Investigating Neuronal Adaptation to Repeated Natural Stimuli in the Visual Cortex

1. Introduction

Neural adaptation is a feature of sensory processing in the brain, which refers to the gradual reduction in a neuron's response when the same stimulus is shown repeatedly. In the visual cortex, this process helps the brain stay efficient by reducing attention to familiar inputs and staying sensitive to changes. In this project, we investigate how neurons in mouse visual cortex subregions (VISp, VISl, VISrl, VISal, VISam) adapt (if they do) when repeatedly exposed to natural scene stimuli.

Neurons in the cortex can be divided into regular-spiking (RS) and fast-spiking (FS) types. Based on previous studies, RS neurons, typically excitatory pyramidal cells, tend to reduce their firing rate during ongoing stimulation. In contrast, FS neurons can maintain high firing rates with little or no adaptation. This distinction in intrinsic firing behavior suggests that different neuron types might contribute differently to adaptation in visual processing (Connors & Gutnick, 1990). We aim to characterize adaptation in FS and RS neurons and evaluate how stimulus characteristics, as well as repetition patterns, influence neural dynamics.

Our central hypothesis is that RS neurons exhibit stronger adaptation than FS neurons. The project explores this through statistical tests, dimensionality reduction (PCA), and controlled comparisons across image presentation schedules.

2. Research Questions

1. Which neurons are best suited for studying adaptation (regular-spiking or fast-spiking)?
2. Which image presentation schedules (uniform, increasing, decreasing) lead to stronger or weaker neuronal adaptation?
3. Do specific image properties influence the degree of neural adaptation?
4. Are RS neurons more adaptive than FS neurons, as commonly believed?

3. Methods

3.1 Neuron Classification

We began by scatter-plotting waveform duration against firing rate for visually responsive neurons, observing an inverse relationship consistent with the idea that longer waveforms correspond to lower firing rates. We then applied unsupervised KNN clustering to separate neurons into putative fast-spiking (FS) and regular-spiking (RS) groups. To formalize this separation, we trained a logistic regression model to define a decision boundary and selected neurons with at least 95% classification confidence. This yielded 49 confident FS neurons and 309 confident RS neurons. Subsequent analyses focused on the RS population, which was further filtered [Appendix 1].

3.2 Filtering for Visually Responsive Neurons

We assessed visual responsiveness by comparing firing rates during the first presentation of a natural scene (to avoid adaptation effects) with a spontaneous baseline. The baseline was defined as the firing rate during the second half of the spontaneous screen period, providing a more stable measure of the neuron's resting state. Units with negative response strength were considered unresponsive and excluded from further analysis, resulting in 249 visually responsive RS neurons [Appendix 2].

3.3 Stimulus Selection

3.3.1 Scene Categorization by Adaptation Score

To measure how much each scene caused neurons to adapt, we used four simple metrics that capture different aspects of response change over repeated trials: delta firing rate (captures the overall drop in response from early to late trials, reflecting adaptation), linear slope (shows whether firing consistently increases/decreases, indicating gradual adaptation), Spearman (measures if there's a consistent trend in firing change even if it's not perfectly linear), and Fano factor (checks how variable the responses are, since strong adaptation can also reduce variability).

These metrics were chosen because they could reflect both magnitude and consistency of adaptation. Since the metrics are partially correlated, we used PCA to combine them into one adaptation score per scene. The first component(PC1) explained 55.1 % of the variation and served as a summary score. Scenes were then grouped into high and low-adaptation categories based on PC1 [Appendix 3].

To understand what might cause stronger or weaker adaptation, we additionally analyzed (using OpenCV library and Sobel filter) simple visual features of each scene: brightness, contrast, edge density, and spectral slope (dominance of low vs. high frequencies) [Appendix 4].

The only statistically significant result was found within negative correlation between brightness (mean intensity) and adaptation in the "most adaptive" scenes: brighter scenes showed less adaptation [Appendix 5]. We found this approach to be not sufficient enough for strong conclusions to be made, likely because the metrics were partially correlated and could be influenced by noise or other factors. Therefore, we attempted another grouping approach.

3.3.2 Scene Categorization by Temporal Structure

As the alternative image selection procedure, we exploited the fact that images were presented in randomized order. We analyzed spacing between presentations to classify scenes as: [Appendix 6]

- **Uniform**: even spacing, which was chosen by finding the minimal std across all frames' presentation IDs.
- To filter sessions with the most increasing and decreasing

order we first computed and stored intervals between consecutive presentations for each frame and then fit a line to those intervals. The most negative slope frame is the one with increasing frequency, and vice versa for decreasing.

- As a result, the frame with uniform spacing turned out to be frame 0, the one with increasing frequency - 18, and with decreasing - 35.

4. Adaptation Analysis

4.1 Mean firing rate of RS neurons for the first 10 and last 10 presentations on selected images.

We investigated neuronal adaptation by comparing the mean firing rates of regular-spiking (RS) neurons between the first 10 and last 10 stimulus presentations across three selected frames (0, 18, and 35). Spike times were aligned to stimulus onset and binned into 10ms intervals within a 250ms post-stimulus window. Mean population firing rates were computed across all RS neurons, and independent two-sample t-tests were used to assess adaptation effects (i.e., decrease in firing rate over repeated exposure).

- **Frame 0 (Uniform)** [Appendix 7]:
  = 0.15, = 0.88
  No statistically significant difference between early and late responses.
  No evidence of adaptation.
- **Frame 18 (Increasing)** [Appendix 7]:
  = 2.43, = 0.029
  Significant reduction in mean firing rate from first to last 10 presentations.
  Clear adaptation effect.
- **Frame 35 (Decreasing)** [Appendix 7]:
  = 1.72, = 0.115
  Slight drop in late responses, but not statistically significant.
  Potential trend toward adaptation.

4.2 PCA of RS Neuron Population Activity

To further investigate neural adaptation, we performed Principal Component Analysis (PCA) on the spike responses of RS neurons during the first and last 10 presentations of selected frames (0, 18, and 35). Each presentation was treated as a 249-dimensional vector (one dimension per neuron), resulting in a 50×249 matrix per frame.

Two types of PCA were conducted for each frame: chronological PCA (trials were kept in temporal order), shuffled PCA (trial order was randomized before PCA).

Early and late trials form distinct clusters in chronological PCA. This structure vanishes when trials are shuffled, reinforcing the idea that the observed change is linked to repeated stimulus exposure. Frames 18 and 35 show varying degrees of adaptation, with Frame 18 showing the clearest evidence through both firing rate and PCA clustering. Frame 0, despite PCA separation, does not show firing rate changes. Shuffled analyses confirm that observed patterns are presentation-order dependent. [Appendix 8]

4.3 PCA Adaptation Analysis for All Selected Frames

We repeated the PCA analysis across three frames (0, 18, and 35). In the chronological labeling, the first and last 5 presentations of each frame were compared. Clear separation in PCA space indi-

cated a shift in population activity over time, consistent with adaptation. As a random control, two non-overlapping random sets of 5 presentations were labeled and compared. These showed no separation, confirming that the temporal structure observed reflects genuine neural adaptation rather than random variability. [Appendix 9]

4.4 Adaptation in FS Neurons

To test whether RS neurons are indeed more susceptible to adaptation, we now turn to FS neurons. Using the most adaptation-prone stimulus (Frame 18), we will repeat the analysis for confident FS neurons. [Appendix 10]

The plot shows a clear decline in firing rate across FS neurons between the first 10 and last 10 presentations of Frame 18, with a significant difference confirmed by the t-test (p = 0.00098). However, when compared to RS neurons (where the firing rate difference was smaller between first 10 and last 10 presentations and p-value was higher), this result does not support the hypothesis that RS neurons show stronger adaptation. Contrary to our initial hypothesis, FS neurons exhibited a stronger adaptation effect than RS neurons for Frame 18, as shown by a larger drop in firing rate and a more significant t-test result (p = 0.00098). However, this result should be interpreted with caution, as the FS group contained only 49 neurons, making it more susceptible to variability and less reliable for generalization.

5. Discussion

The analysis of RS neurons revealed that increasing frequency of image presentation results in the most evident adaptation, as reflected by both PCA separability and statistically significant reductions in firing rates. Uniform schedules showed minimal adaptation, while decreasing schedules suggested a weak trend. These results support the idea that adaptation is not just a function of repetition but also it could be attributed to the temporal structure of stimulus timing. The response under increasing presentation may reflect cumulative synaptic fatigue, habituation, or predictive suppression in RS neurons.

Unexpectedly, FS neurons demonstrated a stronger adaptation effect than RS neurons for Frame 18, with a larger drop in firing rate and stronger statistical significance. This contradicts prior assumptions that FS neurons (typically inhibitory interneurons) are less plastic. This discrepancy may be connected to underpowered FS datasets in prior work or from methodological differences in how FS neurons are identified and analyzed. Overall, our results highlight the need for dynamic, time-dependent modulation of population activity.

Limitations

- Neuronal properties span a continuum, and our classification (based on clustering in the waveform duration–firing rate space and selecting FS and RS units within a 95% confidence region with logistic regression) may still overlook intermediate or functionally distinct subpopulations. Future work could refine this approach using experimental tagging for more precise classification.
- **Sample imbalance**: Only 49 FS neurons were left post-filtering, limiting the robustness of statistical conclusions.
- **Adaptation metrics**: Metrics such as slope and delta firing

rate might capture "surface-level" temporal dynamics and therefore fail to notice non-linear adaptation trends.

- **Stimulus Presentation Constraints**: We analyzed only three exemplar scenes from predefined categories (Uniform, Increasing, Decreasing), which may limit generalizability. Scene selection may also be improved with more advanced image analysis using, for instance, convolutional neural networks.

Future directions could include expanding the analysis to other stimulus types available in the Allen dataset, such as drifting gratings or natural movies, to see whether the adaptation trends observed here hold across different visual conditions. It would also be valuable to assess adaptation across more visual areas and sessions to test how generalizable these results are.

As an alternative test for RS neuron adaptation, we can analyze Frame 18 (the most adaptation-prone stimulus) by counting spikes per visual neuron across its 50 presentations. Linear regression on spike count versus repetition yield a slope for each neuron, representing its adaptation strength. Neurons with the most negative slopes were considered most adaptive and we can compare them to the RS population to assess overlap.

References

- Connors, B. W.,& Gutnick, M. J. (1990). Intrinsic firing patterns of diverse neocortical neurons. Trends in Neurosciences, 13(3), 99–104. https://doi.org/10.1016/0166-2236(90)90185-D
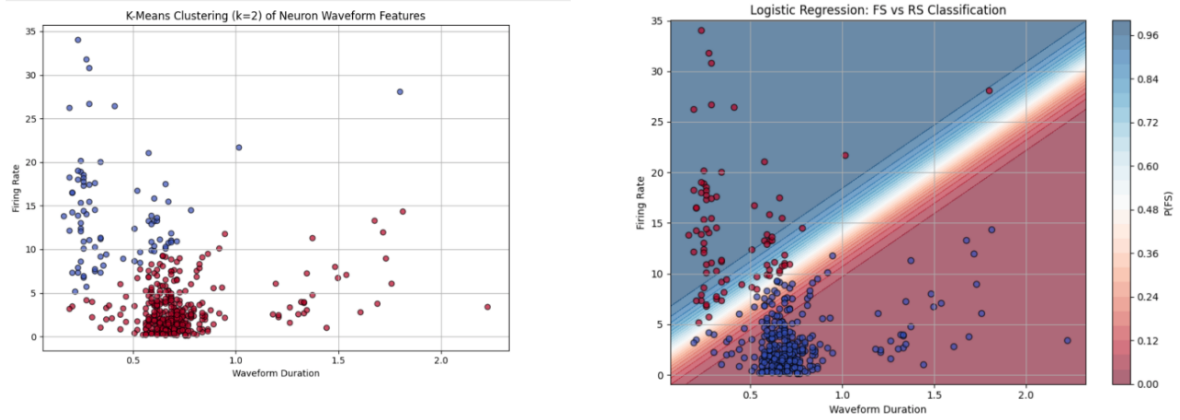
6. Appendix

Appendix 1. Neuron classification

$$\text{response\_strength} = \text{firing\_rate}_{\text{first\_ns}} - \text{firing\_rate}_{\text{spontaneous}}$$

$$\text{Neuron status} = \begin{cases} \text{responsive}, & \text{if response\_strength} > 0 \\ \text{not responsive (filtered out)}, & \text{if response\_strength} \leq 0 \end{cases}$$

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Appendix 2. Filtering for visually responsive neurons

	frame	delta_firing_rate	slope	spearman_r	fano_factor	rank_delta	rank_slope	rank_corr	rank_fano	total_rank	pc1_adapt	type
0	81	-2.294740	0.015866	0.142363	7.293435	1.0	1.0	1.0	47.0	50.0	5.273330	Most Adaptive
1	62	-2.416238	0.021056	0.162462	7.514156	3.0	3.0	9.0	89.0	104.0	3.400493	Most Adaptive
2	114	-2.897548	0.019615	0.155762	7.584179	23.0	2.0	4.0	96.0	125.0	2.988773	Most Adaptive
3	88	-2.358372	0.021507	0.185196	7.086922	2.0	4.0	43.0	19.0	68.0	2.925857	Most Adaptive
4	20	-2.894651	0.022255	0.161538	6.848915	21.0	5.0	7.0	1.0	34.0	2.706151	Most Adaptive
5	111	-2.787705	0.022729	0.159710	7.218863	11.0	6.0	6.0	34.0	57.0	2.682904	Most Adaptive
6	37	-2.539906	0.023892	0.181684	7.070130	5.0	8.0	32.0	14.0	59.0	2.299745	Most Adaptive
7	36	-2.924316	0.023319	0.167141	7.107358	28.0	7.0	11.0	22.0	68.0	2.162442	Most Adaptive
8	63	-2.653974	0.024108	0.186282	7.022228	7.0	11.0	46.0	9.0	73.0	1.942115	Most Adaptive
9	35	-3.220540	0.024745	0.147966	7.375272	79.0	14.0	2.0	63.0	158.0	1.852749	Most Adaptive
10	70	-3.404482	0.033275	0.217798	7.457089	100.0	107.0	111.0	79.0	397.0	-2.202494	Least Adaptive
11	99	-3.409482	0.034063	0.213370	7.437285	101.0	108.0	108.0	75.0	392.0	-2.204575	Least Adaptive
12	79	-3.043334	0.034265	0.234936	7.365449	54.0	110.0	118.0	59.0	341.0	-2.234228	Least Adaptive
13	113	-3.422436	0.034796	0.207452	7.601144	104.0	115.0	100.0	99.0	418.0	-2.255138	Least Adaptive
14	76	-3.850246	0.034486	0.193292	7.392247	118.0	112.0	62.0	69.0	361.0	-2.405629	Least Adaptive
15	42	-3.370023	0.034630	0.225935	6.996606	99.0	114.0	116.0	7.0	336.0	-2.409426	Least Adaptive
16	3	-3.367423	0.035221	0.219706	7.326070	98.0	116.0	112.0	52.0	378.0	-2.479625	Least Adaptive
17	26	-3.450369	0.034509	0.221860	7.280099	107.0	113.0	114.0	44.0	378.0	-2.541881	Least Adaptive
18	107	-3.831576	0.035906	0.205833	7.603390	117.0	117.0	94.0	100.0	428.0	-3.120387	Least Adaptive
19	18	-3.413702	0.038464	0.221063	7.203227	102.0	118.0	113.0	30.0	363.0	-3.121169	Least Adaptive

Appendix 3. Summary table of adaptation scores with PCA

|	frame	type	mean_intensity	contrast	edge_density	spectral_slope
0	81	Most	95.084979	81.673905	0.302313	−1.493829
1	62	Most	103.918334	59.005013	0.379226	−1.415079
2	114	Most	124.448190	77.452301	0.377482	−1.549667
3	88	Most	112.286318	62.551091	0.355574	−1.488530
4	20	Most	125.703541	74.693058	0.330830	−1.616779
5	111	Most	121.706000	57.501863	0.362237	−1.532866
6	37	Most	120.423958	55.679742	0.342976	−1.639152
7	36	Most	124.931469	66.086026	0.387852	−1.588567
8	63	Most	120.433488	55.248628	0.375641	−1.222690
9	35	Most	114.862801	77.008078	0.302959	−1.685120
10	18	Least	125.935272	81.722256	0.196960	−1.774620
11	107	Least	124.736973	64.825924	0.354786	−1.473848
12	26	Least	125.205957	69.993394	0.323850	−1.661044
13	3	Least	122.325376	78.678554	0.292096	−1.673846
14	42	Least	124.805971	67.355961	0.271343	−1.697001
15	76	Least	110.330046	77.404454	0.384737	−1.556749
16	113	Least	125.831191	74.805054	0.374089	−1.543948
17	79	Least	91.960730	69.829218	0.292769	−1.591402
18	99	Least	96.730281	65.049187	0.310203	−1.575357
19	70	Least	124.420220	71.100779	0.379095	−1.790381

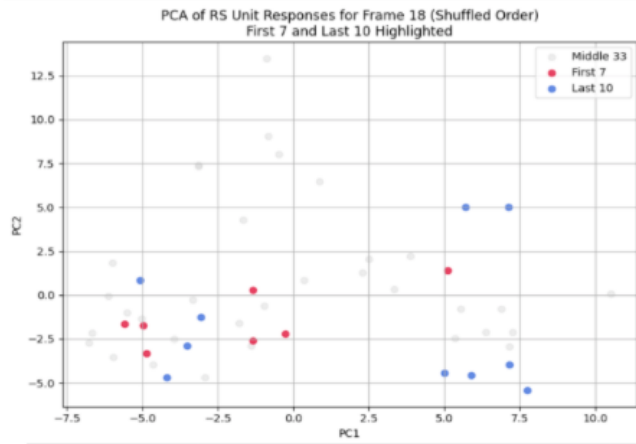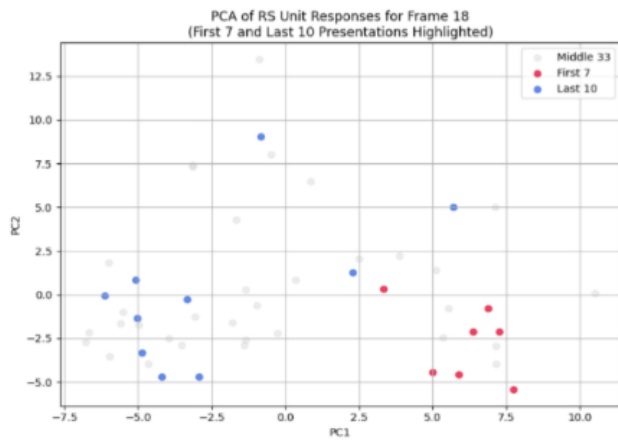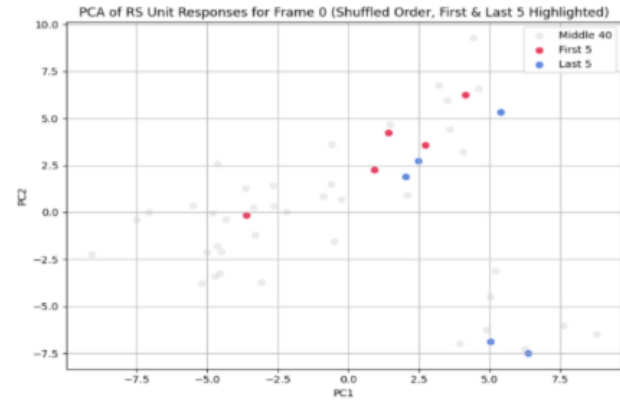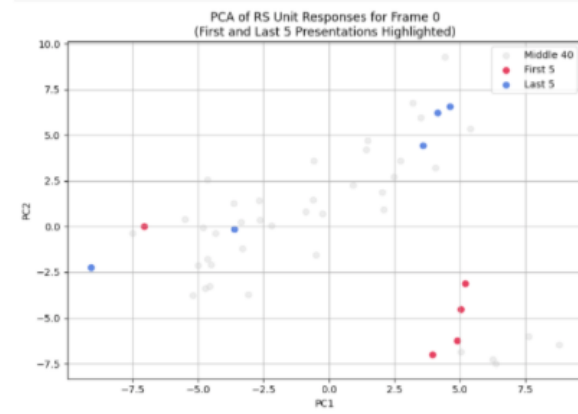**Appendix 4.** Visual Features of most and least adaptive frames
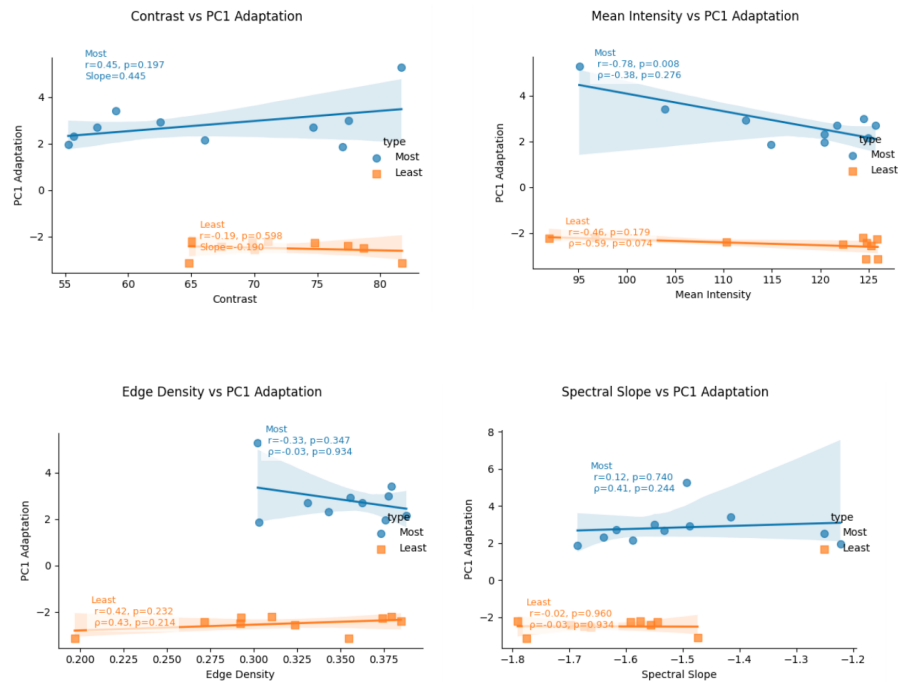
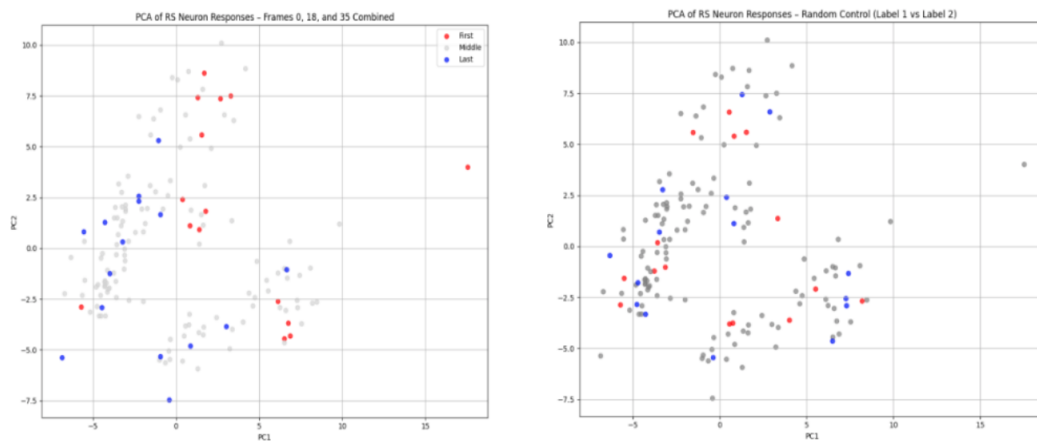**Appendix 5.** Feature scatter plots with statistical information
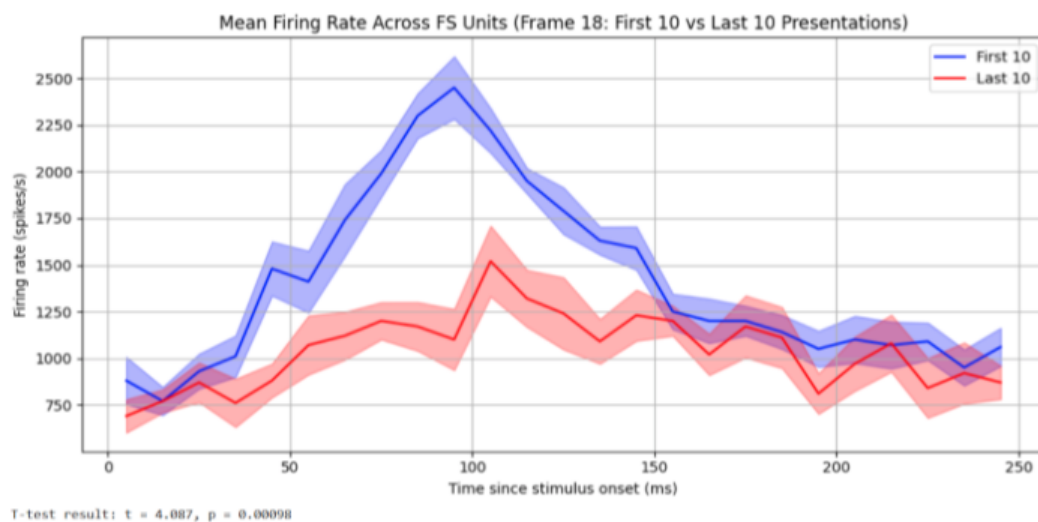

Appendix 6. Selected images
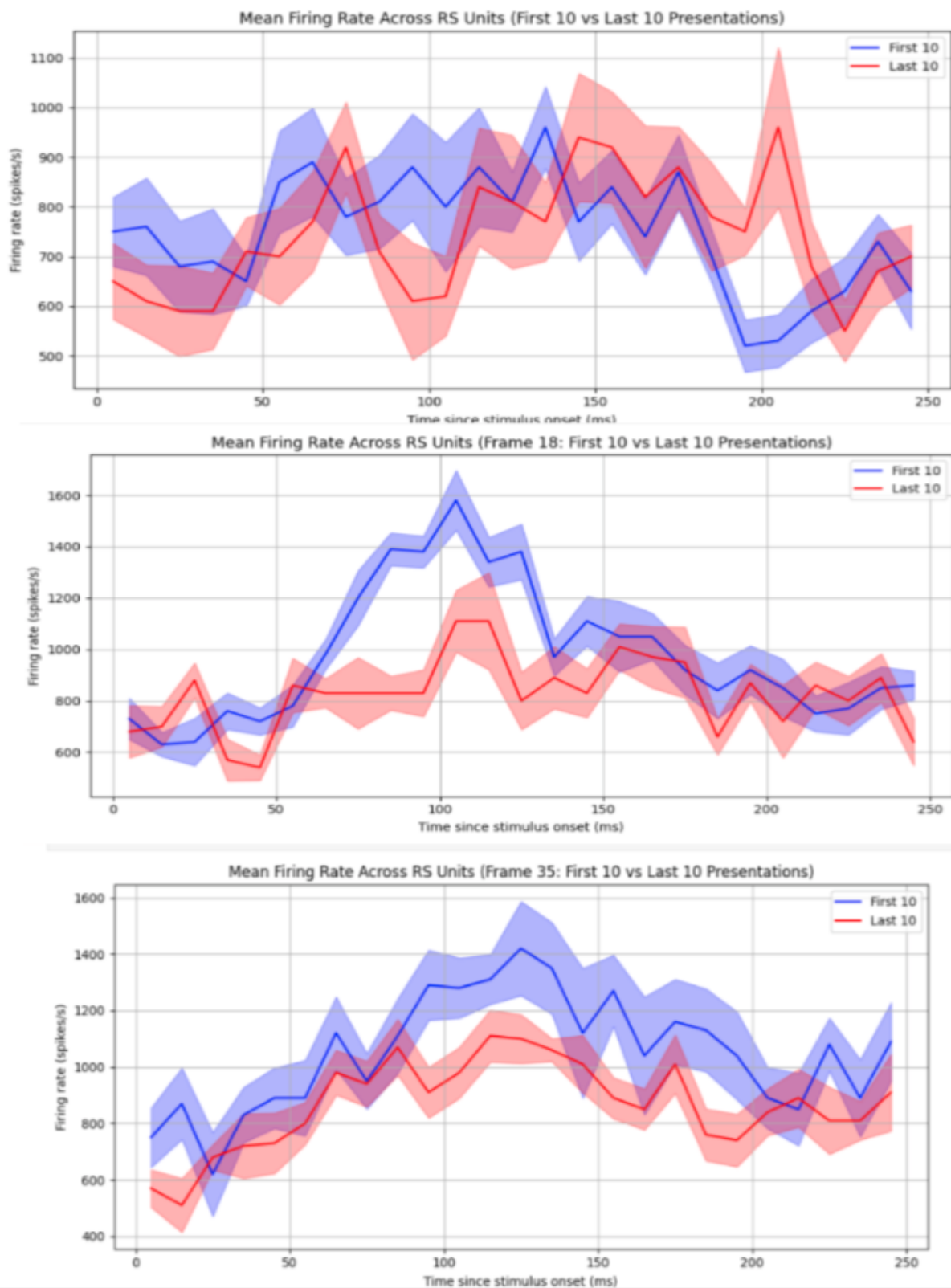
Appendix 7. mean firing rates of first 10 and last 10 presentations of selected frames
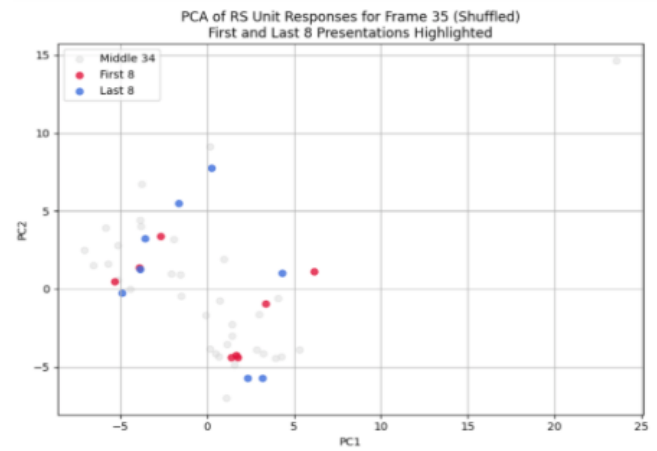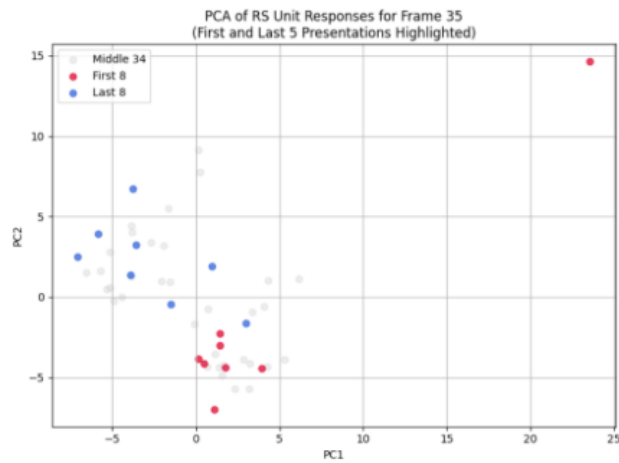
Appendix 8. PCA Analysis of RS Neuron Population Activity

Appendix 9. PCA adaptation analysis for all selected frames

T-test result: t = 4.087, p = 0.00098

Appendix 10. Analysis of adaptation for FS neurons