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Abstract: Rapid analysis of low spatial frequencies (LSFs) in the brain conveys the global shape of the object and allows for rapid expectations about the visual input. Evidence has suggested that LSF processing differs as a function of the semantic category to identify. The present study sought to specify the neural dynamics of the LSF contribution to the rapid object representation of living versus non-living objects. In this EEG experiment, participants had to categorize an object displayed at different spatial frequencies (LSF or non-filtered). Behavioral results showed an advantage for living versus non-living objects and a decrease in performance with LSF pictures of pieces of furniture only. Moreover, despite a difference in classification performance between LSF and non-filtered pictures for living items, the behavioral performance was maintained, which suggests that classification under our specific condition can be based on LSF information, in particular for living items.

Keyword: Living object, manufactured object; Coarse-to-fine, decoding.

1. Introduction

The visual system in the brain consists of two anatomically and functionally distinct pathways: a ventral pathway (occipitotemporal) dedicated to object perception-recognition and a dorsal pathway (occipitoparietal) devoted to movement, spatial localization (Ungerleider & Mishkin, 1982) and visually guided action (Goodale & Milner, 1992). Nevertheless, many studies challenge a purely dichotomous distinction and suggest that fast activation in the dorsal pathway can process object representation regardless of early ventral pathway functioning (Bracci, Daniels, & Op de Beeck, 2017; Freud, Ganel, et al., 2017; Freud, Culham, Plaut, & Behrmann, 2017; Freud, Plaut, & Behrmann, 2016; Konen & Kastner, 2008; Theys, Romero, van Loon, & Janssen, 2015). For instance, by using the global shape of the object, the coarse information conveyed by low spatial frequencies (LSFs) into the dorsal stream produce a minimal set of possible interpretations within a specific category; this fast process significantly reduces the duration and computation required for object categorization or recognition (Bar, 2003). Many aspects of object representations have been explored behaviorally, but little is known about the temporality of the neural mechanism to achieve a dissociation between different items based on the specificity of the global shape category (LSF content).

1.1. Coarse-to-fine and fine-to-coarse computations in object representation

In line with models including interactions between LSF and high spatial frequency (HSF) information through the visual system (Bar, 2003), the extraction of sensory visual inputs activates a coarse-to-fine processing scheme, with LSFs representing the global information about the shape and orientation of the stimulus. HSFs, resulting in finer spatial resolution, correspond to configural information and details. The global shape of an object is rapidly conveyed through the dorsal pathway from the visual cortex to the prefrontal cortex

(PFC) and the parahippocampal cortex, where it can activate a scene schema. In the PFC, this coarse representation generates expectations about the “most likely” interpretations of the visual input, which are then back-projected as an “initial guess” to the temporal cortex to be integrated with the bottom-up analysis. The top-down process facilitates recognition of the object by substantially limiting the number of candidate representations. However, the anterior areas (likely the PFC) do not accomplish the “initial guesses of the stimulus” on the basis of coarse information but need more physical information. Indeed, the perceptual properties of the object (shape, finer detail, spatial frequency content) seem to have a significant role in the dissociation and identification of a particular category (e.g., the discrimination between a living and non-living item; Price & Humphreys, 1989; Vannucci & Viggiano, 2000).

1.2. Semantic category and specific sensitivity to coarse information

The steadiness of the categorization performance (above chance level) in a difficult condition (flashed picture, low contrast, LSF, simulation of dusk or dawn, color suppression, large eccentricities) suggests that object representations underlying behavioral performance are very coarse (Boucart et al., 2016; Delorme, Richard, & Fabre-Thorpe, 2000; Lenoble, Bordaberry, Delord, Rougier, & Boucart, 2013; Macé, Thorpe, & Fabre-Thorpe, 2005; Vannucci, Viggiano, & Argenti, 2001, Levy et al., 2001). Other studies manipulated the spatial frequency content of pictures to explore whether a semantic category can be more easily identified on the basis of coarse information. Vannucci, Viggiano, and Argenti (2001) and Viggiano, Righi, and Galli (2006) showed that living objects can be categorized at a lower level of spatial frequency as compared with non-living items, which require finer levels of detailed analysis. The authors suggested that the advantage for living items was due to a more homogeneous configuration with a classical global shape including a body, legs, and head as compared with a non-living item. Moreover, the homogeneous configuration is readily available with a very brief presentation (e.g., 28 ms) of the picture, whereas the finer details require a longer duration of display to be detected (Bar, 2003). Shape and category representations are closely linked throughout the visual hierarchy, although their processing remains independent (Bracci et al., 2017). The evolution of global shape information from low-level pixels to high-level representation is related to a postero-anterior gradient comparable to the development of shape-to-category processing. To explore the issue further, some studies investigated the neural corelate of categorization processes.

For instance, recent studies have used linear discriminant analysis (LDA) or neural distance to bound analysis to predict reaction times of the observer in animacy categorization tasks based on neural distances measured with human functional MRI magnetoencephalography or electroencephalography (EEG) (Carlson, Ritchie, Kriegeskorte, Durvasula, & Ma, 2014; Carlson, Tovar, Alink, & Kriegeskorte, 2013; Grootswagers, Robinson, Shatek, & Carlson, 2019; Grootswagers, Wardle, & Carlson, 2017; Ritchie, Tovar, & Carlson, 2015). According to distance-to-bound models (Ashby & Maddox, 1994; Pike, 1973), evidence close to a decision boundary is more equivocal, reflecting higher difficulty in categorization, whereas evidence far from the decision boundary is less equivocal with regard to a specific semantic category. Thus, objects that are quickly categorized should be represented at a neural level farther from the classifier decision boundary (Ritchie & Carlson, 2016). In addition, results from Grootswagers et al. (2017) revealed that visual degradation of stimuli could differentially affect object classification with a systematic shift toward the classifier decision boundary for animate but not inanimate objects. However, to date, none of the studies using a classifier with multivariate patter analysis (MVPA) have used LSF flashed stimuli to assess the hypothesis of an advantage for animal picture categorization based on global shape as compared with non-living items.

1.3. Overview of the current paradigm

The present study sought to investigate the contribution of LSF in the rapid object representation of living versus non-living items. Because of their specific global shape structural similarity, living items may be dissociated faster in the brain (EEG recordings) and with better behavioral performance than non-living items particularly under conditions isolating the coarse information of the picture (LSF) with briefly flashed stimuli (28 ms). To assess our hypothesis, in addition to behavioral measures, we used a data-driven approach based on naïve Bayes implementation of LDA (Duda, Hart, & Stork, 2001) for a single trial classification. We used a multivariate pattern analysis (MVPA), which trained a classifier to discriminate a response pattern elicited by stimulus categories before testing it on each point of the time series. Given that we wanted to specify whether and when LSF/HSF information changed object processing, we computed a decoding performance between non-filtered and LSF pictures for each object category separately. A similar procedure was used to compute a decoding performance between animal and furniture categories for each presentation condition (non-filtered and LSF) separately. Homogeneous configuration of living pictures allows for categorization based on global shape under a very brief presentation. As a consequence, we expected a difference in temporal pattern of classification between non-filtered and LSF pictures for animals only. Indeed, the object degradation with the brief display and low pass filter for non-living objects will increase the difficulty to perceive subtle picture details most present in this specific category and will probably induce a higher variability in the results.

2. Methods

2.1. *Participants*

Seventeen volunteers were recruited; three were discarded because of loss of EEG signals during the recording. A total of 14 young healthy participants (mean age 22.1± 3.1 years, range 18 to 35 years; 8 females) participated in the experiment. All were right-handed according to the Edinburgh Handedness Inventory (Oldfield, 1971) and reported normal or corrected-to-normal vision. None reported any sensory, motor or neurologic deficits. They provided written informed consent and were all naïve to the purpose of the experiment. The experiment was conducted in accordance with the Declaration of Helsinki. The methods and procedure of the study were evaluated and approved by the ethical committee of Lille University (no. 2016-4-S46) before recruiting the participants.

2.2. Stimuli and apparatus

Stimuli consisted of grayscale photographs of 400 different objects without a background: 100 images of animals, 100 images of furniture, 100 images of tools and 100 images of vegetables. Images were downloaded from the Internet and their resolution was 512 x 512 pixels covering 5° of visual angle at a viewing distance of 57 cm. The images had similar mean size and mean luminance. The mean relative luminance was at 30.08 cd/m^2 per pixel (SD = 1.45) and mean Michelson contrast at 55% (SD = 0.8%). There was no difference between contrast categories ($F_{3,297}$= 2.48, p=0.061).

Two versions were built for each picture: non-filtered versus low pass filtered (LSF condition). In the non-filtered condition, pictures were presented without any spatial filtering. In the LSF condition, pictures were built by multiplying the Fourier transform of the non-filtered condition with Gaussian filters. We removed the spatial frequency content above 3 cycles per degree of visual angle (Figure 1). We used the Feature Similarity Index (FSIM) algorithm (Zhang et al., 2011) to measure the perceptual similarity between filtered and non-filtered pictures. In particular, an index of perceptual similarity was assessed for each object category. FSIM scores revealed that the filter procedure differentially affected the quality of pictures as a function of object category. Similarity computed between filtered and non-filtered pictures was higher for the animal than furniture category ($t_{198} = 3.83$, $p < 0.001$).

Pictures were presented on a 27" computer screen (1920 x 1080 pixels, sampling rate: 75 Hz). Responses were recorded with the keyboard. The sequence of images displayed, response recording and interface with EEG recording were controlled by custom software using Matlab (Psychotoolbox, Brainard, 1997; Kleiner, Brainard, & Pelli, 2007).

2.3. Procedure

After giving written consent, participants were comfortably seated at 57 cm from the computer screen. Participants had to perform two different blocks of a go/nogo task. They were instructed to respond as fast as possible each time the target category appeared on the screen. Responses were given by a key press with the right hand on the space bar of the keyboard.

A trial started with a black fixation cross displayed for 500 ms, followed by an object picture (a target or a distractor) centrally displayed for 28 ms. After image presentation, the black fixation cross re-appeared during the inter-trial interval lasting 2000 ms (Figure 1). In the first block, participants had to respond as fast as possible to target animals and to refrain from responding to vegetables and tools (distractors). The presentation of pictures of each object category was equiprobable. In each block, the filtered and non-filtered versions of each picture were randomly and equally represented.

In the second block, participants had to respond to pieces of furniture as targets with vegetables and tools as distractors. The block order was counterbalanced across participants. The experiment involved 1200 trials (2 blocks x 300 pictures [100 targets and 200 distractors] x 2 presentation conditions [non-filtered and LSF]). The experiment lasted about 50 min.

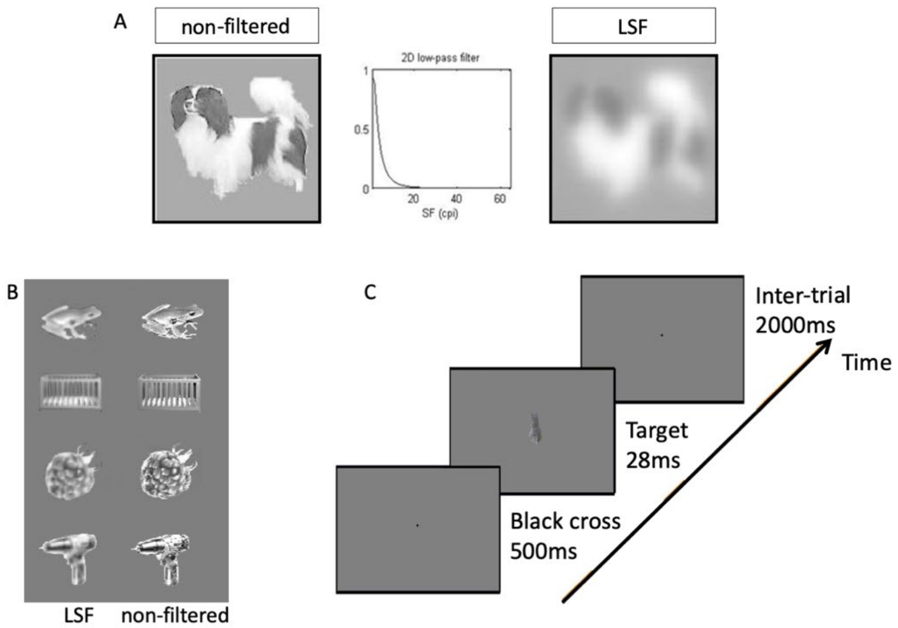

Figure 1: (A) An example of stimuli used (here, a dog) before and after spatial filtering, which removed the spatial frequency content above 3 cycles per degree of visual angle. (B) Examples of images used for each category (animal, piece of furniture, vegetable and tool) in the non-filtered and low spatial frequency (LSF) version. (C) The typical sequence of a trial.

2.4. Data recording and analysis

2.4.1. Behavioral data

We considered only performances on target trials for analysis. Response times (RTs) less than 200 ms and greater than 2000 ms (less than 1%) were excluded from the analyses. In accordance with the main goal of the study, we wanted to investigate whether LSF/HSF information differentially affected object classification of living and non-living items. With an *a priori* planned comparison, we studied whether the percentage of correct response (% CR) and mean RT for each object category (animal, furniture) differed as a function of presentation condition (non-filtered, LSF).

2.4.2. EEG recording and analysis

EEG data were continuously recorded at a sampling rate of 512 Hz by using ActiView software (http://www.biosemi.com). A total of 64 Ag/Agcl electrodes were mounted according to the 10-20 layout system to cover the participant's whole head with an equidistant layout. Electrode offset reflected the voltage difference between each electrode and the CMS-DRL reference. In addition, two electrodes were located at lateral canthi and below the eyes to monitor eye movements and blinks.

The continuous EEG signal was processed offline with EEGLAB 13.6.5b and Matlab 2014b (MathWorks, Natiek, MA, USA). First, the EEG signal was re-referenced based on the average reference after interpolation of noisy electrodes (Delorme & Makeig, 2004). Then, two successive Basic FIR filters were applied to the signal: a high-pass filter (order: 1691 points, transition band width: 1 Hz) followed by a low-pass filter (order: 227 points, transition band width: 7.5 Hz). A relatively restrictive high-pass filter of 1 Hz was constrained by the Independent Component Analysis (ICA) procedure used to correct for blink artefacts (see below). After the filtering procedure, the signal was inspected visually to remove periods still presenting excessive noise artefacts. Then, ICA-based artefact correction (running the ICA algorithm) was used to correct for blink artefacts (Delorme, Sejnowski, & Makeig, 2007). During this preprocessing, we interpolated a mean of 8.33 electrodes (range 5-12) and removed 1.53 ICA components (range 0-2).

EEG data analysis was performed on only target trials with a behavioral response. The EEG signals were segmented into periods of 1200 ms around the target onset (200 ms pre-stimulus and 1000 ms post-stimulus), and event-related potentials (ERPs) were built using the activity -200 to 0 ms as baseline. Muscular contractions or excessive deflection near the stimulus presentation were detected and resulted in an epoch exclusion (total exclusion mean 31%, SD = 10%, at least 48 trials per condition). Finally, to increase the spatial and temporal resolution of the signal, a Laplacian filter was used (Perrin, Pernier, Bertrand, & Echallier, 1989). This method was implemented in custom Matlab code, with the order of the spline used set to 20 and the smoothing constant set to 10-5 (λ parameter).

Then, we used a data-driven approach based on naïve Bayes implementation of LDA (Duda, Hart & Stork, 2001) for a single trial classification. Thus, after signal pre-processing, ERP data were downsampled to 100 Hz and submitted to an LDA classifier (Carlson et al., 2013). This approach allowed us to train a classifier to discriminate a response pattern elicited by a stimulus condition before testing it on each point of the time series. Generalization of the classifier performance was evaluated by using 10-fold cross-validation (ratio 9 folds of training to 1 test). For instance, individual data (trials) were randomly divided into 10 subsets. Nine of these subsets were used to train the classifier and one was used to test it. This procedure was repeated 10 times such that each subset was tested once. For each participant, we computed the classification accuracy as the average decoding accuracy across trials on a sliding window of three successive points (30 ms). Given that we wanted to specify whether and when LSF/HSF information changed object processing, two types of analyses were carried out in parallel. First, we computed a classification accuracy between non-filtered and LSF pictures for each object category separately. Second, we computed a classification accuracy between animal and furniture categories for each presentation condition (non-filtered and LSF) separately. Classification accuracy was compared to the theoretical chance level (50%) with Wilcoxon tests at each time point. The p value was corrected for multiple comparisons with the false discovery rate proposed by Benjamini & Hochberg (1995). Finally, to assess the ties between neural and behavioral data collected in the experiment, we conducted correlation analyses between classification accuracy based on EEG signal, behavioral performance and/or stimulus properties. The first issue was to understand whether the similarity measured by FSIM between filtered and non-filtered stimuli could explain the difference in RT. For each stimulus category, we correlated the FSIM score (comparison between filtered and non-filtered stimuli) with the average RT difference ($RT_{\text{filtered stimuli}} - RT_{\text{non-filtered stimuli}}$) at the item level. In addition, we investigated whether the advantage observed at the neurophysiological level for a condition could translate into a difference in RT. For each condition of interest (object category, condition of presentation), we identified at the individual level the latency of the classification accuracy peak in a 300-ms time window centered on the maximum observed at the group level. Then, we correlated the difference in latency for the maximal classification accuracy identified at the individual level with the corresponding RT difference. For instance, at the behavioral level, we computed the advantage for animal pictures by subtracting the individual mean RT in the animal condition from the mean RT in the furniture condition. Such advantage was then correlated with the advantage for animal pictures observed at the neurophysiological level. It was assessed by the difference in timing for the maximal classification accuracy for furniture pictures minus the timing for animal pictures. The exact same procedure was used to quantify the advantage for non-filtered presentation type versus LSF pictures. Individual/item outliers were removed from the correlation analysis when the value was below or above 2 SD. Given that data normality was not achieved, only Spearman correlation analysis was used.

3. Results

3.1. Behavioral data

The performance (RT and accuracy) under the LSF condition decreased for furniture only (planned comparison between LSF and non-filtered presentation: +13 ms, $F_{1,13}= 11.77$, $p<0.01$, and -2.4% CR, $F_{1,13}= 7.48$, $p<0.05$; see Figure 2). In comparison, the decrease in performance associated with picture filtering did not reach statistical significance for animals (-2 ms, $F_{1,13}= 0.28$, $p=0.60$, and -0.02% CR, $F_{1,13}= 0.15$, $p=0.70$). This difference in pattern of results as a function of object category was revealed by the interaction between object category and condition of presentation on ANOVAs performed on RT ($F_{1,13} = 8.13$, $p<0.05$) and accuracy ($F_{1,13} = 4.54$, $p=0.052$).

Otherwise, ANOVA revealed a main effect of object category: participants were faster to discriminate animals than pieces of furniture (457 ms vs 514 ms; $F_{1,13} = 28.11$, $p<0.001$). We found no main effect of object category on accuracy ($F_{1,13} = 2.52$, $p=0.13$). The main effect of condition of presentation (non-filtered or low pass filtered) was significant for accuracy and RT ($F_{1,13} = 6.4$, $p<0.05$ and $F_{1,13} = 6.82$, $p<0.05$, respectively). Participants were faster and more accurate in discriminating non-filtered than low pass filtered pictures (483 ms, 96.9% CR vs 489 ms, 95.5% CR).

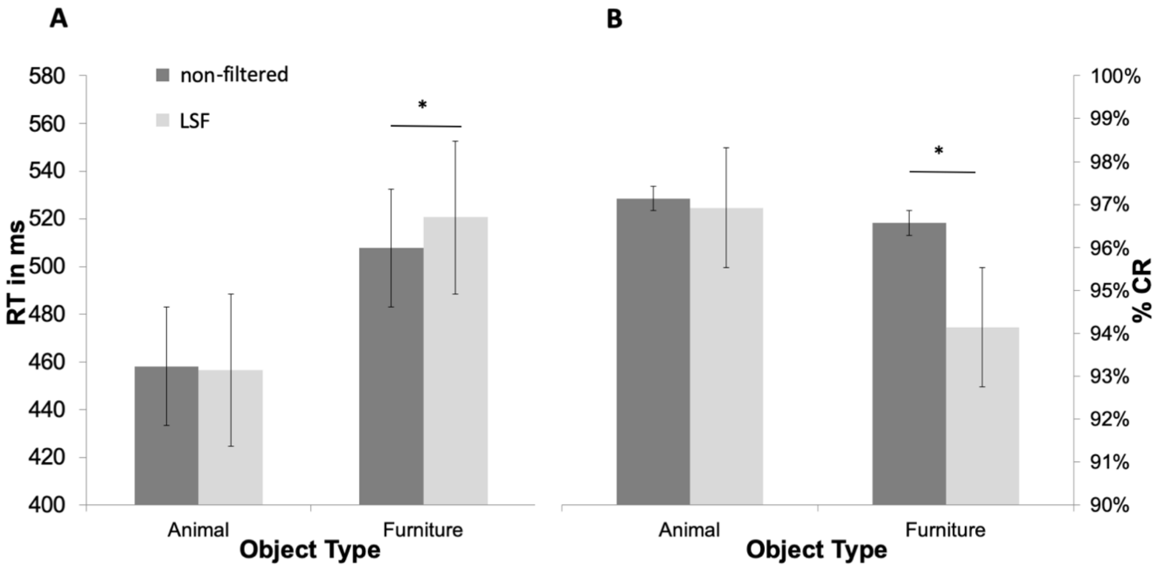

Figure 2: A) Mean response time (RT; left y axis) for non-filtered pictures and low spatial frequency (LSF) pictures as a function of object category (animals or furniture). B) Mean percentage of correct response (% CR; right y axis) for non-filtered and LSF pictures as a function of object category (animals or furniture). Stars indicate significant differences

(planned comparison by contrast, P<0.05) as compared with the chance level (50%). Bars refer to standard deviation.

3.2. EEG data

3.2.1. Classification accuracy between non-filtered and LSF pictures for each object category

The LDA classifier did not correctly classify non-filtered and LSF pictures when the furniture category was presented (Figure 3). By contrast, for the animal category, the classification accuracy reached significance between 130-150 ms, which suggests that ERPs differed between non-filtered and LSF pictures.

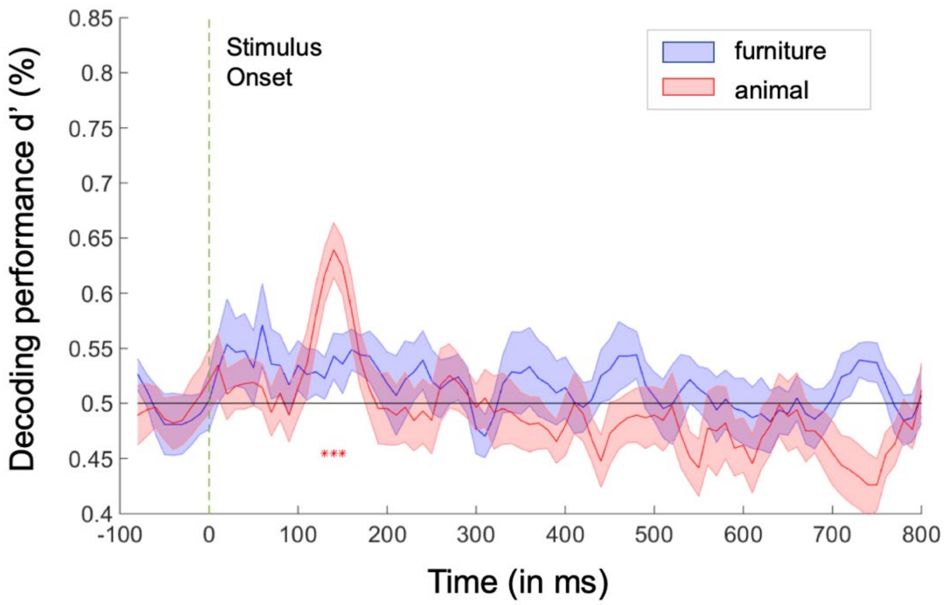

Figure 3: Evolution of classification accuracy between non-filtered and LSF pictures across time as a function of object category considered (animals in red and furniture in blue). At each time point, the graph shows the mean classifier accuracy over participants at the window (t-30 msec, t). Shaded areas show standard error between participants. Stars indicate significant differences (P<0.05) as compared with the chance level (50%).

3.2.2. Classification accuracy between object categories for non-filtered and LSF pictures

The LDA classifier correctly classified animal and furniture pictures for both the LSF and non-filtered conditions (Figure 4). However, the classification accuracy reached significance earlier with non-filtered than LSF stimuli (130 vs 160 ms). This delay suggests that the ERP difference between animal and furniture pictures appeared later under the LSF than non-filtered condition. Also, the decoding performance reached significance in a shorter time window (until 570 ms).

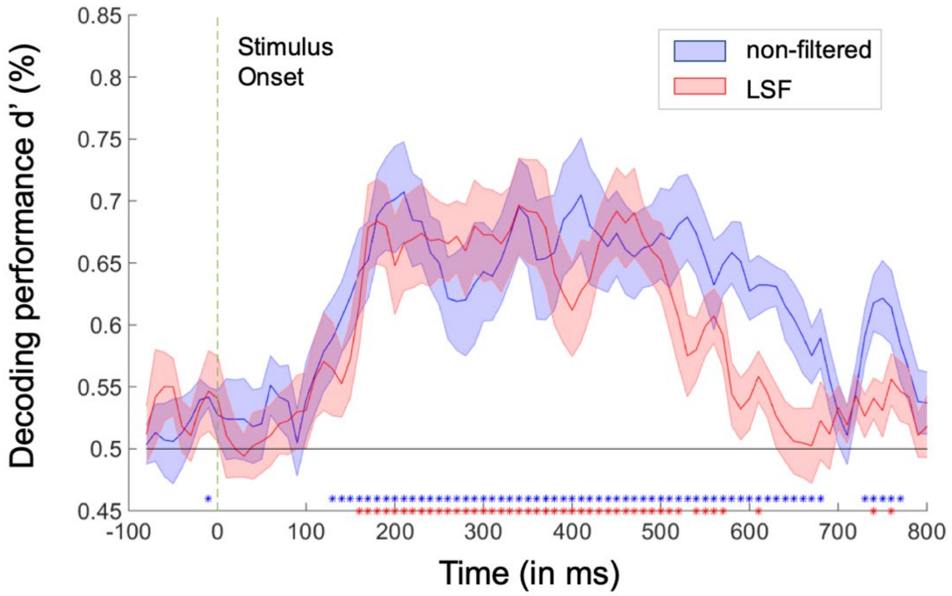

Figure 4: Evolution of classification accuracy between object categories (animal vs furniture pictures) across time as a function of condition of presentation (LSF in red and non-filtered in blue). At each time point, the graph shows the mean classifier accuracy over participants at the window (t-30 msec, t). Shaded areas show standard error between participants. Blue/red stars indicate respective significant differences (P<0.05) as compared with the chance level (50%).

3.3. Correlation analysis between neurophysiological and behavioral measurements

The Spearman correlation analyses of picture similarity (measured by FSIM) and difference in RT between the LSF and non-filtered conditions did not reveal any significant correlation for animals (*rho* = .02, *p* =.86) or furniture (*rho* = -.07, *p* =.46). At the item level, picture alteration due to the removal of HSFs did not indicate a systematic increase in RT.

On considering the advantage for animal categorization observed at both the neurophysiological and behavioral levels, Spearman correlation did not reveal a significant correlation between the difference in RT and the difference in latency in maximal classification accuracy computed at the individual level (*rho* = -.50, *p* =.083).

By contrast, on considering the advantage for the non-filtered condition of presentation at both the neurophysiological and behavioral levels, Spearman correlation revealed a significant positive relation between the difference in RT and the difference in latency in maximal decoding performance computed at the individual level (*rho* = .68, *p* <.05). This result suggests that the later the peak of decoding performance, the longer the RT.

4. Discussion

The aim of the present study was to investigate whether similar perceptual processes (described by the coarse-to-fine model) were at stake during categorization of different object categories. Especially, we wanted to specify the neural dynamic of the contribution of LSF in the rapid object representation of living versus non-living categories. To specify this temporal dynamic, we used an EEG experiment in which participants had to classify objects displaying different spatial frequencies (LSF or non-filtered pictures).

Behavioral data revealed that the decrease in performance for LSF versus non-filtered pictures was confined to pieces of furniture. These behavioral results were associated with a series of neurophysiological observations analyzed via an LDA classifier (Duda, Hart & Stork, 2001) and constituted the key finding of the present paper. First, we observed that the LDA classifier failed to correctly perform the LSF/non-filtered classification for pieces of furniture only, which corroborated the special status of non-living versus living pictures for the rapid categorization task. In addition, even if the classifier managed to correctly classify animal and furniture pictures for both the LSF and non-filtered conditions, the decoding performance reached statistical significance earlier for non-filtered than LSF stimuli (130 vs 160 ms). This delay suggests that the EEG difference between animals and furniture appeared later under the LSF than the non-filtered condition. Finally, correlation analysis of RT and classifier performance suggested that the later the difference between conditions appeared, the longer the RT was.

At the behavioral level, results agree with previous findings (Boucart et al., 2016; Lenoble et al., 2013; Macé et al., 2005; Vannucci et al., 2001). First, we confirmed that humans perceive objects differently as a function of category. We found that performance in discrimination was better (shorter RT) for living than non-living objects. Such advantage for living objects was already reported for different categories such as faces (Collin, 2006; Flevaris, Robertson, & Bentin, 2008; Gold, Bennett, & Sekuler, 1999) or animals (Vannucci et al., 2001). Proverbio et al. (2007) provided evidence of differential RT and specific brain activation (on ERPs) during visual categorization of items belonging to animal and manufactured categories. In addition to the category effect, we also found that categorization performance was decreased for LSF pictures (longer RT and lower accuracy than non-filtered pictures). Here again, this result is consistent with previous observations (Lenoble et al., 2013; Macé et al., 2005; Vannucci et al., 2001) and indicates that the lack of HSF in a picture alters that quality of the visual discrimination. Nevertheless, the magnitude of this alteration (the spatial-frequency effect) was limited to a spatial filter at 3 cycles per degree on the pictures. Indeed, discrimination in our paradigm was still possible despite the absence of HSF information (e.g., outline, contours). Finally, we also replicated the spatial frequency effect (i.e., altered performance for LSF pictures), but it was observed only for the pieces of furniture category (Vannucci et al., 2001). The results showed a deficit of +13 ms and -2.4% CR for LSF pieces of furniture, with no similar impact observed for animals (+2 ms and -0.02% CR). Animal/distractor discrimination seemed easier than pieces of furniture/distractor discrimination because of greater difference in global object shape. Thus, in our specific condition for living items, participants can likely perform the categorization on the basis of LSF only. The selective spatial-frequency effect observed for pieces of furniture could be a result of the use of HSF by the human brain to discriminate objects in that specific category. These effects were obtained while several strict procedures were applied to match the categories of pictures used in terms of low-level features such as contrast and luminance. Nevertheless, the selective spatial-frequency effect for pieces of furniture could be explained by the categorization of these objects needing deeper perceptual process than living items on HSF to identify fine details. In contrast, the need for HSF was not required to categorize living objects (such as animals) for which perception of global shape seemed sufficient. On considering our correlation analysis between RT and picture similarity measured by FSIM, we found no difference in RT between LSF and non-filtered pictures for animals or furniture. In other words, FSIM analysis showed that the physical similarity between filtered and non-filtered pictures cannot give an advantage on RT for any particular semantic category. The FSIM analysis was based on graphical properties of the pictures and did not reflect the brain processing for a specific category such as living items. However, studies with neurophysiological recordings demonstrated the specific category processing in brain for living items (Proverbio et al. 2007; Costanzo et al. 2013). Our entire behavioral and neurophysiological analyses support the hypothesis that our brain is able to detect the change led by the filtering of the pictures (with the processing of coarse information), whereas differences in low level features are subtle.

Neurophysiological correlates of these effects were assessed by an MVPA decoding approach (Carlson et al., 2013; Grootswagers et al., 2017; Petras, ten Oever, Jacobs, & Goffaux, 2019). The rationale behind the analyses rests on the following idea. If the supervised classifier has been able to correctly categorize ERP signals across stimulus categories, then the neurophysiological response (and so, the associate processes) differed in the specific time window.

First, classifier results revealed that neurophysiological responses to the animal pictures category differed as function of HSF presence between 130 and 150 ms after stimulus presentation. Such results suggest that the HSF information was processed as early as 130 ms during the fast object categorization task. The 130- to 170-ms time window effect could rely on visual picture processing. The temporality of the observed effect was compatible with P1 or N2 components that are typically considered a marker of the sensory and perceptual processes (Martinovic, Gruber, & Müller, 2008; Schendan & Kutas, 2003, 2007). This finding indicates that, despite our caution to match picture categories on low-level visual features, LSF and non-filtered pictures were processed differentially as early as 130 ms. This observation suggests that HSFs were integrated to visual processing on this specific time window (Petras et al., 2019), whereas LSFs were likely processed earlier according to the coarse-to-fine model (Bar, 2003). However, we observed that in comparison to animal pictures, for pieces of furniture, the LDA classifier failed to correctly perform the LSF/non-filtered classification, which suggests that the HSF presence did not induce a different neurophysiological response for non-living objects. These results were a priori counter-intuitive with the selective impact of HSF removal in categorization performance for non-living objects, observed at the behavioral level (Vannucci et al., 2001). Some may argue that this pattern of result could reveal some low-level differences between picture categories. For instance, LSF and non-filtered pictures could be more or less similar in a given category and induce a different level of difficulty in the categorization task. Nevertheless, even if we effectively observed a different impact of the filtering procedure for each category, FSIM computation seemed to indicate that the animal category is more similar between LSF and non-filtered pictures than the furniture category. The failure to classify LSF and non-filtered pictures for pieces of furniture seemed not to be explained by low-level similarity features but probably by a lower ability in the brain to discriminate the LSF filtering of a picture for non-living objects versus living items. In fact, the procedure used and especially the exposure time could explain the absence of effect for non-living objects. Indeed, pictures were flashed during only 28 ms, which likely induced a coarse processing that presented a disadvantage for non-living items that will require longer exposure to integrate finer details. Why the classification performance differs depending on the picture image remains to be investigated in more detail in future experiments. Also, these future experiments should focus on understanding why the classification performance is so low (65%, although significant) and appears in a transient time window (130-150 ms).

Second, the classifier analysis also revealed that EEG differed as a function of the picture category as early as 130 ms, which suggests that neurophysiological responses differed between animals and pieces of furniture from this moment. Of note, a similar classification performed on LSF pictures revealed a similar pattern of result with a clear correct classification performance. However, the classification performance overtakes that chance level later (170 ms) and during a shorter time window (up to 570 ms as compared with 700 ms for non-filtered pictures). These results agree with previous observations with a similar protocol using classifiers on neurophysiological signal (Grootswagers et al., 2017; Isik et al., 2014). The authors found that classification between animate and non-animate pictures started before 100 ms in the clear condition and was delayed when stimuli were degraded. However, we did not observe a similar dynamic in classification performance. Indeed, the previous authors found an early peak in classification at 100 ms in the clear condition, which suggested that low-level visual information could allow for discriminating between stimuli categories. In our implementation, classification performance started to significantly differ from chance at about 130 ms after stimulus presentation with a maximal classification performance at 200 ms. Reasons for this discrepancy probably rely to stimuli composition, time exposure and the fact that our categorization task is not similar to previous experiments in this literacy (living/non-living in separate blocks vs. animate/non-animate). Altogether, the delay to start to correctly classify living and non-living objects in the degraded condition (or LSF condition) revealed an advantage for the non-filtered condition of presentation and support an early integration of HSF information (about 130 ms).

To conclude, the present study replicates previous studies and allows us to understand how living and non-living pictures are visually categorized. In addition to the advantage in categorizing living versus non-living objects, performance was decreased with LSF pictures of pieces of furniture. This finding suggests a higher HSF dependence in the classification process for non-living versus living objects. This evidence is supported by neurophysiological correlates allowing us to specify the temporal dynamic of categorization. Performance in classification revealed that HSF information was processed as early as 130 ms. Moreover, despite differences in classification performance between LSF and non-filtered pictures for living items, the behavioral performance was maintained, which suggests that categorization under our specific condition can be based on LSF information, in particular for living items.

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