Task Demands and Stimulus Normalization in Face Perception: an fMRI Study

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Abstract:

Despite much research demonstrating face selectivity within a core set of brain regions, many questions remain regarding this putative network for face perception, including the role of task demands on processing. A recent study (Kaul et. al, 2014) demonstrated that decodability of face race in a fusiform face-selective area (FFA) was significant for fMRI activation patterns elicited during a team-discrimination task but not during a race-discrimination task. This suggests that cognitive task – specifically, the requirement for facial individuation – may play a significant role in the recruitment of FFA. We sought to replicate this research and extend its conclusions by 1) explicitly manipulating stimulus luminance histogram normalization, to determine whether race-decodability in a given region is attributable to low-level properties, 2) analyzing a range of visual cortical ROIs and applying searchlight analyses to examine face information and the influence of cognitive task in regions lying functionally "between" V1 and FFA, and 3) including a gender task to ask whether the influence of cognitive task applies to all simple, binary discriminations (male/female, black/white), or is instead specific to race discrimination. An initial sample (n=8) yields promising decoding of race and gender and paves the way for hypothesis testing with a full sample.

Keywords: functional Magnetic Resonance Imaging (fMRI), multivariate pattern analysis (MVPA), decoding.

Introduction

Face perception is thought to be underpinned by a core network of brain regions including early visual cortex, an occipital face-selective region (OFA), 1-2 fusiform face-selective regions (FFA), along with an extended network of regions in anterior temporal and frontal cortex. Recent evidence that face race can be decoded from BOLD activity patterns in FFA during a team-discrimination task but not a race-discrimination task (Kaul et. al, 2014) suggests that person-level identification may determine the recruitment of regions of the face perception network posterior to the occipital lobe. We also hypothesized that the presence of low-level stimulus properties that reliably indicate race (e.g., color, luminance) would modulate the recruitment of specific regions in the core network. Specifically, the presence or absence of low-level properties should make less difference to the race-decodability of evoked brain patterns in anterior regions such as FFA (thought to employ higher-level, holistic representations) and more difference to race-decodability in posterior regions such as V1. In V1, stimuli possessing low-level properties that indicate race should elicit brain patterns with greater race-decodability than stimuli that do not. Regarding the effect of cognitive task (race-, gender-, or team-discrimination) we hypothesized that it would affect the race-decodability of brain patterns in anterior regions such as FFA more than in posterior regions such as V1 (with the team-discrimination task producing greater race-decodability in FFA than the race or gender tasks). Further, we predicted that task effects for gender-decodability would mimic those for race-decodability, but that stimulus normalization would have little influence on gender-decoding.

Method

Eight individuals (to date) participated in a functional Magnetic Resonance Imaging (fMRI) study at UMass Amherst. Before the scan, participants underwent a short behavioral training in which they learned to assign 12 faces to one of two teams (3 men/women and 3 black/white per team). We trained participants until they assigned all 12 faces to the correct team twice in a row (~20-min, cf. 3-min of study time in Kaul et al. 2014).

The experiment consisted of 8 functional runs, a T1-weighted MPRAGE sequence, field mapping scan, 2 functional localizer scans and 0-2 retinotopic localizer scans. Each functional run consisted of 6 blocks: 3 discrimination task blocks (gender, race and team) crossed with 2 levels of stimulus normalization (non-normed, normed). Each task was presented once per run in pseudorandom order with no task block repeats. Stimulus normalization (full color un-normalized versus grayscale mean-luminance and luminance histogram normalized) alternated across blocks. Normalization was performed using the SHINE toolbox (Willenbockel et. al, 2010). Each block contained a pseudorandom sequence of the faces of 12 individuals, drawn from 2 images of each individual across which face orientation ‘or expression was modulated. Face images were taken from the FERET database (Philips et. al, 1998; 2000) and were cropped to remove hair, jewelry, and background. Stimuli were presented at a size of 6 deg.

The fLOC experimental code (Stigliani, Weiner, Grill-Spector, 2014) was used to map up to 3 face-selective regions per subject and hemisphere in occipital (OFA), posterior fusiform (pFFA) and mid-fusiform (FFA) areas. ROIs were combined across hemispheres, and “FFA-all” was defined by combining both fusiform face-selective regions. Retinotopic regions were defined using a recent V1-V3 atlas (Benson et. al, 2014). Additionally, OFA, FFA, and (in left-hemisphere) aIT were mapped in the group space for visualization.

To perform decoding analyses, we constructed multiple General Linear Models (GLMs) to extract beta-weights. For each variable we sought to decode (gender, race), we constructed three GLMs in which stimulus assignment was split by the decoding variable (black/white, male/female) and neither, one, or the other of {stimulus normalization, behavioral task}. This allowed us to examine decoding performance irrespective of task and stimulus normalization, or as a function of either stimulus normalization or behavioral task. Leave-one-run-out cross-validation resulted in a mean classification score per condition per subject.

Searchlights were carried out in native volumetric space with 100 voxel spheres under a cortical mask. Resulting volumetric maps were intersected with the mid-cortical thickness using Freesurfer to acquire subject-specific surface maps. These maps were then converted to *fsaverage*, smoothed with a 6mm FWHM kernel, and averaged to produce the group maps.

Results

Group means ± 95% confidence intervals for ROI decoding analyses of 8 subjects are shown in Figures 1-3. All statistical tests were performed on logit-transformed classification accuracies (not shown).

Figure 1 shows decoding of race and gender in several ROIs. T-tests comparing accuracy to chance (FDR-corrected for multiple comparisons) indicated that race-decoding was above chance in V1 only, whereas gender decoding was above chance in all ROIs shown. As predicted, Figure 2 shows that race decoding accuracy was lower for normalized than un-normalized (original) images in early visual cortex, and this difference disappeared in FFA. T-tests comparing accuracy to chance revealed significant race-decoding in V1, V2, V3 and OFA for un-normalized stimuli only, and no significant gender-decoding for either stimulus normalization type in any ROI (note: each accuracy score is derived from only half the data per accuracy score in Fig 1).

A 2-way ANOVA on logit-transformed race-decoding accuracies with Factors ROI (V1, FFA) and stimulus-

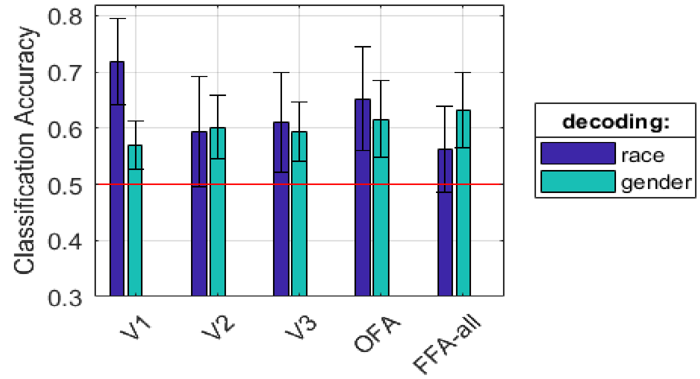


Figure 1. Decoding race and gender using beta weights derived from GLMs collapsed across all three tasks (race, gender, team) and both stimulus normalization conditions.

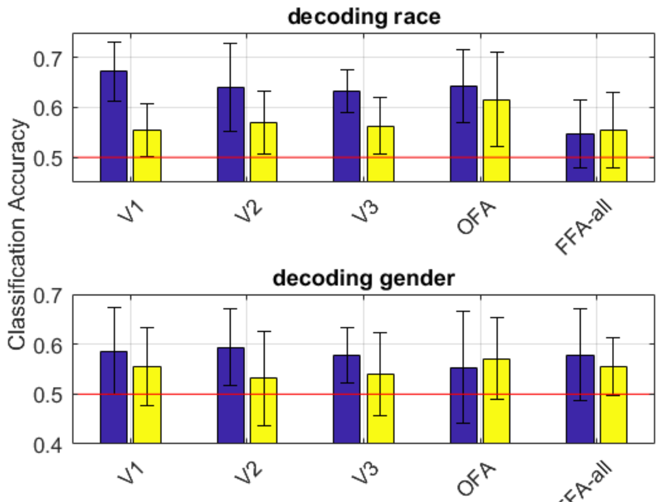
normalization (orig, norm) revealed a borderline interaction between ROI and stimulus-normalization ($F(1)= 3.59$, $p = 0.068$). As predicted, the effect of normalization on gender-decoding was less pronounced and did not differ according to ROI (a 2-way ANOVA revealed no main effect of stimulus-normalization and no ROI*stimulus-normalization interaction).

Figure 3 shows the influence of task on race- and gender-decoding. Numerically, a team-discrimination task, which requires perceptually challenging person-level identification, increases race-decoding relative to a less challenging race task, in both V1 and OFA, but not in FFA. Thus, the pattern across V1 and FFA was not as predicted, because it contrasts with the results of Kaul et al. (2014). However, a 2-way ANOVA on race-decoding accuracy with factors ROI (V1, FFA) and TaskRace, Gender, Team) revealed no main effects nor any interaction, perhaps because this incomplete dataset provides insufficient power to detect such effects.

Figures 4-5 show group mean searchlight decoding maps of race and gender. Due to high variance in our small initial sample, we plot mean accuracy rather than the results of significance tests (e.g., -log(p)).

Discussion

These initial results demonstrate above-chance race and gender decoding in multiple ROIs of the core face processing network. They suggest an effect of stimulus normalization that varies across brain regions as -predicted, being greater in V1 than in FFA. This finding is commensurate with a face-processing network in which earlier regions represent faces in terms of low-level stimulus properties (e.g. luminance), while later regions extract higher-level representations with increasing invariance to those properties. Also in line with this account, the effect of normalization appears more influential for race- than gender-decoding (stimulus luminance is presumed less predictive of face gender than face race). Our next step will be to double our sample size in order to provide greater power to test our hypotheses regarding the influence of cognitive task on decoding in ROIs and cortical searchlights.



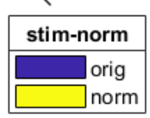
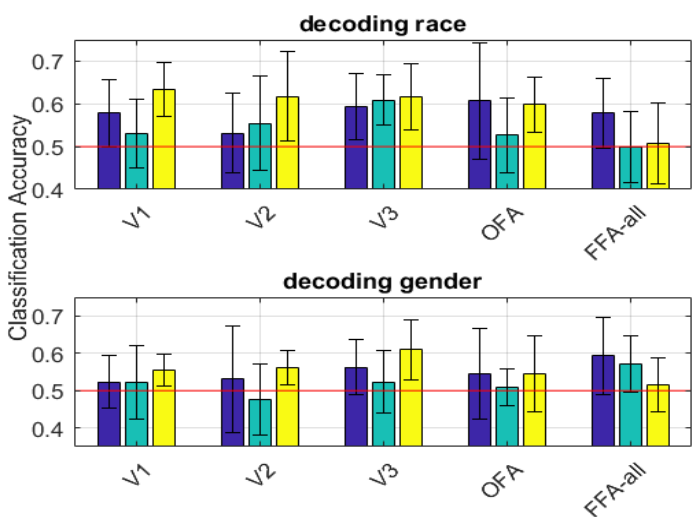


Figure 2. Decoding using beta weights derived from GLMs with separate regressors for each level of stimulus normalization.



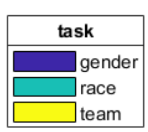


Figure 3. Decoding using beta weights derived from GLMs with separate regressors for each level of task.

Acknowledgments

Work supported by NSF award BCS-1554871 to RAC.

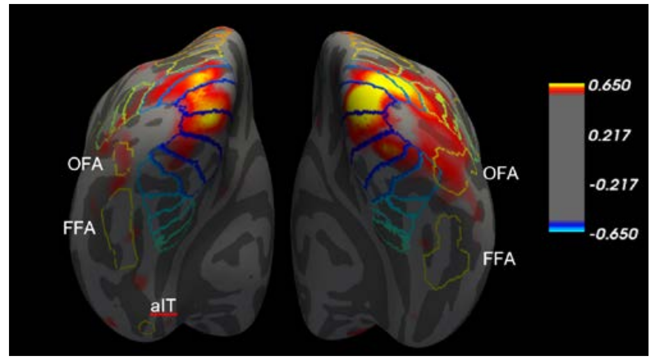


Figure 4. Searchlight decoding of race across all conditions, as in Fig. 1. Mean classification accuracy is plotted on a range from .55 to .65. The occipital atlas of Wang et. al (2015) is outlined, along with a group of face-selective regions, as labeled.

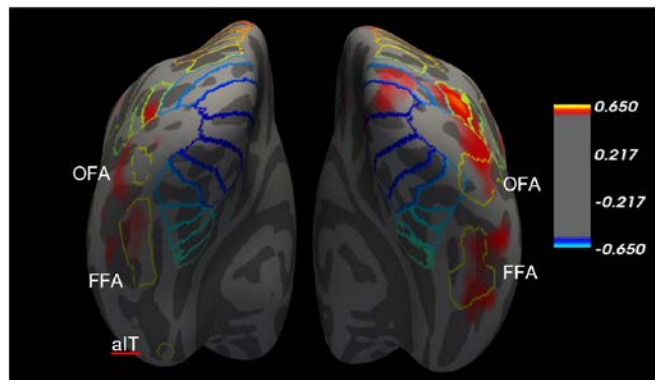


Figure 5. Searchlight decoding of gender. The same scale (.55 to.65) and regions as in Fig 4 are shown.

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