

# Examining the joint neural code of latency and firing rate by Bayesian Binning

*Dominik Endres, Johannes Schindelin, Peter Földiák and Mike Oram*

School of Psychology  
University of St. Andrews  
KY16 9JP, UK

{dme2,js108,pf2,mwo}@st-andrews.ac.uk

## ABSTRACT

### 1. Method

The peristimulus time histogram (PSTH) and its more continuous cousin, the spike density function (SDF) are staples in the analytic tool kit of neurophysiologists. The former is usually obtained by binning spike trains, whereas the standard method for the latter is smoothing with a Gaussian kernel. Selection of a bin width or a kernel size is often done in an relatively arbitrary fashion, even though there have been recent attempts to remedy this situation [4,5].

We develop an exact Bayesian, generative model approach to estimating PSTHs. Our model encodes a spike generator described by an inhomogeneous Bernoulli process with piecewise constant (in time) probabilities, i.e. it is comprised of a finite number of time bins. Within each time bin, the distribution of the number of spikes is binomial.

We show that relevant marginal distributions, e.g. the posterior distribution of the number of time bins, can be evaluated in polynomial time from the full joint posterior distribution over the model parameters. This marginal distribution encodes the model complexity, whence we can perform Bayesian model selection or averaging. Extending earlier dynamic programming schemes [2], we show that expected values, such as the predictive firing rate and its standard error, or the expected bin boundary positions, are also computable with polynomial effort.

We demonstrate the superiority of our approach to two competing methods, Gaussian smoothing and the binning method described in [4] by comparing cross-validation errors on real neural spike trains. We obtained data through [3]. Briefly, extra-cellular single-unit recordings were made using standard techniques from the upper and lower banks of the anterior part of the superior temporal sulcus (STSa) and the inferior temporal cortex (IT) of two monkeys (*Macaca mulatta*) performing a visual fixation task. Neuronal responses to a variety of visual images (faces, everyday objects and abstract images) presented a varying contrasts were collected.

### 2. Information-theoretic analysis of contrast encoding by STSa cells

Previous studies [1,3] indicate that much of the stimulus-related information carried by neurons in IT and STSa is contained in relatively coarse measures of the neural response, such as response latency and firing rate. We investigate the encoding of stimulus contrast and stimulus identity by these measures.

We define latency as the point in time before which the firing probability was below a given noise level, and above that noise level for at least one time bin afterwards. This condition can be fulfilled for at most one point in time, if it is fulfilled nowhere, then a latency does not exist. Because our model is comprised of a discrete number of bins, this latency definition is easily evaluated if the model parameters are known. Thus, we obtain the latency posterior by marginalising the model parameters. The noise level is selected to maximise the probability of a signal, i.e. the probability that a latency exists. We then compute the mutual information between latency  $L$  and stimulus contrast  $C$ ,  $I(L;C)$ , for each cell.

Next, we evaluate the mutual information  $I(F;C)$  between stimulus contrast and the firing rate  $F$  in the time bin which begins at the latency. This time bin often contains the strong transient part of the cell's response to the stimulus and previous studies have shown that this period of the response contains the majority of the total information available [Roll paper, your paper].

We find that latency contains roughly twice as much information about contrast as firing rate, with the relationship between  $I(L;C)$  and  $I(F;C)$  being approximately linear. Moreover, an examination of the joint code formed by latency and firing rate shows that ~40% of the firing rate information is contained in the latency, whereas only ~15% of the latency information can be extracted from the firing rate. Therefore, most of the information about contrast is conveyed by the latency, and a large part of  $I(F;C)$  is redundant with  $L$ .

Next, we look at the stimulus identity  $S$ . We find  $I(L;S) > I(F;S)$  in most cases, but a simple linear relationship between the two information measures could not be established. Also, only ~3% of  $I(F;S)$  is conveyed by  $L$  and vice versa. We would therefore conclude that firing rate and latency convey information about different aspects of the stimulus identity. One possibility is that the variation in response latency with stimulus occurs because the stimuli have different effective contrasts. Thus, while we controlled for the Michelson contrast across the entire image, the contrast “from the neurones perspective” could have differed. Evaluation of alternative contrast measures, such as the root-mean-square measure, gave even more discrepant results.

**Keywords:** Bayesian methods, mutual information, visual cortex.

## References

- [1] Baddeley R., *et al.* (1997) Responses of neurons in primary and inferior temporal visual cortices to natural scenes, in: *Proceedings of Biological Sciences* 264, The Royal Society (London), pp 1775-1783.
- [2] Endres, D. and Földiák, P. (2005) Bayesian Bin Distribution Inference and Mutual Information, *IEEE Transactions on Information Theory*, **51**(11): 3766- 3779.
- [3] Oram, M. W., Xiao, D., Drietschel, B. and Payne, K.R. (2002) The temporal precision of neural signals: A unique role for response latency? *Philosophical Transactions of the Royal Society, Series B*, **357**: 987-1001
- [4] Shimazaki, H. and Shinomoto, S. (2007) A Method for Selecting the Bin Size of a Time Histogram, *Neural Computation*, **19**(6): 1503-1527.
- [5] Shimazaki, H. and Shinomoto, S. (2007) A recipe for optimizing a time-histogram, in: *Advances in Neural Information Processing Systems 19* (Schölkopf B., Platt J. and Hoffman, T.), MIT Press, Cambridge, MA, pp. 1289-1296.