Supervised learning sets benchmark for robust spike detection from calcium imaging signals

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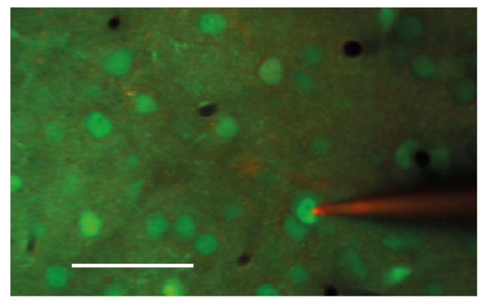
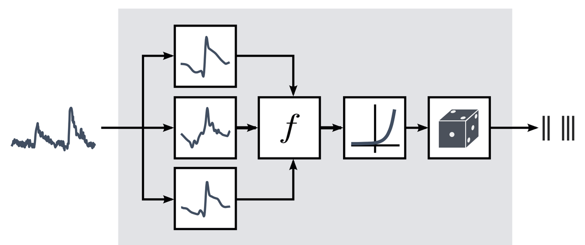
Introduction



Existing methods for spike reconstruction from fluorescence traces make strong assumptions. In contrast, here we try to learn as much as possible about the relationship between calcium images and spikes using supervised learning from simultaneous recordings of fluorescence and spikes [2].

Model



The spike counts k_t are modeled with a Poisson distribution whose rate depends on a 1000 ms window of the fluorescence trace, $\mathbf{x}_t$.

$$p(k_t \mid \mathbf{x}_t) = \frac{\lambda(\mathbf{x}_t)^k}{k!} e^{-\lambda(\mathbf{x}_t)}$$

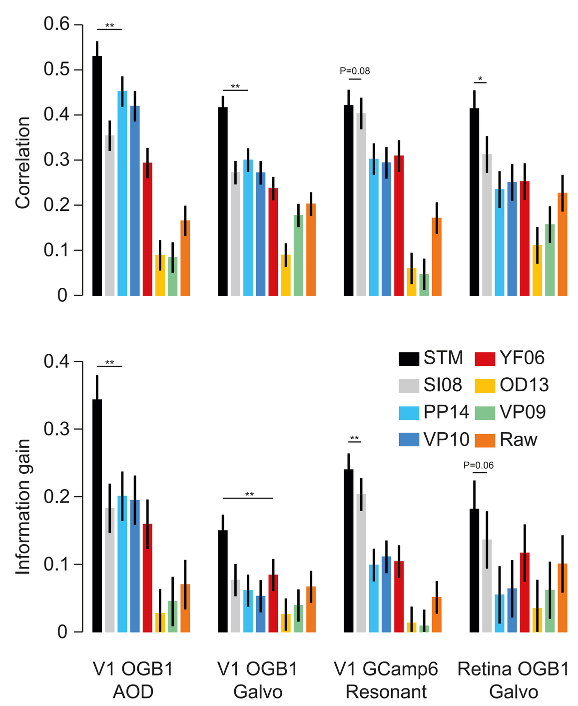
More specifically, we use the spike-triggered mixture model (STM) [1].

$$\lambda_{\mathrm{STM}}(\mathbf{x}_t) = \sum_{k=1}^{K} \exp\left(\sum_{m=1}^{M} \beta_{km} (\mathbf{u}_m^\top \mathbf{x}_t)^2 + \mathbf{w}_k^\top \mathbf{x}_t + \mathbf{b}_k \right)$$

The parameters of the model are fit to simultaneous recordings of fluorescence traces and spikes for some cells, and used for prediction of other cells.

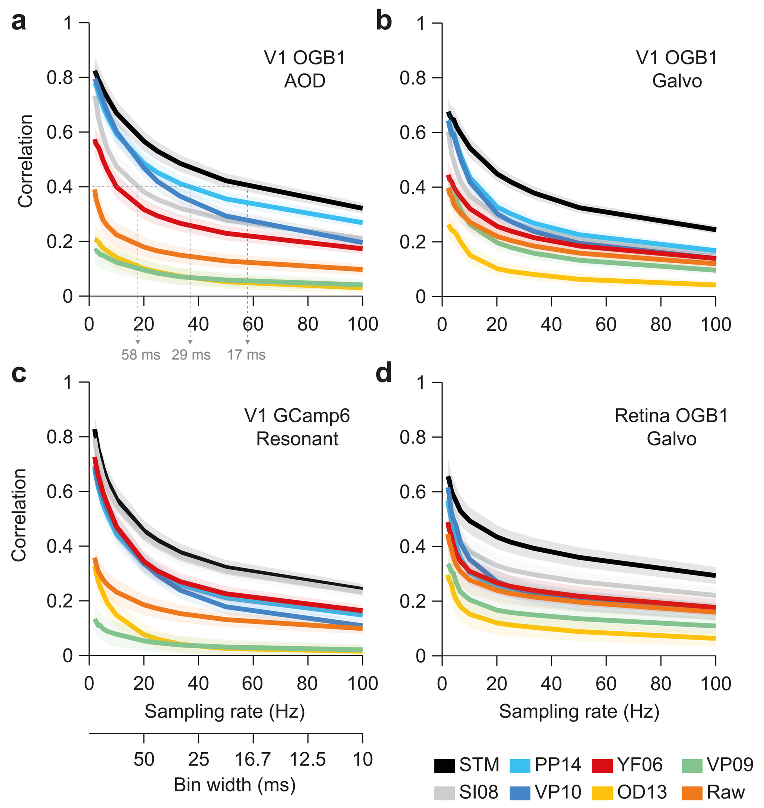
Quantitative comparison

Leave-one-out cross-validation performance for recordings from retina and V1 of anesthesized mice. We compared to a number of methods [3-8].



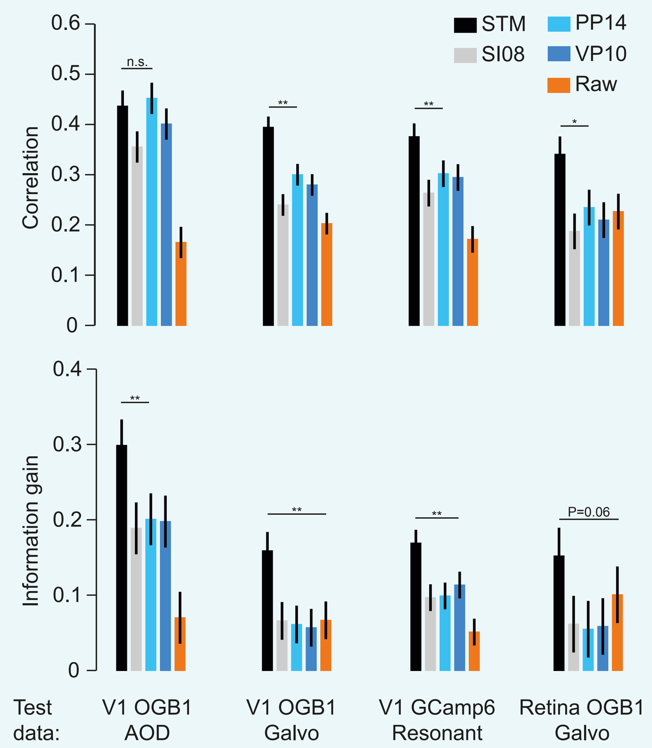
Higher precision at same correlation

Performance as function of sampling rate. For a fixed correlation, our method allows us to use much smaller bin widths.



Without simultaneous recordings

Importantly, our method can also be used when simultaenous recordings are not available. We trained our model on three datasets recorded in different labs and under different conditions, and tested on a fourth dataset. Surprisingly, our model generalizes better than unsupervised approaches.

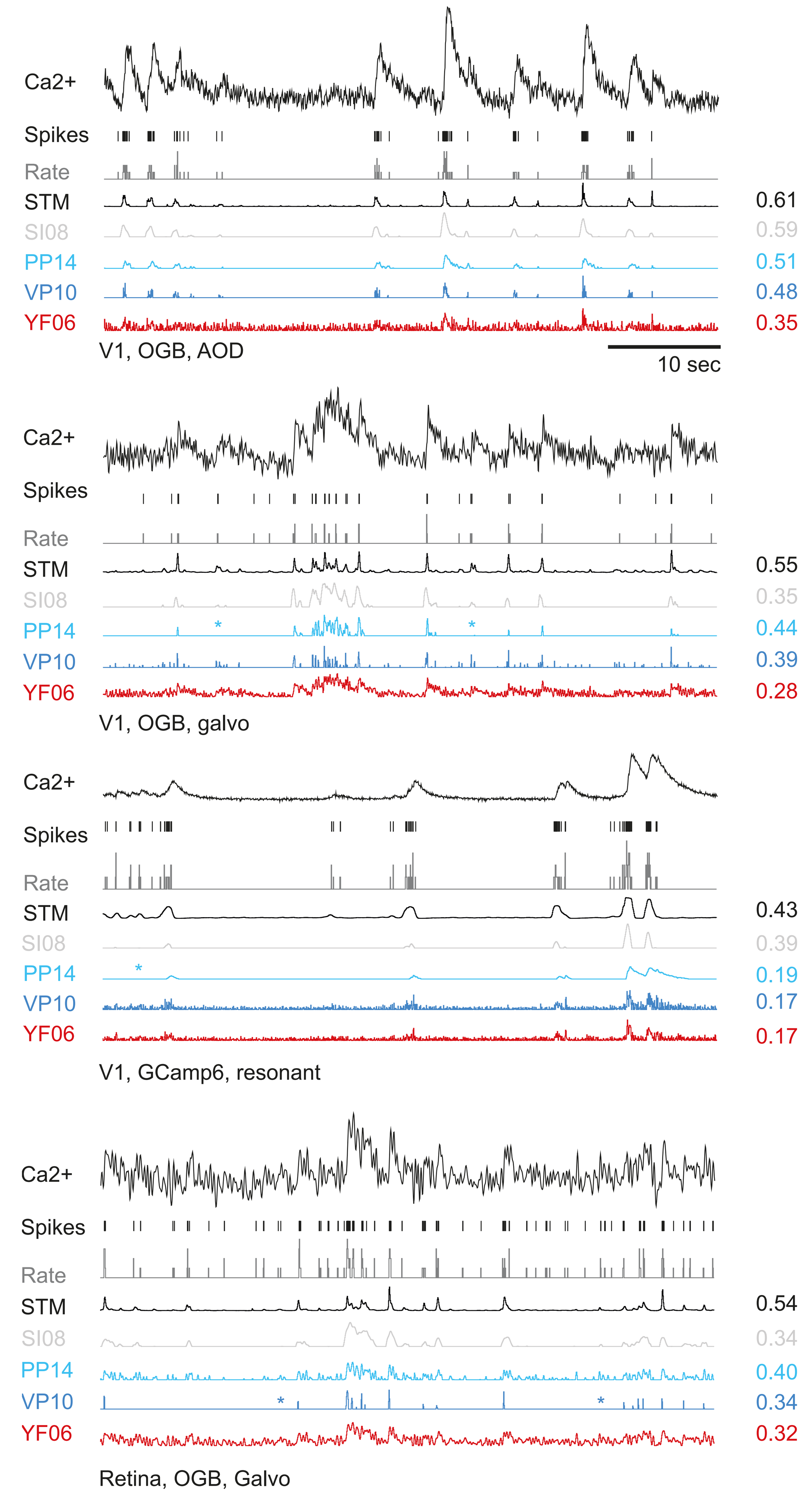


A pretrained model trained on over 100,000 spikes from different labs, recorded under different conditions and in different species is available at:

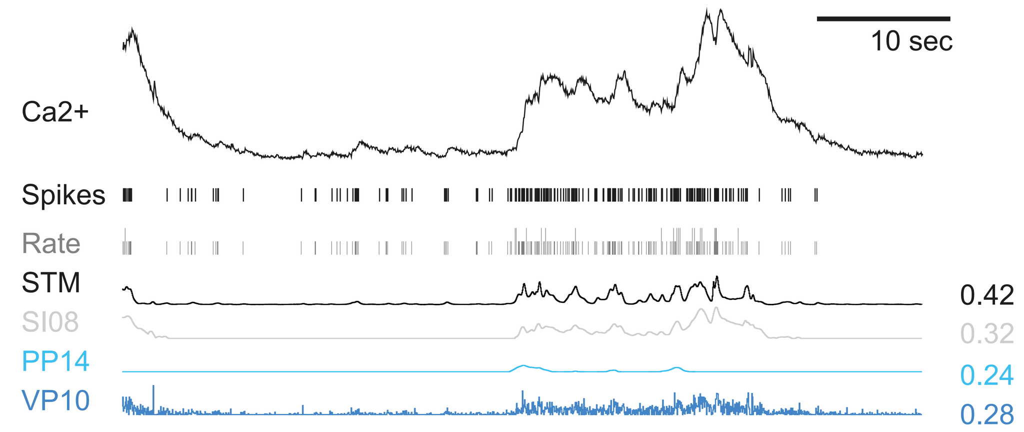
http://github.com/lucastheis/c2s/

Examples

Simultaneous recordings and predictions of various methods:

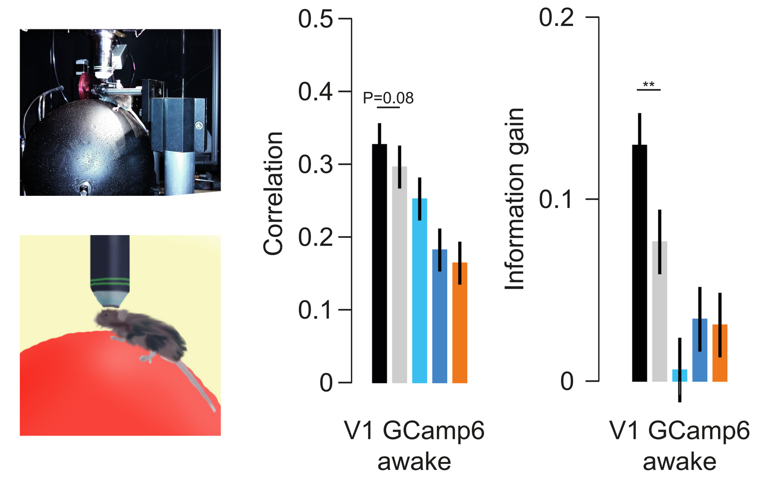


As above but on awake data and without giving the algorithm access to simultaneous recordings:

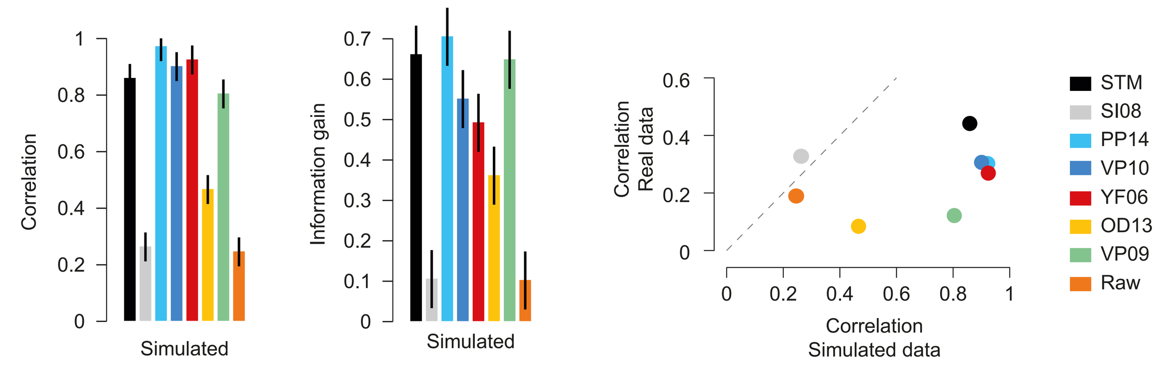


Awake animals

We tested our algorithm on awake animals. The model was trained on recordings from anesthesized mice.

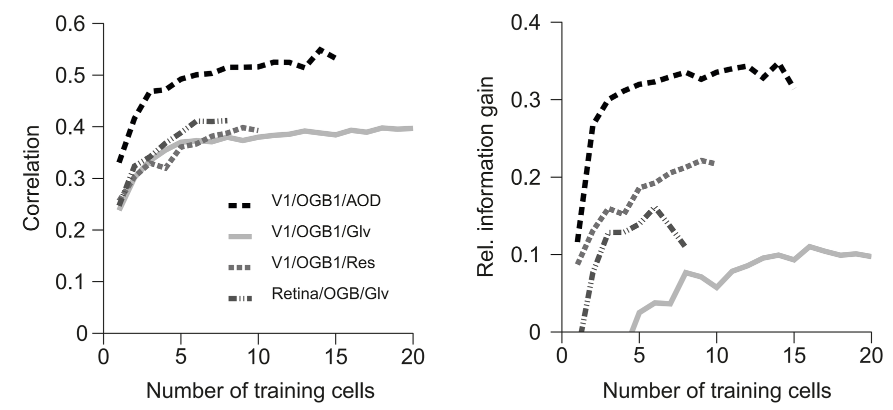


Simulated data



Existing generative approaches work well on simulated data, but performance is not predictive of performance on real data.

How much data is needed for training?



Discussion

Current approaches often perform poorly when applied to real data due to strong but incorrect assumptions. Our data-driven supervised approach can learn a more correct relationship from simultaneous recordings, generalizes across datasets, and can be optimized for specific needs (e.g., new fluorescent markers).

References

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