Decoding Colour Information from EEG Signals in Natural Scenes

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Abstract

Recent years have seen major advances in decoding perceptual information from EEG signals, driven by developments in artificial intelligence—particularly large datasets, transformer-based models, and contrastive learning. Here, we investigate whether colour information can be decoded from EEG signals recorded while participants viewed natural scenes. While earlier work shows that colour features (e.g., the hue circle) are decodable under controlled conditions, it is unclear whether such information persists in complex, real-world settings. Using the THINGS-EEG2 dataset, we analyse EEG recordings from a 64-electrode cap as participants viewed natural images for 100 ms each in a rapid serial visual presentation (RSVP) paradigm. To define colour ground truth, we apply the Segment Anything Model (SAM) to segment images into foreground and background, quantifying each segment's colour using common categories from human colour naming studies. An artificial neural network is trained to predict scene colour content from EEG signals alone, and performance is evaluated by comparing predicted and ground-truth colours for each region. Our findings show that EEG signals retain decodable colour information even in object recognition tasks without explicit colour references, offering new insights into the brain's colour representation and opening doors for naturalistic brain-computer interfaces and neuroimaging research.

Keywords: Colour perception; EEG; Neuroimaging; Decoding

Introduction

Recent advances in artificial intelligence have led to a breakthrough in neuroimaging decoding. In just a few years, visual object recognition from EEG signals has improved from around 6% (Du, Fu, Li, & He, 2023; Song et al., 2024; Li, Wei, Li, Zou, & Liu, 2024) to over 50% accuracy on average—far above the 0.5% chance level—reaching over 61% in the best participants (Wu, Li, Zhang, He, & Ying, 2025). Similarly, speech decoding has achieved over 81% accuracy in some cases (Défossez, Caucheteux, Rapin, Kabeli, & King, 2023), despite a 0.1% chance level. These results are remarkable given the noisy nature of EEG and highlight its growing potential for brain-computer interfaces and cognitive neuroscience. In this work, we investigate how much colour information is encoded in EEG signals. While earlier studies have shown that colour can be decoded from uniform fields as early as 70 ms post-stimulus (Bocincova & Johnson, 2019; Teichmann et al., 2020; Hajonides, Nobre, van Ede, & Stokes, 2021), we extend this to complex natural scenes, exploring colour decoding in a more ecologically valid setting.

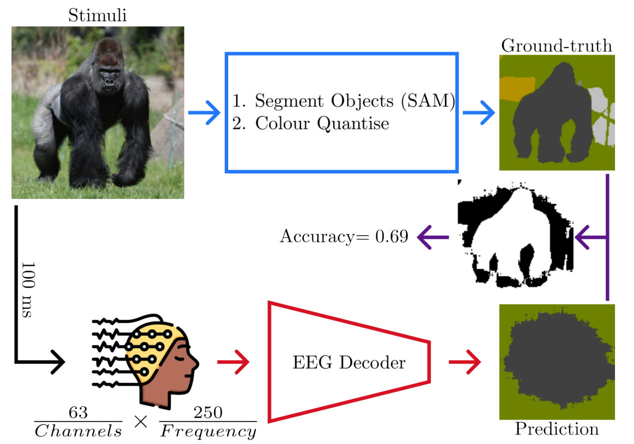

Figure 1: The schematic flowchart of our approach.

Methods

We used the THINGS-EEG2 dataset (Gifford, Dwivedi, Roig, & Cichy, 2022), which contains EEG recordings from 10 participants viewing 16,740 natural images—from 1,854 object concepts in the THINGS dataset (Hebart et al., 2019)—in a rapid serial visual presentation (RSVP) paradigm. Each image was displayed for 100 ms and repeated four times. The training set comprises 66,160 EEG samples, while the test set includes 16,000 samples (200 concepts, 80 repeats), with no overlap in object concepts between sets. As the dataset was originally collected for object recognition and lacks colour annotations, we generated our own ground truth by applying the Segment Anything Model (SAM) to each image (Kirillov et al., 2023), assigning a median RGB value to each segmented object. These RGB values were then quantised into 26 colour categories—21 chromatic and 5 achromatic—based on common English colour terms (Mylonas & MacDonald, 2016). The distribution of colour histograms across these categories for the training and test sets is shown in Figure 2.

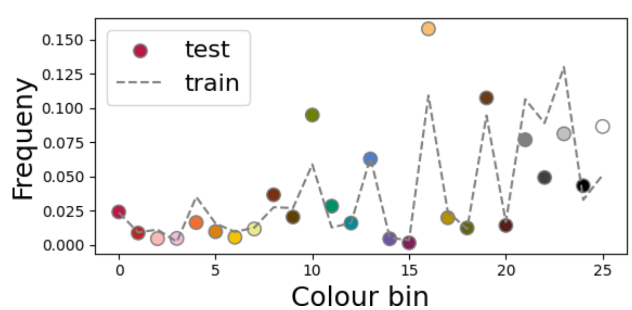

Figure 2: The distribution of colours in the created ground-truth for the THINGS-EEG2 dataset.

For each participant, we trained a 5M-parameter encoder-decoder artificial neural network (ANN) to map each EEG sample (63 channels × 250 time points) to a 128×128 segmentation map with 26 colour classes. The encoder is a transformer (Vaswani et al., 2017) that embeds EEG signals, and the decoder upsamples this to an image using residual convolutional layers (He, Zhang, Ren, & Sun, 2016). Training was done for 40 epochs using the Adam optimiser and categorical cross-entropy loss.

Results[1]

For evaluation, we averaged the 80 EEG repetitions per image in the test set and passed the resulting signals through the trained ANN. Pixel-level accuracy was computed by comparing predicted and ground-truth colour classes, with the mean and median accuracy reaching 45% (Figure 3). As a baseline, we used a naive model that always predicts the most frequent colour class from the training set, which achieved only 20% mean accuracy and 5% median accuracy. This substantial performance gap indicates that the ANN captures meaningful colour information from the EEG signals recorded during viewing of complex natural scenes.

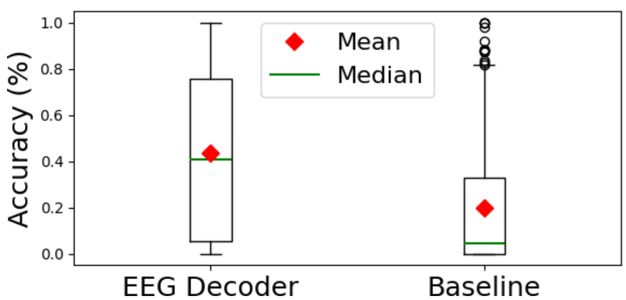

Figure 3: The distribution of accuracies over 200 test samples.

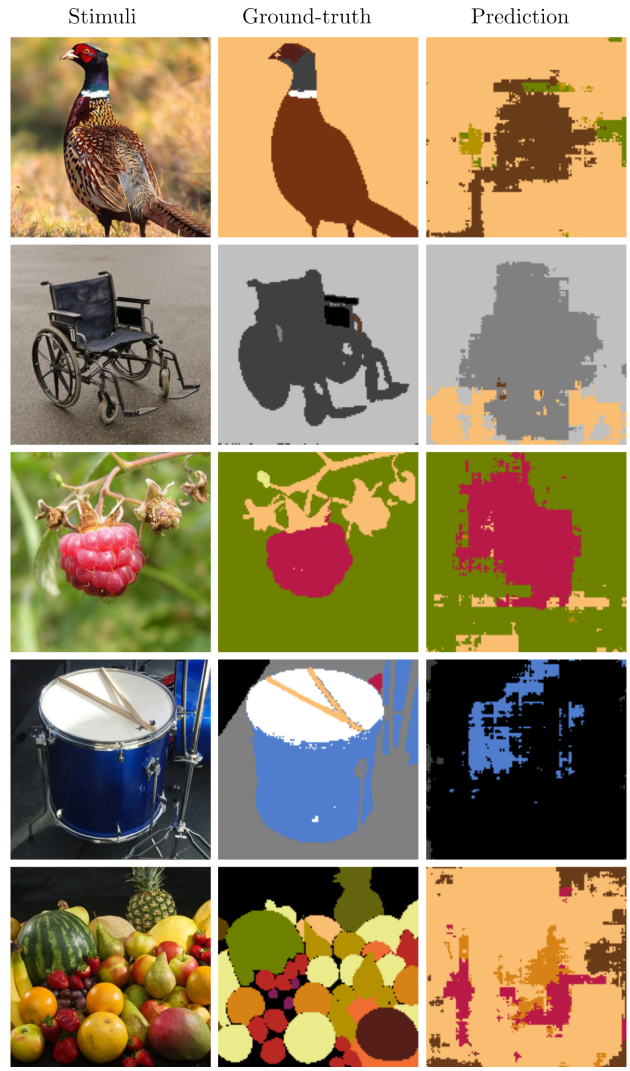

Figure 4: Example qualitative results.

Discussion

Our preliminary results demonstrate that EEG signals contain decodable colour information, even when recorded during object recognition tasks without explicit colour references. While current accuracy is promising, we anticipate further improvements with refined ground-truth and expanded training set.

As shown in Figure 4, the network decodes dominant foreground and background colours. However, challenges remain in creating reliable ground truth. Subtle hue shifts (e.g., shades of brown in the pheasant) or lightness differences (e.g., dark vs. bright grey in the wheelchair) can lead to zero accuracy despite perceptual similarity. Additionally, automatic segmentation may overestimate the colour detail visible within a 100 ms exposure (e.g., the fruit image). We plan to address these issues through psychophysical experiments to determine perceptual thresholds under brief presentations.

Overfitting represents another major limitation: performance on the training set significantly exceeds that of the test set after approximately 20 epochs (midway through training), likely due to the restricted size of the training dataset (66k samples). As demonstrated in large language model research, larger datasets are crucial for improving generalisation. We intend to investigate EIT-1M, which contains over one million EEG recordings (Zheng et al., 2024).

Additionally, the THINGS-EEG2 dataset captures only the first 100 ms of visual processing, missing later stages where shape–colour interactions typically emerge (Teichmann et al., 2020). Future work will explore longer time windows, such as those in the Alljoined dataset, which provides 300 ms recordings (Xu et al., 2024). This duration exceeds the 200 ms threshold necessary for decoding colour information in relation to its associated object (Gegenfurtner, 2025).

Overall, our findings establish a novel approach for decoding colour from neuroimaging signal, highlighting its potential applications for brain-computer interfaces and the study of colour representation under naturalistic conditions.

[1] All experimental materials, including the source code and generated ground truths, are available upon request.

Acknowledgments

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