Information can be extracted from ventral stream multi-voxel patterns across spatial scales using the wavelet transform

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INTRODUCTION

- Multivariate analysis techniques have become a popular approach to analyzing functional magnetic resonance imaging (fMRI) data. Machine learning decoding, and representational similarity analysis (RSA) measure the information content of distributed activity patterns by attempting to distinguish or track different conditions and stimuli. However, the spatial information and the properties of these neural patterns are rarely examined. [1,2]
- The hierarchical structure of the brain motivates the investigation of the neural representations on different spatial scales.[4]
- Wavelet could be a powerful tool to analyze the spatial patterns of complex data and extract multi-scale representations of fMRI data. [3,4,5]
- In this study, we applied a dual-tree complex wavelet transform (dt-CWT) to extract multi-scale representations of multi-voxel patterns. Based on a set of new features generated by the transform, a support vector machine model was used for classification, and decoding accuracy was compared across five different scales.

METHODS

Participants

20 subjects recruited; final $N =$ 18 subjects, female = 10, M_{age}= 22.56

Experiment Design

- The day before scanning, participants were shown brief natural vides of each of 12 animals; four from each of the following taxonomic categories: insect, bird, mammal. Data was reported in Coutanche & Koch (2018). [6]
- The scanning session includes 10 functional runs; in each run, participants were shown a block of images featuring each of twelve animals.

Data pre-processing and dual-tree complex wavelet transform stetps

fMRI Data preprocessing

- Slice-time correction
- Motion correction registration
- High-pass filtering
- Standardized space

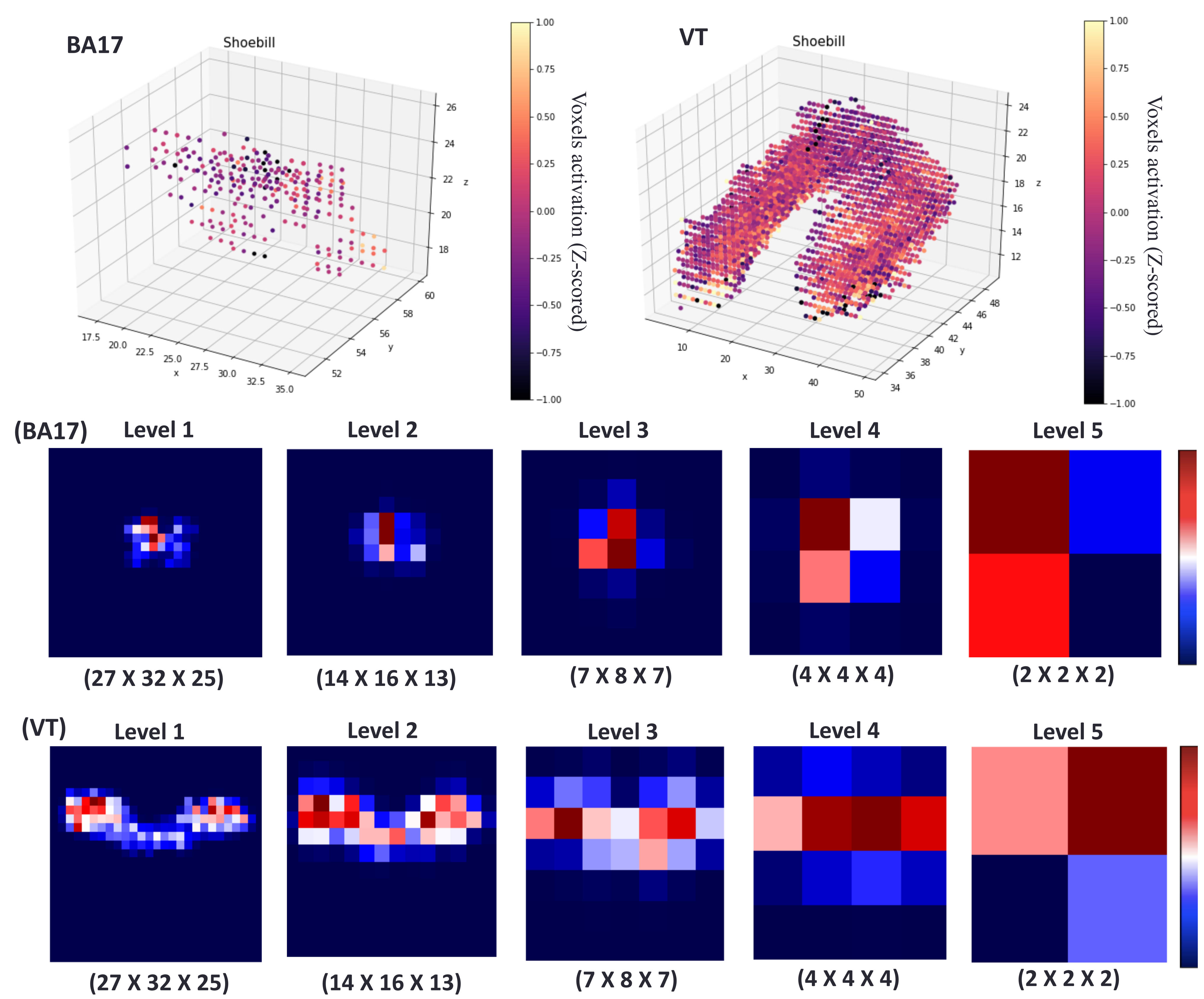
dt-CWT

- Apply the mask (BA17 & VT)
- Calculate dt-CWT for each ROI (BA17 & VT) and for each subject
- Obtain 5 different levels with 28 orientations at each level.
- Calculate the total variance of the coefficients of each orientation, which represent the overall energy magnitude of the voxels at each orientation at each level
- A new set of 28 features (based on 28 orientations) for each animal at each level was used for classification

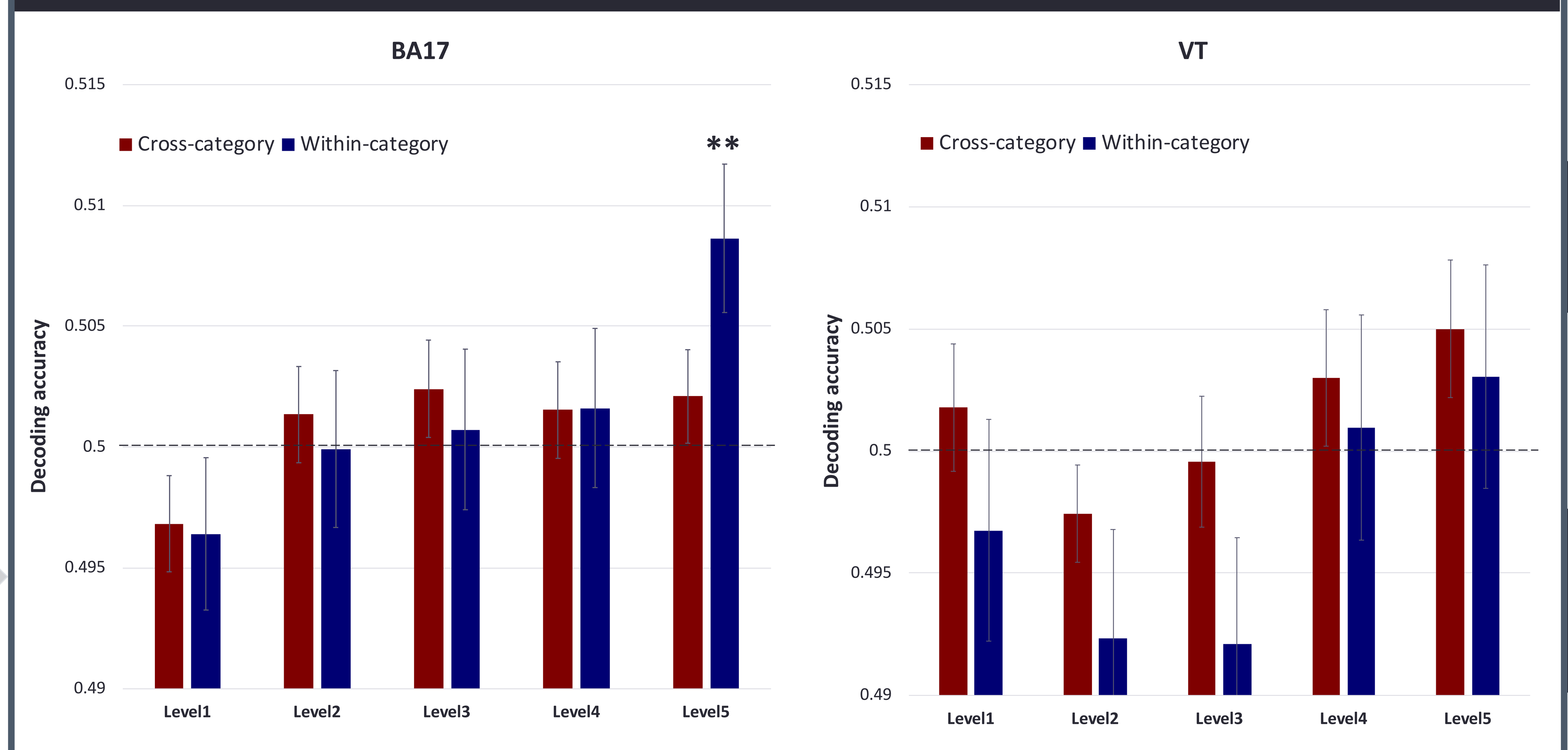
Classification

- Support vector machine
- Classifiers are trained on animal pairs and predict each animal in the pair.
- Leave-one-run-out cross-validation (LORO-CV)
- Repeated for five wavelet levels
- Decoding accuracy was compared between ''Within-category" and "Cross-category" at each level.

WAVELET TRANSFORM



RESULTS



Note. * Indicates p < .05, **p < .01, ***p < .001; error bars reflect SEM

CONCLUSIONS

- In BA17, animals within the same category can be predicted significantly above baseline at 5th scale. The decoding accuracy for animals across different categories did not significantly differ from the baseline. This may imply that animals within the same category might have scale-orientation-dependent representations in this brain region.
- In VT, neither animals within the same category nor across different categories can be significantly predicted. This may imply that animals did not show significant scale-orientation-dependent representations in this brain region.
- By decomposing the multi-voxel patterns into scale-orientation-dependent representations using wavelet transform, it will allow us to analyze the property of the neural representations with spatial information preserved and to understand the relationship between conditions and their corresponding spatial representations in different brain regions.

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