The Effect of Task on Object Processing revealed by EEG decoding

Hoi Ming Ken Yip[1]
Leo Y. T. Cheung[2]
Vince S. H. Ngan[1]
Yetta Kwailing Wong[2]
Alan C.-N. Wong[1*]

[1]Department of Psychology
The Chinese University of Hong Kong, Shatin, N.T., Hong Kong

[2]Department of Educational Psychology, Faculty of Education
The Chinese University of Hong Kong, Shatin, N.T., Hong Kong

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Keywords: object recognition, attention, top-down effect, task, MVPA

Corresponding author:
Alan C.-N. Wong
ORCID: https://orcid.org/0000-0002-2129-3485
334 Sino Building
Department of Psychology
The Chinese University of Hong Kong, Shatin, Hong Kong
Email: alanwong@cuhk.edu.hk
Phone: +852-3943-6505

The data that support the findings of this study are available from the corresponding author upon reasonable request. We have no funding or conflict of interest to disclose. All participants gave written consent according to the guidelines of the Survey and Behavioral Research Ethics Committee of the Chinese University of Hong Kong and the Joint Chinese University of Hong Kong-New Territories East Cluster Clinical Research Ethics Committee.

Abstract

Recent studies showed that task demand affects object representations in higher-level visual areas and beyond, but not so much in earlier areas. There are, however, limitations in those studies including the relatively weak manipulation of task due to the use of familiar real-life objects, the low temporal resolution in fMRI, and the emphasis on the amount and not the source of information carried by brain activations. In the current study, observers categorized images of artificial objects in one of two orthogonal dimensions, shape and texture, while their brain activity was recorded with electroencephalogram (EEG). Results showed that object processing was affected by task demand starting from a relatively late time (220-270ms time window) after image onset. The findings are consistent with the view that task exerts an effect on the later phases of object processing in the ventral visual pathway.

Introduction

Object recognition and categorization depend greatly on the goal of the observer, and yet its underlying mechanism has not been well understood. On the one hand, feedforward theories portrait object processing as a hierarchy in the ventral visual pathway, with representations increasing in receptive field size, complexity, and invariance going from the earlier areas like the primary visual cortex (V1) to later areas in the inferior temporal cortex (IT) (DiCarlo et al., 2012; Grill-Spector et al., 2001; Kriegeskorte et al., 2008). Several computational models of object representation proposed that the processing from V1 to IT is largely feedforward and not influenced by top-down factors such as task (DiCarlo et al., 2012; Riesenhuber & Poggio, 2002; Serre et al., 2005; Serre et al., 2007).

On the other hand, the role of top-down factors in visual object representations is conceivable in more recent perception models with an element of predictive coding (Clark, 2013; Friston, 2010; Hohwy, 2013, 2017; Lupyan 2015; Macpherson, 2017; O'Callaghan et al., 2017; Ransom et al., 2017; Vance & Stokes, 2017). These models share the same basic principle of prediction error minimization: higher-level areas generate predictions and send them to lower-level areas, which compare the predictions with the incoming information and send the prediction errors (difference between the two) back to the higher-level areas for adjusting the predictions. This process is repeated at both high (e.g., whole object representations) and low levels (e.g., edge orientations). Crucially, low-level predictions can

be influenced by top-down factors such that experience, knowledge, and expectations in the form of predictions passed to the lower-level areas, even all the way to the primary visual cortex (Kok et al., 2012; Lupyan, 2015). Accordingly, task can affect object representations even in the earlier phases of visual processing.

Previous studies have examined the effect of task demand on object representations in the visual system. Findings from some event-related potential (ERP) studies suggest that face representations are affected by task (Goffaux et al., 2003; Itier, & Neath-Tavares, 2017; Valdés-Conroy et al., 2014). For example, Goffaux et al. (2003) presented normal, low-spatial-frequency, and high-spatial-frequency faces to participants who were asked to judge the gender or familiarity of the faces. For low-spatial-frequency faces, an enhanced amplitude in the N170 was found when participants performed the gender task than the familiar task. No task effect was found for normal or high-spatial-frequency faces.

Though revealing, there are limitations in the interpretation of the findings from the traditional, activation-based approach as in the aforementioned studies. For example, in Goffaux et al.'s (2003), the task effect in the N170 amplitude was interpreted as enhanced diagnosticity of low-spatial-frequency cues in the gender task than the familiarity task. Nevertheless, an enhanced amplitude for one direction does not necessarily imply information diagnosticity, and can be caused by either a higher neural engagement or lower processing efficiency. Also, similar N170 amplitudes for the two tasks in the

high-spatial-frequency faces does not necessarily mean a lack of task effect. It is possible that the task exerts an effect not on the amplitude of the N170 in general for a few selected channels but on the pattern of activation across channels. In addition, extraneous factors such as changes in dipole position can contribute to the direction of amplitude difference.

MVPA Studies of Task Effects

Compared with the traditional, univariate analysis, multivariate pattern analysis (MVPA) is more suited to research questions concerning the effect of task on object representations (for a detailed introduction of the technique, see Grootswagers et al., 2017; Haynes, 2015; Schwarzkopf & Rees, 2011). A specific type of MVPA is decoding, which involves the use of machine learning algorithms to infer the stimuli or experimental conditions based on the pattern of brain activations across space (e.g., channels for EEG, voxels for fMRI) and time. Classification accuracy indicates the success of such inference and thus how differently the brain responds to two stimuli or conditions. The technique is useful for showing the amount of diagnostic information carried by the spatio-temporal patterns of activations for distinguishing between different objects. Hence, the degree to which the activation patterns between objects are distinguishable under different task contexts can reflect the effect of task demand on object representations.

In recent years, several studies applied MVPA to examine task effect on object processing. The majority of these studies used functional magnetic resonance imaging (fMRI). For

example, by computing the correlations of different objects in either the same task or different tasks, Harel et al. (2014) observed that object identity information differed in the posterior fusiform gyrus (pFs) but not in the lateral occipital cortex (LO). In Bracci et al. (2017), while analyses with the representational dissimilarity matrices (RDM) suggested a task effect in the ventral but not lateral occipitotemporal cortex, the correlation between the response patterns for objects remained similar regardless of whether the task was the same or different in both regions. Kim & McCarthy (2016) reported a task effect on decoding face versus body images in the occipitotemporal fusiform region, but this finding came with a counter-intuitive observation that the face-body decoding was *less* accurate when participants were performing a face-body discrimination task compared with an irrelevant emotion discrimination task. Jackson et al. (2017) reported above-chance decoding in the lateral occipital complex (LOC) only when the task was relevant, although the decoding accuracy in this task-relevant condition was not significantly different from that in the task-irrelevant condition. Two other studies did not observe any significant task effect (Long & Kuhl, 2018; Vaziri-Pashkam & Xu, 2017).

Fewer studies use techniques that are temporally more sensitive. Using magnetoencephalography (MEG), Hebart et al. (2018) observed a task effect on object decoding performance only after 542ms, suggesting that task affects object representation only at a late time. However, in another study using EEG and time-frequency analyses, decoding performance was higher in a task-relevant than a task-irrelevant condition during a much

earlier time frame (100-600ms after stimulus onset), but it was the case only for one of the two tasks included in that study (Bocincova & Johnson, 2019).

Overall, previous findings do not provide conclusive evidences concerning the effect of task on object representations as well as its time-course. Three reasons may have contributed to the mixed findings. First, most studies use real-life objects (Bracci et al., 2017; Harel et al., 2014; Hebart et al., 2018; Kim and McCarthy, 2016; Long & Kuhl, 2018; Vaziri-Pashkam & Xu, 2017). In daily life, we often perform multiple tasks on the same object simultaneously (e.g. recognizing the gender and emotion of a face when you want to know if a girl is happy). It may thus be difficult for participants in those studies to focus on just one dimension as instructed, resulting in weaker manipulation of task across conditions. Consistently, the two studies using artificial stimuli (Bocincova & Johnson, 2019; Jackson et al., 2017) both found some support for the task-dependent object representations.

Second, most studies used fMRI to measure brain activation, a technique with low temporal resolution in the order of seconds. It is thus unclear *when* task starts to influence object processing. On the one hand, task effects have been observed in the brain regions corresponding to visual object processing and representation such as the ventral temporal cortex and lateral occipital cortex (Bracci et al., 2017; Harel et al., 2014; Jackson et al., 2017; Kim & McCarthy, 2016), and can be interpreted as the penetration of task into the initial formation of object representation early in time. An alternative interpretation, however, is that

the effects may have been caused by the late feedback of high-level processing to visual areas to modify existing object representations. Techniques with a higher temporal resolution such as EEG and MEG would be more useful in teasing apart these different interpretations. Indeed, inconsistent findings have been observed between fMRI and EEG studies on visual processing of simple features. For example, attention and expectation have been shown to modulate responses to gratings in primary visual cortex (V1) in previous fMRI studies (e.g. Jehee et al., 2011; Kok et al., 2012), but not the amplitude of C1, the earliest ERP component that originates from V1 and peaks before 100ms, in another ERP study (Alilović et al., 2019). Therefore, it is important to use a time-sensitive method to clarify this timing of the task effect.

The third potential reason of the inconclusive results in the literature concerns what exactly about object representations is affected by task. Typically, previous studies focused on the *amount of information* carried by the pattern of brain activations, and compared the decoding accuracy between task-relevant and irrelevant conditions. Better decoding accuracy in the task-relevant condition would mean that more information is carried by the pattern of brain activations for object distinctions consistent with the observer's current task demand. Yet a lack of difference in decoding accuracy does not necessarily mean that task does not affect object representations. A much less explored possibility is that the *source of the information* useful for object distinction may differ depending on task. That is, the exact features (in terms of channels, time points, etc.) useful for object decoding might change with task. It could

therefore be the case that in some of the previous studies where a task effect on decoding accuracy was not found, task actually did influence object representations in terms of which brain activation features constitute the information useful for object differentiation. Examination of both the amount and source of information carried by the brain action pattern would provide a more complete picture of the effect of task on object representations.

The Current Study

In the current study we asked whether and when task effects start to emerge during the time course of visual object processing to clarify whether task affects object representations during or after their formation. MVPA was applied to the EEG responses of participants performing a verification task on the objects based on one of two possible dimensions (shape and texture). With respect to the limitations of previous studies reviewed above, we introduced a stronger manipulation of task by using novel, artificial objects. This should increase the likelihood that participants attended to only one dimension at a time as instructed. Besides, the use of EEG also offered a better temporal resolution compared with techniques like fMRI.

In addition, we also examined both the amount and the source of the information carried by brain activations. To achieve these, two sets of MVPA analyses were performed. One set of analyses compared the decoding performance of task-relevant classifiers with that of the task-irrelevant classifiers (Table 1) to examine whether task relevance affects the

amount of information useful for object differentiation. If task affects the amount of information in object representations, a higher object decoding accuracy should be observed when the decoded dimension (e.g., texture) is task-relevant than when the dimension is task-irrelevant, i.e., the participant's task was to judge an object along the same dimension (e.g., texture) compared with a different dimension (e.g., shape). The other set of analyses concerned whether classifiers trained on a particular task context performed better when they were tested on the same task context ('task-relevant classifiers') than on a different task context ('across-task classifiers'; Table 1). This directly tested how useful the features extracted during classifier training in one task context were when applied to the decoding in a different task context. If task affects the source of information carried in object representations, the decoding model trained in one task context would generalize better to data in the same task context than to a different task context, i.e., the decoding accuracy for a dimension. e.g., texture, should be better when classifier training and testing were both conducted on data in the texture task context ('task-relevant classifiers'; Table 1) compared with when classifier was trained with data in the texture task context and then tested with data in the shape task context ('across-task classifiers'; Table 1).

Apart from *whether* there is any task effect on object representations, we also asked *when* task effects arise in time. If task affects the formation of object representation, task effects should be observed at or before the time range of the N170 and the N250, two

important ERP components important for visual object recognition (150-330ms; Goffaux et al., 2003; Scott et al., 2006). The N170 has been associated mainly with initial coding of faces and familiar objects (Bentin et al., 1996; Scott et al., 2006; Tanaka & Curran, 2001). The N250, on the other hand, has been shown to be sensitive to the identity of individual faces and objects (Pierce et al., 2011; Schweinberger et al., 2002, Schweinberger et al., 2004; Scott et al., 2006). Source localization studies found that these components have a major source in the fusiform gyrus (Deffke et al., 2007; Herrmann et al., 2005; Schweinberger et al., 2002; Schweinberger et al., 2004; Scott et al., 2006), which correspond well with the brain regions in which task effects have been observed using fMRI (Bracci et al., 2017; Harel et al., 2014; Jackson et al., 2017; Kim & McCarthy, 2016). Alternatively, if task only modifies object representations through feedback signals from higher-level processing, then task effects should only be observed later in time than the time window of these two ERP components.

Materials & Methods

Participants

Forty college students with normal or corrected-to-normal vision were recruited. Four participants were excluded due to low behavioral accuracy (<90%) or excessive artifacts (>20% of total trials rejected in artifact rejection; see below). Data of the remaining 36 participants (17 males, mean age = 21.83 years, SD = 3.47) were included in all subsequent

analyses. All participants gave written consent according to the guidelines of the Survey and Behavioral Research Ethics Committee of the Chinese University of Hong Kong and the Joint Chinese University of Hong Kong-New Territories East Cluster Clinical Research Ethics Committee, and received monetary compensation for their participation.

Materials and stimuli

Artificial objects were generated and modified based on the computer-generated artificial objects (‘Greebles’ and ‘Ziggerins’) used in previous studies (Figure 1; Gauthier & Tarr, 1997; Wong et al., 2009). The objects were in an identical brown color and varied in two dimensions: shape and texture. The luminance levels were controlled across the object groups. The objects were sized such that a circle enclosing each object would span a visual angle of 4° X 4°.

A PC with Matlab (Mathworks, Inc.) and Psychophysics Toolbox extensions (Brainard, 1997; Pelli, 1997) was used to present stimuli and record behavioral responses. Stimuli were presented on a 27” LCD monitor with a refresh rate of 60Hz. The background was grey and the viewing distance was 70cm.

Procedure

A verification task was used in this study (Figure 2). On each trial, a cue (“large”, “small”, “round” or “cubic”) was presented for 500ms, followed by a black fixation cross for 1000ms. Then an object was presented for 1000ms. Participants were asked to press “1” on

the keyboard if the object matched with the cue and “2” if it did not. Trials with “large” or “small” cues required judgment about the texture (i.e., a texture task) and trials with “round” or “cubic” cues required judgment about the shape (i.e., a shape task). Participants were instructed to respond as accurately and as quickly as possible within the 1000ms when the object appeared, and the object remained present after the response. Following the presentation of the object, a white fixation cross was presented for 2000ms. Participants were instructed to blink only during this period.

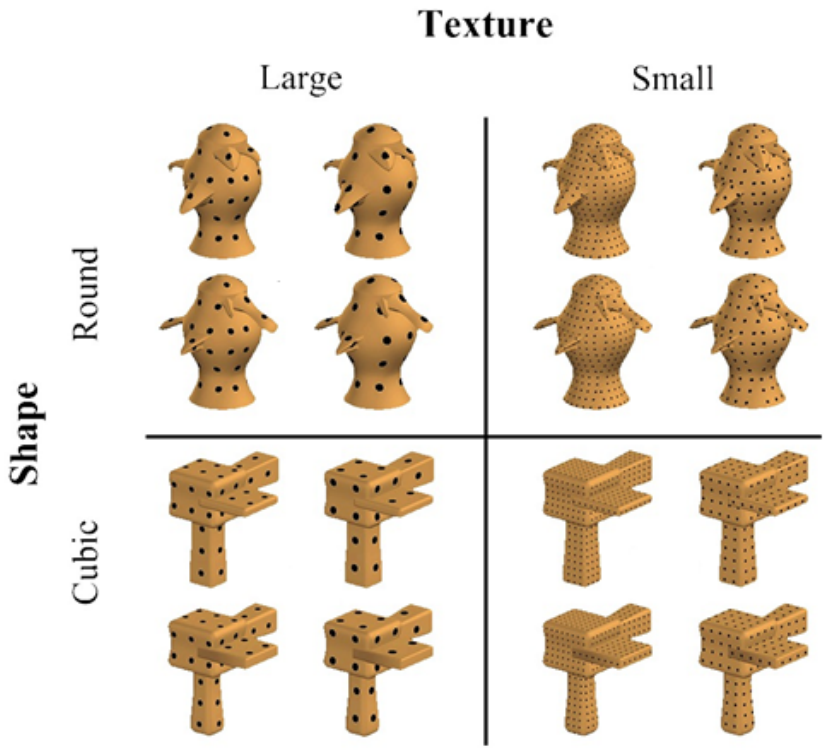

Figure 1. The four groups of objects varying along the shape and texture dimensions. For better visualization the objects were brighter in this figure than in the actual experiment.

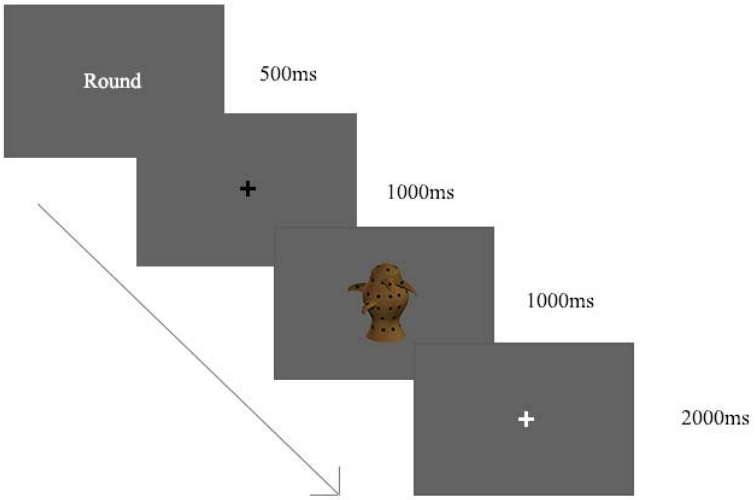

Figure 2. The experimental paradigm. The task was to judge whether the object matched with the cue.

There were 32 blocks and 32 trials in each block, leading to 1024 trials in total. Participants were advised by the experimenter to get at least 30 out of 32 trials correct in each block and received feedback on the number of correct trials after each block. Each mapping of cue and object groups (4 cue X 4 object groups = 16 pairs) was presented twice in a block. The selection of objects within each object group was random. The trial sequence within a block was pseudo-randomized with the following criteria: (i) The same cue did not repeat for more than 3 consecutive trials; (ii) The same object group did not repeat for more than 3 consecutive trials; Sixty-four different trial sequences were generated and 32 of them were randomly selected for each participant. There was a 12-trial short practice before the experiment. Participants were required to obtain 90% accuracy to proceed. Otherwise they would repeat the practice until they attained the required accuracy.

EEG recording and Preprocessing

EEG data were recorded on a 128-channel eego system (ANT Neuro, Enschede, The Netherlands) with a 1000-Hz sampling rate. CPz was used as the online reference and the ground electrode was placed close to the left mastoid. Electrode impedance was kept under 20kΩ during the experiment.

Preprocessing was conducted with EEGLAB (Delorme & Makeig, 2004) and ERPLAB (Lopez-Calderon & Luck, 2014) in MATLAB (Mathworks, Natick, MA). Data were re-referenced off-line to the average reference. Band-pass filtering (0.01–30Hz) was applied to the continuous EEG data, which were then divided into 1000-ms epochs starting at 200ms before and ending at 800ms after the presentation of the object. Since the signals near the end of the stimulus presentation was not of interest, the last 200ms of stimuli presentation (i.e., 800-1000ms) was not used for artifact rejection to avoid rejecting epochs due to artifacts during this time window. Incorrect trials were also excluded from further analyses. Epochs with ocular artifacts were removed by visual inspection and by the moving-window peak-to-peak function in ERPLAB on VEOG, HEOG and the channels selected in the decoding analysis with a threshold of 100 μV, a window size of 200ms and a step size of 50ms. On average, 4.57% and 6.24% of the trials were rejected due to incorrect responses and artifacts respectively.

Multivariate Pattern Analysis (MVPA)

MVPA was implemented in MATLAB with custom-made codes and LIBSVM (Chang & Lin, 2011) using a linear support vector machine (c = 1). Classification was conducted in each participant separately with a sliding time window approach, using a window size of 50ms and a step size of 10ms. A subset of 64 posterior channels (Figure 3) was selected for the MVPA analysis based on the results of a pilot study, which showed that the general decoding accuracy was better with these channels than with all channels, regardless of conditions. We employed a ten-fold cross validation. The trials for classification were randomly assigned to ten bins of roughly equal number of trials and equal proportion of the two classes. Nine bins were pooled to train the classifier and the remaining one bin was used to test its classification accuracy. This step was repeated ten times so that every bin would serve as the test bin once. Principle Component Analysis (PCA) was applied to the 50 (time points) X 64 (channels) features in each time window in the training trials to reduce dimensionality. Principle components (PCs) explaining >99% variance were kept and used as input to train the classifier. The same PCs were applied to the testing trials when testing the classifiers' performance. The purpose of conducting PCA on training trials only, instead of performing it on all trials combined, is to avoid spurious generalizability of training results to the testing data as a result of 'double-dipping' in the feature selection procedure (Kriegeskorte et al., 2009; Mwangi et al., 2014). This cross validation procedure was repeated five times. The resulting accuracy of a classifier in a time window was the average accuracy of these

five iterations of ten-fold cross validation.

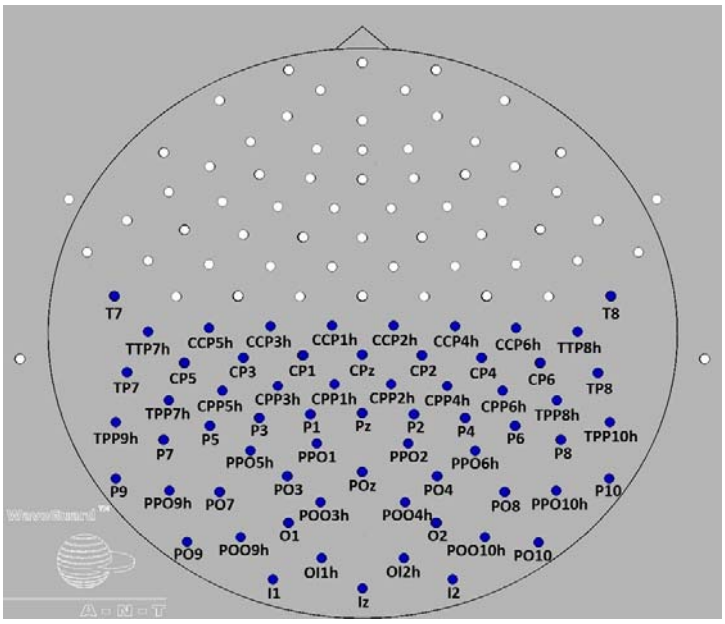

Figure 3. Channels used in MVPA were highlighted in blue.

Two major analyses were conducted to examine the effect of task on object processing. The first analysis involved comparison between the performance of task-relevant and task-irrelevant classifiers (Table 1). Task-relevant classifiers refer to the classifiers trained to discriminate an object dimension (e.g., texture) congruent with the participants' task demand (e.g., as in a texture task trial). In contrast, task-irrelevant classifiers refer to the classifiers trained to discriminate an object dimension (e.g., texture) incongruent with the participants' task demand (e.g., as in a shape task trial). If the task demand could render the object representations more separable along the dimension required by the task (e.g., a larger difference between the representations of Large-Round and Small-Round objects when participants were performing a texture vs. shape task), then the task-relevant classifiers would

demonstrate higher average decoding accuracy than the task-irrelevant classifiers.

Another major analysis concerned whether the classifiers trained on one task can be generalized to another task. Performance of task-relevant and across-task classifiers was compared. Both types of classifiers were trained in the object dimension congruent with that of the participants' task demand, however they were tested on data in different tasks. Task-relevant classifiers were tested on data in the same task with which the classifiers were trained, while across-task classifiers were tested on data in a different task from which the classifiers were trained, e.g., the Large-Round vs. Small-Round classifiers were trained on the texture task trials but tested on the shape task trials. If the features used for distinguishing the same objects differ between tasks, then what the classifiers learnt in one task would not be fully generalized to another task. This would result in a lower average decoding accuracy in the across-task classifiers than the task-relevant classifiers.

To perform significance testing on decoding accuracies, we used a non-parametric sign permutation test with a maximum cluster size method to correct for multiple comparisons (Nichols & Holmes, 2002; Hebart et al. 2018). First, we calculated a difference score at each time window for each participant. To test if the decoding accuracies of a classifier were above chance, we subtracted 0.5 from the accuracies. To test if the decoding accuracies of two classifiers were different, we subtracted the accuracies of one from another. Two-tailed tests with participants as the random factor were conducted to test whether the

difference scores were significant. A permutation procedure was used in which each participant was randomly assigned a value of 1 or -1 and the difference scores at each time window was multiplied by this value. For each time window, a t-value was computed with the mean and SD of this score across participants. Repeating the procedure for 10,000 times, a distribution of 10,000 t-values was obtained for every time window. The primary threshold was set at the 2.5th and 97.5th percentile of this distribution. To obtain the secondary cluster-size threshold, we searched for clusters of significant time windows. Neighboring time windows would form a cluster only if all their t-values exceeded the primary threshold. The maximum cluster size of each permutation set was recorded, and it formed a distribution of maximum cluster sizes. The 97.5th percentile of this distribution served as a secondary cluster-size threshold. Finally, both thresholds were applied to the difference score of each time window. The difference score in a time window would be regarded as statistically significant if the t-value of the empirical data was higher than that of the primary threshold and if the size of the cluster encompassing this time window was larger than the secondary cluster-size threshold.

Results

Behavioral Results

Overall responses were accurate (>93%) and fast (mean = 570ms for correct trials). Figure 4 shows the accuracy and response time (RT) for each object group in each task. We performed a 2 (task: texture, shape) X 4 (object groups: large & round, small & round, large & cubic, small & cubic) repeated measure analyses of variance (ANOVA) to test if there were significant differences in the accuracy and response time (RT) between task and object groups. Incorrect trials were excluded from the analysis of RT.

Participant responses were less accurate and slower for the texture task than the shape task. This was indicated by a significant main effect of task in accuracy, $F(1,35) = 4.606$, $p = .039$, $\eta_p^2 = .116$, and in RT, $F(1,35) = 49.343$, $p < .001$, $\eta_p^2 = .585$. The main effect of object group was significant in accuracy, $F(3,33) = 4.149$, $p = .013$, $\eta_p^2 = .274$, and in RT, $F(3,33) = 9.973$, $p < .001$, $\eta_p^2 = .476$. Post-hoc pairwise comparisons (Bonferroni corrected) revealed a significantly higher accuracy for Large-Round than Large-Cubic objects, $p = .009$. Pairwise comparisons also revealed faster responses for Large-Round than the other object groups, $p \leq .032$. The interaction of task and object group was significant in accuracy, $F(3,33) = 3.462$, $p = .027$, $\eta_p^2 = .239$, and not in RT, $F(3,33) = 1.352$, $p = .275$, $\eta_p^2 = .109$. Subsequent t-tests comparing accuracies of the same object groups in the two tasks found that the accuracy in the texture task was significantly lower than that in the shape task only for Small-Round

objects, p =.001.

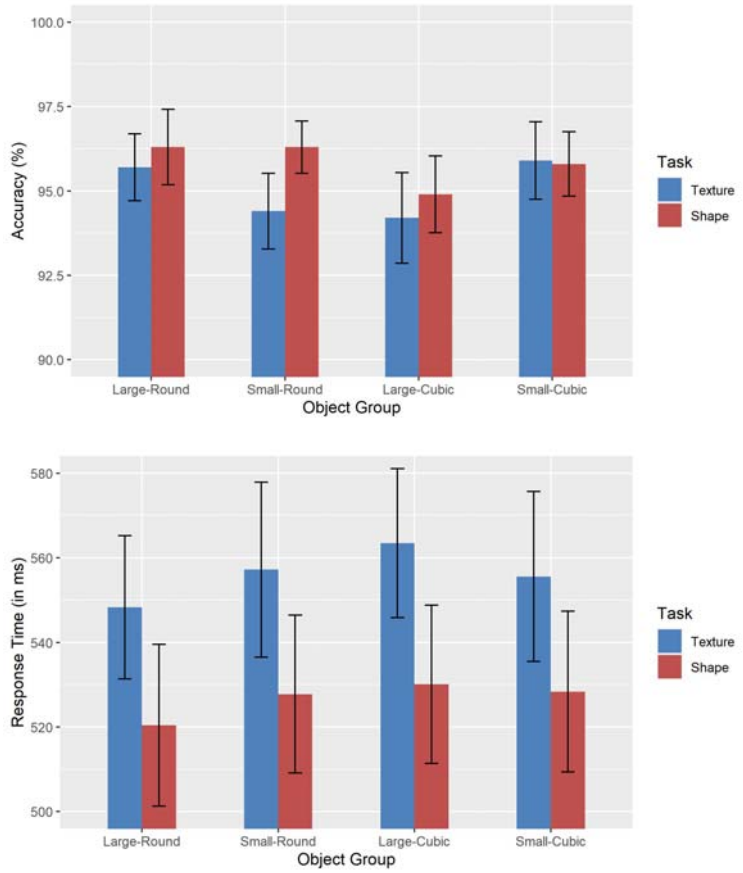

Figure 4. Behavioral accuracy and response time for each object group in each task. Error bars represent 95% confidence interval of the mean estimate.

EEG Results

Figure 5 shows the grand average ERP collapsed across participants for different time points and channels. The selected channels showed clear deflections corresponding to the P1, N170 and N250 components. Univariate ERP analysis comparing the amplitudes of the N170 and the N250 in the two tasks showed that there were no significant difference in the N170 amplitudes, but the N250 amplitudes in the texture task trials were larger than the that of shape task trials in the right hemisphere. Detailed results are included in the Appendix.

In the first decoding analysis, performance of task-relevant classifiers (Table 1) was compared with that of task-irrelevant classifiers to test whether task relevance affects the amount of information useful for object differentiation (Figure 6). Performance of both classifiers rose significantly above chance very early in time (task-relevant: starting at the 60-110ms time window; task-irrelevant: starting at 50-100ms) and remained significant until the end of the epoch. Performance peaked at 140-190ms for both classifiers. There were no significant differences between the accuracy of task-relevant classifiers and that of task-irrelevant classifiers at all time windows, suggesting similar amount of information was available for decoding in the task-relevant and task-irrelevant contexts. Separate analyses for decoding along each dimension (texture or shape) showed that the task effect was significant for texture decoding only (Figure 6, bottom panel; indicated by green dots) at a relatively late time of 400-530ms.

In the second analysis, performance of task-relevant classifiers was compared with that of across-task classifiers to test whether task affects the source of information useful for object differentiation, or in other words, how well the features extracted by trained classifiers in one task generalized to a different task (Figure 7). The across-task decoding accuracy was significantly above chance very early in time (task-relevant: starting at the 60-110ms time window; across-task: starting at 50-100ms) and lasted until the end of the epoch. Performance peaked at 130-180ms for across-task classifiers and 140-190ms for within-task

classifiers. Decoding accuracies of task-relevant classifiers were significantly higher than that of across-task classifiers in several clusters of timepoints (220ms-350ms, 320-410ms, 400-490ms, indicated by green dots). Separate analyses for decoding of each dimension showed that task effect reached significance only for texture decoding (320-430ms, 440-530ms) (Figure 7, bottom panel).

In summary, our findings showed an effect of task on object representations mainly in terms of the source of the information useful for object distinction, which first emerged at the time window of 220-270-ms. The task effect on the amount of information was weak at best, occurring only for the texture task and at a later time window of 400-530ms.

Table 1. The three types of classifiers involved in the current study. Dimension values relevant to the classification were highlighted in bold.

Types of Classifiers	*Type of trials classifiers trained on*	*Type of trials classifiers tested on*
Task-relevant classifiers		
A) Texture classification		
Large-Round vs. **Small**-Round	Texture task	Texture task
Large-Cubic vs. **Small**-Cubic	Texture task	Texture task
B) Shape classification		
Large-**Round** vs. Large-**Cubic**	Shape task	Shape task
Small-**Round** vs. Small-**Cubic**	Shape task	Shape task
Task-irrelevant classifiers		
A) Texture classification		
Large-Round vs. **Small**-Round	Shape task	Shape task
Large-Cubic vs. **Small**-Cubic	Shape task	Shape task
B) Shape classification		
Large-**Round** vs. Large-**Cubic**	Texture task	Texture task
Small-**Round** vs. Small-**Cubic**	Texture task	Texture task
Across-task classifiers		
A) Texture classification		
Large-Round vs. **Small**-Round	Texture task	Shape task
Large-Cubic vs. **Small**-Cubic	Texture task	Shape task
B) Shape classification		
Large-**Round** vs. Large-**Cubic**	Shape task	Texture task
Small-**Round** vs. Small-**Cubic**	Shape task	Texture task

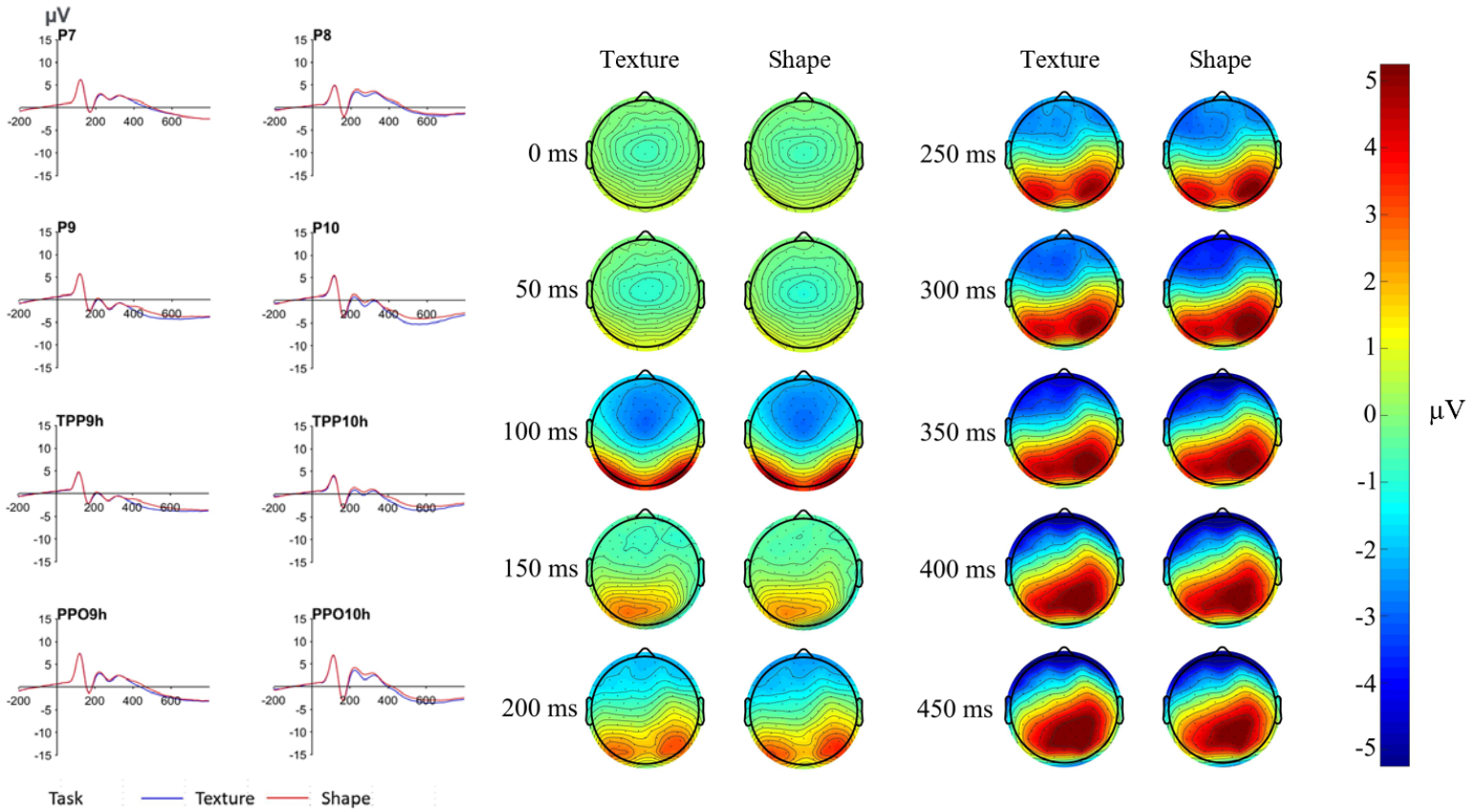

Figure 5. Grand average ERP waveform plots in selected channels (left) and scalp maps (right).

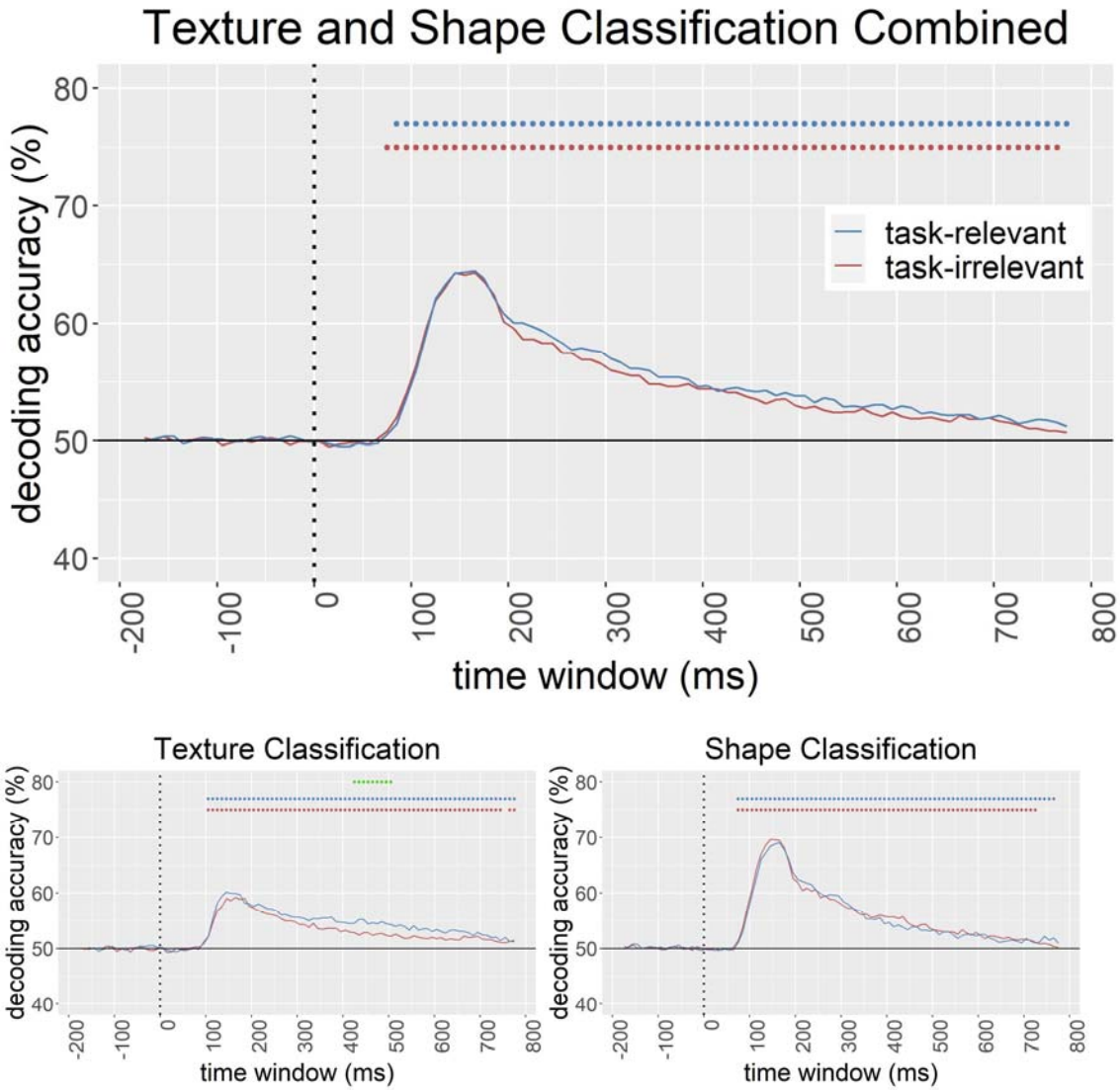

Figure 6. Decoding accuracies of task-relevant and task-irrelevant classifiers for texture and shape classification combined (top), for texture classification only (bottom left), and for shape classification only (bottom right). The *x*-axis depicts the time at which each 50-ms time window used for decoding was centered. The dots at the top indicate time windows with significant differences: blue dots refer to the time windows that were significantly above chance for task-relevant classifiers; red dots refer to the time windows that were significantly above chance for task-irrelevant classifiers; green dots refer to the time windows that were significantly different between task-relevant and task-irrelevant classifiers.

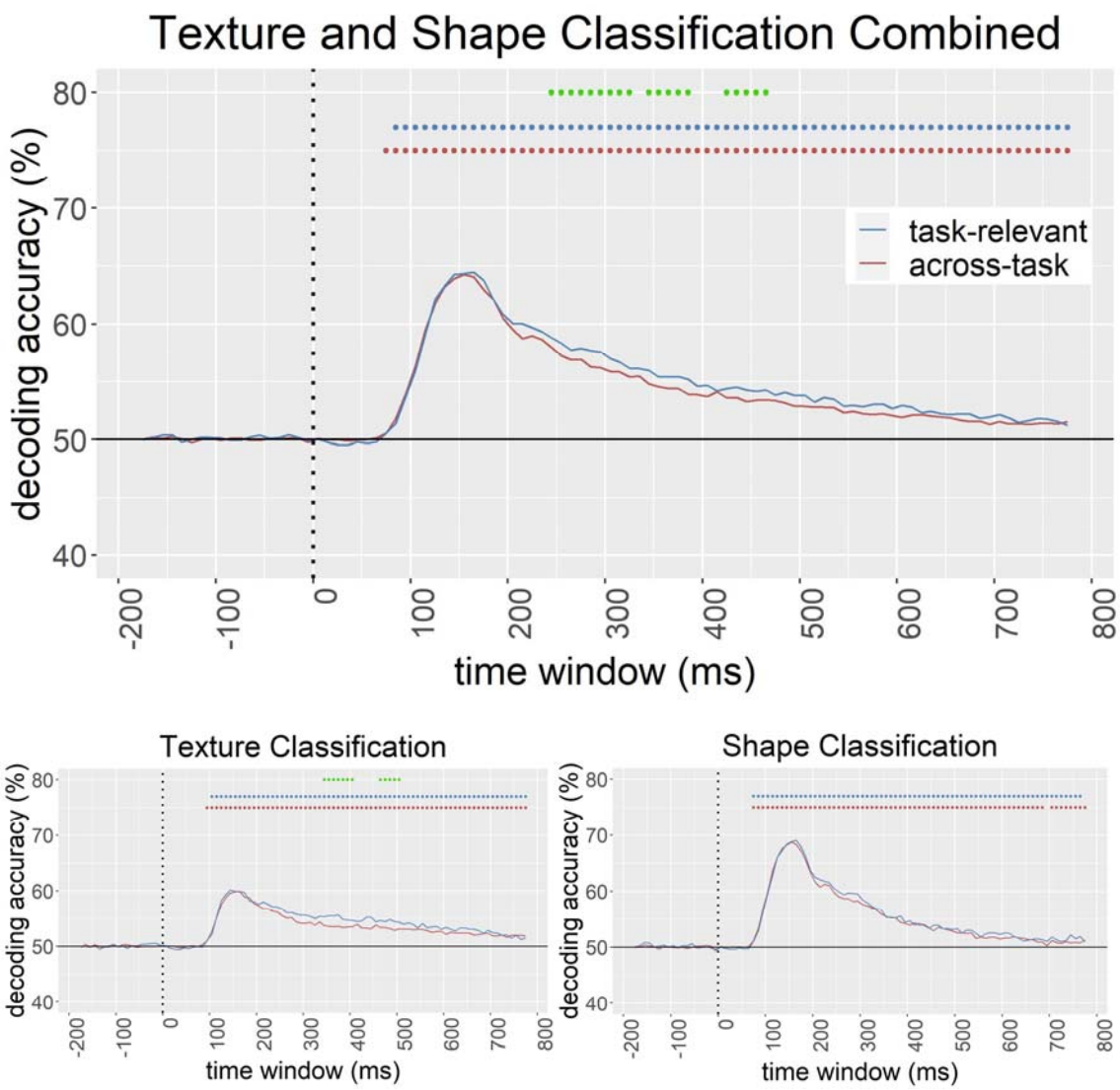

Figure 7. Decoding accuracies of task-relevant and across-task classifiers for texture and shape classification combined (top), for texture classification only (bottom left), and for shape classification only (bottom right). The *x*-axis depicts the time at which each 50-ms time window used for decoding was centered. The dots at the top indicate time windows with significant differences: blue dots refer to the time windows that were significantly above chance for task-relevant classifiers; red dots refer to the time windows that were significantly above chance for across-task classifiers; green dots refer to the time windows that were significantly different between task-relevant and across-task classifiers.

Discussion

The current study examined whether and when task affects object processing with decoding of EEG signals. We presented artificial stimuli that could be categorized along two dimensions (texture and shape) and asked participants to perform object judgment based on one dimension during each task.

Task Effect on Object Representations

Overall, task was found to affect more the source than the amount of information available in object representations. Specifically, decoding accuracy was similar for task-relevant and task-irrelevant classifiers at all time windows, suggesting that the amount of information in the brain activation pattern useful for object distinction was similar in both task-relevant and irrelevant contexts. However, the classifiers trained on a certain task performed better when they were tested on the same task than on a different task, as indicated by the better performance of task-relevant than that of across-task classifiers. This suggests that task affects the features (channels, time points) that constitute the information useful for object distinction. In other words, there existed some qualitative differences in the object representations in the two tasks during this period, and the diagnostic features for object differentiation differed across task contexts.

Several implications arise from the finding of a more conspicuous task effect on the source than the amount of information in object representations. First, the findings may help

resolve the inconsistent findings of the effect of task in previous studies. Studies that analyzed only the amount of information in brain activations and found no task effect have overlooked the possibility that task may change the pattern of activations in certain situations. Second, the studies of object processing would likely benefit from the use of multiple types of tasks. One should beware that the object representations examined in a certain paradigm could change qualitatively in a different paradigm. Similarities and differences found between two object categories may therefore not hold when the task is changed. Finally, it is encouraging to see that EEG, with a lower spatial resolution than techniques like fMRI and MEG, is also capable of demonstrating different neural activation patterns across conditions.

The difference between task-relevant vs. across-task classifiers was only observed when combining the two tasks and for the texture task only (but not for the shape task). A potential reason is that distinguishing the two shapes (round vs. cubic) was easier than distinguishing the two textures (large vs. small dots). Both the behavioral and decoding performance was better for shape than texture discrimination. The shape difference as manifested in this study may be so obvious that shape information in the object representations was preserved well even in an irrelevant task context.

Time-course of Task Effect

The task effect was found in multiple time windows starting from 220ms. This time point lags behind the duration of N170 and corresponds more to the N250. Interestingly, task effect occurred after the peak of decoding accuracy(130-180ms). An intriguing possibility is that the peak decoding accuracy corresponds to relatively task-independent representations in areas such as the lateral occipital cortex (LO), while the subsequent task effect reflects task-dependent representations in the more anterior areas like the fusiform gyrus. Several lines of research suggest that this may be a sensible interpretation. First, EEG source localization studies have identified the fusiform gyrus as a potentially major source of the N170 (Deffke et al., 2007; Herrmann et al., 2005) and the N250 (Schweinberger et al., 2002; Schweinberger et al., 2004; Scott et al., 2006). Second, Cichy & Pantazis (2017) used fMRI-MEG/EEG fusion technique to study the representational structure of objects in time and space, and found correspondence between representations revealed by EEG decoding at different time points and representations revealed by fMRI at different areas along the ventral visual pathway. Specifically, representations at the primary visual cortex (V1) corresponded the best with MEG/EEG representations at about 100ms, while representations at the inferotemporal cortex (IT) corresponded the best with MEG/EEG representations at close to 300ms. Third, Harel et al. (2014) found that the representations changed across tasks in the posterior fusiform area (pFs) but not LO. Lastly, some studies suggest that decoding of object

category could be better in LO than pFs (Hebart et al., 2018; Julian et al., 2017). For example, Julian et al. (2017) found that object category decoding was significant in LO but not in pFs. Results of the fMRI-MEG-model fusion in Hebart et al. (2018) also showed that responses in LO was dominantly explained by the category model at the early time points, while responses in pFs were not that clearly correlated with the category model. Perhaps LO showed the best shape descriptions of objects, and when top-down information was combined with these shape descriptions in the pFs, the representations became less shape-dependent and the decoding accuracy decreased. Taken together, it is reasonable to suspect that the peak of decoding accuracy corresponds to the activities in LO, which offers best information for the decoding but is task independent, and the time range of the N250 corresponds to the activities in the more anterior sites, which still held the object representations for individuation but could be influenced by task.

Hebart et al. (2018) examined the time course of task effect with MEG and fMRI, and similar to the current study, conducted analyses concerning both the amount of information contained in the activation patterns and the exact activation patterns across task contexts. Their findings differed from ours in two aspects. One is that in our study, task effect occurred mainly in terms of the differing activation patterns across task contexts, whereas in Hebart et al. (2018) the task effect was in terms of the amount of information available for object differentiation under different task contexts. Specifically, object representations were more

separable from each other during conceptual tasks than perceptual tasks. Another difference is that the task effect found in the current study occurred much earlier (starting from the 220-270 ms time window) than that observed in Hebart et al. (2018), i.e., after 542 ms.

These different findings might be driven by the differences in the stimuli, tasks and analyses in the two studies. First, in our study, the objects used were novel, while Hebart et al. (2018) used a set of real-world objects, and due to our rich experience interacting with them for different purposes at the same time, it may have been difficult for observers to follow the instruction and focus only on dimensions relevant to the task demand. Second, in our study, both tasks involved were perceptual tasks, so they likely engage partially different sets of neural substrates for perceptual analyses. In Hebart et al. (2018), the perceptual and conceptual tasks in their study differed in depth of processing and could thus involve similar perceptual analyses and different subsequent analyses of conceptual information. Third, our study specifically examined the separability of object representations along different dimensions consistent and inconsistent with the task context, while in Hebart et al. (2018) classification was conducted for all objects in general without comparison between object classifications more consistent with the perceptual vs. conceptual task. Together this may have led to a relatively earlier task effect manifested in terms of the amount of information carried in the object representations instead of the actual pattern of activations in our study than in Hebart et al. (2018).

Bocincova & Johnson (2019) found that classifier performance in the decoding of a part's orientation was higher when it was task-relevant than irrelevant during the 100-600ms time window. Therefore, task apparently had an earlier influence on the formation of representations in their study. One potential reason for the difference is that a blocked design was used in their study and participants were motivated to remember only the task-relevant feature in each block. In the current study, participants focused on different dimensions in each trial depending on the cue. Another, perhaps important difference is that Bocincova & Johnson (2019) conducted time-frequency analysis on the EEG data and input the power of frequencies to the classifiers. This time-frequency decomposition involved temporal smearing, and thus it is uncertain how much of the effect found starting at 100ms was contributed by activations afterwards within the 100-600ms time window.

In conclusion, we found that object representations involved qualitatively different information across different task contexts. Task effects occurred after the peak of decoding accuracy and within the time range of the N250 component, corresponding to object representations at the anterior parts of the ventral visual pathway.

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