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Neural correlates of the food/non-food visual distinction

Kleovoulos Tsourides[a,*], Shahriar Shariat[b], Hossein Nejati[a,d], Tapan K. Gandhi[e], Annie Cardinaux[a], Christopher T. Simons[c], Ngai-Man Cheung[d], Vladimir Pavlovic[b], Pawan Sinha[a]

[a] Massachusetts Institute of Technology, Cambridge, MA 02139, United States
[b] Rutgers State University of New Jersey, Piscataway, NJ 08854, United States
[c] Ohio State University, Columbus, OH 43218, United States
[d] Singapore University of Technology and Design, Singapore 138682, Singapore
[e] Indian Institute of Technology, Delhi, New Delhi 110016, India

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ABSTRACT

An evolutionarily ancient skill we possess is the ability to distinguish between food and non-food. Our goal here is to identify the neural correlates of visually driven 'edible–inedible' perceptual distinction. We also investigate correlates of the finer-grained likability assessment. Our stimuli depicted food or non-food items with sub-classes of appealing or unappealing exemplars. Using data-classification techniques drawn from machine-learning, as well as evoked-response analyses, we sought to determine whether these four classes of stimuli could be distinguished based on the patterns of brain activity they elicited. Subjects viewed 200 images while in a MEG scanner. Our analyses yielded two successes and a surprising failure. The food/non-food distinction had a robust neural counterpart and emerged as early as 85 ms post-stimulus onset. The likable/non-likable distinction too was evident in the neural signals when food and non-food stimuli were grouped together, or when only the non-food stimuli were included in the analyses. However, we were unable to identify any neural correlates of this distinction when limiting the analyses only to food stimuli. Taken together, these positive and negative results further our understanding of the substrates of a set of ecologically important judgments and have clinical implications for conditions like eating-disorders and anhedonia.

1. Background and significance

The ability to visually distinguish between food and non-food is critical for our survival. Disruption of this ability, as in cases of pica, an eating disorder characterized by persistent ingestion of nonnutritive substances (Fig. 1a), can have catastrophic consequences (Francois & Brenet, 2004). On a finer grain, we are also able to make rapid hedonic judgments about food. Given the ecological significance of these distinctions, identifying their neural correlates can yield important benefits. The spatial localization and time course of emergence of these distinctions in brain recordings can provide insights into the underlying processes involved in making the perceptual judgments (Thorpe, Fize, & Marlot, 1996), and also serve as biomarkers for neurological conditions involving anomalous responses to foods and non-foods.

Food selection is guided primarily by the visual, olfactory and taste systems. Past visual studies of hedonic perception in the context of food have focused largely on the relationship between a food's caloric content and its perceived palatability. Palatability is found to be a useful cue for separating foods with high and low caloric contents, and also edible from non-edible items (Ohla, Toepel, le Coutre, & Hudry, 2012). Additional neuro-imaging studies have focused on the neural correlates in visual processing of food images within the context of rare syndromes such as Prader–Willi (Key & Dykens, 2008), anorexia and bulimia (Blechert, Feige, Joos, Zeeck, & Tuschen-Caffier, 2011). More broadly, several studies have examined the neural correlates of aesthetic and affective preferences, but the stimuli they have used do not typically involve the food versus non-food distinction (Amrhein, Mühlberger, Pauli, & Wiedemann, 2004; Jacobs, Renken, & Cornelissen, 2012; Kawabata & Zeki, 2004; Olofsson, Nordin, Sequeira, & Polich, 2008; Osaka, Ikeda, Rentschler, & Osaka, 2007; Schupp, Junghöfer, Weike, & Hamm, 2004) and hence cannot be used to infer the neural correlates of this specific distinction. FMRI studies as in (Van der

* Corresponding author.
E-mail address: tsourk@mit.edu (K. Tsourides).

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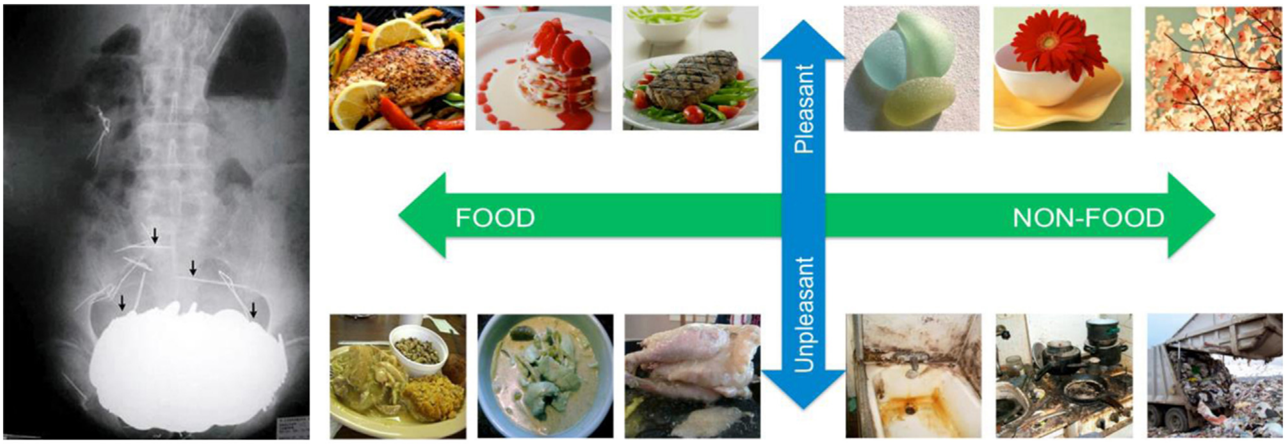

(a) (b)

Fig. 1. (a) X-ray of a 62 year old French man suffering from pica. The patient had ingested over 350 coins, needles and necklaces from (Francois & Brenet, 2004). (b) Sample stimuli used in our experiment. The top row shows food stimuli with the left panel comprising images that were rated as being more palatable relative to those on the right. The lower row shows a few non-food stimuli segregated into pleasant (left) and unpleasant (right) subclasses.

Laan, de Ridder, Viergever, & Smeets, 2011) focus on satiety and its modulation. To the best of our knowledge, no electrophysiological studies thus far have compared the classes of food and non-food imagery while controlling for affective dimensions. Additionally, there appear to be no studies that focus on food images without a confound of calorie and palatability contents or attentional bias (Bradley et al., 2003; Gable & Harmon-Jones, 2008, 2010; Harmon-Jones, Gable, & Price, 2011). Given this background, no firm consensus has emerged regarding the neural markers corresponding to the perceptual distinction between pictures of foods and non-foods.

Our goal in this study is to employ computationally sophisticated pattern classification techniques to identify such correlates. A key question for us is whether our visual system exhibits responses to food stimuli that are different from non-food ones regardless of the level of pleasantness or affective valence.

Furthermore, we examine whether the neural response differences across stimulus categories can be accounted for simply via systematic variations in low-level properties of an image such as color distributions and textural statistics.

Past research on neural correlates of visual categorization has focused on identifying components in electrophysiological data (EEG or MEG) corresponding to object classes such as faces (Bentin, Allison, Puce, Perez, & McCarthy, 1996). These studies serve to contextualize our work and the methods we use. Specifically, although the correlates of the face/non-face distinction are generally accepted (although not without dissent, see Thierry, Martin, Downing, & Pegna, 2007), subtler perceptual distinctions (such as gender, age, familiarity) have been harder to identify in neural data. We believe that part of this difficulty may arise from the limitations of conventional data-analysis techniques. In particular, the evoked response field (ERF) type of analysis, which requires averaging of multiple temporally aligned signal fragments from one or a few sensors, is not well suited to picking up on distributed patterns of neural activity that may correspond to a perceptual judgment. A more 'agnostic' data classification approach drawn from the domain of machine learning may be better suited for this purpose. The dimension of like/dislike has also been examined by a few neuroimaging studies. For instance, Healey, Morgan, Musselman, Olino, and Forbes (2014), have implicated activity in medial pre-frontal cortex in anhedonia in the social context. We have the opportunity to build on these results in two significant ways. First, we can explore the like/dislike dimension in a non-social setting and, second, through the use of electrophysiological recordings, we can obtain more precise temporal information about the onset of the neural distinction.

We used magneto-encephalography (MEG) to record brain activity elicited in response to two categories of visual stimuli: images depicting foods and non-foods. Each of these categories was further subdivided into two equal-sized classes, differing in their hedonic valence (positive and negative). Fig. 1 shows examples of the stimuli we used. We recorded brain activity from 306 sensors distributed across the scalp while subjects passively viewed all 200 of these stimuli in random order. These continuous traces were subsequently segmented into 1 s epochs, temporally aligned to the onset of each stimulus. The collection of these segmented traces was then subjected to pattern classification analyses using techniques drawn from the domain of machine learning, as well as to conventional evoked response field (ERF) analyses common in the EEG domain (Niedermeyer & Silva, 2004; Vecchiato et al., 2011).

Our pattern classification analyses used sparse logistic regression to classify raw MEG signals corresponding to the different image categories. The classifier was provided the first 1000 ms of all magnetometer signals, without any ad-hoc sensor selection. In order to determine information available for classification in different time epochs, we used a 10 ms sliding window over the signals, shifting this window 1 ms at a time. Our classifier therefore receives 10 ms worth of data from all sensors in each step. Furthermore, motivated by the use of resting state signals for reducing the signal noise, we used the first 100 ms baseline (the resting state and before the start of the trigger) as an additional source of training for the classifier, resulting in improvements in classification performance. Details of our classification approach are described in Section 2.

2. Methods

2.1. Stimuli

Full-color images were chosen by 20 volunteers from multiple image repositories and culinary websites. The volunteers rated each image in terms of its hedonic valence. 50 images in each of the four classes (food: appetitive, food: non-appetitive, non-food: pleasant, non-food: unpleasant) that received high or low scores most consistently across the raters were then used to constitute the final stimulus set. Images were processed to all have the same mean luminance and size. Descriptions of all of the images we used are provided in Supplementary material (Although they were not available when we commenced our study, it is worth pointing out that