Decoding Static vs. Dynamic Visual Stimuli from Neural Activity in the Mouse Brain

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Abstract

In this study, we analyzed neural recordings from mice exposed to static and dynamic visual stimuli to investigate differences in neural responses. Using datasets created by The Allen Brain Observatory as part of their Visual Coding Neuropixels project, we compared activity patterns across visual and non-visual brain regions. Our findings suggest distinct encoding mechanisms depending on stimulus dynamics, with specific brain areas such as VISam and CA1, and more in general the visual cortical and the hippocampal regions playing an important role in the encoding differences.

1 Introduction

Understanding how the brain distinguishes between static and dynamic visual stimuli is fundamental to decoding sensory processing. To investigate how the mouse brain reacts to different stimuli we exploit two datasets of The Allen Brain Observatory, which include well-controlled visual stimulus presentations. By comparing average firing rates, Fano factor and latency across various neurons located in a number of brain regions, we seek to understand how the mouse brain encodes visual information, with a particular focus on the intensity and the timing of neural responses.

2 Methods

Our study was facilitated by Python libraries such as numpy, pandas, scipy, matplotlib, scikit-learn, and AllenSDK, the latter of which was used to access neural recordings from two experimental sessions of the Visual Coding Neuropixels project conducted at The Allen Brain Observatory:

- **Session 798911424**: Brain Observatory 1.1 stimulus set, including 118 natural scenes shown 50 times in a randomised order, and two natural movies, namely a 30-second and a 120-second clip from the movie "Touch of Evil", repeated 20 and 10 times, respectively. From this session we also took static and drifting gratings.
- **Session 766640955**: Functional Connectivity stimulus set, including the 30-second natural movie clip shown 60 times in its original, and 20 times in its shuffled version.

Neural activity was recorded using Neuropixels probes, capturing spiking activity across multiple brain regions simultaneously. Each session contains spike times and associated metadata for hundreds of neurons across the thalamus, the hippocampal formation, the visual cortex, the midbrain, and other regions. For each neuron, we extracted spike times aligned to stimulus presentations. For the Brain Observatory 1.1 session we focused on analyzing the difference in responses to natural scenes and natural movies, grouping the two clips together after a preliminary comparison. For Functional Connectivity session, we focused on the difference between one of the natural movies and its shuffled version. After a brief data exploration, we proceeded with extracting the metrics we needed.

Our main goal in the first part of the study was to build a Support Vector Classifier (SVC) able to label static (natural scenes) vs. dynamic (natural movie frames) stimuli. We trained the SVC using the average firing rate, which was retrieved from the recordings following three main steps. First, we got all the spike counts for specific stimulus representations (here natural movie one and three were handled separately). Then, we normalised by bin width, which gave us the firing rate. And finally, we grouped responses by presentations, across which we calculated the means, so as to get the average firing rates. We repeated this process for all types of different stimuli we worked with from the two sessions.

To analyse the differences and similarities between the stimuli we used standard methods, such as distribution plots and PCA. After training the SVC, we used a Mann-Whitney test to identify the top discriminative neurons. The use of this test is justified by independence of stimuli (which we consider a reasonable assumption), and a continuous but non-normal distribution of the average firing rate data. The SVC was then tested on static vs. drifting gratings for generalisation.

We proceeded the analysis on the first session by computing an average on the repetitions of firing rate, Fano factor and latency. Following preliminary checks on normality and homogeneity of variance, performed with the Shapiro-Wilk and the Levene tests, respectively, we compared the results on different areas of the brain, projecting the measures in a 3D space and performing Kruskal-Wallis and Wilcoxon statistical tests. For the Wilcoxon test we

paired static-danymic stimuli. In the second session the average firing rate, Fano factor and latency on the repetitions were computed taking into consideration not only the brain area but also the order in which the frames were shown. In this way we monitored the evolution of the metrics along the visualization of the original movie and its shuffled version.

3 Results

Our rate model achieved perfect classification accuracy. This was expected from the clear distinction seen in the distribution of the firing rates for natural scenes compared with natural movies, as well as the PCA.

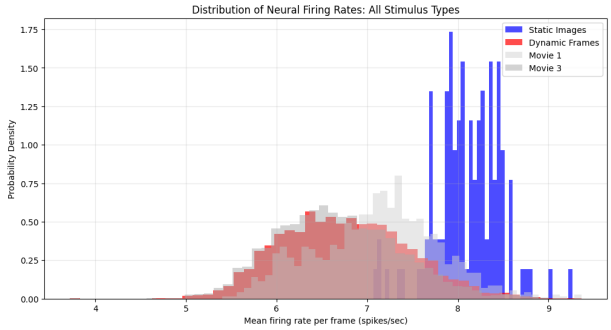

Figure 1: Distribution of average neural firing rates for all stimulus types.

The Mann-Whitney test performed with a very strict p-value ($p < 10^{-10}$) identified as top discriminative neurons more than half of the total in the first session, which suggests that the fundamental differences in encoding static and dynamic stimuli are present across various brain regions. We identified VISam and CA1 as the specific areas that contain most of these top discriminative neurons. This is interesting, because while the visual cortex areas are expected to be among the top, the strong presence of the hippocampal areas shows that memory and context-related processes have a significant role in encoding the distinction between static and dynamic stimuli.

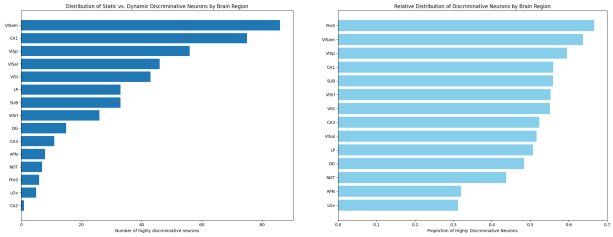

Figure 2: Comparison of discriminative neuron distribution by region: (a) absolute count, (b) relative proportion.

Our analysis showed that dynamic stimuli and static stimuli produce different responses across all metrics.

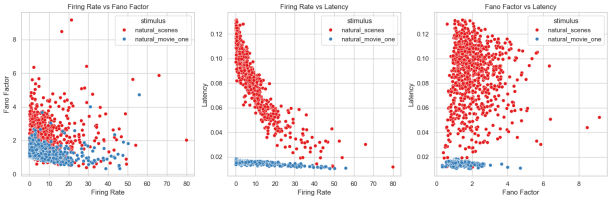

Figure 3: The differences can be seen for all metrics: average firing rate, Fano factor, and latency as well.

PCA shows separated clusters for natural movies, images and shuffled movies. Natural movies showed more coherent responses and reduced Fano factor and latency, especially with respect to the static images. Natural movies had noticeably smaller Fano factor and latency than static images, while the distribution of the metrics was more similar with shuffled movies. Statistical tests showed a significant difference in responses between brain areas. In Brain Observatory 1.1 the tests showed that the differences in responses are the most visible in visual and associative regions. Dynamic stimuli seem to modulate not only strength of the responses, but also timing and consistency. In Functional Connectivity the differences were more subtle and the distribution of the metrics for the stimuli was much closer in all brain areas.

4 Conclusion

These results support the hypothesis that the mouse brain differentiates static and dynamic information through both amplitude and timing of neural activity. The most relevant findings concern visual and hippocampal regions, suggesting the dynamic stimuli induce a sort of adaptation effect, likely due to their continuity and similarity. This is more visible when the static images are completely different from the frames of the shown movie.

5 Discussion and future research

Our study demonstrates measurable differences in mouse brain responses to static versus dynamic visual inputs. The use of open-access, high-density recordings allows for detailed analysis of sensory processing and can be extended to study perception and cognition at the population level. A more in-depth analysis needs to target the specific brain regions identified here, as well as add variety in the stimuli, such as different images, a range of frequencies for the movies (for example slow movies could elicit completely different responses compared to others with quickly changing scenes), and possibly remove bias by separating the stimuli into different sessions.