Bayesian decoding has been recently used to decode arm trajectories based on M1 neurons’ responses. Here we apply a similar technique to decode a visual stimulus, given the responses of V1 neurons. The algorithm, presented in detail below, is a variant of particle filtering, in which the particles, or hypotheses, are predictions of the entire signal sequence for all the time steps in a trial.

The reconstruction has two purposes. (1) A reconstruction allows us to see what the brain is encoding. (2) A successful reconstruction could provide insight into the actual algorithm that the brain is using to understand the visual stimulus.

Panels A–C describe the experiment and data acquisition, as well as the steps taken before the particle filtering algorithm. Panels 1–6 describe the 6 steps of the algorithm. For each successive time step \( t \), the computation iterates from step 1 to step 6.

### Experimental setup

Movies of a sine wave grating in motion were presented to a behaving Macaque monkey. The spatial and temporal frequencies of the gratings were chosen to evoke maximum neuronal responses and maximum modulation in response. Each trial was 2.2 seconds in length, and the monkey needed to maintain fixation throughout the trial.

### Data

For each cell recorded from, 400 distinct random trials were presented for training data, and 60-80 trials of some receptive fields were obtained for the purpose of testing.

### Volterra kernels as the transfer function

The neuronal PSTH is compared to the predicted response of each particle to assess its likelihood. The particles are considered to be competing models, with the highest particle producing a prediction about the neuronal response \( \theta(t) \). The particle’s probability weight is given by the “softmax” equation,

\[
\text{exp}(i \cdot w) / \sum \text{exp}(i \cdot w)
\]

The free parameter \( \sigma \) roughly corresponds to the amount of noise in the data. This varies with the number of particles, since a high number of particles provides more precise estimates of the signal. An optimal \( \sigma \) was found empirically and used in all reconstructions.

### Likelihood by comparing data with predictions

Thus, the particles with high weights are propagated and the particles with low weights tend to be eliminated from the resultant collection. Multiple copies of the highly weighted particles may appear in the resultant collection.

### Resampling particles based on the likelihoods

At this point, the current step has not yet changed, and the particles have been resampled with the neuronal response information available at this time step. This resampled collection can now be treated as one particle.

### References


### Discussion

- Some individual V1 neurons contain sufficient information for decoding the spatio-temporal movement of a sine wave grating, better than the optimal linear decoder.
- Even complex cells (relatively insensitive to spatial phase) allow us to recover the visual stimulus based on prior signals and history. *A PSTH* from 10 trials seems to be sufficient for good decoding, suggesting that we have 10 similar cells, online computation is possible.