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Multiple roles of ventral premotor cortex in BCI task learning and execution

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Abstract

Motor-based brain-computer interface (BCI) use is a learned skill that has been shown to involve multiple cortical areas, though it only explicitly requires modulation of a small area of cortical tissue. The roles being played by these other areas have not yet been determined. In this study, using an electrocorticographic (ECoG) model, we apply a novel computational approach to quantifying the strength and nature of interactions between putative primary motor cortex and ventral premotor cortex (PMv) during BCI use and across BCI skill development. Our findings suggest multiple roles being carried out in PMv that change in strength and nature during skill acquisition.

1 Introduction

Brain-computer interfaces (BCIs) show great promise both as a medical technology and a platform from which to investigate the adaptive capacity of the nervous system (Wander & Rao, 2014). Though it has been shown previously that many cortical (Ganguly et al., 2011; Wander et al., 2013) and subcortical (Koralek et al., 2012) areas are active during use of a motor-based BCI, and that as subjects gain experience activity in some of these areas lessens, it is still uncertain what role these areas play in the initial learning and subsequent execution of the neuroprosthetic skill.

Qualitative review of activity patterns in motor cortical networks during BCI use has revealed that some areas show increased activity only during active execution of motor imagery or overt movement whereas others show increased activity during the task, regardless of the imagery state of the user (Wander et al., 2013). In this study, we employ a newly developed computational method to investigate the roles being played by ventral premotor cortex (PMv) during BCI use. PMv was selected as a cortical area of interest because of its previous implication in effective motor skill execution and adaptation (Xiao et al., 2006). We hypothesize that high-gamma (HG; 70-200 Hz) activity in PMv and HG interactions with the controlling electrode (CTL) will demonstrate multiple roles being carried out by PMv during BCI use. Further, we hypothesize that some of these PMv-to-CTL interactions will lessen in strength as subjects develop automaticity in BCI task execution.

2 Methods

We have previously published methods describing our subject population, ECoG recording methods and right justified box (RJB) task structure (Wander et al., 2013), but will briefly summarize and discuss additional points of note.

The RJB is a one-dimensional BCI task where HG power in a single ECoG electrode is mapped to velocity of a cursor in the control dimension. The cursor travels across the workspace at a fixed horizontal velocity while the user controls its vertical velocity to attempt to move it in to a target area. This is a retrospective analysis of previously collected BCI data. Subject selection criteria were as follows: subjects needed to (a) have conducted at least 40 trials of RJB task, (b) performed above chance levels on the task, and (c) have electrode coverage of PMv. This resulted in inclusion of 10 subjects in the current study. Labels for individual electrodes were estimated using the human motor area template (HMAT) (Mayka, et al., 2006). From all the electrodes recorded (*N=792*), we selected only electrodes that were being used for BCI control (*N=10*) and non-control electrodes determined to be over PMv (*N=39*) for subsequent analyses. The classifications of PMv electrodes were as follows: electrodes were considered *control-like* if they exhibited significant HG increases during the feedback period (relative to rest) for up targets, but not for down targets; they were considered *effort-like* if they exhibited significant HG increases during the feedback period for both up and down targets; and they were considered *non-modulated* if they did not exhibit task-positive modulation.

We assessed transient temporal correlations in HG activity between the CTL and PMv electrodes using short-time windowed covariance/correlation (STWC) (Blakely et al., 2014). This method is specifically suited to teasing out amplitude-amplitude interactions (correlations) in neural signals that are not only transient (i.e. event-driven), but also potentially occur at slightly different points in time in each of the two signals. STWC maps were calculated on smoothed (~50 msec FWHM) HG power, using a window width of 500 msec and a maximum lag of 300 msec. STWC maps were then generated by realigning individual maps based on HG onsets and averaging across all trials. To isolate interactions occurring near the time period of HG onsets (+/- 500 msec), we finally extracted the maximum STWC coefficient and corresponding lag from each average map. Significant interactions were selected using a phase-randomized, surrogate-signal bootstrapping approach where STWC coefficients were considered significant if they had less than a 5% chance of occurring in the distributions of maximal STWC coefficients.

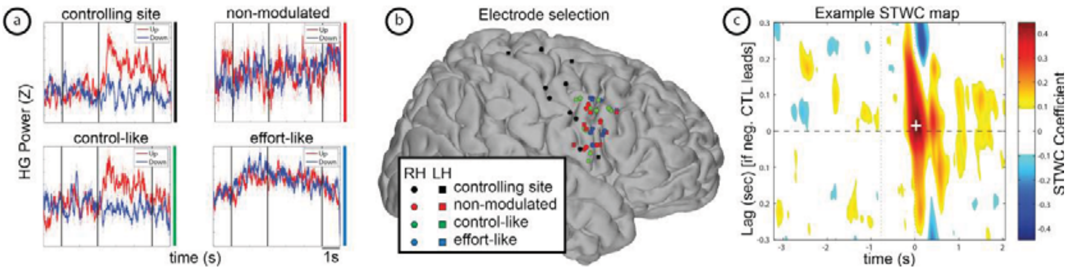

Figure 1 - (a) Example average time series HG activity showing the four electrode classes discussed in this manuscript and (b) anatomical location of all electrodes considered in these analyses. (c) An example STWC map, thresholded at +/- 1 standard deviation from the mean. Lags (y-axis) denote the temporal relationship between the two signals being considered. The white (+) denotes an example peak lag and STWC coefficient that was extracted from the map.

3 Results

Behavioral performance. By design, all subjects performed the BCI task at above chance level, as was discussed previously. Mean task performance was 74.2% (σ=8.57%, *N=10*). For individual subjects, task performance ranged from 60% to 86.2%.

HG activity at CTL and PMv. All subjects were able to significantly modulate HG power at CTL for up targets relative to rest periods (two sample student's t-test, $p<0.05$ in all cases, employing

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within-subject false discovery rate [FDR] correction). Each subject had at least one electrode over PMv that exhibited significant modulation during the feedback period relative to rest. All PMv electrodes were classified according to the methodology described above. There were 14 electrodes classified as *non-modulated*, 13 electrodes classified as *control-like*, and 12 electrodes classified as *effort-like*.

PMv-to-CTL HG interactions. In looking at the STWC maps generated for the multiple PMv-to-control interactions, it was clear that there is no single role carried out by PMv during BCI task execution. Figure 1 gives a clear example of PMv becoming active before CTL, but other examples exist showing both contemporaneous and lagging interactions. To quantify these relationships, we used the STWC peak-finding approach described above to determine single lag values relative to HG onset for all electrodes meeting the STWC threshold criteria. 23 of the 39 PMv electrodes exhibited significant interactions with CTL (*$p<0.05$*; previously described bootstrap approach).

Figure 2 depicts the lags and interaction strengths for each of these 23 electrodes. When considered together, peak covariance lags are not statistically different from zero (one-sample two-tailed t-test, $N = 39$, $p = 0.3157$), however, there is an interesting relationship between PMv electrode classes and covariance lags. Specifically, electrodes classified as being *effort-like* significantly lag CTL by an average 81.1 msec (+/- 29 msec s.e.m.; one-sample two-tailed t-test, *$N=8$, $p=0.0267$*) and at lags significantly lower than *control-like* electrodes (two-sample two-tailed t-test, *$N=[9, 8]$, $p=0.0398$*). Neither *control-like* nor *non-modulated* electrodes demonstrated lags that were significantly different from zero, nor were they significantly different from each other. We also observed that *effort-like* electrodes showing significant interactions were typically located more anteriorly and superiorly within PMv, though we recognize that the transformations necessary to map electrode locations to common brain space are approximations and may not be appropriate to uncover spatial relationships on such a small scale.

The above results suggest that there are multiple meaningful interactions that take place between PMv and M1 during the execution of a BCI task, yet it remains an open question as to which of these interactions are involved in the continued execution of the task, and which are specifically associated with the original acquisition of the neuroprosthetic skill. With that purpose in mind, we divided all trials in half chronologically into early and late trials, and re-evaluated STWC maps on these subgroups. Overall, PMv-to-CTL STWC strengths decreased significantly (*$p=0.0301$*) from early to late trials, and lags changed significantly from lagging CTL by 44.2 +/- 19.7 msec (*$p=0.0305$*) to not

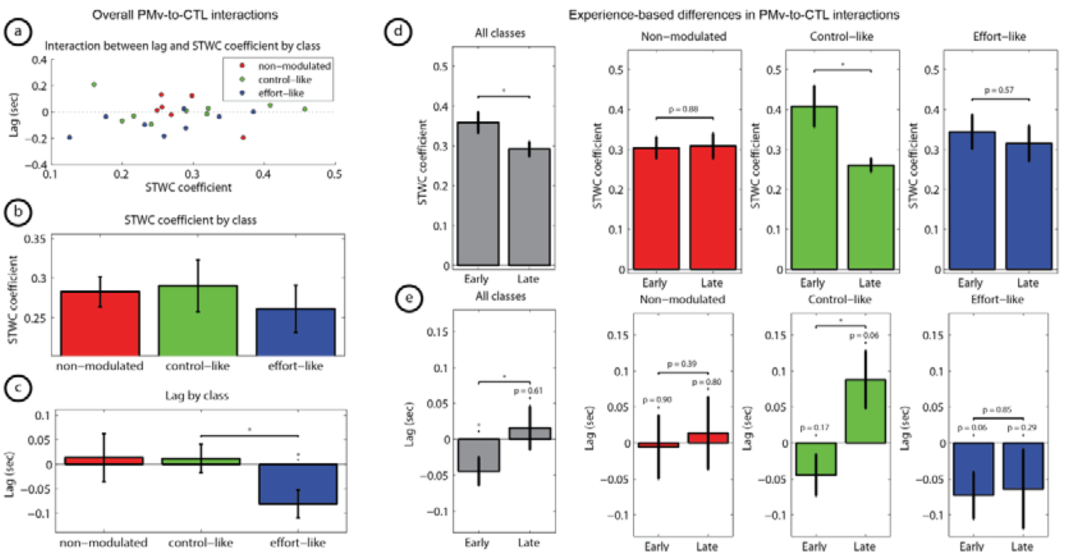

Figure 2 - STWC results. (a) Scatter plot showing lags and STWC coefficients for all PMv-to-CTL interactions, taken across all trials. (b-c) By-class comparison of distributions for STWC coefficients and lags, respectively. (d) Early-to-late comparison of STWC coefficients overall and by electrode class. (e) Early-to-late comparison of lags overall and by electrode class. See text for summary and discussion.

statistically lagging. When breaking down electrodes by class, we found significant decreases in STWC for the *control-like* PMv electrodes (*p=0.0419*), a significant change in lags for *control-like* electrodes (from lagging to leading CTL, *p=0.0139*), and no change in lags for *effort-like* electrodes.

4 Discussion

In this brief manuscript we have demonstrated that there are multiple statistically significant and meaningfully different roles being performed by PMv during BCI task execution and that the nature of at least one of these roles changes as BCI users gain task experience. These findings suggest that previously demonstrated distributed activity changes seen over the course of BCI skill acquisition may not be solely attributable to optimization of cortical activity, but that they may also play a meaningful role in task learning and execution.

It is important to note that interactions evaluated by the STWC method are correlative in nature and not causal. Interventional studies specifically altering function in one or more of these distributed cortical areas will be necessary to understand the causal interactions between these regions.

Ventral premotor cortex was an excellent first candidate for this type of analysis, but as we have demonstrated previously, other distributed cortical areas also appear to be task-modulated during BCI use. A necessary extension to this work will be to evaluate the activity and interaction patterns taking place in these areas. Additionally, for the sake of brevity, we have limited our analyses simply to HG-HG interactions. There may be an excellent opportunity to uncover some of the neural underpinnings of so-called BCI illiteracy by expanding the field of view to include cross-frequency interactions between HG and the sensorimotor rhythms commonly used in non-invasive BCIs.

References

Blakely, T., Ojemann, J. G., & Rao, R. P. N. (2014). Short-time windowed covariance : A metric for identifying non-stationary , event-related covariant cortical sites. *J Neurosci Meth*, *222*, 24–33.

Ganguly, K., et al. (2011). Reversible large-scale modification of cortical networks during neuroprosthetic control. *Nature Neuroscience*, *14*(5), 662–7.

Koralek, A. C., Jin, X., Long II, J. D., Costa, R. M., & Carmena, J. M. (2012). Corticostriatal plasticity is necessary for learning intentional neuroprosthetic skills. *Nature*, *483*, 331–335.

Mayka, M., et al. (2006). Three-dimensional locations and boundaries of motor and premotor cortices as defined by functional brain imaging: a meta-analysis. *Neuroimage*, *31*(4), 1453–1474.

Wander, J. D., et al. (2013). Distributed cortical adaptation during learning of a brain-computer interface task. *Proceedings of the National Academy of Sciences*, *110*(26), 10818–10823.

Wander, J. D., & Rao, R. P. (2014). Brain–computer interfaces: a powerful tool for scientific inquiry. *Current Opinion in Neurobiology*, *25*, 70–75.

Xiao, J., Padoa-Schioppa, C., & Bizzi, E. (2006). Neuronal correlates of movement dynamics in the dorsal and ventral premotor area in the monkey. *Exp Brain Research*, *168*(1-2), 106–19.