Estimating similarity judgment processes based on neural activities measured by near-infrared spectroscopy (NIRS)

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Summary

Similarity takes a crucial role in various kinds of cognitive processes. In the present study, we investigated the neural activities during similarity judgments on 1225 pairs of images using the near-infrared spectroscopy. The predictability of similarity judgments were analyzed with a hierarchical Bayesian framework applied on the neural activities. It revealed that the neural activities located in a prefrontal region had a sharp increase prior to onsets of subjects' responses. Given the findings, we discussed about a key process, information integration of various domains, underlying similarity judgments.

1 Introduction

Semantic judgments such as association, similarity, and categorization are fundamental capability that appears in any contexts. In past works, it has been empirically studied in two approaches: One is subjective method in which it relies on common trends in multiple subjects' association, similarity or category judgments [1], and the other is relatively more objective method in which brain activities measured by advanced techniques, such as EEG, MEG, and fMRI, are analyzed in behalf of subjective judgments [2]. In order to bridge and integrate findings in the two empirical approaches, it is crucial to take advantage of theoretical models on semantic cognition. In particular, here we focus on similarity judgment. Similarity judgment has been generally accepted as a key piece of computation in theoretical approaches (e.g., mathematical models [3] and neural network models [1]) with massive empirical supports.

The goal of the present study is to understand relationship among subjective rating, neural signals, and computational models on similarity judgments. Specifically, our question here is whether there exists neural basis which correlates with similarity *regardless* of various kinds of stimuli. In order to answer the question, we asked subjects to answer similarity of various pairs of images. Subjects had no specific criterion about "similarity" –they can evaluate similarity by visual features such as color, shape, and texture or they may also evaluate similarity of associated properties such as monkey from a picture of a banana. Here we report a first step of research showing that particular patterns in neural activity may reflect "similarity computation" invariant to various kinds of visual stimuli.

2 Methods

Subjects

Ten subjects (6 males and 4 females) were recruited from graduate students in Japan Advanced Institute of Science and Technology in Japan. The mean age of subjects is 26.1 (S.D. = 4.33). All the subjects were right-handed and had good corrected or non-corrected visual acuity.

Experiment Procedure

The subjects were instructed to answer, by pressing one of five keys (“1”, “2”, “3”, “4”, and “5”) that are mapped on scales, “very similar” to “very dissimilar”, similarity of two images presented on the screen in one trial of the experiment. We have two sets of mapping between keys and similarity codes, “1” as “very similar” or “1” as “very dissimilar”, and each subject was assigned one of either randomly. The experiment consists of 1225 trials. In each trial, subjects were presented a pair of two images drawn from the unique 1225 combinations (pairs sampled from 50 categories without a pair of an identical category). The presentation order was randomized and counterbalanced across subjects.

The time course of each trial is shown in Figure 1. Each trial starts with presentation of a pair of two images at left and right boxes with a beep sound, and took no response during the first one second. After the first second, subject could make a response by pressing a key in his/her own timing. During one second right after the subject’s response, the blank screen was presented, and it was followed by the next trial with another pair of images.

During the experiment, we measure the relative changes in oxy-hemoglobin concentrations of frontal lobe using a near-infrared spectroscopy (NIRS) (ETG-4000, the Hitachi Medical). The probes were attached with a cap on subject’s scalp which was located based on the International 10-20 system. The Probe 1 (3 by 5) covered the prefrontal area, and the Probe 2 (two separate 3 by 3 sets) covered the left and right lateral area next to the Probe 1.

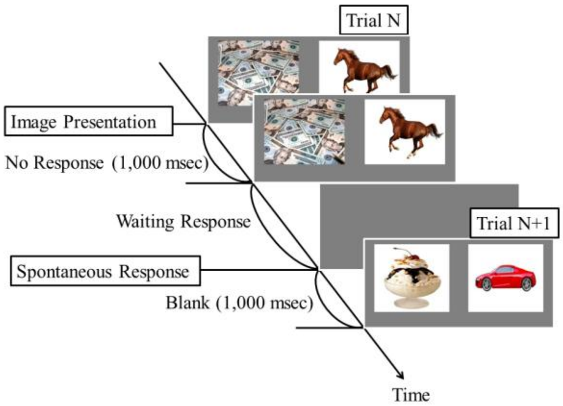

Figure 1: The time course of each trial

Noun categories

The 50 categories were selected from a normative list of 300 English nouns that typical three-year-olds have learned [4]. Specifically, 50 nouns are as follows: *butterfly, cat, fish, frog, horse, tiger, arm, eye, hand, knee, tongue, boots, gloves, jeans, shirt, banana, egg, ice cream, milk, pizza, salt, toast, bed, chair, door, refrigerator, table, rain, snow, stone, tree, water, camera, cup, keys, money, paper, scissors, plant, balloon, book, doll, glue, airplane, train, car, bicycle, truck,* and *bird*.

Images

Five images for each of 50 nouns were collected [5]. All the pictures have a still and real object on the center (see also Figure 1 for examples).

Sparse Regression Analysis

We employed a hierarchical Bayes model for analysis of neural signals obtained from NIRS measurements in similarity judgments. We assume that a prototypical pattern of neural signals over channels and time emerges when a subject judges similarity between a given pair of stimuli. The present hierarchical Bayes model is inspired by the hierarchical linear regression model proposed by

Nambu et al. [6]. Nambu et al. have proposed the *sparse linear regression* in which the regression coefficients with non-zero values are penalized by the sparseness prior distribution on them. In the sparse linear regression, only few parameters can be non-zeros due to the presumed sparseness of parameters, and this may solve the over-fitting problem which a typical NIRS experimental setting tends to have. In the present analysis, we employed the logistic regression with the sparseness prior distribution for the regression coefficients. The likelihood of binary responses (binomial distributions) and the sparseness prior distribution forms the posterior distribution of parameters which is sampled by the Monte Carlo Markov Chain.

3 Results

The average reaction time across the subjects is 1.70 second (S.D. 0.54). The similarity judgments on 1225 pairs (50 categories) average over the subjects were visualized with hierarchical clustering (Figure 2). The overall patterns were consistent to the previous experiment with a similar procedure [5]: several superordinate categories such as vehicles, animals, cloths, and household objects were clustered.

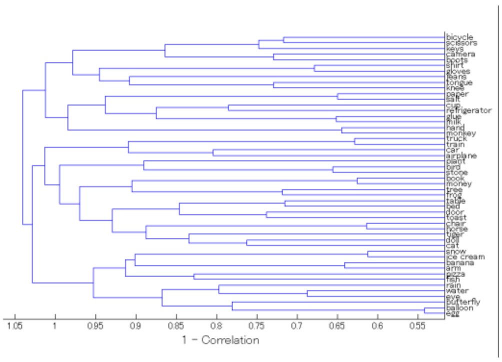

Figure 2: Clustering tree of the similarity judgements

In the experiment, the timing of similarity judgment was up to subjects' decision. The present experimental design allows us to analyze the temporal structure of subject's similarity judgments. Therefore, we applied the sparse logistic regression model to the similarity judgment dataset in eight different conditions (2 by 4) which have the neural signals obtained in different time intervals. In *stimulus-trigger* condition, we analyzed the similarity judgments based on the neural signals from the stimulus onset (i.e., image presentation as the trigger) to 1, 2, 3, and 4 second. In *response-trigger* condition, we analyzed them based on the neural signals from 1, 2, 3, and 4 second prior to the response onset. In each condition, we evaluated four models with different set of regression coefficients (over the interval 0 to 1, 2, and 4 seconds) using Deviance Information Criterion (DIC; [7]). We found that, for the majority of subjects, the model on the one-second interval after stimulus or before response was the best model (5 (stimulus-trigger) and 7 (response-trigger) out of 10 subjects). In the best models for all the subjects, the odds ratios of the correct prediction of subjective similarity judgment from the neural signals[1] were better than the baseline model[2] in which no neural signals is available for prediction. ($p<0.01$). The result confirmed that the sparse logistic regression captured the neural signals with significant predictive power for similarity judgments.

Next we analyzed the regression coefficients (averaged over subjects and the posterior distribution) in the best model in each of stimulus-trigger and response-trigger conditions. Figure 3 showed the topographic map of the absolute

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1 The odds ratio is $P_{correct}/(1-P_{correct})\overline{P}_{correct}/(1-\overline{P}_{correct})$, where $P_{correct}$ and $\overline{P}_{correct}$ are correct prediction of the best model and the baseline model.

2 The base line model has two parameters, slope and intercept, for baseline-frequency of response.

regression coefficients of the sparse logistic regression analysis based on the neural signals in (a) one second from stimulus onset and in (b) one interval to response onset. In both Figure 3a and 3b, we found a sharp peak in prefrontal area. Moreover, the peak tends to become strong at the end of the intervals which is right before subject's responses.

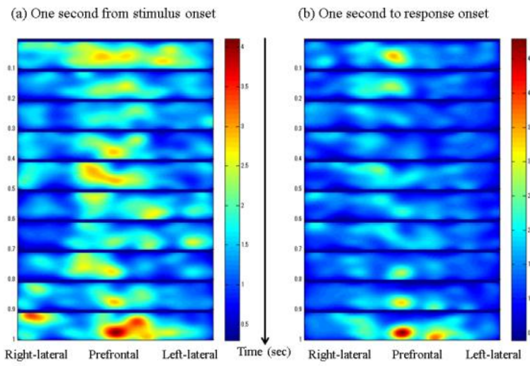

Figure 3: The topographic map of the average absolute coefficients in (a) one second from stimulus onset and in (b) one second to response onset (10Hz).

4 Discussions

In the present study, we investigated the spatio-temporal neural activities in similarity judgments on presented paired images drawn from 50 basic categories. The Bayesian hierarchical model has revealed that subjects' similarity judgment can be significantly predicted with the neural activities in the prefrontal area prior to their decision making.

The peak was located in Inferior prefrontal region. This region is close to the ventromedial prefrontal cortex (VM), which is supposed to take a key role in decision making in a gambling task [8], although the NIRS is limited to capture the neural activities in only surface areas. In the previous study, it has been considered that the VM takes a crucial role in integration of a wide range of information. It leads us to hypothesize that integration of multiple types of attributes (i.e., visual, associative, and semantic attributes) may be crucial to the timing of decision making in similarity judgments.

Acknowledgments

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