

# Decoding Neural Representation of Words in Language Production from Magnetic Signals Measured by a Superconducting Self-Shield MEG

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## Abstract

From neural signals measured by EEG and MEG, previous studies successfully decoded words or phrases when the participants comprehended visually or auditorily presented. Such results indicate that information about individual words are represented as neural activities in the course of language comprehension. However, relatively less research was conducted about the neural representation of words in language production. In this study, we decoded words from signals recorded by a superconducting self-shield MEG when the participants orally named visually presented images of familiar objects. Five native Japanese speakers are asked to (i) see the images of six objects, (ii) imagine the action related to the objects, (iii) silently name the objects, and (iv) orally pronounce the objects' names. MEG signals were recorded from 64 channels of SQUID sensors during these tasks. The classification analysis using the support vector machine resulted in significantly higher accuracy above the chance level (permutation test,  $p < 0.05$ ) in (i) and (iv) but not in (ii) and (iii). The result indicates that words are represented neurally in the course of language production, but representations vary during the time course. In addition, it shows that the higher S/N rate of superconducting self-shield MEG is effective in research on higher-ordered cognitive functions such as language production that involve rapid changes of neural representations.

## Experiment

The magnetoencephalography measurement experiment was conducted at Tokyo Denki University, and data of five participants were collected. The experimental task consisted of the following four steps. Six images(sushi, gyoza, cookie, kushi, knife, pencil) were prepared, and each image was randomly presented 50 times during the experiment.

### Stages

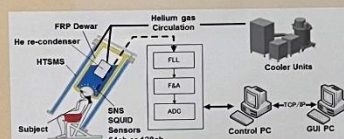
- ① see the images of six objects
- ② imagine the action
- ③ silently name the objects
- ④ orally pronounce the objects' names

### Trials



The trial is as shown in the above figure. Before each step, there is a 400 millisecond blank time to refresh consciousness. The actual time each step was performed was 1600 milliseconds.

## Superconducting self-shield MEG



- Created by Sumitomo Heavy Industries Ltd.
- No need for a magnetic shield room
- Significantly High S/N ratio
- No need for the helium recharge
- Significant reduction of cost

## Analysis

### Preprocessing Pipeline

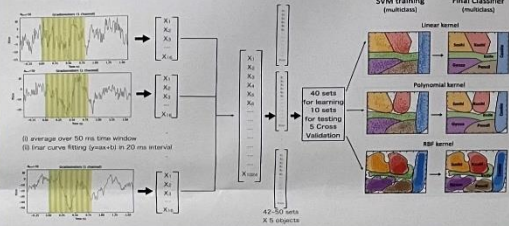
- ① Resample & Filtering & Outlier Removal & Epoching
- ② Empirical Mode Decomposition
- ③ Feature Scaling
- ④ Slicing

### Preprocessing Summary

- Resampling: 500 Hz
- Filtering:
  - Band Pass Filter(BPF): 0.1-40Hz
  - Discrete Cosine Transform(DCT): 1Hz
- Outlier Removal:
  - Classical standard deviation based approach
- Epoching: 0-800ms(Stage1)
  - Baseline: 200-0ms(Stage1)
- Empirical Mode Decomposition(EMD):
  - Intrinsic Mode Functions(IMFs): 5 cycles
- Feature Scaling:
  - Standardization by scikit-learn
- Slicing:
  - Window Size: 100ms
  - Number of window: 8

## Decoding

### Decoding (MPVA) using Machine Learning

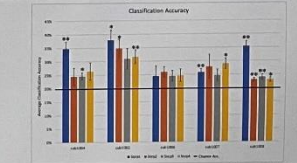


## Analysis 1

Sixteen time-windows of 50 milliseconds were selected to reduce the effects of noise contained in the data. Magnetic fields strength were averaged in each of 64 channels and extracted as features for machine learning. Data was first separated into a learning set of 40 epochs and a test set of 10 epochs. 5-fold cross-validation was conducted.

## Results

### Classification accuracy for each subject/step

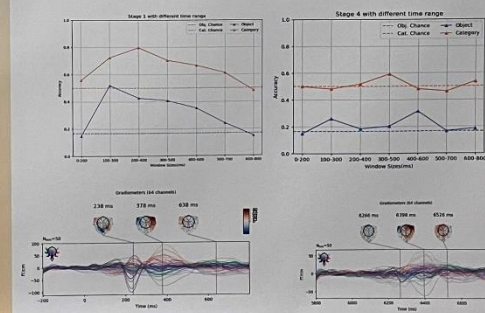


\* Significantly high accuracy compared to the chance as a result of the permutation test (\* $p < 0.05$ , \*\* $p < 0.01$ )

## Analysis 2: Time-Resolved MVPA

Seven time-windows of 200 milliseconds were selected as: 0-200, 100-300, 200-400, 300-500, 400-600, 500-600, 600-700 ms. Within each time-window, data were averaged over ten 20 milliseconds windows. Curve fitting to a linear function ( $y=ax+b$ ) was conducted and the slopes and the intercepts were extracted for features used for machine learning.

## Temporal Generalization



## Conclusion

- Significantly high classification accuracy above chance level indicates that information about neural representation of words can be decoded from MEG signals.
- Time-Resolved MVPA shows that there is a time lag between the peaks of accuracy rates of object identification and category identification. This difference indicates the timing activations of neural representations of visual image and semantic information.
- The two peaks of identification accuracy rates in Stage 4 correspond to the neural representations of phonological information and vocal movements.

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