**Title:**

A general framework for optimal selection of the learning rate in closed-loop brain-machine interfaces

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**Abstract:**

Brain-machine interfaces (BMIs) decode subjects' movement intention from neural activity to allow them to control external devices. Various decoding algorithms, such as linear regression, Kalman, or point process filters, have been implemented in BMIs. Regardless of the specific decoder, recent studies have demonstrated that closed-loop decoder adaptation (CLDA) techniques, which learn the decoder parameters in closed loop, improve BMI performance. A main design parameter that needs to be selected in any CLDA algorithm is the learning rate, which dictates how fast the decoder parameters should be updated on the basis of new neural observations. So far, the learning rate of CLDA algorithms has been selected empirically using ad-hoc methods. Here, we develop a principled calibration algorithm to select the learning rate in adaptive decoders. The learning rate introduces a trade-off between the convergence rate and the steady-state error of the estimated decoder parameters. Hence to solve the problem, we find an analytical expression of the steady state error as a function of the learning rate and use an inverse map to compute the optimal learning rate that guarantees the error to be below a desired tolerance. We test this calibration algorithm in closed-loop numerical BMI experiments. For illustration purposes, we first evaluate the calibration in an adaptive optimal feedback-controlled point process filter (OFC-PPF) decoder that we have recently developed in a primate model. We show that the calibration algorithm selects the optimal learning rate that meets the requirement on steady-state error level while achieving the fastest convergence rate possible. We then show that the calibration algorithm generalizes to other decoders such as Kalman filters. Hence our calibration algorithm provides a general framework for selection of the optimal learning rate in closed-loop adaptive BMIs.