Current-Source Density in Higher Visual Areas Reflects Distinct Signaling Motifs for Oddball Processing

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Abstract:

Sensory areas of the mammalian cortex possess a regular six-layer motif, often interpreted functionally in terms of a canonical microcircuit and computation. Many have proposed that this canonical computation could be a form of predictive coding, but previous experiments have sometimes failed to deconfound prediction error as such from other possible causes for neural response dynamics, such as stimulus specific adaptation. We recorded spiking and local field potentials from seven areas in nine (N=9) mice as they passively viewed visual sequences with varying contextual cues and sequence structures. Current-source density analysis in mouse visual area rostrolateral (RL) showed distinct patterns when oddball stimuli were dissociated into stimulus specific adaptation, global oddballs, and deviance detection.

Keywords: cortical microcircuit; predictive coding; electrophysiology; intralaminar circuit

Introduction

A wide variety of behavioral evidence suggests that the neocortex implements a probabilistic internal model of the sensorimotor environment (McNamee & Wolpert, 2019). The cortex also appears, at a gross level, to consist of *canonical microcircuits* (Douglas et al., 1989), suggesting that each six-layer column of the repeating circuit implements a canonical computation. Theorists have suggested that this canonical computation may take the form of Bayesian prediction, either in the form of predictive coding (Bastos et al., 2012; Friston & Kiebel, 2009; Rao & Ballard, 1999; Srinivasan et al., 1982) or predictive routing (Bastos et al., 2020). While the experimental literature contains abundant evidence for a form of temporally "local" predictive coding, in which the decoded "prediction error" arises from a change in stimulus, this "local oddball" paradigm conflates the possible causes of such a neural signal (Gabhart et al., 2023). These can include stimulus-specific adaptation of selectively responsive neurons performing a purely feedforward computation, detection of stimulus deviance from a repeated sequence, or a general prediction error.

Our experiment sought to disentangle these possible sources of variation in spiking activity and local field potentials. We recorded in six visual areas in mice across contexts (uncued or cued surprises, local and global oddball stimuli) and found that stimulus-selective adaptation, local deviance, and global oddball processing generated distinguishably different patterns of neural response.

Methods

We recorded spiking and local field potentials from six (6) visual cortical areas and one thalamic area in mice (n=9) using six (6) Neuropixels probes; Figure 1 shows the experimental design used and a cortical hierarchy taken from (Harris et al., 2019). Prior to recording sessions, mice were habituated for 5-10 sessions to a specific sequence of visual stimuli containing a local oddball. We write the local oddball blocks xxxY, using X/x vs Y/y for stimulus identity, lowercase letters x for fully deterministic stimuli, and capital letters Y for randomized stimuli. During recording, mice passively observed the habituated local oddball (LO, xxxY) sequence, intermixed with global oddball sequences (GO, xxxX, 20% of trials). Following the main block, two control blocks were presented. The first was a selectivity control block in which each stimulus of a sequence was pseud-randomly presented (B2 in Fig. 1). The second was an adaptation control block in which the stimulus sequence xxxx alternated with yyyy (B3 in Fig. 1).

Per-trial local field potential data was averaged across animals and trials within each condition, with grand sample means and (corrected) sample standard variances being calculated relative to a sample-size in trials. Current-source density (CSD) analysis was performed after grand-averages within conditions, but before statistical comparison, using the standard CSD method included in the Elephant package for electrophysiology analysis (Yegenoglu et al., 2018). CSD results are shown in nano-amperes per millimeter squared (nA/mm^2). A two-tailed Welch's t-test for a difference of means in normal distributions was used to locate statistically significant ($p < 0.05$) differences between the condition means.

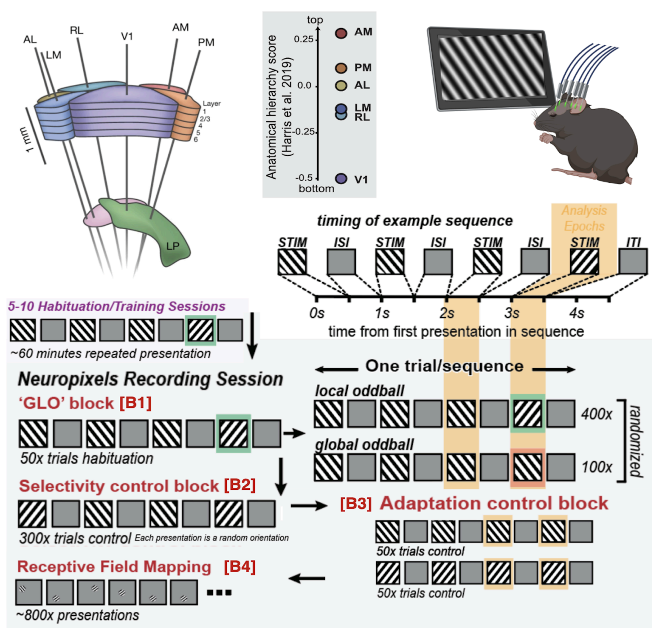

Figure 1: Six visual cortical areas were recorded as mice were presented with a main block of local and global oddball sequences, followed by control blocks.

Results

We measured three cross-condition contrasts in CSD: stimulus-specific adaptation (SSA, xxxY vs yyyy in control block B2), deviance detection (DD, XXXY in the random control block B2 vs the first 50 trials of xxxY both during the main block B1), and global novelty or prediction error (PE, xxxX vs xxxx). We subtracted the 3rd stimulus response from the 4th response to remove the time-in-task confounder.

Figure 2 shows the current-source density analyses of the contrast responses in the rostrolateral visual cortex (RL). The top row contrasts xxxY and yyyy sequences, which reflects stimulus-specific adaptation; a minor but significant relative sink starts in L4 and spreads to L2/3 and L5/6 around a relative source in L4. The middle row shows the contrast between XXXY and xxxY responses; the former display a significant current sink in L4 compared to xxxY trials that spreads to superficial layers with a delay. The bottom row shows the contrast between xxxX and xxxx trials; the contrast is not significant during stimulus processing. The stimulus offset shows enhanced sinks in L2/3 and L5/6.

Our results show that stimulus-specific adaptation and deviance detection evoked a FF laminar circuit response but that global novelty yielded distinct responses in stimulus processing.

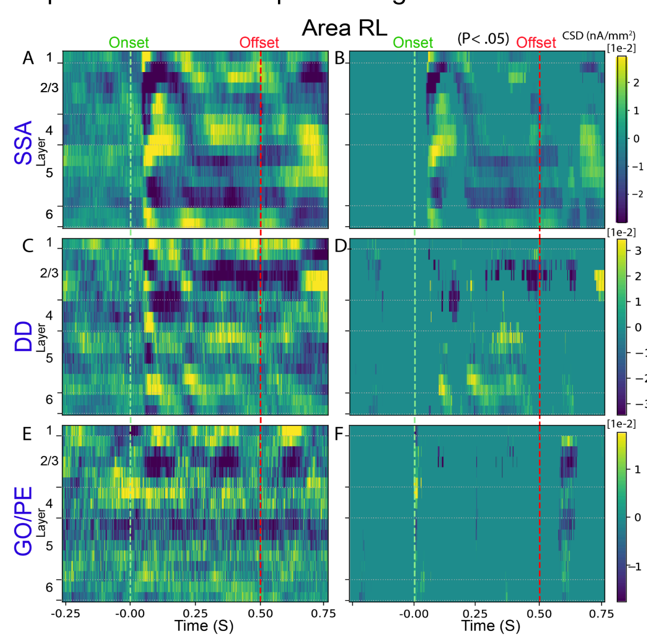

Figure 2: Responses (left) and statistical significance (right, p<0.05) for oddball relative to third stimulus, in

Stimulus-Specific Adaptation, Deviance Detection, and Prediction Error contrasts.

Discussion

This abstract studied cortical responses in a local/global oddball experiment design to test the layer-specific encoding of prediction errors. We studied the current sinks and sources elicited by stimulus-specific adaptation, deviance detection, and global novelty. Stimulus specific adaptation showed the stereotyped current sink spreading from L4 outward after stimulus onset, consistent with a feedforward (FF) pattern of canonical circuit activation. Global oddball prediction error showed a distinct pattern with enhanced current sinks in superficial and deep layers only after stimulus offset. Deviance detection showed a current sink that began later than that for stimulus-specific adaptation in L4 and spread to L2/3 during stimulus presentation, again reminiscent of a FF pattern.

This argues against a canonical computation for all types of prediction error and in favor of a specialized circuitry for different types of prediction error. Ongoing work is characterizing these computations in cortical and subcortical structures.

Acknowledgments

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