A

Adaptive Stimulus Optimization

Christopher DiMattina[1] and Kechen Zhang[2]
[1]Department of Psychology, Florida Gulf Coast Univerisity, Fort Myers, FL, USA
[2]Department of Biomedical Engineering, Johns Hopkins University, Baltimore, MD, USA

Synonyms

Adaptive design optimization; Adaptive sampling; Closed-loop experiments; Optimal experimental design; Optimal stimulus design

Definition

Adaptive stimulus optimization refers to an experimental approach in neuroscience where neuronal or behavioral responses to stimuli presented on previous trials are utilized to adaptively generate new stimuli in an iterative, closed-loop manner, usually by optimizing an objective function. There are different choices for the objective function. For example, if the objective function is the neural response itself, the optimization procedure finds an optimal stimulus that drives maximum response or is at least a local optimum in the stimulus space. When the objective function is the mutual information between the responses and the unknown parameters of a stimulus-response model, the optimization finds the stimulus set that yields the most accurate parameter estimation.

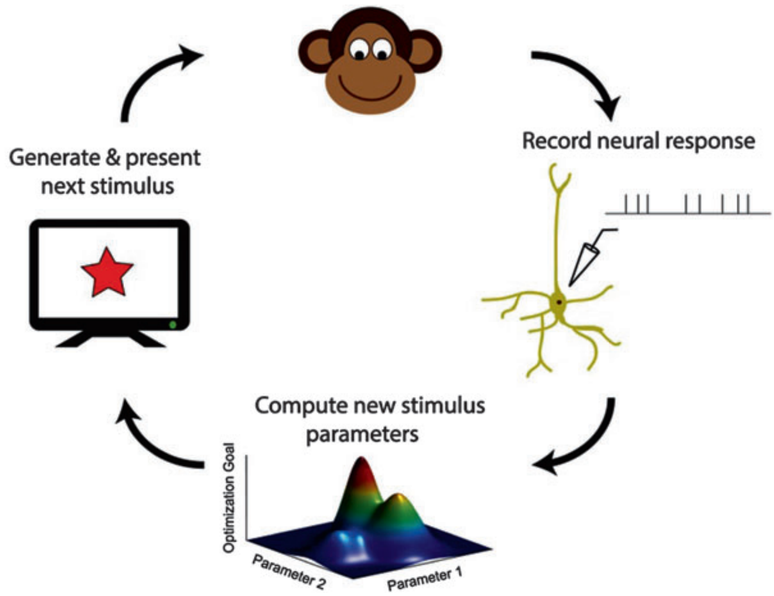
Detailed Description

Overview

Traditional experiments in the neurosciences have typically a fixed set of stimuli chosen *a priori* to elicit responses from neurons in an open-loop paradigm, with data analysis and model fitting taking place post hoc. In recent years, with increases in computer power and improvements of algorithms, there has been a growing interest in adaptively generating stimuli online during the course of experimentation in an iterative, closed-loop manner, where neuronal responses from previous trials are used to generate new stimuli (Benda et al. 2007; DiMattina and Zhang 2013; Potter et al. 2013; Park and Pillow 2016). This general paradigm is illustrated schematically in Fig. 1.

Adaptive stimulus optimization has long been used in psychophysics for estimating sensory thresholds (Watson and Pelli 1983; Kontsevich and Tyler 1999) and enjoys a large body of theoretical results from the statistics and machine learning literature (Paninski 2005; Chaloner and Verdinelli 1995). In sensory neuroscience studies, stimuli have been adaptively optimized for a wide variety of experimental goals, including maximizing neural firing rates (O'Connor et al. 2005; Chambers et al. 2014), finding maximally informative stimulus ensembles, (Machens et al.

D. Jaeger, R. Jung (eds.), *Encyclopedia of Computational Neuroscience*,
https://doi.org/10.1007/978-1-4614-7320-6_100655-1



Adaptive Stimulus Optimization, Fig. 1 Schematic illustration of adaptive stimulus optimization, where responses to preceding stimuli are used to generate subsequent stimuli in a closed-loop manner (Reproduced from DiMattina and Zhang 2013)

2005), and estimating and comparing models of sensory processing (Lewi et al. 2009; DiMattina and Zhang 2011; Tam 2012; Park and Pillow 2012, 2016). In addition to applications in systems-level sensory neuroscience, closed-loop approaches have also been applied in many diverse areas including cognitive science, cellular neurophysiology, and brain-computer interfaces (Myung et al. 2013; Potter et al. 2013).

Optimizing Firing Rate

Methods for adaptive optimization of neuronal firing rate fall broadly into two categories: (1) hill-climbing methods and (2) genetic algorithms. Hill-climbing methods utilize local perturbations of a reference stimulus to estimate the local response surface from noisy neural responses, iteratively moving the reference stimulus in a direction (e.g., the gradient) which increases neural firing rate (Harth and Tzanakou 1974; O'Connor et al. 2005; Nelken et al. 1994; Koelling and Nykamp 2012). Genetic algorithms mimic biological evolution by broadly populating the stimulus space with numerous stimuli and using their elicited neural responses as a measure of fitness. The fittest stimuli in each generation are then used to define the next generation of stimuli by recombination of their features in a manner analogous to sexual reproduction (Yamane et al. 2008; Chambers et al. 2014). Genetic algorithms have the advantage of being more robust to local maxima than hill-climbing methods and more extensively sampling the stimulus space.

Iso-response Surfaces

Instead of finding the single stimulus that optimizes the firing rate, it is also useful to find the set of all stimuli which elicit the same firing rate response. The shape of these firing rate level sets can tell us about how a sensory neuron combines stimulus dimensions. This method has been applied in diverse contexts, including studies of spectral integration in grasshopper auditory neurons and integration of photoreceptor inputs by V1 neurons (Gollisch et al. 2002; Horwitz and Hass 2012).

Optimizing Information

Instead of characterizing a neuron by its preferred or "optimal" stimulus, an alternative approach is to characterize the neuron in terms of the stimulus ensemble which its responses most reliably distinguish. This may be quantified by maximizing the mutual information between the stimuli and neural responses, and this technique was applied by Machens et al. (2005) in a study of grasshopper auditory receptor neurons.

Estimating and Comparing Models

Given an accurate model of the input-output relationship for a sensory neuron, it is possible in principle to predict the neuron's response to an arbitrary stimulus. However, estimating high-dimensional models from limited experimental data often poses a serious technical challenge. A study by Lewi et al. (2009) demonstrated that adaptively selecting stimuli to optimize expected mutual information between neural responses and model parameters allowed fast and robust estimation of generalized linear models. Subsequent work by DiMattina and Zhang (2011) extended this idea to arbitrary stimulus-response models and also considered the problem of adaptively optimizing stimuli for comparing multiple, competing neural models. These methods were verified experimentally in a study of spectral integration in the primate inferior colliculus (Tam 2012). More recent work has considered the use of well-chosen priors to further speed convergence of receptive field estimates (Park and Pillow 2012, 2016). Optimization of sensory stimuli for model estimation and comparison have also been recently applied in vision psychophysics and cognitive science (Wang and Simoncelli 2008; Myung et al. 2013; Kim et al. 2014).

Cross-References

- ► Bayesian Approaches in Computational Neuroscience
- ► Estimation of Neuronal Firing Rate
- ► Information Theory: Overview
- ► Spectrotemporal Receptive Fields
- ► Neural Coding

References

Benda J, Gollisch T, Machens CK, Herz AV (2007) From response to stimulus: adaptive sampling in sensory physiology. Curr Opin Neurobiol 17(4):430–436

Chaloner K, Verdinelli I (1995) Bayesian experimental design: a review. Stat Sci 10(3):273–304

Chambers AR, Hancock KE, Sen K, Polley DB (2014) Online stimulus optimization rapidly reveals multidimensional selectivity in auditory cortical neurons. J Neurosci 34(27):8963–8975

DiMattina C, Zhang K (2011) Active data collection for efficient estimation and comparison of nonlinear neural models. Neural Comput 23(9):2242–2288

DiMattina C, Zhang K (2013) Adaptive stimulus optimization for sensory systems neuroscience. Front Neural Circuits 7:101

Gollisch T, Schu¨tze H, Benda J, Herz AV (2002) Energy integration describes sound-intensity coding in an insect auditory system. J Neurosci 22(23):10434–10448

Harth E, Tzanakou E (1974) Alopex: a stochastic method for determining visual receptive fields. Vis Res 14(12):1475–1482

Horwitz GD, Hass CA (2012) Nonlinear analysis of macaque v1 color tuning reveals cardinal directions for cortical color processing. Nat Neurosci 15(6):913–919

Kim W, Pitt MA, Lu Z-L, Steyvers M, Myung JI (2014) A hierarchical adaptive approach to optimal experimental design. Neural Comput 26(11):2465–2492

Koelling ME, Nykamp DQ (2012) Searching for optimal stimuli: ascending a neurons response function. J Comput Neurosci 33(3):449–473

Kontsevich LL, Tyler CW (1999) Bayesian adaptive estimation of psychometric slope and threshold. Vis Res 39(16):2729–2737

Lewi J, Butera R, Paninski L (2009) Sequential optimal design of neurophysiology experiments. Neural Comput 21(3):619–687

Machens CK, Gollisch T, Kolesnikova O, Herz AV (2005) Testing the efficiency of sensory coding with optimal stimulus ensembles. Neuron 47(3):447–456

Myung JI, Cavagnaro DR, Pitt MA (2013) A tutorial on adaptive design optimization. J Math Psychol 57(3):53–67

Nelken I, Prut Y, Vaadia E, Abeles M (1994) In search of the best stimulus: an optimization procedure for finding efficient stimuli in the cat auditory cortex. Hear Res 72(1):237–253

O'Connor KN, Petkov CI, Sutter ML (2005) Adaptive stimulus optimization for auditory cortical neurons. J Neurophysiol 94(6):4051–4067

Paninski L (2005) Asymptotic theory of information-theoretic experimental design. Neural Comput 17(7):1480–1507

Park M, Pillow JW (2012) Bayesian active learning with localized priors for fast receptive field characterization. In: Advances in neural information processing systems. Cambridge, MA: MIT Press, 25:2348–2356

Park M, Pillow JW (2016) Adaptive bayesian methods for closed-loop neurophysiology. In: El Hady A (ed) Closed loop neuroscience. Cambridge, MA: Academic Press/Elsevier, pp 3–16

Potter SM, El Hady A, Fetz EE (2013) Closed-loop neuroscience and neuroengineering. Front Neural Circuits 8:115

Tam W (2012) Adaptive modeling of marmoset inferior colliculus neurons in vivo. PhD thesis, The Johns Hopkins University School of Medicine

Wang Z, Simoncelli EP (2008) Maximum differentiation (mad) competition: a methodology for comparing computational models of perceptual quantities. J Vis 8(12):8

Watson AB, Pelli DG (1983) Quest: a bayesian adaptive psychometric method. Percept Psychophys 33(2):113–120

Yamane Y, Carlson ET, Bowman KC, Wang Z, Connor CE (2008) A neural code for three-dimensional object shape in macaque inferotemporal cortex. Nat Neurosci 11(11):1352–1360