

V1 neurons track the rate-of-change of behavioral variables

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Abstract

Population-level neuronal dynamics across the brain are shaped by behavioral state variables, such as running speed or pupil area. Given this real-time integration of state variables within sensory networks, we hypothesized that neurons also track their rate-of-change, providing additional valuable information about fluctuations in behavioral state. We demonstrate that both state variables and their rate-of-change (first temporal derivatives) can be decoded from population-level activity in mouse primary visual cortex (V1), during both spontaneous behavior and sensory stimulation. This parallel encoding regime relies on partially-overlapping neural populations, with some neurons encoding behavioral state, its rate-of-change, or both. Our findings suggest that neural activity within a primary sensory region not only represents an animal's current behavioral state, but also tracks its immediate fluctuations.

Introduction

Adaptive behavior requires sensory cortical networks to act as precise detectors, continuously monitoring and adapting their activity to internal and external information. Physiological recordings from sensory cortical networks across species have demonstrated that the underlying networks encode both self-motion and external sensory variables even in early sensory regions. For instance, middle temporal area (MT) in monkeys and mouse primary visual cortex (V1) activity in mice are modulated by behavioral state, with neuronal populations encoding running speed (Traschütz et al., 2015, Avitan et al., 2021; Stringer et al., 2019, 2021). Beyond locomotion, recent work has shown that the rate-of-change of arousal-related variables, like pupil dilation, can actively modulate sensory processing in mouse V1 according to behavioral demands (Franke et al., 2022). In order to expand on those priors across variables and contexts, we sought to understand how rate-of-change of self-motion and external stimulus-related variables could be represented in sensory networks, using large-scale neuronal population dynamics from mouse V1 in spontaneous or evoked conditions. Our findings indicate a mixed encoding regime, where neural activity captures both absolute behavioral states and their relative change.

Results

To investigate how behavioral variables are encoded in the sensory cortex, we analyzed large-scale V1 population recordings in spontaneous (Stringer et al., 2019) and evoked conditions (Stringer et al., 2021; Fig. 1A). The datasets included behavioral state variables (e.g., pupil area, running speed) and stimulus features in the evoked condition (grating angle θ). Additionally, we computed their corresponding rate-of-change variables (e.g., pupil dilation, acceleration, the absolute angle difference ($\Delta\theta$) and its logarithmic ratio $\log(\Delta\theta/\theta)$).

By applying dimensionality reduction techniques (UMAP, PCA), we observed that both state and rate-of-change variables contributed to the neural manifold structure (Fig. 1B, SF1–2). Specifically, color-coding these representations as a function of most variables revealed clear clustering patterns, indicating encoding of both state and rate-of-change information. Similar patterns persisted in the evoked dataset, except for the case of $\Delta\theta$ and $\log(\Delta\theta/\theta)$, with no evident structure in the dimensions shown (Fig. S2).

Driven by these indications and to further leverage the advantages of dimensionality reduction (such as noise reduction, improved signal-to-noise ratio, and reduced risk of overfitting in decoding), we extracted functional assemblies from the data referred to as ‘superneurons’, using non-negative matrix factorization (NMF) and Gaussian mixture models (GMM) (Fig. 1C, SF3).

Next, using single neurons or superneurons, we performed a correlation analysis that revealed significant linear relationships between neural activity and several behavioral variables of interest (Fig. 1D, SF3). For example, in the evoked dataset, specific superneurons correlated with either state or rate of change variables or both (speed/acceleration, NMF6/NMF5), but also

stimulus variables alone (θ , NMF21) or along behavioral variables (e.g., NMF19), suggesting functional diversity and mixed encoding.

To further investigate the nature of these encoding, we next trained linear decoders (Ridge regression) to predict the target variables (Fig. 1E, SF4) from either the superneurons or all of the individual neurons. The linear decoders effectively reconstructed both state (e.g., pupil position, $R^2 = 0.86$) and rate-of-change variables (e.g., pupil velocity, $R^2 = 0.75$), across datasets. Prediction output indicated that superneurons often approximated single-neuron predictions, particularly in the spontaneous dataset (Fig. 1F).

Isolating the highest weight neurons for the prediction revealed that the substrate of this decoding is a partially-overlapping population of mixed-selectivity and specialized neurons (Fig. 1G, SF5). In the example shown, approximately 10% of neurons were orientation-selective, 50–60% encoded speed, while 32.2% of those involved in both speed and acceleration further validating the presence of mixed encoding.

Although our linear regression models were unable to effectively predict the change in stimulus $\Delta\theta$, to further investigate whether stimulus change could be captured in the network at least at a coarse level, we trained a logistic regression classifier to predict $\Delta\theta$ classes binned per 30° . The model achieved 47% accuracy (Fig. 1H, chance = 33%) implying a non-additive, yet still linearly separable, representation of angular stimulus change.

Finally, to assess whether non-linear decoders could better predict state or rate-of-change variables, we trained non-linear models (Transformer Autoencoders and CNN-LSTM architectures, Fig. 1I, S6). Notably, $\log(\Delta\theta/\theta)$ was predicted with high accuracy from GMM superneurons ($R^2 = 0.63$; Fig. 1I, SF6), while acceleration remained poorly predicted, which may

be due to overfitting of these more complex architectures. These findings reveal that non-linear models are critical for decoding certain types of stimulus change-related variables.

Figure 1

A: Example neural traces and behavioral variables.

B: Projection of spontaneous activity in UMAP space.

C: Superneuron computation.

D. Example of correlation analysis outputs using NMFs superneurons (*: $p < 0.05$, **: $p < 0.01$, *** $p < 0.001$).

E: Linear decoder predictions (cross-validated, R^2 on test set)

F: Comparison of linear decoder predictions across variables.

G: Mixed-encoding: Venn diagrams (%)

H: Logistic regression: Confusion matrix (% , TP in diagonal).

I: Comparison of non-linear decoder predictions across variables.

Discussion

State and rate-of change variables are linearly encoded within V1

Projecting population activity into a low-dimensional space revealed that both state and rate-of-change variables are clearly organized in the embeddings. Interestingly, $\Delta\theta$ and $\log(\Delta\theta/\theta)$ showed no evident patterns in PCA or UMAP latent spaces (S1). However, given that we could decode these variables (Fig 1I), we hypothesize that structure may arise in further dimensions than the first two principal components that we plotted. Furthermore, our superneurons were significantly correlated with both self-motion-related state and rate-of-change variables in both spontaneous and evoked conditions, agreeing with previous studies which showed that cortical neurons form distinct, behavior-specific co-active assemblies (Okun et al., 2019). Indeed, linear decoders accurately predicted the variables of interest, indicating that V1 keeps track not only of its current self-motion status, but also its instantaneous change, largely in a linear way (Fig. 1E, 1F). We hypothesize this tracking could help V1 efficiently integrate recent temporal aspects of self-motion variables and enable informed reactions for the next timepoints (Viskaitis et al, 2024). Interestingly, decoding was high for horizontal pupil position and pupil motion speed, highlighting the value of saccadic eye-movements for sensory processing. The importance of saccades that act as rapid sampling events is supported by previous studies that show they help disambiguate self-generated from externally-generated motion and relate self-motion with visual inputs (Leinweber et al., 2017). Notably, decoding performance for acceleration was markedly higher in the evoked scenario. This could reflect enhanced precision and reduced variability and thus, noise of neural responses in the presence of salient stimuli that could subsequently improve decodability. These results support previous studies that showed that external stimuli and self-motion signals can jointly enhance neural representations in sensory cortices (Christensen et

al., 2022, Musall et al., 2019). Besides self-motion, V1 also encoded relative change in external stimulus, as logistic decoders predicted the relative change in stimulus angle, suggesting linear encoding, but in a non-additive way (Fig 1H). This finding supports previous studies demonstrating that stimulus change, like relative contrast or luminance shifts, directly affect sensory representations (Ghodrati et al., 2019). Notably, we could not identify a linear relationship between neural data and stimulus change ($\Delta\theta$), suggesting potential non-linear relationships (Jin et al., 2019).

Mixed-selectivity in the encoding of state and rate-of-change variables

We uncovered a parallel pathway of information processing, with specialized and mixed-selectivity neurons coexisting within V1, suggesting that subsets of neurons focus on tracking specific behavioral aspects, while others hold an integrative role. In detail, we identify approximately 10% of orientation specific neurons, while speed and acceleration involve many more – approximately 40% and 60% respectively, out of which 32.2% display mixed-selectivity, contributing to all three variables. Our results are consistent with previous findings, where approximately 50% of V1 neurons are positively or negatively modulated by locomotion (Mineault, 2016, Erisken et al., 2014, Niell & Stryker, 2008). Importantly, mixed-selectivity and integrative coding could offer V1 a strategy to maximize its computational power for flexible behavior, by adding functional versatility to individual neurons, as reported in previous studies (Tye et al., 2024, Rigotti et al., 2013).

Non-linear decoders capture stimulus change better

Due to previous indications of non-linearity, we went on to decode using a non-linear decoder (Figure 1I and S6). Out of the models tested, a CNN-LSTM could predict the $\log(\Delta\theta/\theta)$ ($R^2=0.63$) from GMM superneurons, indicating that neural activity scales nonlinearly and not linearly as we initially supposed, as a function of angle change. Overall, further building on the logistic regression outputs, the CNN-LSTM model captures angle change, suggesting the rate-of-change encoding extends to external stimuli. While CNN-LSTMs can model both linear and nonlinear dynamics, their poor performance on acceleration may reflect overfitting due to unnecessary complexity for a simpler, possibly linear relationship.

Implications for sensory information processing

Our study indicates that neurons can track rate-of-change in mouse V1, mapping both behavioral state variables and their instantaneous dynamic change over time. This finding extends our understanding on how sensory networks process different aspects of internally and externally-generated motion variables.

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References

- Avitan, L., Pujic, Z., Mölter, J., Zhu, S., Sun, B., & Goodhill, G. J. (2021). Spontaneous and evoked activity patterns diverge over development. *eLife*, 10, e61942.
<https://doi.org/10.7554/eLife.61942>
- Born, R. T., & Bradley, D. C. (2005). Structure and function of visual area MT. *Annual review of neuroscience*, 28, 157–189.
- Christensen, A.J., Pillow, J.W. Reduced neural activity but improved coding in rodent higher-order visual cortex during locomotion. *Nat Commun* 13, 1676 (2022).
- Cong, S., Wang, H., Zhou, Y., Wang, Z., Yao, X., & Yang, C. (2024). Comprehensive review of Transformer-based models in neuroscience, neurology, and psychiatry. *Brain-X*, 2(2), e57.
- Erisken, S., Vaiceliunaite, A., Jurjut, O., Fiorini, M., Katzner, S., & Busse, L. (2014). Effects of locomotion extend throughout the mouse early visual system. *Current Biology: CB*, 24(24), 2899-2907. <https://doi.org/10.1016/j.cub.2014.10.045>
- Franke, K., Willeke, K.F., Ponder, K. et al. State-dependent pupil dilation rapidly shifts visual feature selectivity. *Nature* 610, 128–134 (2022).
- Ghodrati, M., Zavitz, E., Rosa, M.G.P. et al. Contrast and luminance adaptation alter neuronal coding and perception of stimulus orientation. *Nat Commun* 10, 941 (2019).
- Harris, K. D. (2021). *Nonsense correlations in neuroscience* (p. 2020.11.29.402719). bioRxiv. <https://doi.org/10.1101/2020.11.29.402719>
- Miaomiao Jin, Jeffrey M. Beck and Lindsey L. Glickfeld. Neuronal Adaptation Reveals a

Suboptimal Decoding of Orientation Tuned Populations in the Mouse Visual Cortex *Journal of Neuroscience* 15 May 2019, 39 (20) 3867-3881;

<https://doi.org/10.1523/JNEUROSCI.3172-18.2019>

Latimer, K. W., Barbera, D., Sokoletsky, M., Awwad, B., Katz, Y., Nelken, I., Lampl, I., Fairhall, A. L., & Priebe, N. J. (2019). Multiple Timescales Account for Adaptive Responses across Sensory Cortices. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, 39(50), 10019-10033. <https://doi.org/10.1523/JNEUROSCI.1642-19.2019>

Leinweber, M., Ward, D. R., Sobczak, J. M., Attinger, A., & Keller, G. B. (2017). A Sensorimotor Circuit in Mouse Cortex for Visual Flow Predictions. *Neuron*, 95(6), 1420–1432.e5.

Mineault PJ, Tring E, Trachtenberg JT, Ringach DL. Enhanced Spatial Resolution During Locomotion and Heightened Attention in Mouse Primary Visual Cortex. *J Neurosci*. 2016 Jun 15;36(24):6382-92. doi: 10.1523/JNEUROSCI.0430-16.2016.

Musall, S., Kaufman, M.T., Juavinett, A.L. *et al.* Single-trial neural dynamics are dominated by richly varied movements. *Nat Neurosci* 22, 1677–1686 (2019).

Niell, C. M., & Stryker, M. P. (2008). Highly selective receptive fields in mouse visual cortex. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, 28(30), 7520–7536.

Okun, M., Steinmetz, N. A., Lak, A., Dervinis, M., & Harris, K. D. (2019). Distinct structure of cortical population activity on fast and infraslow timescales. *Cerebral Cortex*, 29(5), 2196–2210. <https://doi.org/10.1093/cercor/bhz023>

Stringer, C., Michaelos, M., Tsyboulski, D., Lindo, S. E., & Pachitariu, M. (2021). High-precision coding in visual cortex. *Cell*, 184(10), 2767-2778.e15.

<https://doi.org/10.1016/j.cell.2021.03.042>

Stringer, C., Pachitariu, M., Steinmetz, N., Reddy, C. B., Carandini, M., & Harris, K. D. (2019). Spontaneous behaviors drive multidimensional, brainwide activity. *Science (New York, N.Y.)*, 364(6437), 255. <https://doi.org/10.1126/science.aav7893>

Rigotti, M., Barak, O., Warden, M. *et al.* The importance of mixed selectivity in complex cognitive tasks. *Nature* 497, 585–590 (2013).

Traschütz, A., Kreiter, A. K., & Wegener, D. (2015). Transient activity in monkey area MT represents speed changes and is correlated with human behavioral performance. *Journal of neurophysiology*, 113(3), 890–903.

Tye, K. M., Miller, E. K., Taschbach, F. H., Benna, M. K., Rigotti, M., & Fusi, S. (2024). Mixed selectivity: Cellular computations for complexity. *Neuron*, 112(14), 2289–2303.

Viskaitis, P., Tesmer, A. L., Liu, Z., Karnani, M. M., Arnold, M., Donegan, D., Bracey, E., Grujic, N., Patriarchi, T., Peleg-Raibstein, D., & Burdakov, D. (2024). Orexin neurons track temporal features of blood glucose in behaving mice. *Nature Neuroscience*, 27(7), 1299–1308. <https://doi.org/10.1038/s41593-024-01648-w>

Wang, C., Wang, X., Jing, X., Yokoi, H., Huang, W., Zhu, M., ... & Li, G. (2022). Towards high-accuracy classifying attention-deficit/hyperactivity disorders using CNN-LSTM model. *Journal of Neural Engineering*, 19(4), 046015