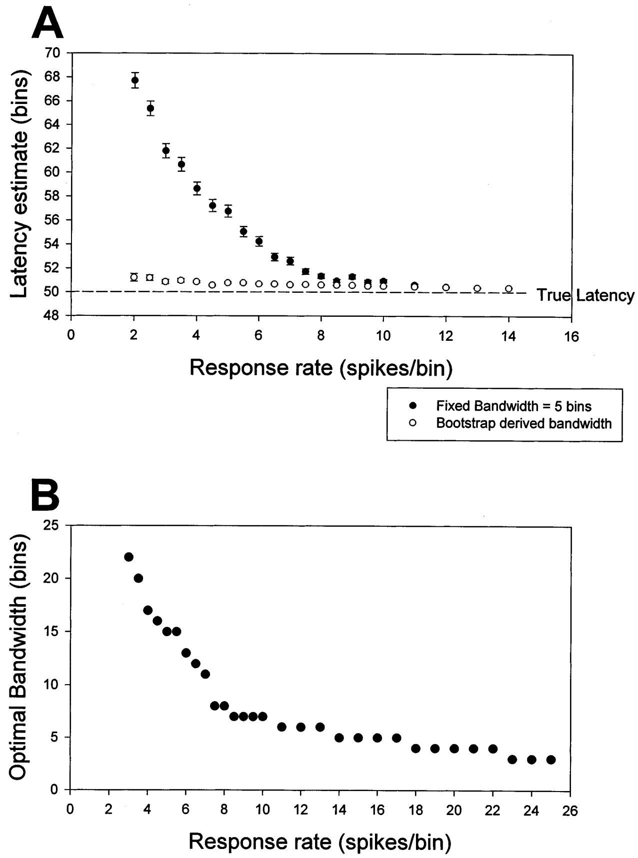

Fig. 6. Bootstrap example. For each value of the response rate, 500 vectors were simulated in which the spontaneous activity was 1 spike/bin, and the lengths of the spontaneous and initial response were 50 bins (so that the true latency = 50 bins). For each simulated vector, the latency was estimated using a fixed bandwidth (5 bins) and a bootstrap-derived bandwidth. As seen in plot A, the bootstrap-derived bandwidth provides more accurate and precise latency estimates than the fixed bandwidth estimator for all values of response rate. Plot B demonstrates the fact that the optimal bandwidth decreased as the response rate increased when the spontaneous rate was fixed at 1 spike/bin. In general, for a fixed spontaneous rate, this relationship was true.

bins, mean of fixed bandwidth latencies $= 54.2 \pm 0.4$ bins, true latency = 50 bins).

One issue that must be emphasized is that the optimal bandwidth is a function of the spontaneous rate, response rate, and latency. We illustrate this point by comparing the latency estimation from the fixed bandwidth and bootstrap-derived bandwidth smoothers using different values of the response rate. For each value of the response rate, 500 vectors were simulated in which the spontaneous activity was 1 spike/bin, and the lengths of the spontaneous and initial response were 50 bins (so that the true latency = 50 bins). For each simulated vector, the latency was estimated using a fixed bandwidth (5 bins) and a bootstrap-derived bandwidth. As seen in plot A of Fig. 6, the bootstrap-derived bandwidth provides more accurate and precise latency estimates than the fixed bandwidth estimator for all values of the response rate. Plot B of Fig. 6 demonstrates the fact that the optimal bandwidth decreases as the response rate increases when the spontaneous rate was fixed at 1 spike/bin. In general, for a fixed spontaneous rate, this relationship appears to be true.

Since the smoothing bandwidth plays a critical role in the accuracy of latency estimation, it is imperative that the experimenter select the bandwidth in an informed manner. Our bootstrap methodology provides a simple and robust automated method for choosing the smoothing bandwidth.

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