

Shaping Reality through Mental Rehearsal

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Previous research has shown that mental rehearsal can improve performance. A new study by Vyas et al. (2018) reveals that direct modulation of neural dynamics using a brain-computer interface can also modify physical movements. The study further demonstrates that “mental practice” and physical movements share a common neural subspace.

Imagine you are Stephen Curry at the NBA finals. You have two free throws coming up with the game on the line. Before flicking your wrist, you proceed to do what nearly every coach in your life might have encouraged: take a deep breath and mentally rehearse the free throw. Indeed, research has shown that this act of covert mental rehearsal can transfer over to the overt domain, translating into better performance (Di Rienzo et al., 2016). In the laboratory, neuroimaging research has typically asked subjects to “imagine” performing movements. The drawback of this approach, however, is that the exact form of neural dynamics representative of the subject’s imagination is unknown. Now, in a new study in this issue of *Neuron*, Vyas et al. (2018) use Brain Computer Interfaces (BCIs) to shine a light on mental rehearsal and how it transfers to overt movements.

How can BCIs be used to probe mental rehearsal? The BCI paradigm consists of a subject controlling an effector, in this case a computer cursor, by directly modulating neural activity (Figure 1). Thus, practicing brain control of the cursor may resemble mental rehearsal. In a BCI, the “decoder” transforms recorded neural activity into cursor movements. In this case, a variant of the Kalman Filter was trained using neural activity from motor cortex (M1) and dorsal premotor cortex (PMd) recorded during passive observations of the cursor (Vyas et al., 2018). Importantly, as the decoder contains the mapping from the cursor to neural activity (Figure 1), it may capture the neural underpinnings of imagined movements.

In this study, Vyas et al. (2018) tested the intriguing hypothesis that adapting to a visuomotor rotation (VMR) via rehearsal in the BCI domain (i.e., “covert rehearsal”) would transfer to physical movements in the real world (i.e., overt). As the authors themselves note, the BCI paradigm may not truly reflect mental rehearsal as the subjects got real-time visual feedback of their neural state from the cursor. Nevertheless, the experimental design is a clever use of the BCI paradigm to assess how direct neural control may generalize to real-world movements. Vyas et al. (2018) specifically applied a visual perturbation by means of a counter clockwise angular offset in the displayed cursor (Krakauer, 2009). To counter the imposed angular offset, the subject had to learn to overcome the offset. An important consequence of VMR adaption is the “after-effect” (Krakauer, 2009), where reach movements show an opposite deviation after VMR removal.

Fascinatingly, the two subjects in the study (adult male monkeys) exhibited the tell-tale aftereffects when they performed arm-reaching movements following BCI VMR adaptation (Figure 1C). This indicates that there was partial generalization of BCI adaptation learning to the physical domain. Moreover, covert rehearsal of VMR resulted in faster overt adaptation to VMR. To understand the neural substrates of this transfer across domains, Vyas et al. (2018) used dimensionality reduction methods to show that neural population preparatory activity were similar in both the BCI and manual contexts; they also appeared to elicit common

population trajectories during control. It is, of course, essential to confirm that the animals were truly performing VMR adaptation exclusively using the BCI interface in the absence of physical adaptations (i.e., truly conducting covert rehearsal). The authors addressed this by performing video monitoring of the limbs and demonstrating that there was no significant correlation between observed movements and BCI cursor movements.

There are important implications for the observed generalization of motor adaptation from the BCI domain to the physical domain. That adaptation transferred to the overt domain suggests that BCI VMR adaptation taps into a common controller that governs the *dynamics* of limb movement. Stated another way, population activity in motor cortex appears to represent an internal model of the world that can be altered in the absence of limb movements and/or sensory feedback from the limb. Moreover, such an alteration appears to be sufficient to result in partial generalization to the physical world. It remains unclear, however, if the adaptation process observed in the BCI domain is exclusively reliant on M1/PMd or also perhaps recruits the broader motor network, i.e., parietal areas, cerebellum, or even the brainstem/spinal cord. Monitoring neural signals from related motor areas and even muscle activations using EMG can provide further insights into the broader network.

Generalization after VMR Adaptation

Classical VMR adaptation studies in humans have shown that generalization



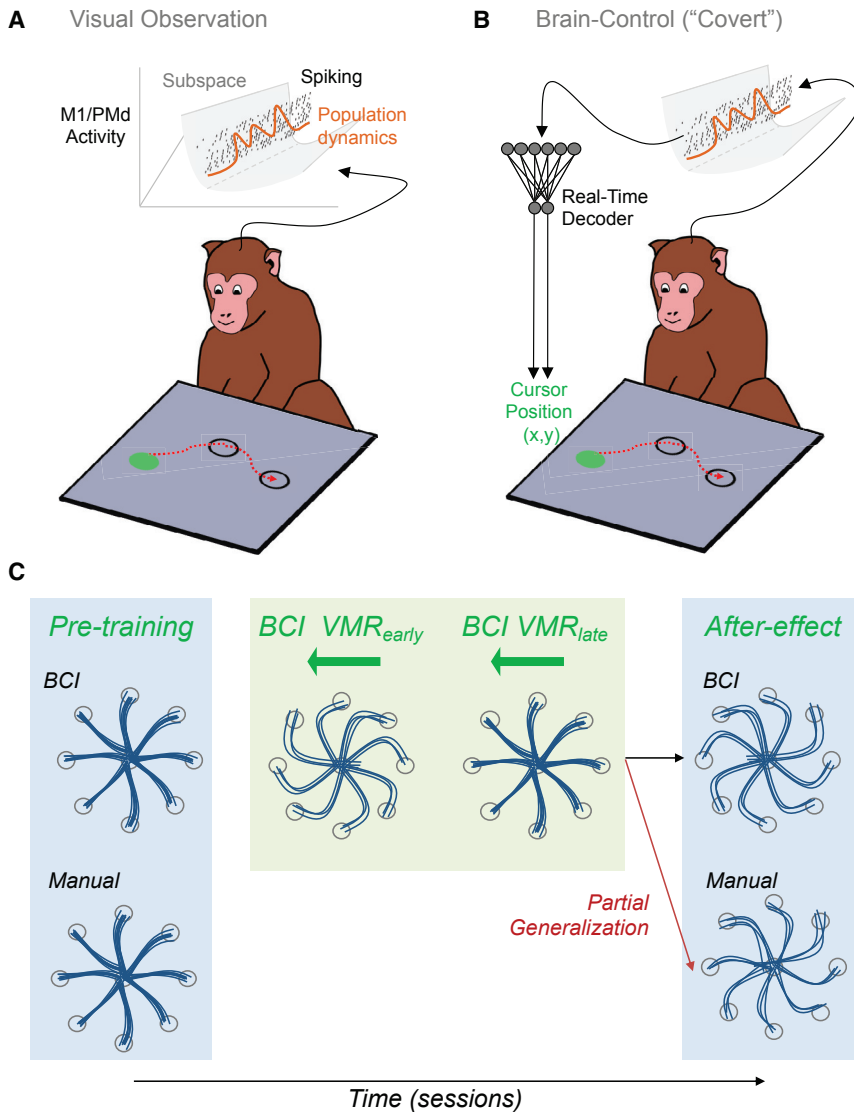


Figure 1. Schematic of “Covert” Brain Control and Generalization of After-effects to the Overt Domain

(A) Subjects visually observed cursor movements while neural signals were recorded. (B) During “Brain Control” the decoder was used to convert neural activations to cursor position in the absence of overt arm movements (i.e., covert). (C) In the first column, typical movement trajectories are illustrated for both BCI control and manual control. The second column illustrates BCI-controlled trajectories in the immediate presence of VMR (30° counter clockwise). Third column illustrates BCI trajectories after adaptation. Intriguingly, the fourth column shows a VMR after-effect for both manual and BCI movements.

of such learning can be narrow and exhibit hierarchies (Taylor and Ivry, 2013). For example, adapting to VMR via the wrist does not generalize to shoulder movements, yet VMR adaptation via the shoulder generalizes to the wrist (Krakauer et al., 2006). Covert movement tasks enable further exploration of the asymmetries in generalization.

The study here further suggests that VMR adaptation can transfer from covert to overt domains due to a shared neural subspace. Interestingly, while Vyas et al. (2018) used observational neural activity to train their decoder, one can also envision using a static decoder with randomly seeded mapping of neural activity to BCI control. The resultant decoder appears to live in a separate subspace from overt

movements (Ganguly et al., 2011). Would VMR adaptation transfer in such a scenario? Manipulating the seeding of decoder weights is one way to explore generalization and its link to neural subspaces (Sadler et al., 2014). Other approaches could involve training the BCI on an effector different from the one used during manual control (Sainburg and Wang, 2002). More generally, the BCI paradigm deployed here can be a powerful tool to explore how adaptation generalizes across contexts.

Can BCIs Isolate “Mental” from “Covert” Rehearsal?

As Vyas et al. (2018) themselves state, the subjects received visual feedback of cursor position and thus the imagined movement may not resemble “mental rehearsal.” Indeed, the presence of the cursor as visual feedback is explicitly modeled in the uncertainties recursively propagating through the Kalman Filter. Removing visual feedback could force the subject to truly rely on “mental rehearsal” during cursor control. While such an approach might also require modifying the BCI paradigm, it could provide a means to compare mental versus covert rehearsal processes.

Implications for Neurorehabilitation

The fact that covert and overt rehearsal appear to share neural substrates can potentially be advantageous for neurorehabilitation. For example, there is increasing interest in using BCIs for rehabilitation after stroke (Gulati et al., 2015). A recent study further demonstrated that modulation of neural signals using EEG could enhance recovery after stroke (Ramos-Murguialday et al., 2013). Such studies are part of a broader field of “neurofeedback” in which feedback about neural activity is provided in order to modulate physical and cognitive processes. The results of this study provide a striking example of how directly tapping into neural dynamics may change behaviors. It strongly suggests that improving our understanding of the neural substrates of movements will allow experiments to sculpt neural dynamics in order to selectively target behavioral gains. It is not too difficult to imagine a future wherein precise, causal manipulation of

neural dynamics can restore motor and cognitive functions.

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DECLARATION OF INTERESTS

K.G. has filed a PCT Patent Application for Systems Methods and Devices for Closed Loop Methods To Enhance Motor Recovery After Stroke (Application No. PCT/US17/39293).

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