

Animacy Decoding During Early Visual Processing Using Large-Scale EEG Data

Stewart S. Lee¹, Ioannis Delis

1. Stratford High School, 14555 Fern Dr, Houston, Texas, 77079, USA; trawets9788@gmail.com
Mentor: Ioannis Delis

ABSTRACT: The human visual system can rapidly recognize meaningful information from images, sometimes within a fraction of a second. Previous research has shown that animacy, the distinction between living and non-living objects, can be decoded from neural signals shortly after the stimulus presentation. However, the exact timing and spatial distribution of animacy in electroencephalography (EEG) remain under investigation. In this paper, I examined whether animacy can be decoded from EEG signals within the first 200 milliseconds after image presentation. Using the Naturalistic Object Dataset EEG (NOD-EEG), a large publicly available dataset containing responses to thousands of object images, I applied time-resolved decoding, permutation-based significance testing, Haufe-transformed forward-model scalp mapping, event-related potential (ERP) testing, and EEG-Behavior correlations. The results showed that animacy could be decoded above chance (>50%) beginning around 100 ms, with peak activity at approximately 200 ms. Haufe-transformed forward-model analyses also revealed the strongest activity over occipital and parieto-occipital areas (posterior scalp regions). Overall, these results indicate that animacy-related information emerges rapidly in EEG signals and appears in distributed posterior visual regions during the early stages of visual processing.

KEYWORDS: Behavioral and Social Sciences, Neuroscience, Electroencephalography, Animacy, Visual.

■ Introduction

The human visual system can quickly convert raw sensory input into meaningful representations of objects. Within just a few hundred milliseconds of seeing an image, the brain can recognize what the object is and use that information to guide behavior. Figuring out how and when these visual representations form over time is a major focus in visual neuroscience.¹ One key factor in object perception is animacy, which refers to whether an object is animate or inanimate. Animate objects are often more behaviorally important because they can signal potential danger or opportunities for social interaction.^{2,3} Because of this, the brain may prioritize animate objects more quickly or prioritize them over inanimate ones. Neuroimaging research using fMRI has shown that animate and inanimate objects are processed differently in the high-level visual and temporal cortex.^{2,3} However, while these studies provide strong evidence for where animacy is represented, they offer limited insight into when animacy information first emerges during visual processing.

Electroencephalography (EEG) is a valuable tool for studying early visual processing because it captures brain activity with very high temporal resolution. Previous EEG studies have shown that meaningful object information can be rapidly decoded from neural signals, even when images are presented briefly or under more naturalistic conditions.^{1,4} Certain event-related potential (ERP) components, such as the P1 (around 80-120 ms) and N170 (around 140-200 ms), are associated with early visual and categorical processing and have been linked to differences in how the brain responds to objects and faces.⁵

More recent work has demonstrated that animacy-related distinctions can be decoded from EEG signals within the first few hundred milliseconds after the stimulus onset.⁶ Other recent work has shown that transforming decoding weights into activation patterns using Haufe-transformed forward models provides a more interpretable representation of how neural activity contributes to decoding performance.⁷ However, it remains unclear how early animacy information can be reliably extracted from EEG data when using these image datasets.

Although previous studies have shown that animacy information can be decoded from EEG signals in early visual processing, not many studies have looked at whether these findings hold up across large naturalistic image datasets with thousands of object categories. This paper, therefore, examines whether the brain responds differently to animate versus inanimate stimuli within the first 200 milliseconds, and whether early EEG signals can reliably decode this information across a highly diverse set of stimuli. This question is important because it clarifies whether high-level semantic distinctions, such as animacy, emerge during early stages of visual processing or only after more extensive cortical processing.⁸ As a result, I used a combination of resolved decoding, permutation testing, ERP analyses, Haufe transformed forward models, and EEG-behavior correlations to examine both the timing and spatial distribution of related activity. From there, I hypothesized that animate objects would elicit stronger or earlier neural responses than inanimate objects during early stages of visual processing. In order to address this hypothesis, I analyzed EEG data from the Naturalistic Object Dataset (NOD-EEG). This is a large, publicly available dataset containing brain responses to thousands of object images.⁹ The images used in the NOD-

EEG are derived from the THINGS-EEG dataset, another large-scale stimulus set designed to sample naturalistic object concepts across a broad range.¹⁰ Although activity beyond 0 ms and 200 ms is examined for contextual purposes, the core analyses and conclusions of this paper focus specifically on the 0–200 ms early visual processing window.

■ Materials and Methods

EEG dataset and preprocessing:

EEG data were obtained from the Naturalistic Object Dataset EEG (NOD-EEG), which contains magnetoencephalography (MEG) and EEG recordings from human participants viewing thousands of naturalistic object images in rapid serial visual presentation streams. Specifically, the EEG recordings were collected using a 64-channel NeuroScan system using the international 10–20 electrode configuration, sampled at 500 Hz in an electromagnetically shielded room. This study used preprocessed and epoched EEG data from 15 participants (6 female, 9 male, mean age = 20.47 years, standard deviation = 1.28 years) with behavioral data. These 15 participants represented all subjects with usable EEG recordings and complete metadata available after preprocessing. The participant IDs were the following listed: sub-01, sub-02, sub-04, sub-07, sub-08, sub-10, sub-11, sub-12, sub-13, sub-14, sub-24, sub-26, sub-27, sub-29, and sub-30. Information about participants' handedness, height, and weight was not available in the dataset. Four participants (sub-03, sub-05, sub-06, and sub-09) were excluded because their EEG files were corrupted and could not be properly loaded during preprocessing. All the data used were originally identified and collected by the original authors, and I collected no new data for this project.

Each EEG .fif file contained epochs from -100 ms to 800 ms around image onset, along with metadata for each trial. This indicated whether the object was animate or inanimate, the participant's response, and their reaction time. The stimulus set consisted of a large, diverse collection of real-world objects, spanning thousands of unique images and categories, and each image was presented once per session. Participants subsequently performed a binary animacy judgment on each trial.

EEG data analysis:

Participants viewed rapid streams of animate (e.g., animals and people) and inanimate (e.g., tools and furniture) object images and had to judge whether each image was animate or inanimate on each trial. Behavioral responses and reaction times were recorded in the metadata. Additionally, behavioral accuracy was calculated as the proportion of correct responses, and reaction time was measured as the median response time across correct trials.

All analyses were done in Python using open-source libraries, including MNE, NumPy, SciPy, scikit-learn, and Matplotlib in Google Colab. ChatGPT was used to help with programming, mainly for debugging and figuring out code issues. All analytical decisions, statistical methods, interpretations, and conclusions were my own and independently verified by me. For each participant, I loaded the pre-epoched EEG data from

-100 ms to 800 ms relative to stimulus onset. The original files did not include baseline correction or active projections. Using the metadata field `stim_is_animate`, I then created a binary label for each trial (`animate = 1`, `inanimate = 0`). Trials missing behavioral data were excluded from behavior-related analyses but retained in the decoding analyses if they had a valid animacy label.

To focus on early visual processing, EEG data were cropped to the 0–200 ms window after the stimulus appeared and downsampled to 50 Hz to reduce computational demands and to help with signal stability, while preserving coarse temporal dynamics within the early visual processing window. Although this reduced temporal precision, the sampling rate was still sufficient to capture broad ERP timing differences within the early 0–200 ms window. A 3-fold cross-validation approach was used to try to balance computational efficiency with getting stable estimates, given the large number of trials each participant had. For each subject, this resulted in a data array with dimensions corresponding to trials, channels, and time. The number of trials varied slightly across participants (approximately 4,000 per subject) due to preprocessing and data-quality constraints. All available EEG channels in the decoding and forward-model analyses were used.

Time-Resolved Multivariate Decoding of Animacy:

To determine when animacy information could be decoded from EEG signals, I conducted a time-resolved multivariate decoding analysis using a ridge classifier and cross-validation. For each time point, I reshaped the EEG data into a trials-by-channels matrix and passed it through a pipeline that included a `StandardScaler` followed by a `RidgeClassifier`. Animacy decoding accuracy was estimated using a 3-fold cross-validation, which was performed separately for every time point in Python. This analysis produced a time-resolved decoding curve showing how classification accuracy changed over time for each participant. The highest decoding accuracy within the 0–200 ms window was then taken as that participant's peak decoding score. It was later used in the EEG-behavior analysis discussed in the results section.

Permutation-based group-level significance testing:

To assess whether decoding performance exceeded chance, I conducted subject-level permutation tests for each participant and then combined the resulting p-values across participants. For each participant, EEG data from the 0–200 ms window were reshaped into a trials by channels by time matrix and collapsed into a single feature vector. Decoding accuracy was calculated using the same `StandardScaler` and `RidgeClassifier` pipeline with 3-fold cross-validation, just like in the time-resolved analysis.

A null distribution was then generated by shuffling the animacy labels 1,000 times and recomputing the cross-validated decoding accuracy for each permutation. I assigned a p-value to each participant by calculating the proportion of permuted accuracies that were at least as high as the observed decoding accuracy. Across the 15 participants, real decoding accuracies generally ranged from 0.57 to 0.63, and all p-values

were below 0.05. Accordingly, for each individual, these values indicated statistical significance and above chance for animacy decoding. Group-level p-value distributions are reported in the Results section.

Forward models and group-average scalp maps

To understand where on the scalp animacy information was expressed, Haufe-transformed forward models (activation patterns) were estimated for each subject and then averaged at the group level. For each subject, a sensor-space pattern was derived to quantify how strongly each EEG channel contributed to animacy decoding within the early 0-200ms time window. Then, these subject-level pattern vectors were stacked into a subjects-by-channels matrix.

Because activation patterns derived from linear models can vary in sign across participants, each individual's pattern was sign-aligned to a reference pattern by checking their correlation and flipping the sign when the correlation was negative. After aligning the data, I averaged the patterns across all subjects to create a group-level scalp map, which I visualized using a topographic plot. The group map showed the strongest weights over occipital and parieto-occipital sensors, which matched early visual cortex involvement in animacy processing. To illustrate this, I computed Haufe-transformed, time-resolved maps for all the participants. I plotted them at evenly spaced time points (e.g., 40, 80, 120, 160, and 200 ms) to show how the spatial distribution of animacy-related activity changed over time. These examples are presented and discussed in the results section, which describes the temporal dynamics of these scalp patterns.

Event-related potentials (ERPs) and the occipital region of interest (ROI):

To complement the decoding analyses, I also examined event-related potentials (ERPs) to assess how EEG responses differed between animate and inanimate objects. ERPs were computed by averaging EEG responses across trials for each category, with the focus on an occipital region of interest (ROI) because it is closely associated with early visual processing.

Since the group forward model showed strong activity in posterior regions, I defined an ROI at the sensor level to get a clearer view of early visual responses. This group-average and difference-wave ROI included occipital and parieto-occipital electrodes (O1, O2, Oz, PO7, PO8) from the NOD-EEG dataset. The epochs were baseline-corrected using the -100 to 0 ms pre-stimulus interval and analyzed within the 0-200 ms window after stimulus onset. These ERP results, together with the forward-model scalp maps, support the idea that early animacy information mainly appears over occipital and parietal regions.

EEG-behavior relationships:

Finally, I examined whether early EEG decoding of animacy was related to behavioral performance. For each participant, I computed Behavioral accuracy (The mean proportion of correct animacy judgments, where the response correctly matched the true animacy label), Median reaction time (The median

reaction time (RT) across the correct trials), and Peak EEG decoding accuracy (the maximum decoding accuracy within 0-200 ms from the time-resolved decoding curve).

I then calculated Pearson correlations between peak decoding and behavioral accuracy, as well as between peak decoding and median RT across the subjects. In the results section, correlation coefficients and p-values, along with scatter plots showing that early animacy decoding relates to behavioral performance, are reported.

Results and Discussion

Early animacy decoding from EEG:

Across participants, animacy could be reliably decoded from early EEG signals. Using time-resolved decoding in the 0-200 ms window, the group average decoding accuracy rose above chance shortly after stimulus onset. It remained consistently above 0.5 for the rest of the early time window (Figure 1). The mean peak decoding accuracy across the 15 participants was 0.59 (Group peak = 0.59, ± 1 SEM = 0.02). Individual peak accuracies ranged from 0.57 to 0.63 (Figure 1). These results indicate that even a simple linear classifier can distinguish between animate and inanimate images based on early neural activity.

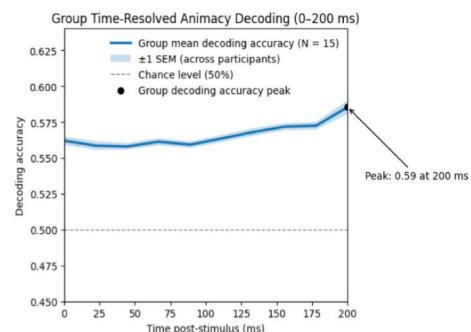


Figure 1: Group-average time time-resolved decoding accuracy for animate versus inanimate stimuli within the first 200 ms after stimulus onset. The solid line represents the mean decoding accuracy across participants, the shaded region indicates ± 1 SEM, the dashed line marks chance performance (50%), and the dot indicates the group's peak decoding accuracy. Decoding accuracy rose above chance beginning around 100 ms and reached its maximum near 200ms, demonstrating that animacy related information emerges rapidly during early visual processing.

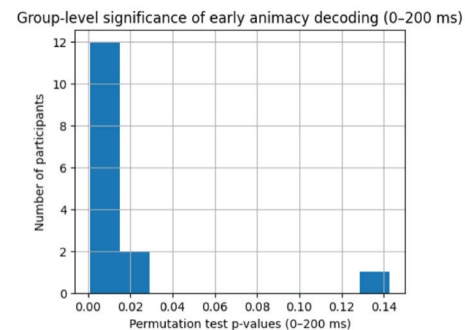


Figure 2: Histogram of participant participant-level permutation test p-values for animacy decoding accuracy within the 0-200 ms post post-stimulus window. Each bar shows how many participants reached a given significance level based on 1,000 label permutations. The strong clustering of values near zero indicates consistent above above-chance decoding across participants. This indicates that animacy decoding was reliably above chance across the dataset.

Permutation tests confirmed that these decoding results were statistically significant for each participant. For each subject, decoding accuracy using the true animacy labels in the 0-200 ms post-stimulus period was compared to a null distribution of 1,000 permutation accuracies computed with shuffled labels (Figure 2). The null distributions were centered around chance (0.50), while all participants showed p-values below 0.05, with most under 0.01 (Figure 2). Together, these findings suggest that early animacy information was reliably detected at the individual and group levels.

Spatial distributions for forward models and occipital focus:

Haufe-transformed forward-model analyses showed that animacy-related EEG activity was strongest over posterior scalp regions. For each participant, I calculated a Haufe-transformed forward model for the 0-200 ms window to identify the channel-level patterns related to animacy decoding. These group-average forward models were then sign-aligned and averaged across participants. After this sign alignment was performed, the average spatial pattern remained highly consistent across the subjects. Overall, the strongest activity appeared over occipital and parieto-occipital electrodes, with weaker activity observed at central and frontal sites (Figures 3 and 4).

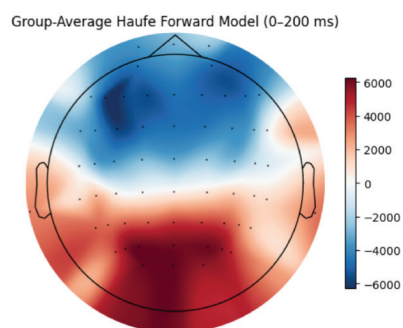


Figure 3: Group-average Haufe forward model for animacy decoding within the 0 0-200 ms postpost-stimulus window. Warmer colors indicate stronger positive contributions to decoding performance, whereas cooler colors indicate weaker contributions. The strongest activity was concentrated over occipital and parieto-occipital regions, suggesting a major role for early visual cortical processing in animacy decoding.

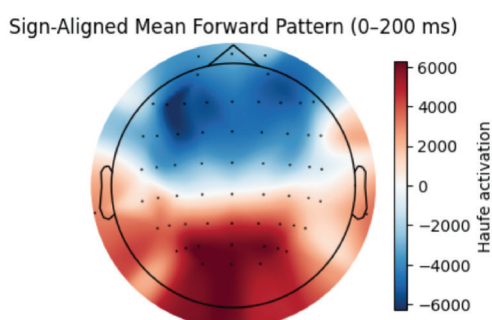


Figure 4: Sign-aligned group group-average Haufe forward model for animacy decoding within the 0 0-200 ms post post-stimulus window. Individual participant patterns were aligned before averaging to improve consistency across subjects. The resulting scalp map remained strongly posterior, demonstrating that animacy animacy-related activity was highly consistent across participants.

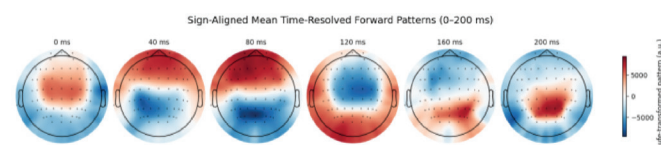


Figure 5: Time-resolved group group-average Haufe forward models shown at selected time points between 0 and 200 ms after stimulus onset. Topographic maps illustrate the evolving spatial distribution of animacy animacy-related neural activity over time. Posterior sensor patterns became increasingly prominent between approximately 120 and 200 ms, indicating that animacy animacy-related information emerged primarily within occipital and parieto-occipital regions during early visual processing.

The time-resolved forward maps supported this posterior focus. At 0, 40, and 80ms, the strongest positive weights appeared over frontal sites. However, when the time window reached 120, 160, and 200 ms, the weights shifted to posterior sites, peaking between 100 and 200 ms (Figure 5). This spatial pattern is consistent with early visual cortical activity. It suggests that animacy information is represented in distributed patterns over occipital regions around 100ms after stimulus onset.

Occipital ERP/ROIs for animate versus inanimate objects:

Event-related potentials over occipital and parieto-occipital electrodes showed clear differences between animate and inanimate objects. Using an occipital ROI (O1, O2, Oz, PO7, PO8), separate ERPs were calculated for each condition for animate and inanimate trials and then averaged across each participant. Both group-average waveforms exhibited typical early visual components, including a P1 around 100 ms and an N170 around 170 ms (Figure 6-7).

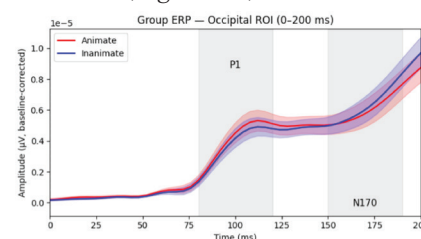


Figure 6: Group-average event event-related potentials (ERPs) from an occipital region of interest (O1, O2, Oz, PO7, PO8) for animate and inanimate stimuli within the 0 0-200 ms window. The colored regions represent ± 1 SEM across participants, and the shaded time intervals indicate the P1 and N170 components. Differences between animate and inanimate responses were most apparent between approximately 100 and 200 ms, suggesting early category category-sensitive visual processing.

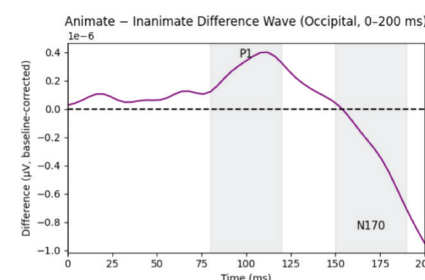


Figure 7: Group-average difference waveform (animate - inanimate) from the occipital region of interest within the 0 0-200 ms window. Shaded areas mark the P1 and N170 time ranges, showing early ERP differences related to animacy. The divergence from zero during the N170 interval suggests that animacy animacy-related neural differences emerge during early stages of visual processing.

The animate condition showed slightly lower amplitudes than the inanimate condition between 150 and 200 ms in the Occipital ROI, reflecting early category-sensitive processing (Figure 6). The group difference wave (animate minus inanimate) diverged from zero in this window (Figure 7), suggesting that related differences show up in early visual activity rather than only emerging during later cognitive stages. Although decoding was the focus in this study, these ERP differences support the view that animacy-related differences are reflected in early visual responses.

EEG-behavior relationships and correlations:

Participants overall performed well on the animacy task, with an average accuracy of approximately 0.84 (range = 0.77–0.91). This indicated that they could reliably distinguish animate from inanimate images. Median reaction times for correct trials were approximately 1040 ms, with values ranging from 0.69 to 1.30 seconds across all the participants (Figure 8–9).

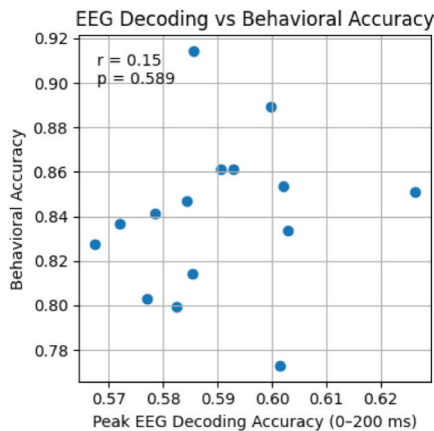


Figure 8: Relationship between peak EEG decoding accuracy (0–200 ms) and behavioral accuracy in the animacy classification task across participants. Each point represents one participant, with the correlation coefficient and p-value shown. Although participants with stronger decoding tended to show slightly higher behavioral accuracy, the relationship was not statistically significant.

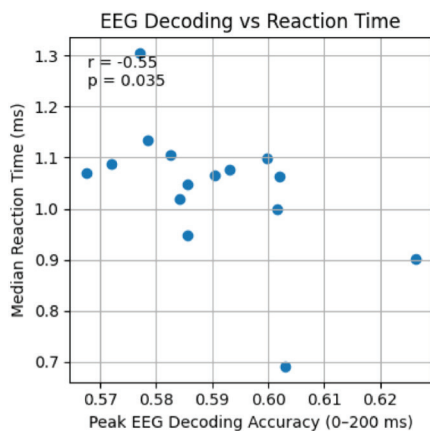


Figure 9: Relationship between peak EEG decoding accuracy (0–200 ms) and median reaction time for correct trials across participants. Each point represents one participant, with the correlation coefficient and p-value reported. Participants with stronger early animacy decoding generally responded more quickly, resulting in a significant negative correlation between decoding performance and reaction time.

To test whether early decoding was behaviorally relevant, I correlated peak decoding accuracy within 0–200 ms with each participant's behavioral accuracy and median reaction time. Peak decoding accuracies across the 15 participants ranged from around 0.57 to 0.63 (Standard deviation = 0.016). Peak EEG decoding accuracy showed a non-significant positive correlation with behavioral accuracy (Pearson $r = 0.15$, $p = 0.589$) (Figure 8). Additionally, the decoding accuracy showed a significant negative correlation with median reaction time (Pearson $r = -0.55$, $p = 0.035$) (Figure 9). These results suggest that participants who had stronger early decoding also tended to respond faster in the animacy task. However, because the sample size was quite small and several behavioral correlations were tested, this finding should be interpreted cautiously.

This study looked at whether animacy information can be decoded from EEG signals during the earliest stages of visual processing, and also tried to clarify when and where in the scalp this information shows up. I hypothesized that animate objects would elicit stronger or earlier neural responses than inanimate objects within the first 200 milliseconds after the stimulus onset. The results supported this hypothesis. Animacy-related information could be decoded from EEG activity beginning around 100 ms, with the best classification occurring between 100 and 200 ms. These findings replicate previous evidence showing that the human visual system can distinguish animacy quickly during early visual processing, while also extending this to a much larger and more naturalistic EEG dataset. The early timing of animacy decoding observed in this study is consistent with previous EEG and MEG research, which shows that object and category information can be extracted from neural signals shortly after stimulus onset.^{1,4} The observed timeframe aligns with known early visual ERP components, such as the P1 and N170, which have been linked to category-sensitive processing, including face processing.⁵ Although the study did not focus just on faces, the broader distinction between animate and inanimate objects appears to be reflected in similar early time windows, supporting the idea that animacy is a fundamental organizing factor of visual representations.

The spatial results from the Haufe-transformed forward-model analyses further support early visual involvement. The strongest activity appeared over occipital and parieto-occipital areas, consistent with early visual processing. These group-average forward models align with past findings that object information is represented across distributed occipital regions.^{2,3} In line with ERP results, these results indicate that animacy is not solely represented in high-level temporal regions, as shown by fMRI studies, but is already present in early visual responses measurable at the scalp.^{6,7}

One important implication of these findings is that animacy-related differences can still be detected even across highly diverse and naturalistic stimulus sets, which suggests that these early category signals are not just limited to more controlled lab image sets. Rather than relying entirely on later semantic processing, the results suggest that broad categorical differences may already be partly represented during early perceptual processing. Because animate objects are often behaviorally rel-

evant, being able to quickly tell them apart from inanimate stimuli could be advantageous during natural scene perception.

Interestingly, early decoding was also associated with behavior. Participants who showed stronger early decoding typically responded more quickly during the animacy task. This suggests that stronger early animacy decoding may be associated with faster visual detections. Similar connections between early neural decoding and behavior have been reported in prior work on object recognition and category processing, and the present findings extend this evidence to large-scale, naturalistic image datasets.⁸⁻¹⁰

Although this study has many strengths, there are several limitations to consider. First, while the NOD-EEG dataset includes a large and diverse set of images, this analysis focused on just 15 participants of similar age due to data quality issues. Because the sample size was quite small and mostly made up of young adults, the findings may not fully generalize to other populations or different age groups. Second, while decoding analyses reveal when information is present in the EEG signal, they do not identify its source within the brain. Lastly, the analysis was limited to the 0-200 ms window, so additional timeframes were not explored in detail. Future studies that combine EEG with MEG source localization could help identify the cortical sources of these early animacy signals, and extending the analyses to later time periods may also help reveal how early perceptual encoding connects to more complex processing.

■ Conclusion

This study shows that animacy is encoded very early in the human visual system and can be decoded from EEG signals within the first 200 milliseconds after image onset. Using large-scale naturalistic EEG data and time-resolved multivariate decoding, I found that animate and inanimate objects become distinguishable in neural activity within that early time window. Decoding accuracy peaked between 100 and 200 ms, and Haufe-transformed forward models showed consistent activity across posterior scalp regions, indicating early involvement of the visual cortex. ERP results also showed clear category-related differences in early brain responses, whereas behavioral results indicated that participants with stronger early decoding tended to respond more quickly during the tasks.

Altogether, these results support the conclusion that animacy is represented during the earliest stages of human cortical processing. By combining decoding, ERP, and behavioral analyses with large-scale naturalistic stimuli, this project helps connect controlled lab results with more realistic visual experiences. For future work, it would be interesting to examine finer distinctions within animacy, study differences across individuals or age groups, and combine EEG with other neuroimaging methods to gain deeper insight into the neural processes that support rapid perception.

■ Acknowledgments

I want to thank my mentor, Ioannis Delis, for his guidance throughout this project. I am especially grateful for his feed-

back on the paper's structure, the design of the analysis, and the interpretation of the results, all of which improved the study. I am also grateful to the creators of the Naturalistic Object Dataset EEG (NOD-EEG) for providing open access to their data, which enabled the study of large-scale patterns in visual object representations. This work would not have been possible without these open neuroscience resources and tools. All analyses were performed using open-source software, including Python, MNE, NumPy, SciPy, scikit-learn, and Matplotlib, and were run in Google Colab. ChatGPT was used to assist with writing and debugging code and to provide explanations. As the author, I attest that the ideas, graphics, and writing in this paper are entirely my own.

■ References

1. Grootswagers, T.; Wardle, S. G.; Carlson, T. A. Decoding Dynamic Brain Patterns from Evoked Responses: A Tutorial on Multivariate Pattern Analysis Applied to Time-Series Neuroimaging Data. *J. Cogn. Neurosci.* **2017**, *29* (4), 677–697. https://doi.org/10.1162/jocn_a_01068.
2. Jozwik, K. M.; Kriegeskorte, N.; Storrs, K. R.; Mur, M. Disentangling Five Dimensions of Animacy in Human Brain and Behavior. *Commun. Biol.* **2022**, *5*, 1247. <https://doi.org/10.1038/s42003-022-04194-y>.
3. Rogers, T. T.; Devereux, B. J.; Hodges, J. R.; Patterson, K. Evidence for a Deep, Distributed and Dynamic Code for Animacy in Human Ventral Anterior Temporal Cortex. *eLife* **2021**, *10*, e66276. <https://doi.org/10.7554/eLife.66276>.
4. Grootswagers, T.; Robinson, A. K.; Carlson, T. A. The Representational Dynamics of Visual Objects in Rapid Serial Visual Processing Streams. **2019**, *188*, 668–679. <https://doi.org/10.1016/j.neuroimage.2018.12.046>.
5. Eimer, M. The Face-Sensitivity of the N170 Component. *Front. Hum. Neurosci.* **2011**, *5*, 119. <https://doi.org/10.3389/fnhum.2011.00119>.
6. Wang, R.; Cichy, R. M.; Albada, S. J.; Oliva, A.; Kaiser, D. Mid-Level Feature Differences Support Early Animacy and Object Size Distinctions: Evidence from Electroencephalography Decoding. *J. Cogn. Neurosci.* **2022**, *34* (9), 1670–1680. https://doi.org/10.1162/jocn_a_01883.
7. Haufe, S.; Meinecke, F.; Görgen, K.; Dähne, S.; Haynes, J.-D.; Blankertz, B.; Bießmann, F. On the Interpretation of Weight Vectors of Linear Models in Multivariate Neuroimaging. *NeuroImage* **2014**, *87*, 96–110. <https://doi.org/10.1016/j.neuroimage.2013.10.067>.
8. Gifford, A. T.; Dwivedi, K.; Roig, G.; Cichy, R. M. A Large and Rich EEG Dataset for Modeling Human Visual Object Recognition. *NeuroImage* **2022**, *264*, 119754. <https://doi.org/10.1016/j.neuroimage.2022.119754>.
9. Zhang, G.; Li, S.; Li, Y.; Wang, Y.; Liu, H.; Wang, L.; Song, Y.; Liu, Z. A Large-Scale MEG and EEG Dataset for Object Recognition in Naturalistic Scenes. *Sci. Data* **2025**, *12*, 857. <https://doi.org/10.1038/s41597-025-05174-7>.
10. Grootswagers, T.; Zhou, I.; Robinson, A.; Hebart, M.; Carlson, T. Human EEG Recordings for 1,854 Concepts Presented in Rapid Serial Visual Presentation Streams. *Sci. Data* **2022**, *9*, 3. <https://doi.org/10.1038/s41597-021-01102-7>.

■ Author

Stewart S. Lee is a recent graduate of Stratford High School in Houston, Texas. He will attend Harvard College as a mem-

ber of the class of 2030 and plans to study neuroscience. His academic interests include visual perception, EEG decoding, and large-scale neural datasets.