

Predicting Changes in Neural Tuning During BCI Learning

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Abstract. The tuning of cortical neurons changes as subjects learn to control Brain-Computer Interfaces (BCIs). We hypothesized that these changes may be predicted from patterns of neural activity recorded during natural movements prior to learning. We analysed neural tuning as monkeys learned BCIs with arbitrary mappings between firing rates and cursor position, and compared two learning models to predict tuning changes: uniform vs. constrained. We found that the constrained model explained more of the observed variation, with learning restricted to only a small number of naturalistic dimensions within the neural space.

Keywords: Single-Unit Activity, Motor Cortex, Learning, Plasticity, Optimal Control

1. Introduction

BCIs are redundant motor tasks with more control signals (neurons) than output dimensions (cursor axes), so different strategies at the neural level could drive improvements in performance [Jackson and Fetz, 2012]. Often the strategy that emerges with training appears sub-optimal (e.g. neurons become tuned for directions different from their true action on the cursor) suggesting learning is constrained to a limited subset of dimensions within the neural space. Here we examine whether these constraints reflect activity patterns observed during natural movement.

2. Material and Methods

Spiking activity was recorded from primary motor (M1) and ventral premotor (PMv) cortices of two rhesus macaques (monkey D: $N = 20$ neurons, monkey R: $N = 12$) performing 2D wrist- and 1D brain-controlled cursor tasks over multiple sessions. During brain control, neurons were assigned to *up*, *down* and *off* ensembles according to an arbitrary mapping (*Map1* or *Map2*) represented by a vector in the neural space (\mathbf{m}). Instantaneous cursor position (y) was determined from neuronal firing rates (v_i , normalized by their range during wrist control) according to:

$$y = \sum_{i=1}^N m_i \cdot v_i = \mathbf{m} \cdot \mathbf{v} \quad \text{where } m_i = \{-1, 0, +1\} \text{ for } \textit{down}, \textit{off} \text{ and } \textit{up} \text{ neurons respectively} \quad (1)$$

Monkeys had to move the cursor to targets appearing at random in *high* and *low* locations on the screen. *Performance* was quantified as the separation between average cursor trajectories following the appearance of high and low targets ($\bar{y}_{high}, \bar{y}_{low}$), which in turn depended on the *tuning* of each neuron (T_i). Therefore, *improvement* across consecutive sessions can be expressed as a vector product:

$$\begin{aligned} \textit{Performance} &= \int_0^{5s} (\bar{y}_{high} - \bar{y}_{low}) dt = \sum_{i=1}^N m_i \cdot \int_0^{5s} (\bar{v}_{i,high} - \bar{v}_{i,low}) dt = \sum_{i=1}^N m_i \cdot T_i \\ \Rightarrow \textit{Improvement} &= \mathbf{m} \cdot \Delta \mathbf{T} \end{aligned} \quad (2)$$

where the change in tuning across consecutive sessions is also represented by a vector in the neural space ($\Delta \mathbf{T}$). To maximize improvement, $\Delta \mathbf{T}$ should be aligned with the current map vector \mathbf{m} (i.e. *up* neurons should become tuned for *high* targets, *down* neurons should become tuned for *low* targets) which we call ‘uniform learning’. However, if learning is constrained, tuning changes will be biased to particular dimensions of the neural space. To estimate these dimensions we calculated the *principal components* (PCs) of low-pass filtered (<5 Hz) firing rate profiles observed during natural movements (wrist control performed prior to the first session of brain control). The ‘constrained learning’ model assumes that the tuning change along each *naturalistic PC* should decrease exponentially with increasing component number:

$$\text{Uniform learning: } \Delta T'_n \propto m'_n \quad \text{Constrained learning: } \Delta T'_n \propto m'_n \cdot e^{-n/N_c} \quad (3)$$

where $\Delta T'_n$ and m'_n are the projections of $\Delta \mathbf{T}$ and \mathbf{m} respectively along the n^{th} PC. To assess significance, the ability of naturalistic PCs to predict tuning changes of individual neurons was compared against 10000 Monte Carlo simulations of the same constrained model based on random rotations of the neural space.

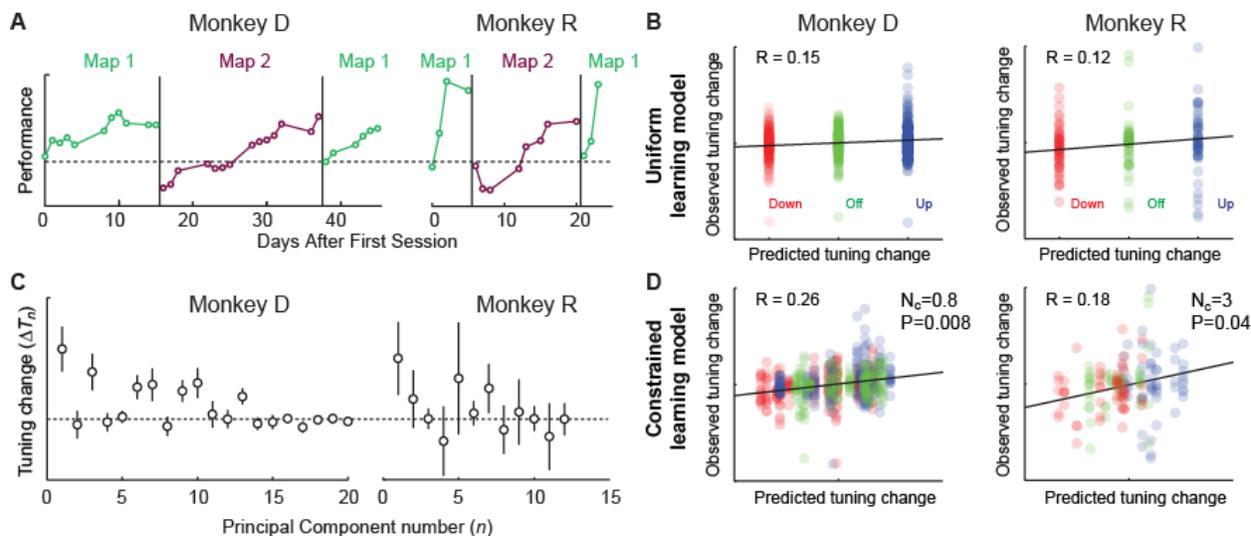


Figure 1. (A) Training over multiple sessions produces map-specific improvements in abstract BCI performance. (B) Changes in tuning of individual neurons are poorly predicted by their action on the cursor alone. (C) Average tuning changes are biased towards lower principal components of naturalistic activity patterns. (D) Constrained learning model improves prediction of tuning changes for individual neurons.

3. Results

For both monkeys, BMI performance increased progressively over consecutive training sessions with *Map1* and *Map2* (Fig. 1A). After switching from *Map1*→*Map2* and *Map2*→*Map1*, performance returned to baseline before rising again. Map-specific learning resulted from changes in the tuning of individual neurons, but these were only weakly related to the action of neurons on the cursor (uniform learning model; monkey D: $R = 0.15$; monkey R: $R = 0.12$; Fig. 1B). However, when tuning changes were rotated into the naturalistic PC space, map-specific learning was greater along the lower components, with the first PC in both animals accounting for the largest tuning change (Fig. 1C). Therefore we fit a model in which tuning changes along each PC decreased exponentially with increasing component number (Eq. 3), resulting in robust improvements to the prediction of individual tuning changes (constrained learning model; monkey D: $R = 0.26$; monkey R: $R = 0.18$; Fig. 1D). Since this new model included an additional free parameter, the decay constant N_c , we compared the predictions based on naturalistic PCs against the same model applied to random rotations of the neural space. The model performed significantly better when constrained to naturalistic PCs versus random rotations (monkey D: $P = 0.008$; monkey R: $P = 0.04$).

4. Discussion

Successful BCI performance requires searching for control solutions within a high-dimensional neural space. Constrained learning likely arises from biased exploration along particular dimensions of the space. These dimensions may reflect neural ‘priors’ appropriate for natural behaviors that are co-opted for BCI control. We have shown that principal component analysis of activity patterns recorded during natural movement provides one method to estimate constraints on learning and thereby predict subsequent tuning changes. This or more sophisticated techniques may in future allow decoders to be tailored to constraints on cortical activity such that learning over multiple sessions progresses along dimensions that are optimal for BCI control.

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References

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