Rapid adaptation impacts the population coding of parametric and natural stimuli in mouse visual cortex

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Background

Adaptation alters visual processing in response to input history

- Suppression of neural response to repeated or prolonged presentation of stimuli
- Proposed to reduce redundancy in population response toward frequently shown stimuli, and increase coding efficiency in terms of energy use

Questions:

- Do different stimuli evoke the same level of adaptation? What feature of visual stimuli might affect adaptation magnitude?
- What is the distribution of adaptation magnitude in neuronal population? What are the consequences of heterogenous adaptation?

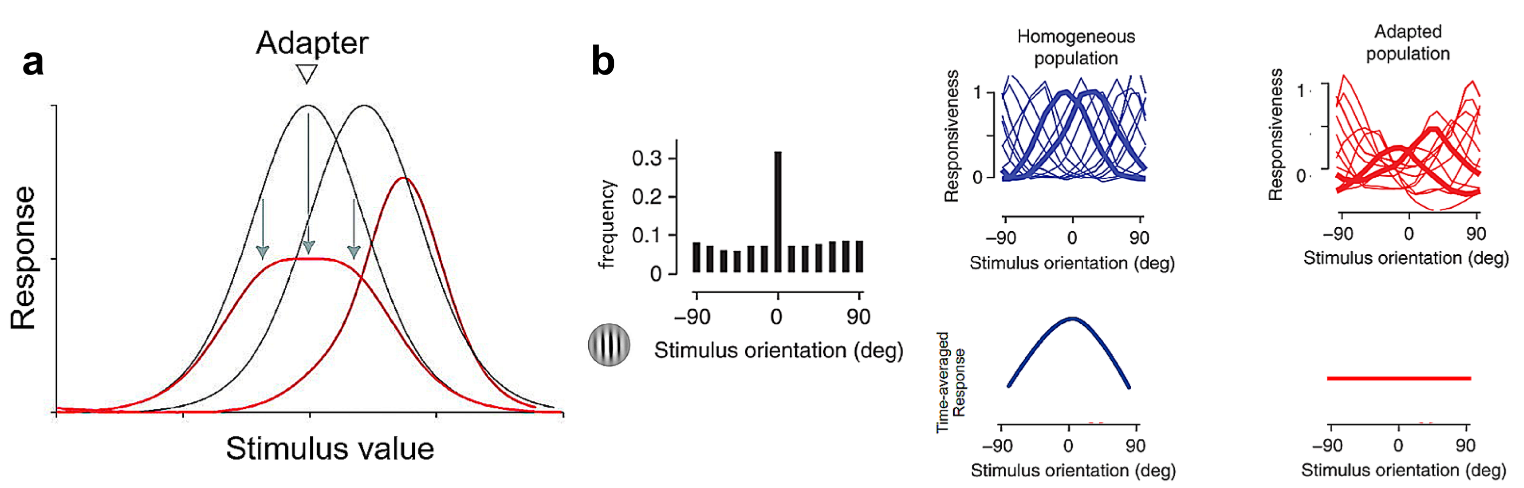


Fig 1. Neural response is reduced following adaptation to brief stimulus presentation, reducing the redundant representation of frequent stimuli

a. Adaptation in V1 generates repulsive bias of neuronal tuning, which flattens tuning curves of neurons that prefer the adapter and repels tuning curves of neurons that prefer stimuli neighboring the adapter.

b. In the presence of an environment where one stimulus (adapter) is more frequently presented than others, a neuronal population adapts by suppressing the response of neurons that are tuned to the adapter and creating a repulsive bias of tuning. This enables the population response over time to be more uniform across stimulus space instead of over-representing the adapter with redundant response. (Benucci et al, 2013, adapted by Jennifer Li)

Methods

- Present to mice stationary gratings or natural images
- Two-photon calcium imaging recording from primary visual cortex (V1)
- Leverage Allen Institute visual behavior open source dataset

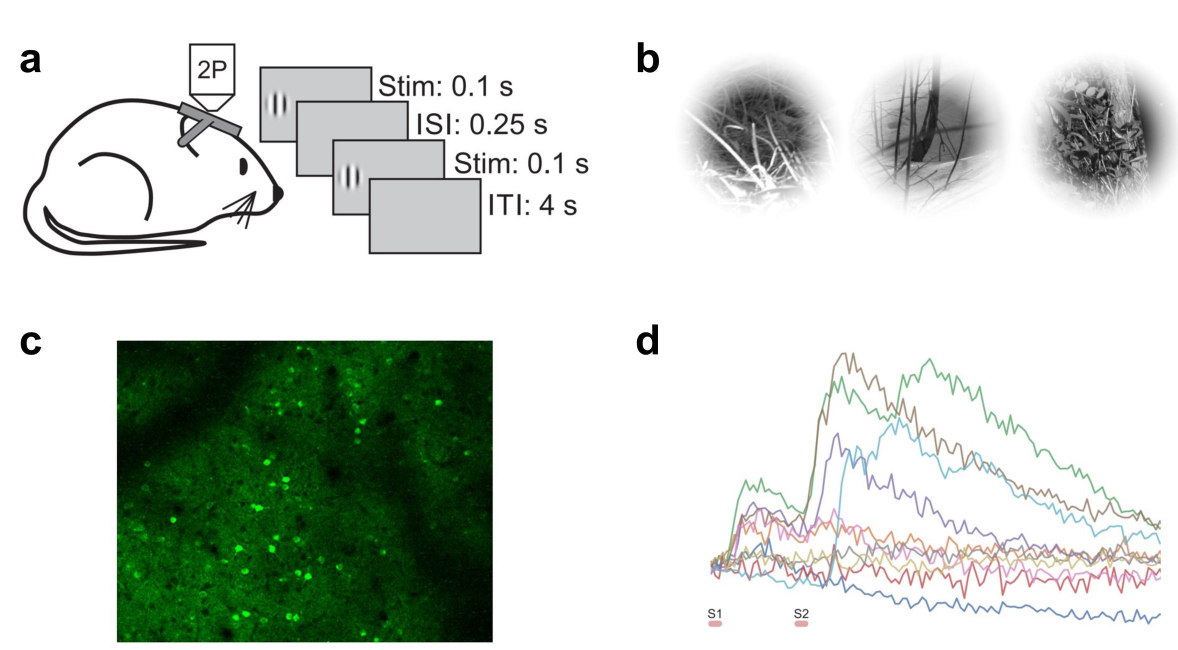


Fig 2. Experiment and data pre-processing schematics

a. Two-photon imaging on mice passively viewing pairs of repeated gratings or natural image. ISI, inter-stimulus interval. ITI, inter-trial interval.

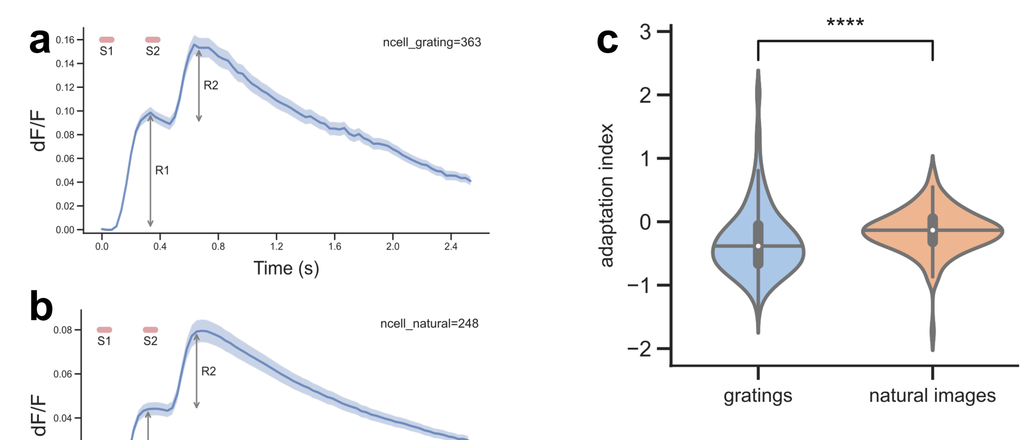
b. Example natural images shown to mice, taken from McGill Calibrated Colour Image Database.

c. Field of view in V1 under the scope of two-photon imaging. Automatic segmentation of neurons is achieved using cellpose, a generalist algorithm for cellular segmentation (Pachitariu et al. 2020)

d. Example trace of calcium signals (normalized change of fluorescence, dF/F) of single neurons, aligned to the first stimulus onset (S1) of an example trial.

Results

Fig 3. Static gratings evoke a larger rapid adaptation in V1 than the natural images used in our experiments.



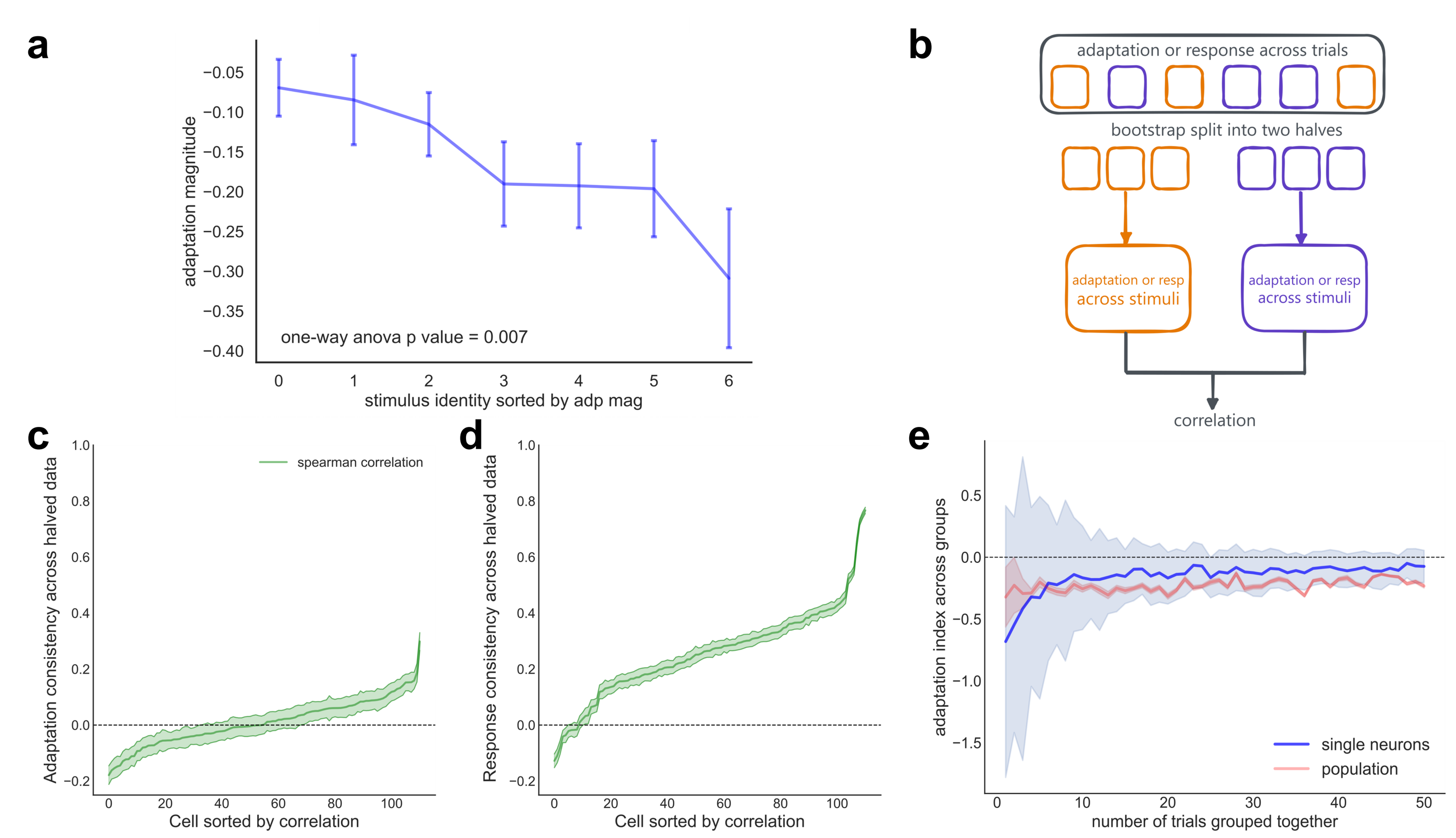
$$\text{Adaptation index} = \frac{R_2 - R_1}{R_1 + epsilon}$$

a. Neural activity trace of all visually responsive cells when presenting static gratings as visual stimuli to mice. A pair of gratings (first stimulus S_1 and second stimulus S_2) result in first response R_1 and second response R_2. Error is standard error of mean across cells.

b. Same as A, but using natural images from McGill Calibrated Colour Image Database as visual stimuli.

c. Despite long tails of the distributions, adaptation index of static grating is more negative than that of natural images. Adaptation index is defined as difference between R_2 and R_1 normalized by R_1.

Fig 4. Lack of consistency of adaptation magnitude to different natural images



a. Preliminary data with 7 natural images suggest that adaptation index is different among different natural images.

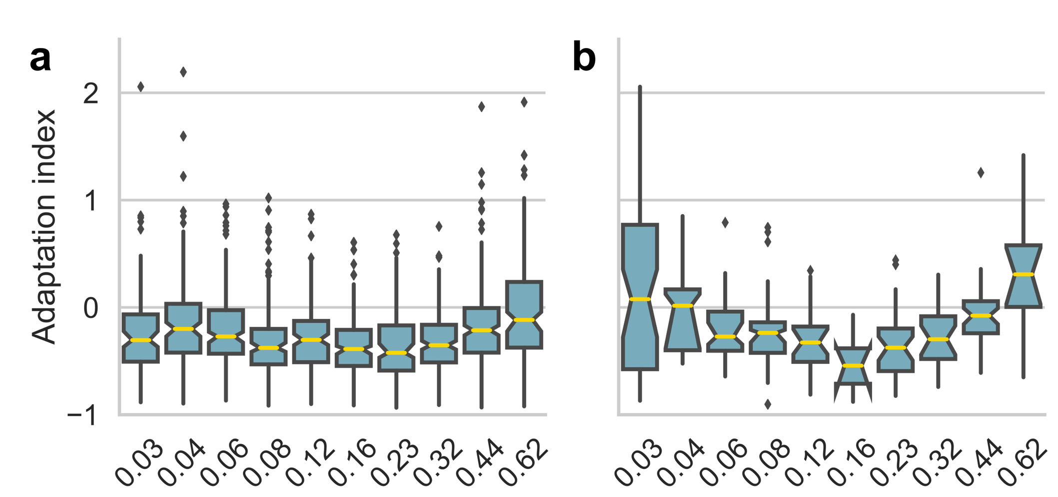
b. A single recording session's data is split in two halves repetitively by bootstrap. Then for each neuron, the two halves are analyzed to get adaptation magnitude or neural response across 30 natural image stimuli as a vector. Finally, the correlation between the adaptation or response vector between the two halves is calculated to check if the neuron is adapting or responding to different images similarly and consistently across two halves.

c. Spearman correlation of adaptation vector for single neurons, which are sorted by correlation value. The error bars represent the 95% confidence interval in 100 bootstrap iterations. The correlation values are small and highly symmetrical, centering on correlation = 0. This suggest that whatever apparent correlation between two halves is coincidental, and single neurons in fact do not adapt consistently to different natural images across trials.

d. On contrary, the responses (R_1) to different natural images are much more consistent across halves, indicating that the lack of adaptation consistency is not due to low signal-to-noise (SNR) ratio.

e. The trial-to-trial variability of adaptation index can be quantified by calculating the standard error of means of adaptation across trials of the same stimulus. Here we present the same vertical grating for 219 trials, then group various numbers of trials together, sum R_1 and R_2 of all trials in the groups respectively, and finally use the summed response to calculate the adaptation of grouped trials. It takes grouping about 20 trials together to reduce the inter-group variability of adaptation index.

Fig 5. Spatial frequency preference of neurons correlate with adaptation.



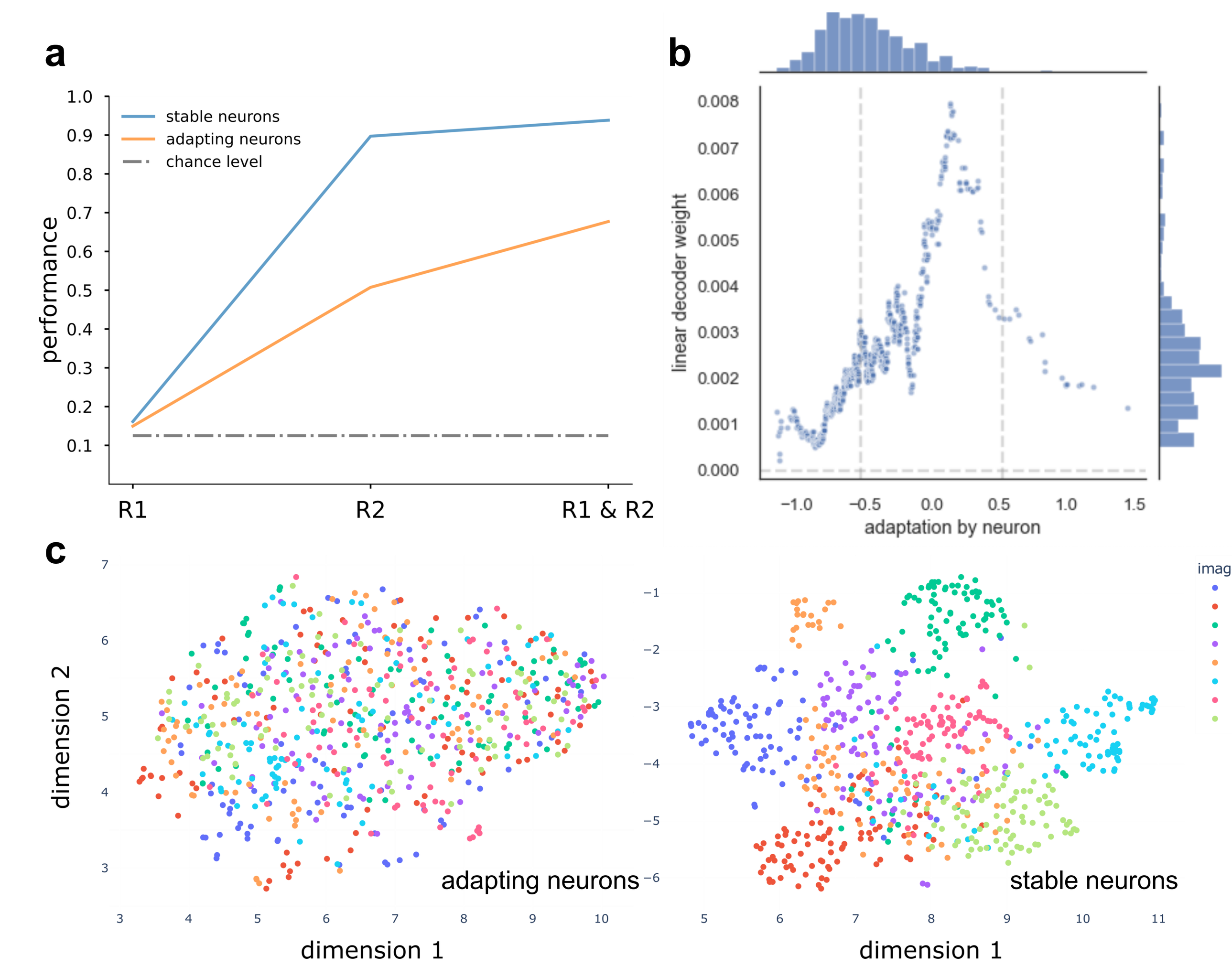
a. Adaptation magnitude across neurons responsive to different spatial frequencies. Median shown in yellow. The notch of boxplot shows the 95% confidence interval around the median.

b. Adaptation magnitude across neurons that prefer different spatial frequencies. Neurons that prefer low (0.04 cpd) and high (0.64 cpd) spatial frequencies exhibit less adaptation than mid spatial frequencies, such as 0.1 cpd which matches the spatial frequency of gratings used in our experiment.

This could explain the observed differences between natural images and gratings since natural images contain more diverse spatial frequencies, while the grating we used contains only 0.1 cpd spatial frequency.

Results

Fig 6. Neurons that adapt less encode natural image identity in a lower dimensional space than neurons that adapt more



a. Multiclass linear classifier optimized by grid search and elastic net regularization is trained to decode image identity from neural activity. Training with R_1 or R_2 or all responses of more adapting cells or more stable cells respectively.

b. Distribution of adaptation index among neurons against the distribution of neuronal weights in the linear decoder trained with all responses of all neurons.

c. Uniform Manifold Approximation and Projection (UMAP) of the responses of adapting cells (left) and stable cells (right), colored by stimulus identity of each trial.

Conclusions & Future Directions

Conclusions

1. Static grating stimuli evoke larger adaptation in V1 than natural images used in our experiments, providing weak evidence of different stimuli driving different degrees of adaptation
2. Trial-to-trial variability of adaptation index calls for a better metric: group trials together to calculate a grouped adaptation index.
3. Heterogenous adaptation in the neuronal population leads to a functional consequence, where less-adapting neurons which have more stable response to stimuli before vs after adaptation encodes stimulus identity in a lower dimensional space and plays a more important role in linear decoders.

Future Directions

- To explore what image features might affect adaptation, interleave the presentation of grating, random noise and natural stimuli in the same session and correlate image features with grouped adaptation.
- To validate conclusion 3, replicate the result with our data.

References

Credit: Caitlin Lienkaemper (dimensionality reduction analysis), Yuansi Chen (statistics and metrics design)

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