Robust and efficient receptive field inference from binary responses with stochastic gradient descent

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Characterization of neural response properties by means of the receptive field corresponds to estimation of the linear part of a linear-nonlinear cascade model [1]. It commonly involves estimation of the stimulus auto-covariance matrix as in the reverse correlation method as a way to remove second-order stimulus correlations that occur in many stimuli of interest, in particular natural stimuli. However, non-Gaussian stimulus distributions and higher-order stimulus correlations in conjunction with nonlinear response properties result in biased estimates of the true receptive field for covariance-based approaches [2]. We show that the problem of receptive field estimation may be reformulated in terms of a binary classification problem, an approach that alleviates the aforementioned problems. In contrast to regression-like modification of the reverse correlation method, it works on single spikes, and unlike the spike triggered average (STA), it uses spike-eliciting and non-spike-eliciting stimulus portions for receptive field estimation. Using simulations and recordings from inferior colliculus neurons of mongolian gerbils, we show that receptive field estimates obtained using the support vector machine (SVM, [3]) classification based receptive field estimator show better decorrelation properties of higher-order stimulus correlations and are more robust against asymmetric stimulus intensity distributions than typical covariance-based approaches. We also present an algorithm based on a stochastic gradient descent SVM (SGD, [4]), which replaces the computationally expensive batch gradient update step based on all examples by an update involving only a randomly chosen subset. This reduction in computational cost may enable the proposed approach to monitor RF properties during experiments.

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