Transient and sustained visuomotor selection during working-memory guided behavior.

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Abstract

Recent theoretical conceptualizations of visual working memory have begun to emphasize the action-oriented nature of this system. To guide behavior, visual information stored in memory must be selected and mapped onto task-appropriate responses. We show that the selection of task-relevant working memory is transient, beginning and ending prior to action onset. Thus, visual working-memory guided actions do not require continuous access to the internal representations on which they are based.

A fundamental purpose of any memory system is to inform future decisions and actions. This is particularly important in the case of working memory (WM), a duration- and capacity-limited system that forms a temporal bridge between fleeting sensory phenomena and possible actions (1). Recent theoretical conceptualizations of WM have begun to emphasize the action-oriented nature of this system (e.g., 2-5), and recent empirical findings suggest that behavioral (6-7), circuit-level (8-10), and systems-level (11-20) mechanisms of WM storage and action planning are tightly interwoven.

Many everyday behaviors require that WM-guided actions be timed to a future event or executed in a specific sequence (e.g., making your favorite cup of coffee involves performing a series of actions in a specific order and only when certain external conditions – e.g., the water in the kettle has begun to boil – have been met). Once a future goal state becomes obvious, what happens to the mnemonic representations of visual and motor information needed to reach it? One possibility is that task-relevant visuomotor representations are selected and prioritized until an action is completed. This formulation is implicit in several descriptions of WM-guided behavior (e.g., 17), and would support precise and continuous memory-guided control of behavior by forming a persistent bridge between the visual and motor contents of WM. A second possibility is that task-relevant visuomotor representations are selected and transformed from retrospective stimulus- and rule-based representations into prospective action-based representations, consistent with recent studies demonstrating that population-level representations of WM content are mapped into new subspaces following changes in priority or behavioral relevance (e.g., 6, 21-22).

To evaluate these alternatives, we recorded EEG while 31 human volunteers performed a retrospectively cued orientation memory task (Fig 1a). Participants remembered the orientations of two gratings over a blank delay. 1.5 sec after encoding, a 100% valid color cue indicated which of the two gratings would be probed for report at the end of the trial and which hand should be used for memory recall (i.e., left or right; response hand/cue color mappings were counterbalanced across participants). A response display containing a vertically oriented grating was presented 1.0 seconds later; participants adjusted the orientation of this probe to match the orientation of the grating held in memory using the cued response hand. Participants performed this task well, recalling the orientation of the probed grating with an average (±1 S.E.M.) absolute error of 13.6° ± 0.75° and responded with the correct hand on 93.8% ± 0.89% of trials.

We considered three models describing how visual and motor WM representations are selected when planning future memory-guided behaviors. In the first model (Fig 1a), task-relevant visual and motor WM representations are selected immediately after cue onset, and these representations remain selected until a final response is made. In the second model (Fig 1b), task-relevant visuomotor selection is delayed until action is imminent. In the third model (Fig 1c), task-relevant visual representations are selected and transformed from a retrospective stimulus-based format to a prospective motor-based format, yielding a pattern of transient visual selection and persistent motor selection.

We tested these models by tracking neural signals associated with the selection of visual and motor information stored in memory in near-real-time (tens of milliseconds). We first identified EEG signals that co-varied with the physical location of the retrospectively cued stimulus (i.e., left vs. right visual hemifield; Fig 2a) and EEG

signals that co-varied with the retrospectively cued response hand (i.e., left vs. right; Fig 2b). Because stimulus location and response hand were independently manipulated over trials (i.e., a stimulus requiring a right-hand response was equally likely to appear in the left vs. right visual field) we were able to characterize the selection of both attributes in trial-averaged EEG data independently of one another and any nuisance effects (e.g., volume conduction or other signal mixing). We therefore attributed patterns of neural activity that covaried with stimulus location to the selection of visual information stored in WM and patterns of neural activity that covaried with response hand to the selection of motor information stored in WM. While this approach is familiar from earlier work (e.g., 17), our task additionally allowed us to probe the dynamics of visuomotor selection during development of a *planned* action: upon presentation of retrocue display participants were free to select task-relevant visuomotor representations stored in WM but could not execute a response until one second later.

Visual selection was associated with a robust but transient decrease in 8-13 Hz alpha power over electrode sites contralateral to the location of the cued stimulus (Fig 2a). This modulation was strongest over occipitoparietal electrode sites (Fig 2a; inset), consistent with prior reports linking changes in lateralized alpha power to shifts of attention in perception and WM (17; 23-24). Conversely, motor selection was associated with a robust and sustained decrease in 8-13 Hz mu-alpha power and 15-30 Hz beta power over electrode sites contralateral to the location of the cued response hand (Fig 2b). This modulation was strongest over frontocentral electrode sites (Fig 2b; inset), consistent with prior reports linking changes in lateralized mu-alpha and beta power to response preparation and execution (25). Direct comparisons of EEG signals associated with visual and motor selection revealed transient visual selection lasting approximately 250-850 ms and sustained motor selection lasting 250-3000+ ms after retrocue onset. These observations are difficult to reconcile with models of WM-guided behavior that require the continuous selection of visual information (Fig 1b, c) but can be explained by a hybrid selection model where visual WM representations are selected and transformed from a stimulus-specific to a response-specific format (Fig 1d).

In a complementary analysis, we decoded the location of the retrospectively cued stimulus (i.e., left vs. right visual hemifield) and the retrospectively cued response hand (i.e., left vs right) from broadband (1-50 Hz) EEG responses measured over occipitoparietal and frontocentral electrode clusters where spectral signals associated with visual and motor selection were largest (occipitoparietal 10-20 electrode sites O1/2, PO3/4, PO7/8 and frontocentral 10-20 electrode sites C1/2 and C3/4; Fig 3). This allowed us to probe task-relevant information in evoked (as compared to induced) EEG activity with an even greater temporal resolution (i.e., absent all but the most liberal spectral filters needed to remove low-frequency drifts and line noise from the EEG signal). We also attempted to decode the orientations of the cued and uncued gratings but were unable to do so except during the probe period where a physical orientation was present on the screen (Fig S1).

A comparison of stimulus location and response hand decoding performance over occipitoparietal electrode sites (Fig 3a) revealed transient above-chance decoding of stimulus location during the delay separating the retrocue and probe displays. However, these effects were dwarfed by robust decoding of response hand during both the cue-to-probe interval and during the response period. An identical analysis of

stimulus location and response hand decoding performance over frontocentral electrode sites (Fig 3b) revealed a complementary pattern, with stimulus location decoding performance reaching above chance levels for a brief interval only during the cue-to-probe delay and response hand decoding performance reaching above-chance levels during both the cue-to-probe delay and during the response period. Thus, response-specific signals dominate stimulus-specific signals over occipitoparietal and frontocentral electrode sites during the planning and execution of a WM-guided behavior.

Although several recent studies have examined circuit-, network-, and brain-level interactions between WM and motor planning during imminent action (17-20), no studies have examined how visuomotor representations stored in WM are selected to plan and implement future actions. Leveraging the high temporal resolution of human EEG recordings, we show that when planning a memory-guided behavior the brain initially selects task-relevant visual and motor information stored in WM, but the selection of visual WM content ends well before an overt action is produced.

We defined visual selection by tracking EEG signals that co-varied with stimulus location. Since location was an incidental feature of our task (i.e., participants could in principle perform the task by remembering two orientations independent of where they appeared), one could argue that observations of transient visual selection based on location are also incidental. However, several lines of evidence indicate that position information is automatically and inextricably bound to other visual features stored in WM: Position-specific signals can be decoded from scalp EEG activity during WM tasks where stimulus location is task-irrelevant (e.g., 26) or from population spiking activity in prefrontal, parietal, and visual cortex following a cue that renders stimulus location task-irrelevant (e.g., 10). Other studies have documented gaze biases towards task-relevant stimuli during WM tasks where stimulus location is task-irrelevant (e.g., 18-19, 27). Thus, location is an integral component of visual WM storage, even when this feature is nominally task-irrelevant.

Transient selection of visual information in WM (e.g., Fig 2c, Fig 3c) could reflect the operation of mechanisms that transform retrospective, stimulus-oriented memory representations into prospective, action-oriented representations. This explanation dovetails with recent findings from cellular and systems neuroscience demonstrating that population-level representations of WM content are mapped into new subspaces following changes in priority or behavioral relevance (e.g., “rotational remapping”; 10; 21-22). A possible benefit of this transformation is that sensory regions thought to mediate WM storage (e.g., visual cortex; 28-29) would be freed up for the processing of other sensorimotor representations or motor signals in a way that facilitates memory performance (e.g., 30). While these possibilities await further investigation, the current findings conclusively reject the hypothesis that working memory-guided behaviors require the continuous selection of visual information on which these behaviors are based.

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Supporting Online Methods

Research Participants. 32 human volunteers (both sexes) from the University of Nevada, Reno community completed a single 2.5-hour testing session in exchange for monetary remuneration ($15/h). All volunteers self-reported normal or corrected-to-normal visual acuity and gave both written and oral informed consent before enrolling in the study. Data from one participant who completed the study were excluded from final analyses due to chance-level task performance (i.e., the participant used the correct response hand on only 52% of trials); thus, the findings reported here reflect the remaining 31 participants.

Testing Environment. Participants were seated in a dimly lit room for the duration of testing. Visual displays were generated in MATLAB and rendered on a 27-inch LCD monitor (1920 x 1080 resolution) cycling at 240 Hz using Psychophysics Toolbox software extensions (31). Participants were seated approximately 80 cm from the display (head position was not constrained). Participants responded via buttons on a standard US computer keyboard.

Visuomotor Recall Task. A task schematic is shown in Figure 1A. Each trial began with a 500 ms sample display containing two colored gratings (radius 4.5° visual angle [DVA] from a viewing distance of 80 cm; 1.0 cycles/°) presented 7.0 DVA to the left and right of a central fixation point. The sample display was followed by a 1500 ms blank display and a 1000 ms retrospective cue display. The color of the retrospective cue instructed participants which grating would be probed at the end of the trial (i.e., blue or red) and which hand should be used to make a behavioral response (left or right). Cue-response mappings (i.e., red cue/left vs. right hand) were counterbalanced across participants. Each trial ended with a 2000 ms probe display containing a vertically oriented grating; participants recalled the orientation of the cued grating by adjusting the probe grating to match the corresponding sample grating using the cue-specific response hand. If participants were satisfied with their response before the end of the 2000 ms, they were instructed to refrain from pressing any other buttons. Participants completed 3 (N = 1), 7 (N = 2), or 8 (N = 28) blocks of 60 trials. Due to a coding error, we were unable to estimate response times (i.e., elapsed time between the onset of the probe display and the participant's initial button press) for any of the 31 participants.

EEG Acquisition & Preprocessing. Continuous EEG was recorded from 63 scalp electrodes using a BrainProducts actiCHamp system using a left mastoid reference (10-20 electrode site TP9). Data were digitized at 1 kHz and later re-referenced to the algebraic mean of the left and right mastoids (using 10-20 site TP10 as the right mastoid reference). The following preprocessing steps were applied, in order: (1) resampling from 1 kHz to 500 Hz; (2) bandpass filtering from 1 to 50 Hz (zero-phase forward- and reverse- finite impulse response filters as implemented by EEGLAB software extensions; 32); (3) identification, removal, and reconstruction of noisy epochs via artifact subspace reconstruction (implemented via EEGLAB; 32-34), (4) epoching from -1.0 to +5.0 sec relative to the start of each trial, and (5) application of a surface Laplacian to remove low spatial frequency components from the signal (35).

Spectral Analyses. Spectral analyses focused occipitoparietal and frontocentral 10-20 electrode site pairs O1/2, PO3/4, PO7/8, C1/C2, and C3/C4; analyses were restricted to a period spanning -500 to +2500 ms before and after retrocue onset. We extracted broadband spectral power from each electrode on each trial using a short-time Fourier transform (STFT) with a frequency range from 1-40 Hz (in 0.25 Hz steps) using a 200 ms sliding window and 2 ms step size. Power was computed by squaring the absolute value of the complex Fourier coefficients within each STFT window.

To quantify changes in lateralized activity during visual selection, we sorted power estimates at each occipitoparietal electrode site by the location of the retrospectively cued stimulus, i.e., contralateral vs. ipsilateral hemifield, and expressed this difference as a normalized percentage:

$$L_i = 100 \times \frac{(c_i - s_i)}{(c_i + s_i)}$$

where c_i and s_i are the trial-averaged responses of electrode *i* when the retrospectively cued grating appeared in the contralateral or ipsilateral visual field, respectively. Lateralization estimates were pooled across occipitoparietal electrode sites, yielding a single time-frequency matrix of power estimates per participant. These matrices were averaged across participants to produce the data shown in Fig 2A.

An identical approach was used to quantify changes in lateralized activity during motor selection, with the exceptions that (a) analyses focused exclusively frontocentral electrode sites, and (b) trial-wise power estimates were sorted by the retrospectively cued response hand rather than stimulus location. This analysis was used to generate the data shown in Fig 2B.

To generate the topographical maps of alpha- and beta-band lateralization shown in Figs 2A and 2B, we repeated this analysis for every scalp electrode and averaged power estimates over 8-13 Hz (“alpha-band” activity) and 15-30 Hz (“beta-band” activity) over a period from 500-1000 Hz. These frequency bands were chosen a priori based on commonly reported values in the literature (e.g., 23-25); this specific temporal window was chosen a priori based on prior reports suggesting that it takes human observers ~300-500 ms to process and respond to a retrospective memory cue (e.g., 30).

An analogous procedure was used to measure frontocentral beta-power lateralization, with the exceptions that (a) analyses focused on frontocentral electrode sites and (b) trial-wise recordings were sorted as contralateral or ipsilateral relative to the retrospectively cued response hand.

To visualize changes in occipitoparietal alpha power, frontocentral mu-alpha power, and frontocentral beta power (e.g, Fig 2C), we extracted and averaged lateralization

estimates from 8-13 Hz over electrode sites O1/2, PO3/4, and PO7/8, lateralization estimates from 8-13 Hz over electrode sites C1/2, C3/4, and lateralization estimates from 15-30 Hz over electrode sites C1/2, C3/4. Statistical analyses of lateralization were performed using nonparametric sign permutation tests with temporal cluster-based correction (see *Statistical Analyses*, below).

Stimulus Location and Response Hand Decoding. Decoding analyses (Fig 3; Fig S2) were applied to broadband (1-50 Hz) signals measured at occipitopartietal electrode sites O1/2, PO3/4, PO7/8 and frontocentral electrode sites C1/2, C3/4. Decoding performance was computed separately for each time sample using 10-fold cross-validation. During each cross-validation fold, we designated 90% of available trials as a training data set and the remaining 10% of trials as a test data set, taking care to ensure that the training data set contained an equal number of observations for each possible outcome (e.g., for stimulus location decoding, we ensured that the training data set contained an equal number of left- and right visual field trials; likewise, for response hand decoding we ensured that the training data set contained an equal number of left- and right-hand trials). Decoding performance was computed by fitting a multivariate normal density to observations associated with each class in the training data set (using a pooled diagonal covariance matrix estimate), then assigning observations in the test data set to groups based on likelihood ratios. Qualitatively similar findings were obtained using other decoding approaches (e.g., using multivariate distance as in 36-37; Fig S2).

Decoding performance was quantified by computing the proportion of test trials where the classifier predicted the correct stimulus location or response hand. Performance estimates were averaged across cross-validation folds, yielding a single stimulus location and response hand decoding time series per participant and electrode cluster (i.e., occipitoparietal vs. frontocentral). Since stimulus location and response hand were binary variables, we evaluated decoding performance against a chance level of 50%.

Statistical Comparisons. All statistical comparisons reported here were based on nonparametric sign permutation tests (38). Specifically, each test we performed assumes a null statistic of 0 (i.e., no difference in alpha- or beta-band lateralization, or no difference in observed vs. chance decoding performance). We therefore generated null distributions of the differences between dependent variables (e.g., alpha- and beta-band lateralization, or location vs. response hand decoding) by randomly relabeling each participant's data with 50% probability and averaging the data across participants. This step was repeated 10,000 times, yielding a 10,000-element null distribution for each time point. Finally, we implemented a cluster-based permutation test with cluster-forming and cluster-size thresholds of $p < 0.05$ to evaluate differences with respect to this null distribution while correcting for multiple comparisons across time.

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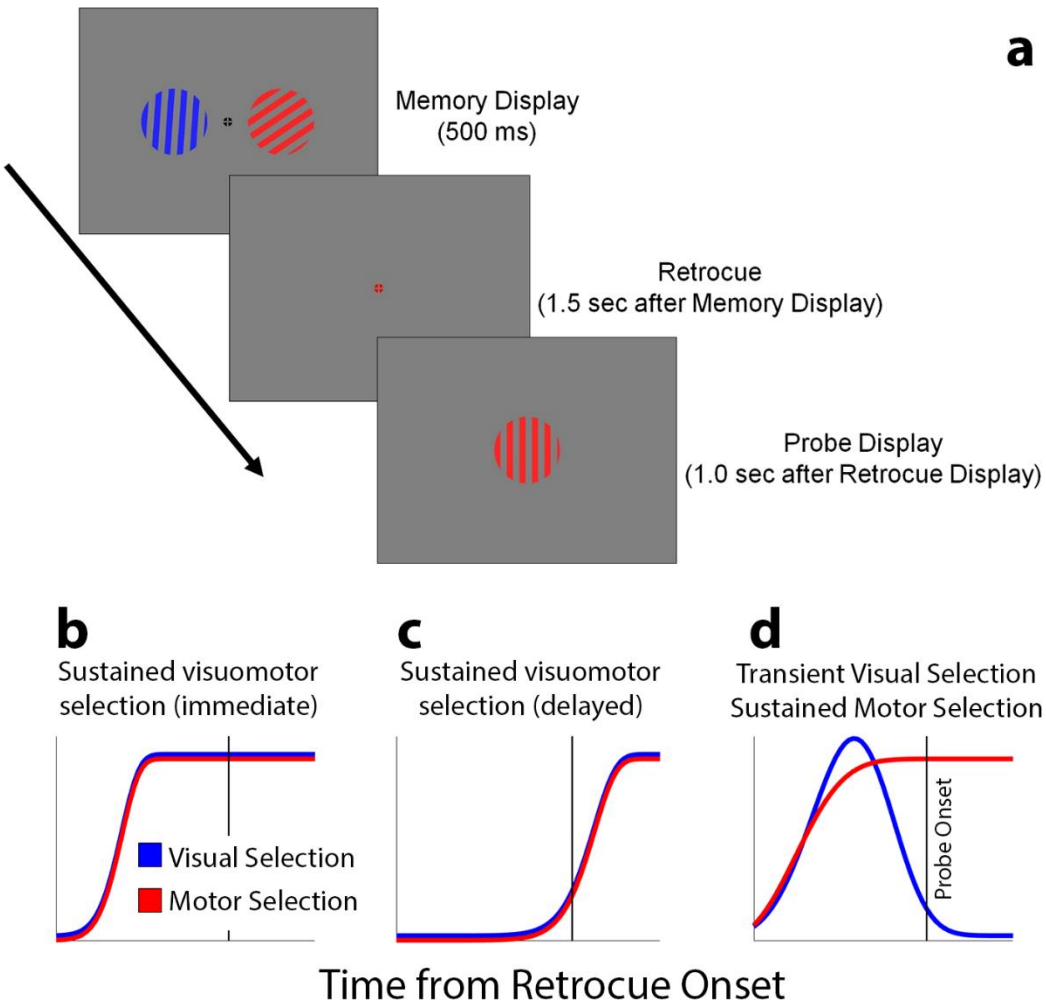

Fig. 1. Retrospectively Cued Visuomotor Selection Task and Possible Outcomes*. (a) Retrospectively cued orientation recall task. See text and Supporting Online Materials for more details. visual and motor selection. (b-d) Hypothetical time courses of visual and motor selection.*

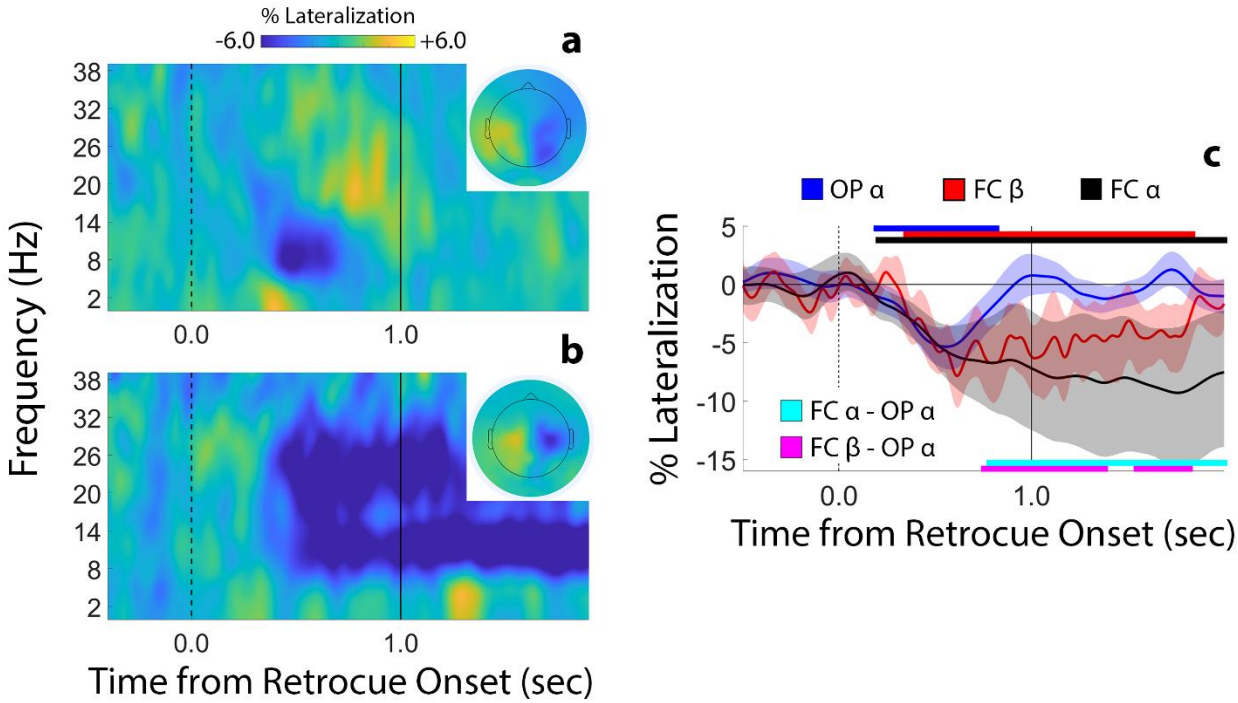

Fig. 2. Spectral signals associated with visual and motor selection during WM-guided behavior. *(a) Broadband frequency-specific lateralization over 10-20 occipitoparietal electrode site pairs O1/2, PO3/4, and PO7/8. Inset shows the distribution alpha-power lateralization (8-13 Hz) over all recorded electrode sites. (b) Broadband frequency-specific lateralization over 10-20 frontocentral electrode site pairs C1/2 and C3/4. Inset shows the distribution of beta-power lateralization (15-30 Hz) over all recorded electrode sites. (c) Occipitoparietal alpha-power lateralization, frontocentral alpha-power lateralization, and frontocentral beta-power lateralization time-locked to retrocue onset. Blue, red, and black bars at the top of the plot show periods where occipitoparietal/frontocentral lateralization was < 0. Cyan and maroon bars at the bottom of the plot show periods where frontocentral alpha lateralization was significantly greater than occipitoparietal alpha lateralization and periods where frontocentral beta lateralization was significantly different from occipitoparietal alpha lateralization, respectively. Shaded regions depict the 95% confidence interval of the mean. The vertical lines at time 0.0 and 1.0 depict the onset of the retrocue and probe displays, respectively. OP = occipitoparietal, FC = frontocentral.*

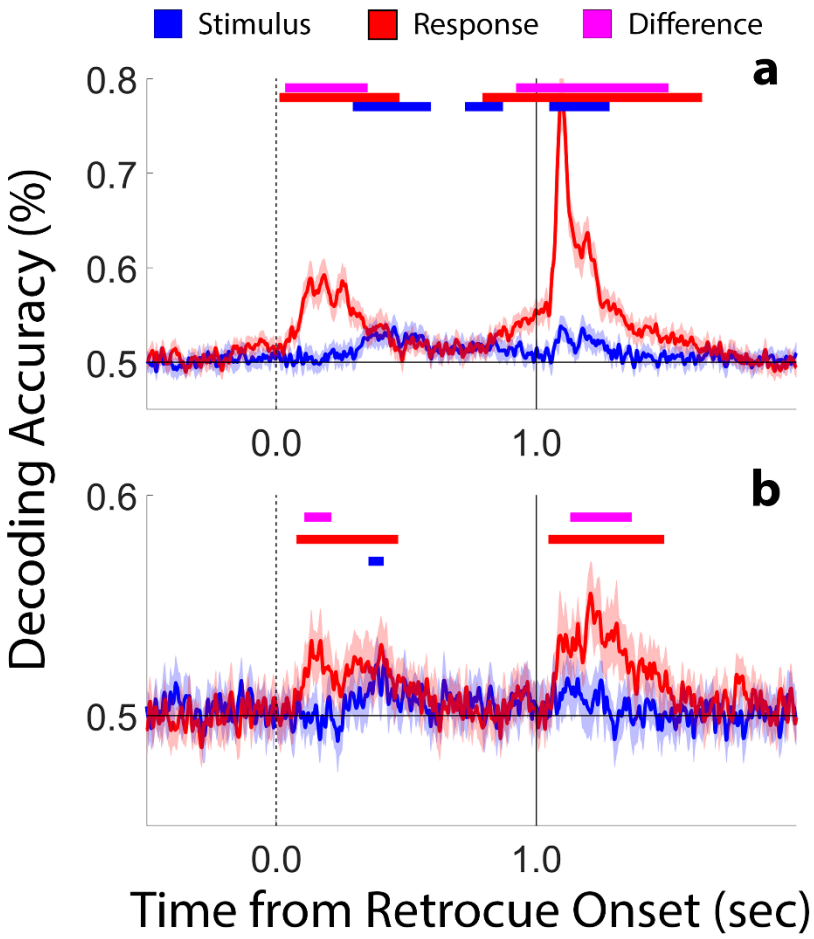

Fig 3. Location and Response Hand Decoding Performance in Occipitoparietal (a) and Frontocentral (b) Electrode Clusters. *We used a linear discriminant classifier (see Supporting Online Methods) to predict the location of the retrospectively cued grating (i.e., left vs. right visual field) and response hand (i.e., left vs. right hand) from broadband activity measured at occipitoparietal electrode clusters (O1/2, PO3/4, PO7/8; panel a) and frontocentral electrode clusters (C1/2, C3/4; panel b). Note that stimulus location and response hand were randomly and independently manipulated across trials; thus, similarities and/or differences in decoding performance across electrode clusters cannot be explained by volume conduction or signal mixing. Decoding time courses have been smoothed with a 10 ms Gaussian kernel for presentation; smoothing had no qualitative effect on statistical conclusions. Shaded regions around each line depict the 95% confidence interval of the mean. Blue and red bars at the top of each plot depict epochs where stimulus location and response hand decoding were significantly greater than chance (50%; nonparametric cluster-based permutation test; see Supporting Online Methods); maroon lines depict intervals where response hand decoding was significantly greater than stimulus location decoding. Vertical lines at time 0.0 and 1.0 depict the onset of the retrocue and probe displays, respectively.*