

Neuron, Volume 107

Supplemental Information

Cortical Observation by Synchronous

Multifocal Optical Sampling Reveals

Widespread Population Encoding of Actions

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Supplementary figures for: Cortical observation by synchronous multifocal optical sampling reveals widespread population encoding of actions

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Figure Legends

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(A) Geometry of curved glass window implant. (B) Screenshot of software interface for selecting keypoints. (C) Coordinates of keypoints in Panel B, with approximate thickness of the skull at each keypoint. Thickness varies for mice of different ages and sizes. (D) Photograph of robotic stereotax and setup. (E) After cutting skin back, ear bars are placed above skin and muscle, and skull is cleaned. (F) Conductive clip is attached to inside of the skin, and keypoints are drilled using robotic stereotax. Depth is determined using a conductivity-based autostop mechanism, or alternatively, inspection and knowledge of the rough depth of each keypoint based on previous mice. (G) Based on keypoints, robotic stereotax interpolates and automatically cuts full craniotomy. (H) After skull flap is loose, it is pulled off quickly using forceps and blood is cleaned using absorptive sponge swabs. (I) Curved glass implant is positioned using a blunt needle connected to vacuum, and pushed down such that glass is in contact with brain across the full window. (J) Window is cemented into position. (K) A depth-colored 120 μ m thick two-photon stack demonstrating density and health of the neurons. (L) High magnification histological section demonstrating GCaMP expression, with DAPI nuclear staining.

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Figure S5. Further details about task-responsive sources and their spatial distributions (relates to Figure 3).

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Figure S6. Additional data related to unaveraged correlation structure (relates to Figure 4).

(A) Trial-averaged activity correlations: (top) spatial distribution, (bottom) correlation vs. distance to the seed. Seed location is represented as a black dot in right visual cortex, referenced by the labelled arrow. (B) Unaveraged activity correlations: (top) spatial distribution, (bottom) correlation vs. distance to the seed. This source exhibits symmetrically bilateral localized correlation. (C) Example of unaveraged correlated activity between the seed source and a neighboring source (locations indicated on atlas inset). Z-scored fluorescence and inferred spikes are shown. Red arrows indicate timepoints when the seed source and its neighbor are active simultaneously. (D) Single trial responses of seed source. (E-H) Same, but for an additional mouse, with seed source in retrosplenial cortex. (I-L) Same, but for an additional mouse, with seed source in motor cortex.

Figure S7. Additional analyses related to decoding motor actions and plans (relates to Figures 5-7).

(A) Ability of each neural source to discriminate between any of four behavioral states (licks towards one of the three spouts, or no lick). P-value computed for each source using Kruskal-Wallis H-test and FDR-corrected. Dashed horizontal line represents $p = 0.05$. (B) Spatial distribution of sources with significant motor action discrimination capacity ($p < 0.05$). (C) Example decoding of lick direction from neural activity at 30 Hz (on test dataset). Vertical lines represent trial onsets. (D) Model prediction accuracy versus the number of PLS basis vectors used. Five models were trained for each basis set size. (E) Pre-odor neural decoding performance as a function of number of neuronal sources used. Red lines indicate means across mice. Gray lines indicate performance of models trained and evaluated against circularly permuted true-spout labels. Black lines similarly represent models trained against randomly shuffled true-spout labels. Red lines indicate means across mice. Error bars show 99% bootstrapped confidence intervals. Vertical line at 500 indicates that all analyses that pooled across cortical regions used only the top 500 sources with most discrimination capacity for decoding to avoid model overfitting. (F) Spatial distribution of sources with significant discrimination capacity ($p < 0.05$) for the spout that was most-licked during the pre-reward period. P-values were computed for each source using a Kruskal-Wallis H-test and FDR-corrected. (G) Comparison of decoding performance of either the active spout (left) or the most-licked spout (right). Corrected paired t-test p-value shown between the active and preferred conditions. Note that trials where the active spout and most-licked spout were not identical were never used for the training of any PLS models. (H) Neural decoding of the preferred spout as a function of fraction of pre-reward licks towards the preferred spout. (I) Model AUC when evaluated on “correct go trials” (defined as those where at least 70% of total licks were to the active spout), “no go” trials, “2nd trials”, and “incorrect go trials” (“go” trials where less than 70% total trial licks were towards the active spout). “Incorrect go trials” are defined differently here, versus the main text (where less than 30% was the criterion), because multiple unique trials towards each spout were needed to accurately compute the AUC. (J) The total variance explained, shown for the top four basis vectors computed using either PLS (bottom, gray) or Principal Components Analysis (PCA, top, black), averaged across all four mice.

Figure S8. Active spout decoding from high speed videos of mouse behavior and cross-temporal neural decoding (relates to Figures 6 and 7).

(A) Extracting motion-related features from high-speed behavior videos. (B) Variance explained by behavioral video motion

energy principal components. (C) Results from PLS decoding of active spout from pre-odor video motion features. (D) Results of decoding using pre-odor motion features from specific regions of interest. (E) We asked if there might be a difference between widespread neural representations of motor plans, and of motor plan execution. To do this, we compared sets of PLS models trained on different epochs of the trial. By training models on a single time bin (e.g. during the pre-odor period) and evaluating prediction performance on a different time bin (e.g. during movement), we tested the similarity of the PLS models over the trial. The goal was to understand whether a single projection of the data might best discriminate the trial types, or whether cortex might represent motor plans during the intertrial interval differently from actual directed licking during the peri-movement period (between lick onset and lick offset). Examining how well each of the time-specific models predicted other time bins revealed clear structure. In grouping these time bins into pre-, peri-, and post-task epochs based on the average time of lick onset and offset, we found a dissociation between models trained on intertrial interval data (from the pre- and post-task epochs) versus those trained using peri-task period data. Specifically in this panel, AUC was computed for PLS bases trained to predict the active spout position from neural data in one time window, and then tested on neural data from all time windows and each mouse. AUC is normalized by the maximum AUC for each testing time window, and averaged across four mice. Dashed lines represent the average time of lick onset and offset within the trial. For this analysis (panels E-G), testing was only done on trials where the active spout and preferred spout were identical (trials where the active spout and preferred spout were not the same were always excluded from training in all analyses). (F) Quantification of results in Panel E for individual mice, comparing cross-temporal prediction performance of three distinct time blocks: pre-task, peri-task, and post-task. For each testing time block, we statistically compared the mean prediction performance of bases trained on each time block (corrected t-test). These results are consistent with the interpretation that motor plans and consequent movements are represented by two distinct, but related, neural population representations. (G) Unnormalized cross-temporal AUC for each mouse. ns denotes corrected $p > 0.05$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

Figure S9. Inhibition of non-motor areas impairs lick-to-target task performance (relates to Figures 5-7).

(A) In addition to recording neuronal activity, we tested if the task-activity we found distributed across many non-motor areas was causally involved in task performance. We investigated this because it is known that specific areas of cortex can modulate the firing of neurons in primary and secondary motor cortex. For example, projections from S1 can drive M1 activity and drive the initiation of whisking (Sreenivasan et al., 2016). But in addition, posterior regions like retrosplenial cortex and primary sensory areas (Barthas and Kwan, 2017; Yamawaki, Radulovic, and Shepherd, 2016; Zingg et al., 2014), also project to secondary motor cortex and may thus play an important role in producing any dynamics observed in motor areas. We therefore set out to study whether mice could accomplish our task without normal input from all of these non-motor areas by simultaneously inhibiting multiple cortical regions using the Digital Micromirror Device (DMD) system shown here. This approach avoided the possibility that uninhibited areas in cortex might compensate for the acute shutdown of a single area. (B) Atlas alignment. (C) Intensity calibration. (D) Stimulation protocol. (E) Stimulation patterns. (F) Success rate on peri-odor stimulation vs. no stimulation trials, for each stimulation pattern, $n=5$ mice, corrected paired t-test between stimulation patterns. (G) Success rate on pre-odor stimulation vs. no stimulation trials, for each stimulation pattern, $n=5$ mice, corrected paired t-test between stimulation patterns. (H) Success rate on peri- and pre-odor stimulation for a mouse not expressing ChR2. (I-L) Summary of lick selectivity averaged across $n=5$ mice (with S.E.M. shown) after odor delivery, but before (top) or after (bottom) reward delivery during non-stimulation trials or stimulation trials, for each stimulation pattern. Colors denote the normalized number of licks towards each spout on trials when a given spout is active. (M-O) Example lick rasters demonstrating that licking is not fully abolished during photoinhibition, but rather the specificity of it is disrupted (for each stimulation pattern, some sessions showed incorrect preference for a single spout, while others showed nonspecific licking towards multiple spouts). (P) Comparison of total number of peri-odor and post-reward licks during no-stimulation (gray) and stimulation (blue) trials (mean \pm S.E.M. across mice, corrected paired t-test between stimulation patterns). ns denotes corrected $p > 0.05$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

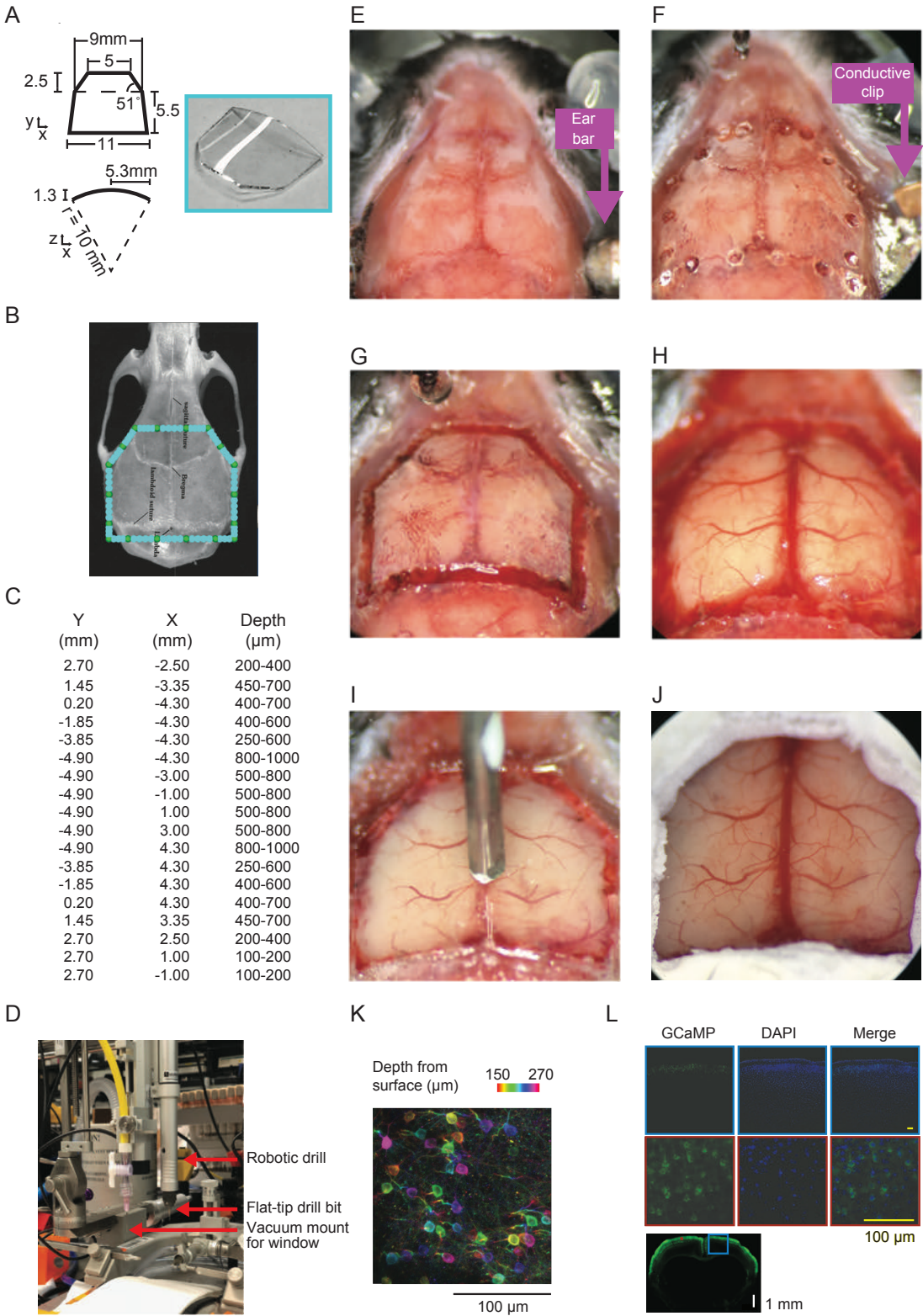


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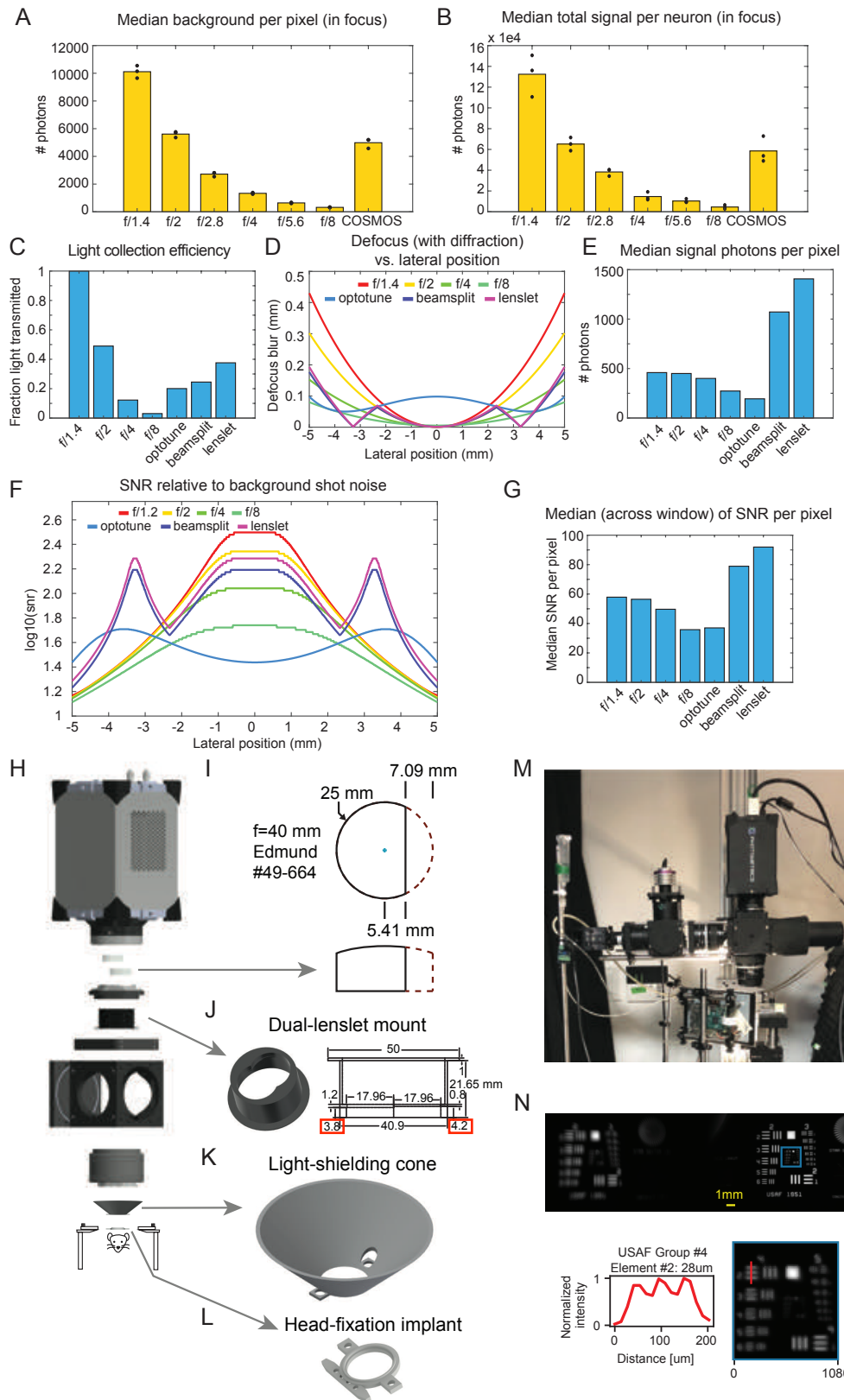


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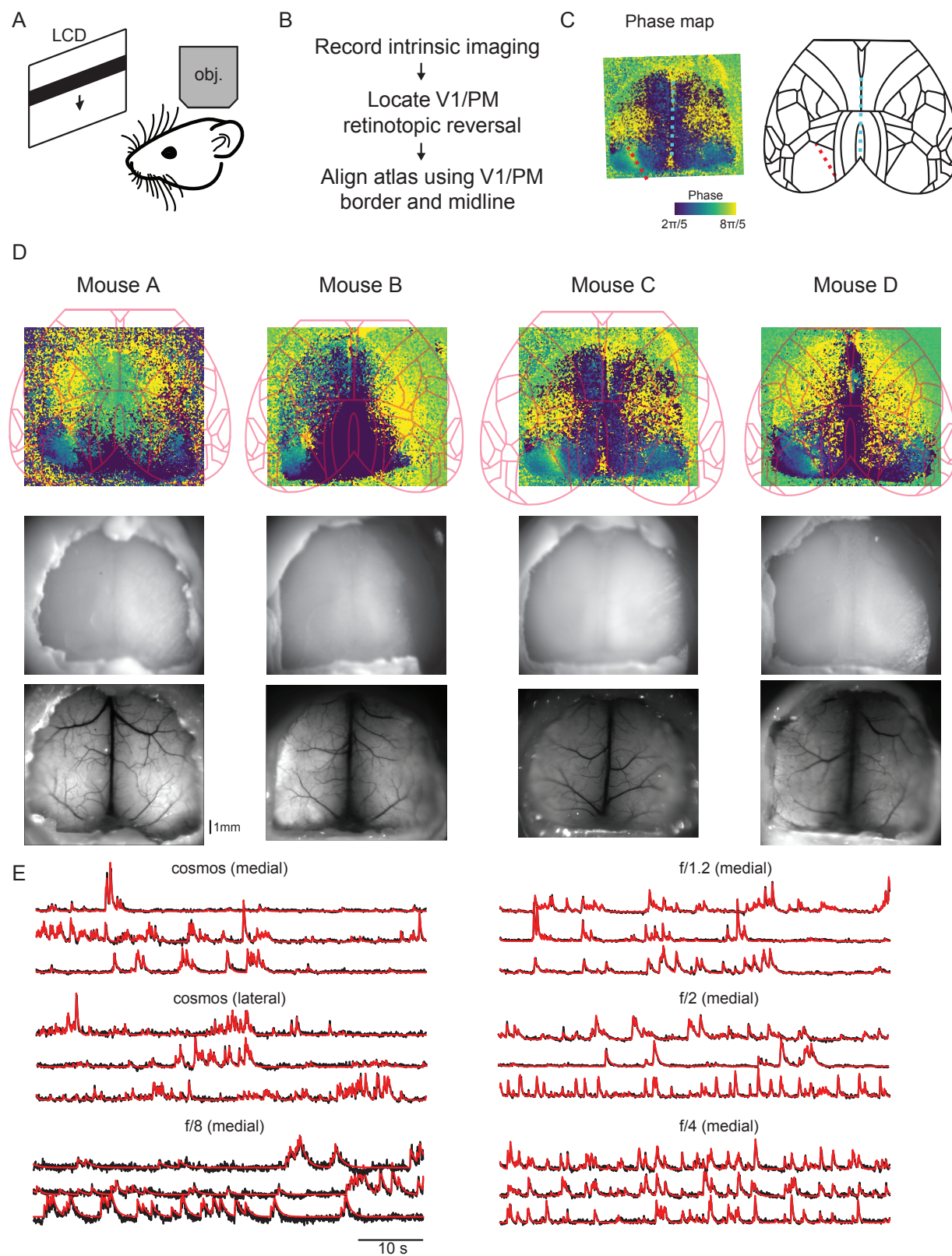


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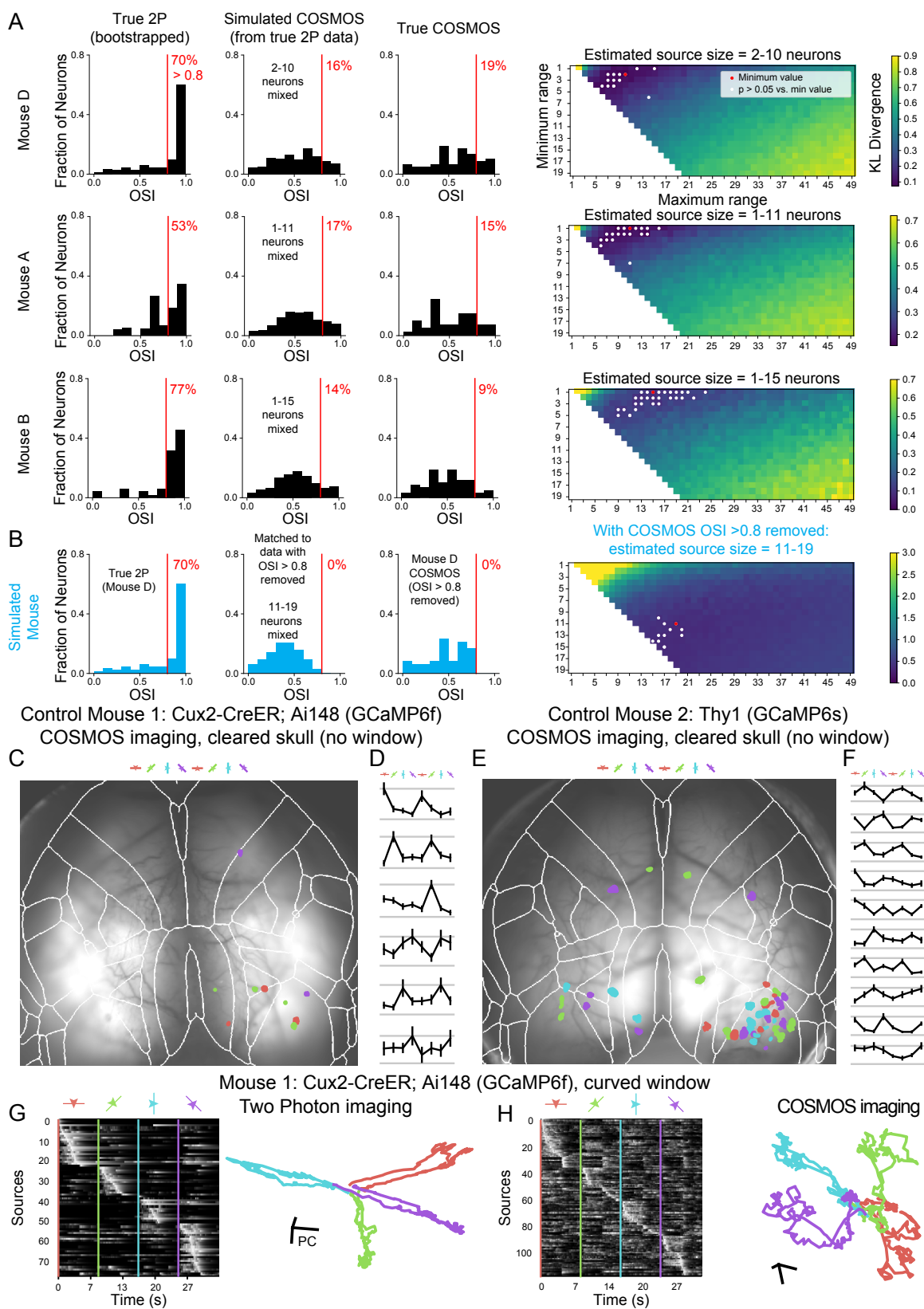


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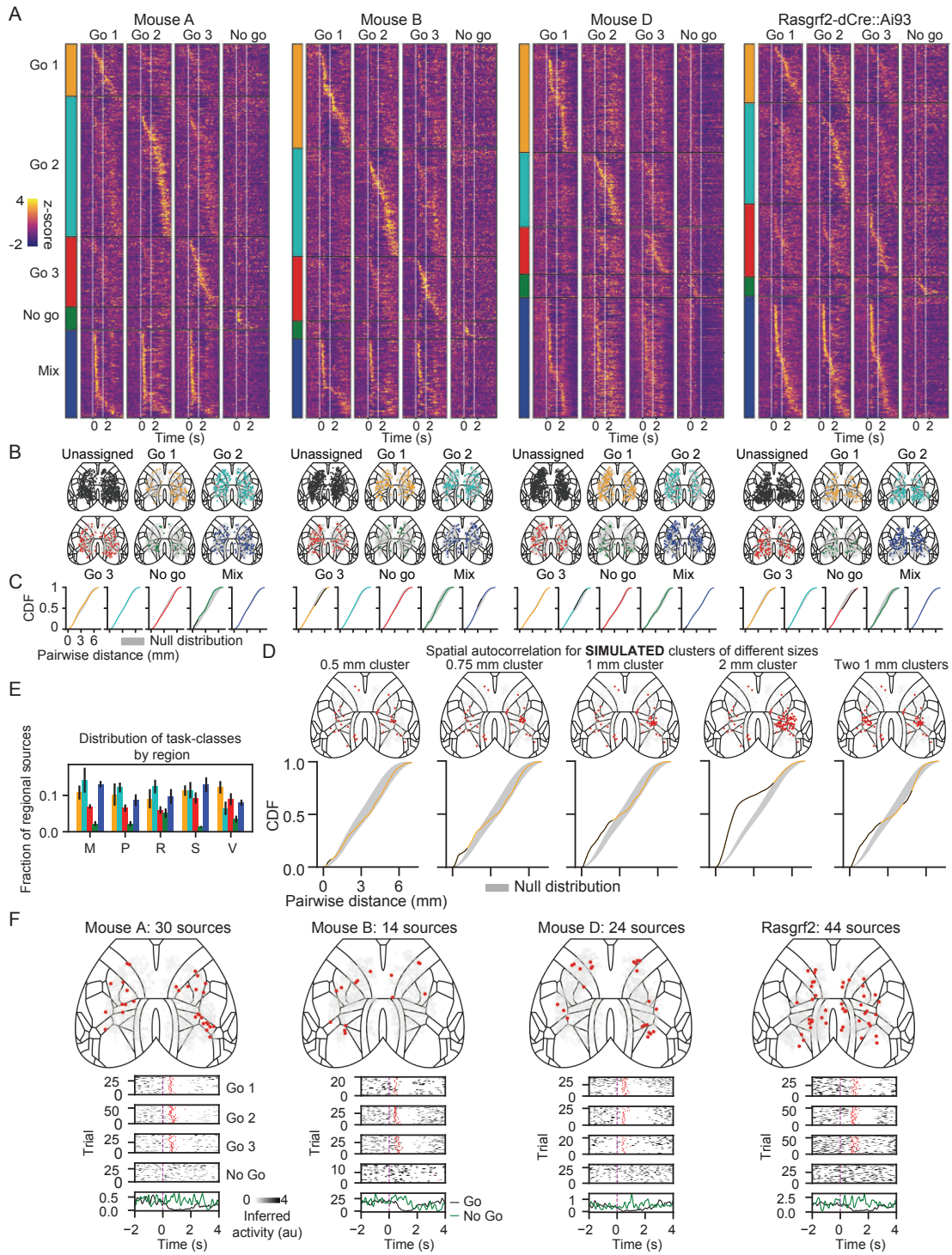


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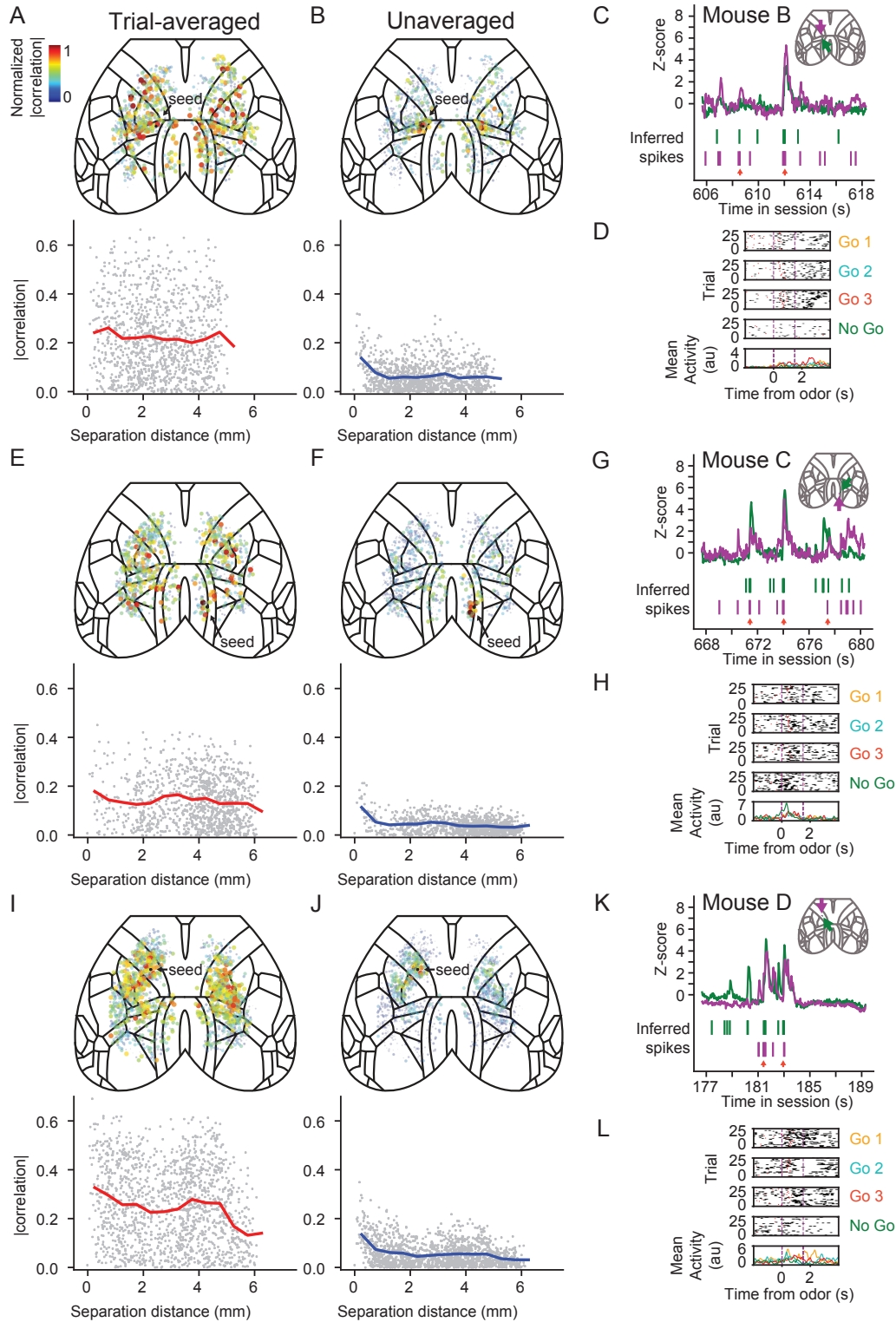
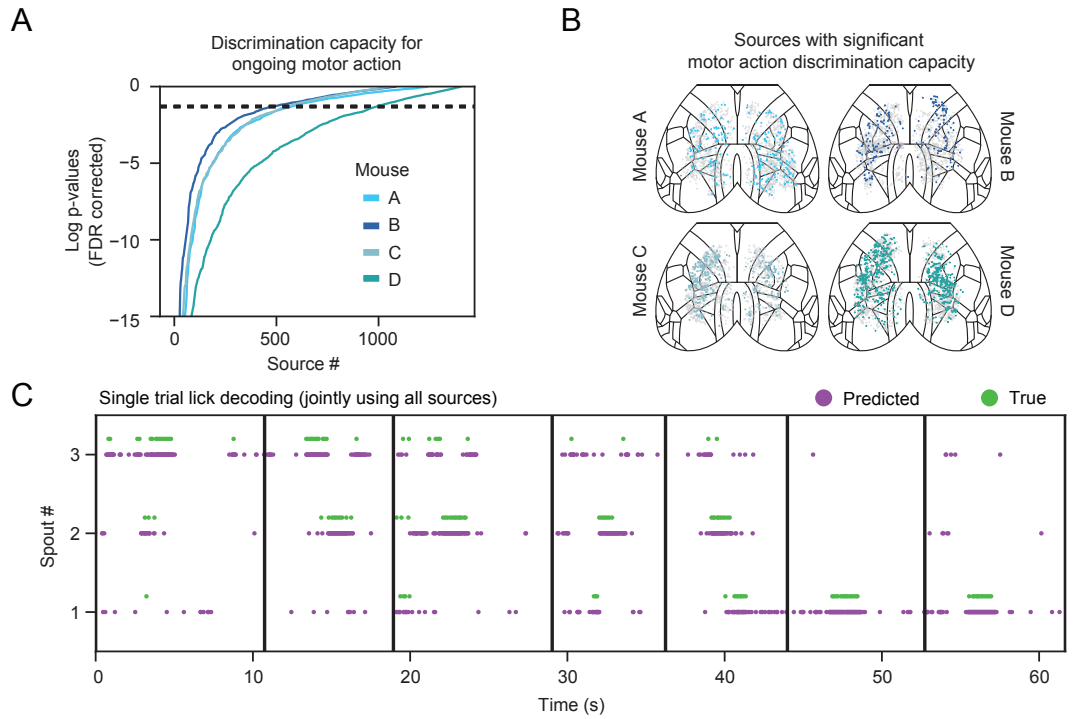


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Decoding ongoing motor action



Decoding history-dependent motor plans

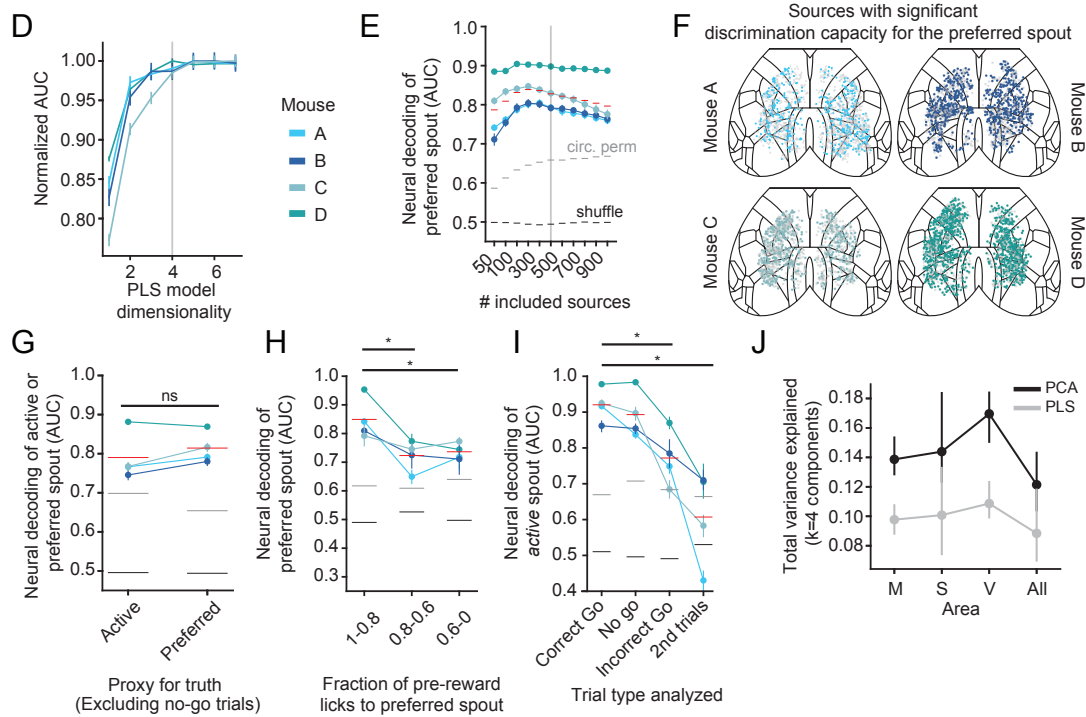


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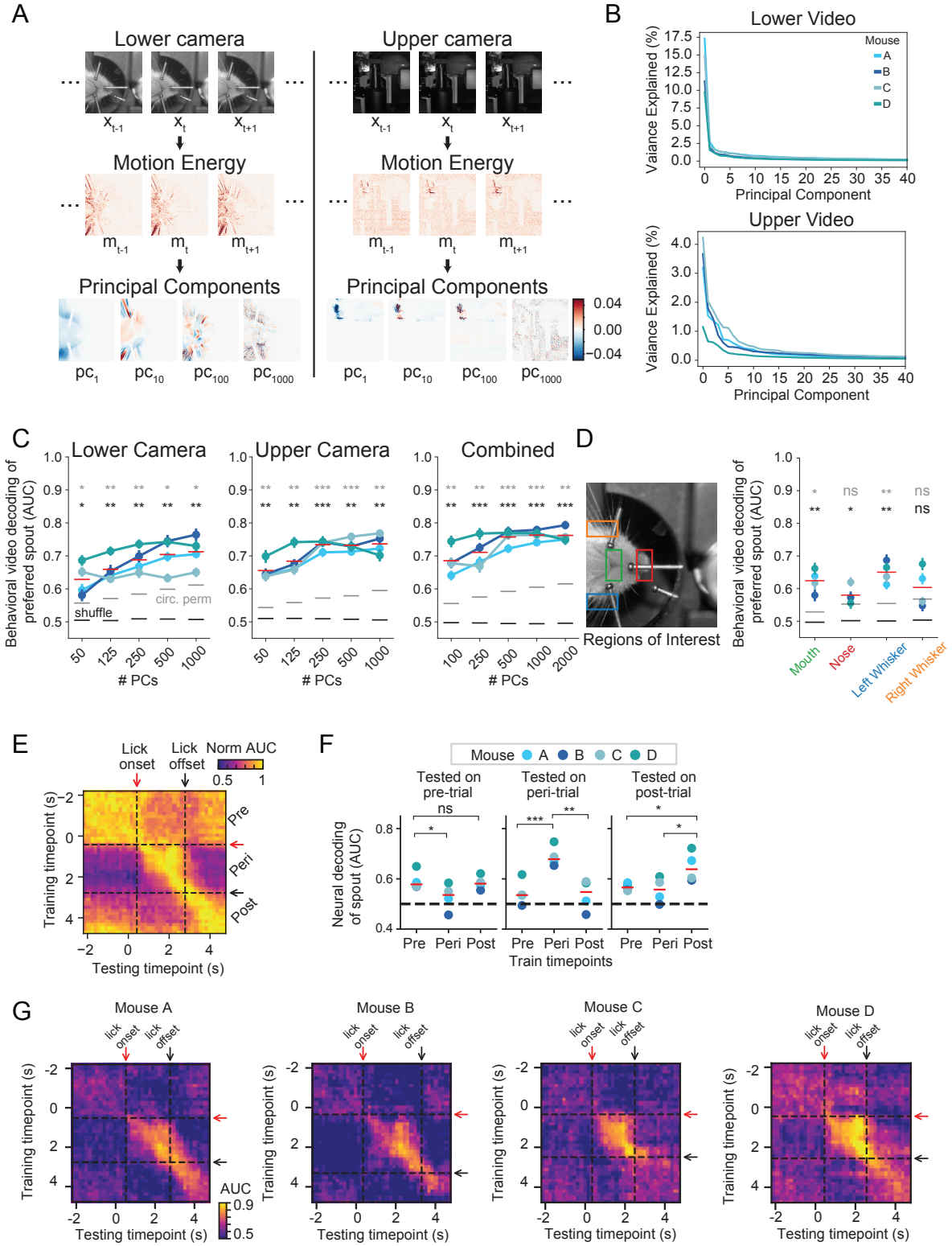


Figure S8 (preceding page). Active spout decoding from high speed videos of mouse behavior and cross-temporal neural decoding (relates to Figures 6 and 7).

(A) Extracting motion-related features from high-speed behavior videos. (B) Variance explained by behavioral video motion energy principal components. (C) Results from PLS decoding of active spout from pre-odor video motion features. (D) Results of decoding using pre-odor motion features from specific regions of interest. (E) We asked if there might be a difference between widespread neural representations of motor plans, and of motor plan execution. To do this, we compared sets of PLS models trained on different epochs of the trial. By training models on a single time bin (e.g. during the pre-odor period) and evaluating prediction performance on a different time bin (e.g. during movement), we tested the similarity of the PLS models over the trial. The goal was to understand whether a single projection of the data might best discriminate the trial types, or whether cortex might represent motor plans during the intertrial interval differently from actual directed licking during the peri-movement period (between lick onset and lick offset). Examining how well each of the time-specific models predicted other time bins revealed clear structure. In grouping these time bins into pre-, peri-, and post-task epochs based on the average time of lick onset and offset, we found a dissociation between models trained on intertrial interval data (from the pre- and post-task epochs) versus those trained using peri-task period data. Specifically in this panel, AUC was computed for PLS bases trained to predict the active spout position from neural data in one time window, and then tested on neural data from all time windows and each mouse. AUC is normalized by the maximum AUC for each testing time window, and averaged across four mice. Dashed lines represent the average time of lick onset and offset within the trial. For this analysis (panels E-G), testing was only done on trials where the active spout and preferred spout were identical (trials where the active spout and preferred spout were not the same were always excluded from training in all analyses). (F) Quantification of results in Panel E for individual mice, comparing cross-temporal prediction performance of three distinct time blocks: pre-task, peri-task, and post-task. For each testing time block, we statistically compared the mean prediction performance of bases trained on each time block (corrected t-test). These results are consistent with the interpretation that motor plans and consequent movements are represented by two distinct, but related, neural population representations. (G) Unnormalized cross-temporal AUC for each mouse. ns denotes corrected $p > 0.05$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

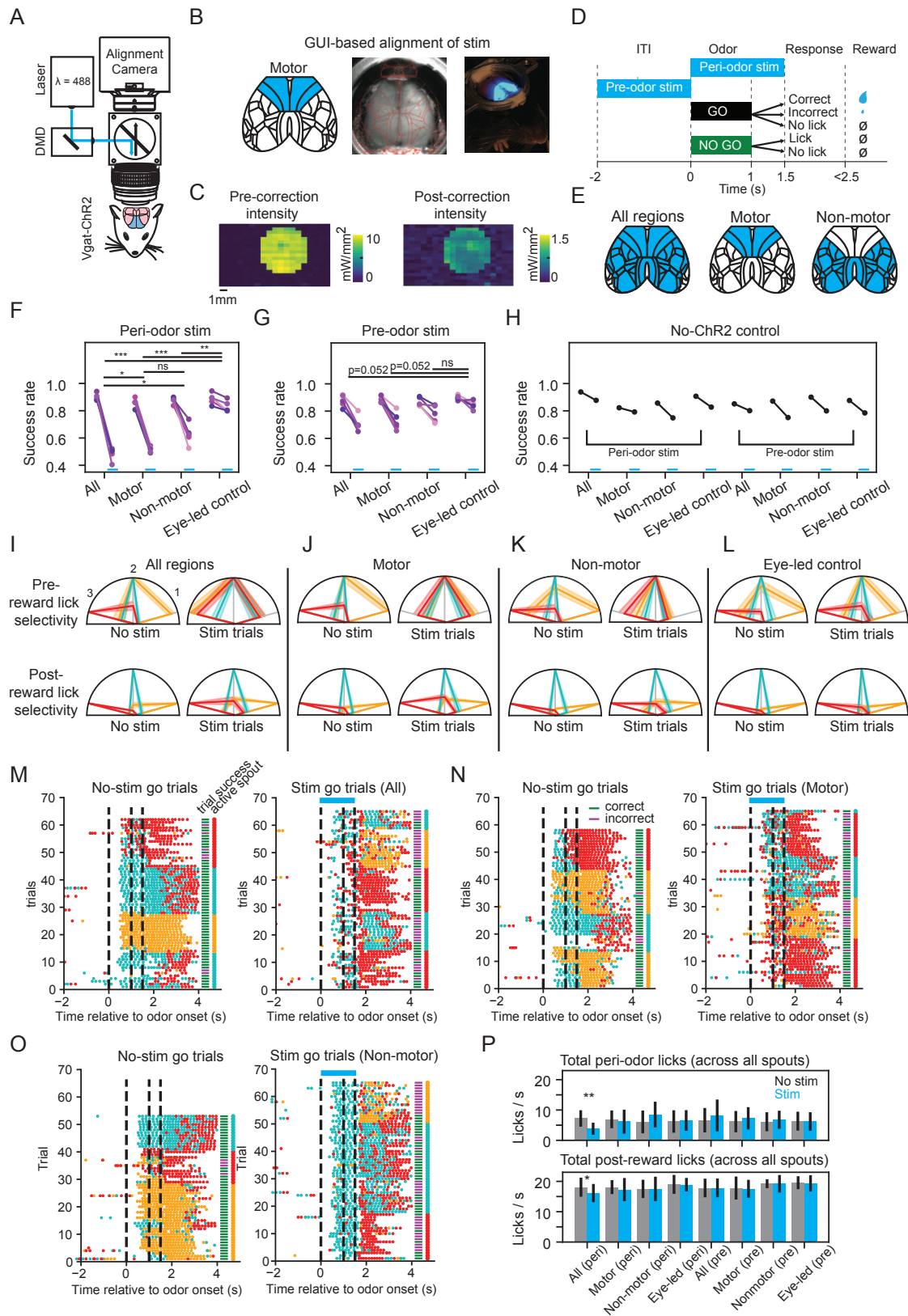


Figure S9 (preceding page). Inhibition of non-motor areas impairs lick-to-target task performance (relates to Figures 5-7).

(A) In addition to recording neuronal activity, we tested if the task-activity we found distributed across many non-motor areas was causally involved in task performance. We investigated this because it is known that specific areas of cortex can modulate the firing of neurons in primary and secondary motor cortex. For example, projections from S1 can drive M1 activity and drive the initiation of whisking (Sreenivasan et al., 2016). But in addition, posterior regions like retrosplenial cortex and primary sensory areas (Barthas and Kwan, 2017; Yamawaki, Radulovic, and Shepherd, 2016; Zingg et al., 2014), also project to secondary motor cortex and may thus play an important role in producing any dynamics observed in motor areas. We therefore set out to study whether mice could accomplish our task without normal input from all of these non-motor areas by simultaneously inhibiting multiple cortical regions using the Digital Micromirror Device (DMD) system shown here. This approach avoided the possibility that uninhibited areas in cortex might compensate for the acute shutdown of a single area. (B) Atlas alignment. (C) Intensity calibration. (D) Stimulation protocol. (E) Stimulation patterns. (F) Success rate on peri-odor stimulation vs. no stimulation trials, for each stimulation pattern, n=5 mice, corrected paired t-test between stimulation patterns. (G) Success rate on pre-odor stimulation vs. no stimulation trials, for each stimulation pattern, n=5 mice, corrected paired t-test between stimulation patterns. (H) Success rate on peri- and pre-odor stimulation for a mouse not expressing ChR2. (I-L) Summary of lick selectivity averaged across n=5 mice (with S.E.M. shown) after odor delivery, but before (top) or after (bottom) reward delivery during non-stimulation trials or stimulation trials, for each stimulation pattern. Colors denote the normalized number of licks towards each spout on trials when a given spout is active. (M-O) Example lick rasters demonstrating that licking is not fully abolished during photoinhibition, but rather the specificity of it is disrupted (for each stimulation pattern, some sessions showed incorrect preference for a single spout, while others showed nonspecific licking towards multiple spouts). (P) Comparison of total number of peri-odor and post-reward licks during no-stimulation (gray) and stimulation (blue) trials (mean \pm S.E.M. across mice, corrected paired t-test between stimulation patterns). ns denotes corrected $p > 0.05$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.