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Cross-Modality and Cross-Subject Decoding of Semantic Categories

Identifying Generalizable Neural Codes with Magnetoencephalography (MEG)

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Abstract: This study investigates the generalizability of neural codes for semantic categories across different sensory modalities and individuals. Using MEG, we employ picture naming and word reading paradigm for In-Subject cross-modality and cross-subject cross-modality analysis. Successful cross-subject decoding provides strong evidence for subject-independent neural representation.

Keywords: Neural Codes, Neuroimaging, Cross-Modality Decoding, Cross-Subject Decoding, MEG

Introduction

The human brain represents concepts in an abstract manner, independent of the sensory modality through which they are perceived (e.g., picture vs. word). This study uses a time-generalization decoding approach [1] to investigate the temporal dynamics of these shared representations. Dirani et.al. [1] decode cross-modality paradigm of two categories (animals and tools). The authors acknowledge that their results may be associated with somato-sensory representations unique to tools. To address this limitation, our study uses four different categories (animals, foods, plants and tools). Additionally, we aim to assess cross-subject generalizability. Previous studies predominantly performed analyses within individual subjects, leaving the existence of a universal neural code across people less explored. Identifying such codes would advance our understanding of shared cognitive architecture and aid the development of universal Brain-Machine Interfaces (BMIs).

Methods

Our data was collected using a Sumitomo Heavy Industry (SHI) Self-Shielded Magnetoencephalography (MEG) machine equipped with SQUID sensors. Ten healthy subjects who have signed an informed consent, performed picture naming and word reading tasks. Images and corresponding handwritten words (i.e. stimuli) from 4 different categories were presented at random. The data was preprocessed using the following procedure: discarding of bad channels, downsampling to 500Hz, band-pass filtering of 1-40Hz, discarding of bad epochs, Empirical Mode Decomposition (EMD) filtering of high-frequency noise and PCA-based filtering [2]. This preprocessing pipeline proposed by Patashov et.al. was shown to significantly improve in-subject classification.

Pre-Machine Learning (ML) operations included Combinations Averaging (CA), a data augmentation technique that reduces white noise while increasing the number of usable epochs for the ML model [2]. Averaging of multiple epochs is a common procedure in Electroencephalography (EEG) and MEG studies. It reduces whit noise and improves interpretability of the data. Patashov et.al. [2] proposed a method of utilizing this concept while augmenting the data, thus producing more epochs for the ML model to learn. We then used a Logistic Regression classifier on a 256ms moving time-window with a 10ms stride to perform neural decoding: 1) Within-Subjects, and 2) Cross-Subjects. The resulting time-generalization matrices from the 10 subjects were aggregated using the following procedure: For each time-point, outlier accuracy scores were removed (IQR method), the remaining accuracies were tested for significance above chance (0.25) using Wilcoxon test. Only the time points that passed the statistical significance test were analyzed further. In Figure 1, we present time-generalization using only significantly above chance level accuracies. The presented accuracies show time-generalization percentiles 25 (Q1), 50 (median) and 75(Q3). This allows for visual analysis of the inter-subject differences and generalization of the neural codes learnt by the ML model.

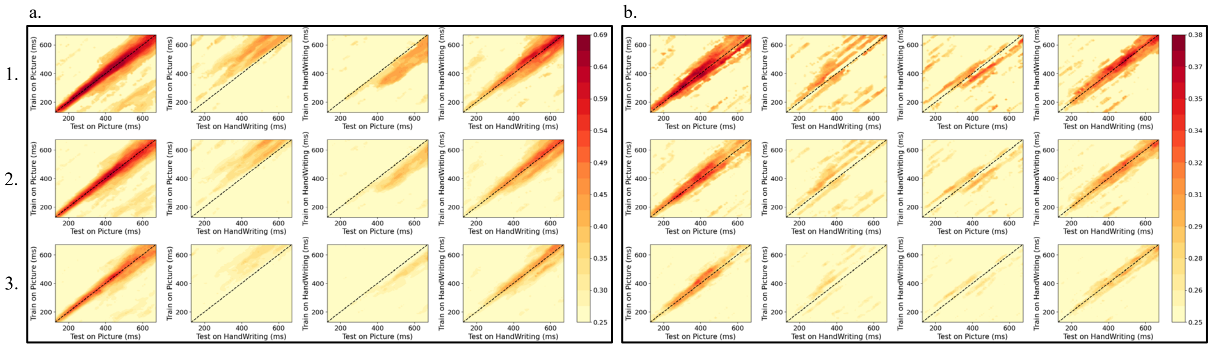

Figure 1: Time-generalization maps of decoding accuracy percentiles for the Within-Subject (a) and Cross-Subject (b). Rows 1-3 representing the 75th, 50th, and 25th accuracy percentiles respectfully. In total there are four train-test combinations: Picture-Picture, Picture-Handwriting, Handwriting-Picture, Handwriting-Handwriting. Each column corresponds to one of such combinations. Y-axes represent modalities on which the model was trained and X-axes represent modalities on which the model was tested. Color represents the decoding accuracy. Any time points that were not found to be significant were set to chance level.

Results

Within-subject decoding produced higher classification accuracy than those of cross-subjects. Within-modality decoding revealed an increased classification accuracy along the diagonal, indicating temporal specificity. Cross-modality conditions show an increased classification accuracy off the diagonal, confirming a shared semantic code with differing activation latencies. Importantly, cross-subject decoding also achieved decoding accuracies significantly above chance level. This demonstrates that subject-independent features of semantic representation can be successfully learned and generalized. Interestingly, classification accuracy patterns of cross-modality classification are different for within-subject and cross-subjects cases.

Discussion

Our results provide evidence for two levels of generalization. First, successful cross-modality decoding confirms that the brain uses an abstract, modality-independent code for concepts. The observed temporal shift between modalities suggests a processing hierarchy from sensory analysis to a shared conceptual space. More importantly, the success of the cross-subject decoding reveals that there are common neural representation codes across different individuals. While lower accuracy compared to personalized models reflects individual variability, the ability to leverage a shared neural pattern is a crucial step towards universal BMIs. Our robust methodology was instrumental in extracting these findings. Future work should identify the neural sources of these codes and test their generalizability to other domains.

Conclusions

We demonstrate successful decoding of semantic categories across different modalities and subjects. This provides strong evidence for a shared, generalizable neural code for concepts. This code is largely independent of sensory modality and individual neuroanatomy, pointing to a generalizable organization of semantic knowledge in the human brain.

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References

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