In modern neurophysiology experiments it is often necessary to determine the tuning properties of the neurons to be studied to relate their responses in a given task to their intrinsic properties. Usually there is a parametric model for the response of the cell, and the model parameters are estimated by showing a range of tuning stimuli. For example, one might fit the parameters of a Gaussian to responses obtained with stimuli moving in 16 different directions. In simple cases where only one parameter of the stimulus is varied (e.g. direction), one usually performs an extensive scan over a set of predetermined stimuli, generally with some repetition to account for the trial to trial variability, and then fits the parametric model. However, when the number of parameters of the probe stimuli becomes large, the extensive scanning becomes unfeasible due to the explosion in the number of presentations required to explore the whole tuning space and perform the tuning with accuracy. An example would be to test V1 neurons with stimuli having 16 different directions, 10 different speeds and 10 different spatial frequencies, for an impractical total of 1600 combinations (i.e. 1600 stimuli).

The typical approach to multidimensional tuning has been to do it sequentially. For example, one finds the preferred orientation of a cell; setting stimulus orientation to this value, one then varies the spatial frequency; and so on. However, there is a growing tendency to study multiple neurons simultaneously, and this trend will continue as channel capacity continues to increase. When multiple cells are being studied simultaneously, it is no longer practical to sequentially tune each one.

We present an adaptive technique to solve this problem when a real time acquisition system is available such that firing estimates are available in approximately real time. Using the information collected up to a given point, the method uses the assumed parametric model to determine the probe stimulus that will give, on average, the maximum increase in information about the neuron's parameters. The algorithm computes the entropy of the parameters of the model that one would obtain after the presentation of a stimulus, conditional on the actual estimates available (or on some priors in the case of the first iteration). This computation is repeated for all the possible stimuli, and the one with the maximum average entropy is taken as the next stimulus to be presented. After presentation the estimates are updated in a Bayesian fashion and the process restarts. The algorithm stops when a given variance on the estimates is reached.

We set up a toy model of a neuron with speed and direction preference and studied the system with a 5-parameter model. The adaptive method was able on average to converge to the true values of the parameters with a given accuracy in 1/8 the number of trials required for an all-combinations approach, and in about 1/2 the number of trials needed for the same Bayesian method to converge without adaptation. Even when the parametric model was not totally exact, the algorithm proved to be able to improve consistently the search in tuning space.

In order to simplify the computational complexity of the method and to speed up the total computing time between one stimulus and the next (a critical issue given that the algorithm has to run in real time), we have assumed independence between the parameters even where this would not be statistically justified. Although this is a non-optimal approximation, the method proved nevertheless robust and efficient.