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A method for real-time visual stimulus selection in the study of cortical object perception

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ABSTRACT

The properties utilized by visual object perception in the mid- and high-level ventral visual pathway are poorly 18 understood. To better establish and explore possible models of these properties, we adopt a data-driven approach 19 in which we repeatedly interrogate neural units using functional Magnetic Resonance Imaging (fMRI) to estab- 20 lish each unit's image selectivity. This approach to imaging necessitates a search through a broad space of stim- 21 ulus properties using a limited number of samples. To more quickly identify the complex visual features 22 underlying human cortical object perception, we implemented a new functional magnetic resonance imaging 23 protocol in which visual stimuli are selected in real-time based on BOLD responses to recently shown images. 24 Two variations of this protocol were developed, one relying on natural object stimuli and a second based on 25 synthetic object stimuli, both embedded in feature spaces based on the complex visual properties of the objects. 26 During fMRI scanning, we continuously controlled stimulus selection in the context of a real-time search through 27 these image spaces in order to maximize neural responses across pre-determined 1 cm³ rain regions. Elsewhere 28 we have reported the patterns of cortical selectivity revealed by this approach (Leeds et al., 2014). In contrast, Q4 here our objective is to present more detailed methods and explore the technical and biological factors influenc- 30 ing the behavior of our real-time stimulus search. We observe that: 1) Searches converged more reliably when 31 exploring a more precisely parameterized space of synthetic objects; 2) real-time estimation of cortical responses 32 to stimuli is reasonably consistent; 3) search behavior was acceptably robust to delays in stimulus displays and 33 subject motion effects. Overall, our results indicate that real-time fMRI methods may provide a valuable platform 34for continuing study of localized neural selectivity, both for visual object representation and beyond. 35 © 2016 Elsevier Inc. All rights reserved. 36

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Q5 Introduction

How do humans visually recognize objects? Broadly speaking, it is 48 held that the primate ventral occipito-temporal pathway of the 49human brain implements a feedforward architecture in which the 50features of representation progressively increase in complexity as infor-5152mation moves up the hierarchy (Felleman and Essen, 1991; Riesenhuber and Poggio, 1999). In almost all such models, the top layers of the hier-53archy are construed as high-level object representations that correspond 5455to and allow the assignment of category-level or semantic labels. Critically, there is also the presupposition that while early levels along 56 the pathway encode information about edge locations and orientations 5758(Hubel and Wiesel, 1968) and information about textures (Freeman 59et al., 2013), one or more levels, between what we think of as early

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http://dx.doi.org/10.1016/j.neuroimage.2016.02.071 1053-8119/© 2016 Elsevier Inc. All rights reserved. vision and high-level vision, encode *intermediate* visual features. Such 60 features, while less complex than entire objects, nonetheless capture 61 important – and possibly compositional – object-level visual properties 62 (Ullman et al., 2002). Remarkably, for all of the interest in biological 63 vision, the nature of these presumed intermediate features remains 64 frustratingly elusive. To help address this knowledge gap, we introduce 65 new methods that leverage human fMRI to explore the intermediate 66 properties encoded in regions of human visual cortex. 67

Any study investigating the visual properties employed in cortical 68 object perception faces multiple challenges. First, the number of 69 candidate properties present in real-world objects is large. Second, 70 these properties are carried by millions to billions of potential stimulus 71 images. Third, feature and image space can be parameterized by an 72 uncountable number of potential models. Fourth, the time available in 73 a given human fMRI experiment is limited. Scanning time for an individ-74 ual subject is limited to several hours across several days. Fifth, during a 75 given scan session, the slow evolution of the blood-flow dependent 76 fMRI signal necessarily limits the frequency of single stimulus display 77 trials to one every 8 to 10 s; more frequent displays produce an overlay 78 of hemodynamic responses difficult to recover without carefully tuned 79

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pre-processing or careful dissociation of temporally adjacent stimuli. 80 81 Moreover, even with these considerations, the neural data recovered will be noiser and less amenable to use on a trial-by-trial basis. As 82 83 such, assuming a minimum of 8 s to display each trial, at most several hundred stimuli can be displayed to a subject per an hour. 84

Here we suggest that dynamic stimulus selection, that is, choosing 85 new images to present based on a subject's neural responses to recently 86 87 shown images, enables a more effective investigation of visual feature 88 coding. Our methods build on the dynamic selection of stimuli in studies 89 of object vision in primate neurophysiology. For example Tanaka 90 (2003), explored the minimal visual stimulus sufficient to drive a 91given cortical neuron at a level equivalent to the complete object. He found that individual neurons in area TE were selective for a wide 9293 variety of simple patterns and that these patterns bore some resemblance to image features embedded within the objects initially used to 94 elicit a response. Tanaka hypothesized that this pattern-specific selectiv-95 ity has a columnar structure that maps out a high-dimensional feature 96 space for representing visual objects. In more recent neurophysiological 97 work Yamane et al. (2008) and Hung et al. (2012), used a search proce-98 dure somewhat different from Tanaka and a highly-constrained, param-99 eterized stimulus space to identify the contour selectivity of individual 100 neurons in primate IT. They found that most contour-selective neurons 101 102 in IT encoded a subset of the parameter space. Moreover, each 2D contour within this space mapped to specific 3D surface properties meaning 103 that collections of these contour-selective units would be sufficient to 104 capture the 3D appearance of an object or part. 105

At the same time, there has been recent interest in real-time human 106 107neuroimaging. For example Shibata et al. (2011), used neurofeedback from visual areas V1 and V2 to control the size of a circular stimulus 108 displayed to subjects and Ward et al. (2011) explored real-time 109mapping of the early visual field using Kalman filtering. Most recently 110 111 Sato et al. (2013), have developed a toolbox ("FRIEND") that imple-112 ments neural feedback applications in fMRI, applying classification and 113 connectivity analyses to study the encoding of emotion. These studies support the idea of incorporating real-time analysis and feedback into 114 neuroimaging work to expanding fields, such as the study of object 115 perception. 116

117 Here we explore new methods for the real-time analysis of fMRI data and the dynamic selection of stimuli. More specifically, our procedure 118 selects new images to display based on the neural responses to 119 previously-presented images as measured in pre-selected brain regions. 120121 Our overall objective is to maximize localized neural activity and to identify the associated complex featural selectivity within image spaces 122 123 that are organized on the basis of insights from earlier studies in object perception (Leeds et al., 2013; Williams and Simons, 2000). We employ 06 two sets of objects and their corresponding spaces - real-world objects 125126organized based on similarities computed by the SIFT computer vision method (Lowe, 2004) and synthetic "Fribble" objects (Williams 127and Simons, 2000) organized based on morphs in the shapes of their 128component appendages (see Fig. 5). 129

In previously published results, we reported the nature of the cor-130131tical selectivities uncovered by this novel approach (Leeds et al., 1322014). Here we study the technical and biological factors influencing the performance of our real-time stimulus search, as well as the be-133havior of our search across subjects and stimulus sets. In particular, 134using synthetic stimuli, we found that searches exhibited some 135136 convergence onto a small number of preferred visual features and consistency across repeated searches for a given brain region within 137 an individual subject. In contrast, using real-world object stimuli, 138 we found only weak convergence and consistency, possibly as a result 139of the visual diversity of the real-world stimuli included in this image 140 space. More generally, we observe that our methods are robust to 141 undesired actions from subjects (e.g., head motions) and program 142flaws (e.g., stimulus selection delays), suggesting that our methods 143 offer an important first-step in developing effective methods for 144 145 real-time human neuroimaging.

Material and methods

Stimulus selection method

Our study is unique in that it relies on the dynamic selection of 148 stimuli in a parameterized stimulus space, choosing new images to 149 display based on the BOLD responses to previous images within a 150 given pre-selected brain region. More specifically, we automatically 151 choose the next stimulus to be shown by considering a space of visual 152 properties and probing locations in this space (corresponding to stimuli 153 with particular visual properties) in order to efficiently identify those lo- 154 cations that are likely – based on prior neural responses to other stimuli 155 in this space - to elicit maximal activity from the brain region under 156 study. As discussed in the Defining SIFT space and Defining Fribble 157 space sections, we employed two somewhat different representational Q7 spaces, one based on SIFT features derived from real-world images, 159 and one based on synthetic "Fribble" objects (see Fig. 5). SIFT was 160 used for the first group of ten subjects, while Fribbles were used for 161 the second group of ten subjects. For both groups, each stimulus *i* that 162 could be displayed is assigned a point in space p_i based on its visual 163 properties. The measured response of a given brain region to this 164 stimulus r_i is understood as: 165

$$r_i = f(p_i) + \eta \ . \tag{1}$$

That is, a function f of the stimulus' visual properties as encoded by its location in the representational space plus a noise term η , drawn 168 from a zero-centered Gaussian distribution. The process of displaying 169 an image, recording the ensuing cortical activity via fMRI, and isolating 170 the response of the brain region of interest using the preprocessing 171 program we model as performing an evaluation under noise of the func- 172 tion describing the region's response. For simplicity's sake, we perform 173 stimulus selection assuming our chosen brain region has a selectivity 174 function f that reaches a maximum at a certain point in the representa- 175 tional space and falls off with increasing Euclidean distance from this 176 point. Our assumption is consistent with prior work in primate neuro- 177 physiology, such as Tanaka (2003), Hung et al. (2012), and Yamane 178 et al. (2008), in which stimuli were progressively adapted to maximize 179 response of a single neural unit to converge on the single (complex) 180 visual selectivity presumed to be associated with the unit. We also 181 note that our assumption is consistent with recent work in human 182 fMRI that finds that selectivity for object categories is organized in a 183 smooth gradient across cortex whereby the amount of neural "real 184 estate" apportioned to shared features across visually-similar categories 185 is minimized (Huth et al., 2012). Under these assumptions, we use a 186 modified version of the simplex simulated annealing Matlab code avail- 187 able from Donckels (2012), implementing the algorithm from Cardoso 188 et al. (1996). This method seeks to identify new points (corresponding 189 to stimuli) that evoke the highest responses from the selected cortical 190 region. An idealized example of what a search run might look like 191 based on this algorithm is shown in Fig. 1b. The results of our study 192 indicate our assumption of a single peak in cortical response is not 193 always accurate. Nonetheless, the simplex simulated annealing method 194 achieves convergence for several real-time stimulus searches. 195

For each of four distinct stimulus classes – mammals, human-forms, 196 cars, and containers for real-world objects and four classes distin- 197 guished by core body shape and appendage orientation for Fribble 198 objects (described further in the Interleaving searches section and in 199 Leeds et al. (2014)) – we performed searches in each of two scan 200 sessions. To probe the consistency of our search results across different 201 initial simplex settings, we began the search within each session at a 202 distinct point in the relevant stimulus representational space. In the 203 first session, the starting position was set to the origin for a given stim- 204 ulus class, as specific stimulus examplars were distributed in each space 205 relatively evenly around the origin. In the second scan session, the 206 starting position was manually selected to be in a location opposite 207

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