A learning-based approach to artificial sensory feedback: intracortical microstimulation (ICMS) replaces and augments vision

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Brain-Machine interfaces (BMIs) cannot be expected to attain natural levels of movement control relying solely on visual feedback, and will instead require additional sensory input that can both replace and be integrated with vision to improve behavioral performance. Previous psychophysical and computational work, from our lab [1] and others, suggests that sensory integration is a highly adaptive process, driven by temporal and spatial correlations between sensory signals. We hypothesized that imposing a strict temporal congruency between a visual and artificial sensory signal would be sufficient for a monkey to learn to interpret and integrate a novel input. We tested this hypothesis by delivering artificial sensory feedback to an awake, behaving monkey via ICMS of primary somatosensory cortex.

Rhesus macaque monkeys were used both because of their ability to flexibly perform complex, sensory-guided movements and because they are the best model for human prosthetics. A monkey was initially trained to perform a reaching task to an unseen target guided by a moving-dot visual-flow field, where the direction and speed of flow indicated the direction and distance to the reach target. Next, the monkey was trained to interpret an eight-channel ICMS signal that encoded this error vector, with mean stimulation frequency encoding error amplitude and the relative frequencies across the eight electrodes encoding error direction. Training was achieved by pairing the correlated ICMS and visual cues. Learning was subsequently probed with three trial types: vision-only, vision and ICMS, and ICMS-only. Importantly, the reliability of the visual signal was manipulated by changing the *coherence* of the flow field, i.e., the percentage of dots moving in the same direction.

We quantified the monkey's use of sensory feedback during movement initiation, using measures such as error in the initial angle (Figure 1), and during online feedback control, using behavioral parameters such as trial duration and path length (not shown). After training, the monkey was able to complete reaches using the ICMS signal alone, with performance comparable to low-to-mid range visual coherences. In the multisensory feedback case, when both visual and ICMS inputs were available, performance exceeded that for either cue alone, suggesting that the ICMS signal was also able to augment the visual cue.

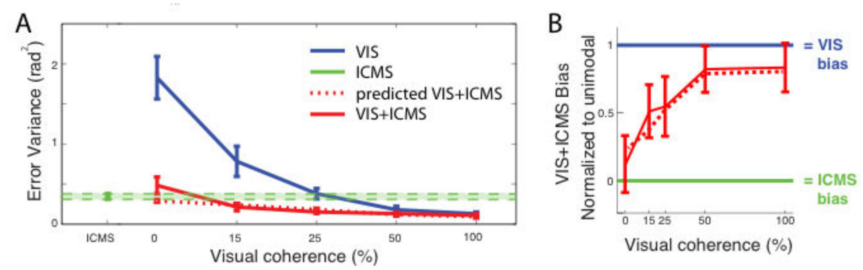

Figure 1. **A)** Initial angle error variance. Multisensory performance (red) lies at the optimal, minimum-variance solution (red dashed line). **B)** Movement biases in the multisensory trials closely follow predicted, optimal values, transitioning from the ICMS bias to the visual bias as visual coherence increases.

Given unisensory error variances for initial angles (Fig. 1A, green, blue), we can estimate the error variance in the multisensory condition assuming optimal, or minimum variance, integration [2]. We find that the error variance in these trials matches the predicted variance (Fig. 1A, red and dashed-red respectively). We next looked at the patterns of initial angle movement biases across the workspace. By taking a weighted average across space, we quantified how close the biases in the multisensory condition were to each of the unisensory conditions, as a function of visual coherence. Figure 1B shows that at lower visual coherences, the multisensory bias is closer to 0 (the ICMS bias), at higher coherences it is closer to 1 (the visual bias), and there is a smooth transition in between. These data (Fig. 1B, solid red) match the predictions based on minimum variance cue combination (Fig. 1B, dashed red), again showing that the ICMS signal is optimally integrated with vision during performance of this task. These results validate a learning-based approach for artificial sensory feedback and indicate that artificial sensory information can be integrated with natural sensory feedback to improve motor control.

References

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