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Individual differences in lifetime face exposure predict behavioral and neural responses to faces

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Abstract

Face recognition abilities are impacted by exposure to faces belonging to distinct categories over the lifespan. Specifically, biased exposure to faces of particular races and ages frequently leads to impaired face memory and discrimination such that faces observers do not frequently see are substantially more difficult to process effectively than faces that are closer to their typical visual experience. Here, we considered the possibility that variation in the sheer amount of faces participants see during the course of their development may also systematically impact face processing. That is, if you grow up seeing a limited set of faces, are you generally less able to process faces effectively? To examine this question, we recruited participants who grew up in very small communities and compared their behavioral and neural responses to face and object images to the responses made by participants from larger communities. We find that observers with limited face exposure do show poorer face memory and also neural responses consistent with limited face-specific processing.

Introduction

There are many ways in which individual variation in exposure to faces has profound effects on observers' abilities to recognize, remember, and discriminate between faces. Easily the most well known example of such an effect is the "other-race effect," which refers to the often very large deficits in observers' recognition abilities for faces belonging to racial categories that are not representative of their experience [1]. For example, most white observers who grow up seeing primarily white faces will find it far more difficult to perform face recognition tasks effectively for Black faces or East Asian faces. This does not reflect any intrinsic difference in how easy faces are to recognize and discriminate as a function of race, since observers from other racial groups typically exhibit the opposite effect: White faces are harder to tell apart than the Black or Asian faces that have dominated their experience [2]. Varying abilities to recognize faces belonging to distinct categories as a function of experience extends to categories other than race, as well. Faces belonging to "other-age" categories are also typically more difficult to recognize and discriminate depending on observers' experience with faces of different ages [3], and identity-matched artificial faces also appear to belong to an "other-group" class defined by synthetic face appearance [4].

These effects of biased experience appear to largely be acquired during the first year of life, and follow a trajectory described as "perceptual narrowing." [5]. Infancy appears to be characterized by an early stage during which infants are sensitive to a broad range of differences in facial appearance and a later stage when their recognition abilities are supported by representations of facial appearance that are more specific to the categories of faces that they have been exposed to. Individual variation in experience has effects on face recognition beyond the first year of life, however, and changes in biased experience to faces of different races, ages, etc. can lead to changes in face recognition capabilities across stimulus groups. [6].

Besides these well-known results describing how biased experience shapes face recognition abilities in the context of face categories, there are also several results describing more general effects of visual experience on face processing. One particularly striking example of such work is the substantial literature describing the impact of monocular deprivation on various aspects of face recognition [7,8]. Briefly, these studies describe the face recognition abilities of patients who were born with congenital cataracts that were removed relatively early in development. These patients, due to this early visual impairment, have intriguing, specific deficits in perceiving properties of face images related to configural information [9]. In some reports, these patients exhibit clear face processing deficits years after the initial impairment has been treated, suggesting a critical period for developing face recognition competence. This is of course an extreme example of individual differences in experience impacting face recognition, but there are recent studies demonstrating more benign examples of varying face experience affecting subsequent face processing. For example, children's face recognition abilities appear to change markedly after the beginning of school [10]. While the face environment children are immersed in before reaching school age would generally not be considered truly impoverished, this result suggests that the increase in face exposure that follows the beginning of school leads to fairly rapid improvements in face processing efficiency. Similarly, face recognition hyper-fidelity can result from overexposure to a small set of face exemplars [11], again suggesting that face recognition abilities are sensitive to the statistics of face experience in a category-general manner.

Currently, we chose to investigate the nature of how similar natural variation in overall face exposure during development might impact face recognition considered broadly. Specifically, to examine the consequences of face experience that is impoverished, but not an example of true deprivation, we worked with undergraduate observers who grew up in very depopulated regions and other observers who grew up in larger urban communities. Anecdotally, these "small-town" observers (some of whom have lived either on family farms or in small towns with under 100 people) often report difficulty with face recognition after arriving on campus, which suggested to us that there may be fundamental differences in the way they represent and recognize faces in general.

In a prior report [12] we have described how our participants from small-town communities exhibit poorer face memory for unfamiliar faces as well as ERP responses at the N170 component (a face-sensitive ERP component [13]) that differ from those of a control group in terms of face selectivity. Specifically, the effect of object category (face vs. non-face images) was smaller within our small-town group than in our group of participants from larger communities. The goals of our current study are to further explore

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the differences in electrophysiological response between these two groups of participants by examining their ERP data using single-trial pattern classifiers [14]. Compared to traditional analyses of ERP waveforms, single-trial pattern classifiers applied to EEG data have the potential to reveal differences between participant groups and effects of stimulus manipulations that are not expressed solely at a single ERP component, which in some cases means that they offer increased sensitivity. For example, while neither the P100 nor the N170 responds in gradient-like fashion to parametrically-varied "faceness" in natural images, pattern classification of the data obtained from the same electrodes where the N170 is measured has revealed that there is a neural representation of face appearance that does exhibit a similar smooth variation in response as non-face targets more closely resemble true face images [15].

A key goal of this current analysis is to investigate the possible difference in how upright and inverted faces are processed in our small-town and large-town groups. The orientation-dependence of face recognition, typically referred to as the "Face inversion effect" [16] is often used to develop the argument that faces are processed by distinct mechanisms that implement recognition strategies and representations that differ from those used to recognize other objects. Critically, inversion effects appear to extend beyond face images to include other object categories observers may have expertise for [17,18]. This suggests that differential processing of inverted images may signal expert-level processing, and so we might expect that this effect may be less prevalent in observers from small towns who may lack sufficient face exposure to have developed expert-level face processing mechanisms. However, when we have examined visual ERPs to upright and inverted faces in small-town and large-town observers, we have found no evidence supporting an interaction of the face inversion effect with visual experience [12]. Presently, we explore the possibility that while such an effect may not be evident at individual components of the visual ERP, analyzing the ERP signal with more sophisticated tools may reveal differences in processing that are in line with our hypothesis regarding impoverished face experience and the face inversion effect.

We continue by describing the properties of our participant sample, the design of both our behavioral task and the electrophysiological recordings that are the basis for our pattern classification analysis.

Methods

Participants

We recruited a total of 37 participants from the NDSU undergraduate study pool. All participants responded to a screening questionnaire as part of their Introductory Psychology course that included a question regarding the size of their hometown. Based on their responses, we invited participants who either grew up in communities with a population smaller than 1000 people (our "Small-town" sample) or who grew up in communities that had a population greater than 30,000 (our "Large-town" sample). All individuals recruited to participate in the study reported either normal or corrected-to-normal vision and no history of neurological impairment.

Behavioral testing

To assess each individual's ability to recognize and remember unfamiliar faces, we administered an online version of the Cambridge Face Memory Test (CFMT) [19]. This assessment requires participants to study a small set of novel faces during a training period and then subsequently distinguish previously studied individuals from new faces during test phases that include variation in face viewpoint and the presence of visual noise. The CFMT takes approximately 15-20 minutes to complete and observers completed this task prior to participating in our EEG recording sessions. The task was administered on a desktop computer positioned at a comfortable viewing distance from the observer. Neither head position nor eye movements were constrained or monitored during task performance.

Electrophysiological testing

We collected continuous EEG data from our participants during our electrophysiological recording sessions using an EGI GES300 NetAmps amplifier and 64-channel Hydrocel Geodesic Sensor nets (Figure 1). Raw EEG was bandpass filtered online between 0.1Hz-100Hz and recorded using NetStation v4.0 with a sampling rate of 250Hz. Before recording began, we established stable impedances below 50 kilo-ohms to ensure adequate signal-to-noise and all testing was carried out in a sound-attenuated electrically isolated chamber. Recording was carried out using the vertex electrode as a reference.

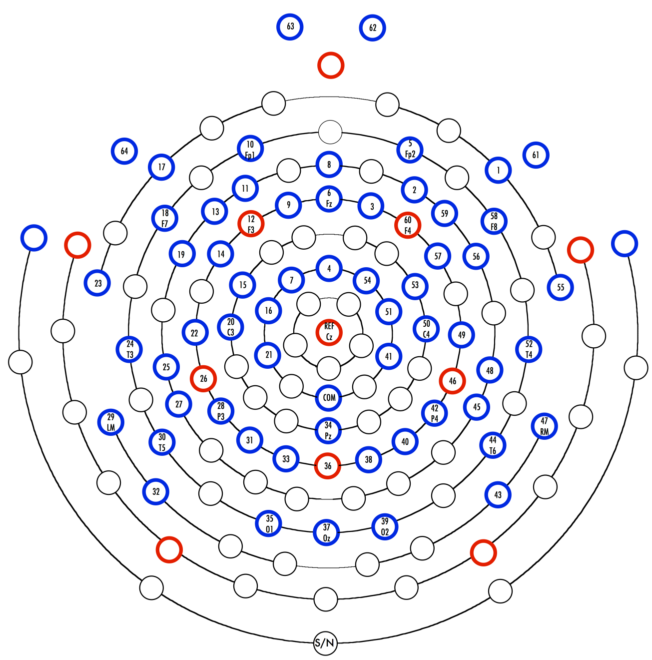

Figure 1 – The layout of the sensor array used to collect ERP data from our small-town and large-town observers. The front of the head is at the top of the figure, the back of the head at the bottom. Continuous EEG was referenced to the vertex electrode and eye movement data was collected from sensors positioned on the cheeks and above the eyes.

Visual stimuli were presented to the participants on a 1024 x 768 LCD monitor with all stimulus timing and response collection routines controlled using EPrime v2.0 with extensions for NetStation. Participants were seated approximately 50cm away

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from the display and used a 4-button response box to categorize stimuli as they appeared.

Participants' task during the recording session was to label images of faces and chairs according to their planar orientation. Each image was either presented upright or upside-down (inverted) and participants were asked to indicate the orientation of the image after it disappeared from view using the button box. The right/left arrangement of the buttons for signaling upright vs. inverted image orientation were alternated across participants to ensure that motor behavior would not be a confounding factor across subjects. The stimulus set used for this task was comprised of 60 grayscale faces [20] and 60 grayscale chairs (Figure 2) each presented in both orientations for a grand total of 240 images. Images were presented in a pseudo-randomized order that was different for each participant, and each image was presented onscreen for 500ms. The interstimulus interval was sampled on each trial from a uniform random distribution bounded between 700ms and 1500ms to ensure that participants could not reliably anticipate the onset of new images.

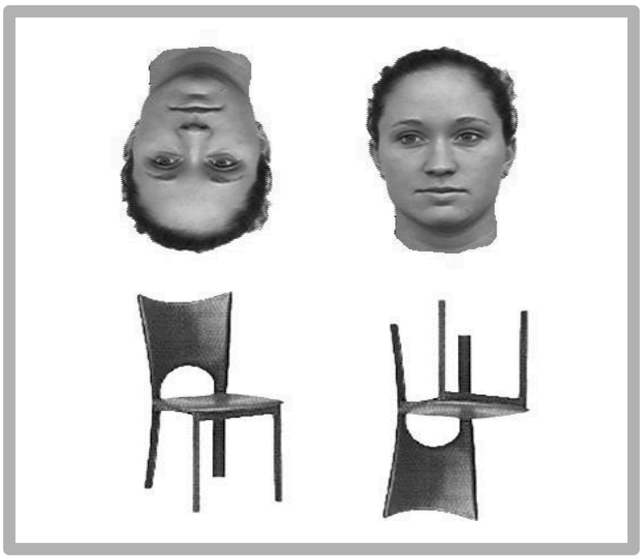

Figure 2 – Examples of upright and inverted face and chair stimuli as presented to participants during EEG recording. Participants' task during image presentation was to report the orientation of the images using a button box.

Results

Behavioral results

As we have reported elsewhere [12], we found significant differences in participants' performance in the CFMT as a function of their lifetime experience. Specifically, we found that participants from the small-town group were significantly less accurate at this task (Average accuracy = 72.9%) than participants from the large-town group (Average accuracy = 79.0%; $t(35)=1.98$, $p=0.028$, one-tailed independent samples t-test). We report this result here as well to motivate the correlations we examined in this analysis between CFMT performance and the results of applying single-trial classifiers to the ERP data obtained from these two participant groups.

Electrophysiological results

In our original report, we used our raw EEG data to identify two ERP components that exhibit face sensitivity: the P100 [21] and the N170 [22]. We observed that participant group had a significant impact on the P100 amplitude, and also that participant group interacted with the effect of category at the N170 component [12]. However, we found no significant interaction between participant group and the orientation of face or non-face images, which suggested that there were not differences in face-specific processing that were reflected by these two components of the visual ERP response. The focus of our current report is to examine this latter issue in more depth by using single-trial classifiers to consider the entire ERP waveform at once rather than isolating specific peaks and troughs from the ERP signal and characterizing neural responses solely in terms of the amplitudes and latencies of these signals.

EEG preprocessing

We obtained single-trial event-related potentials from our continuous EEG data by implementing most of our standard pre-processing pipeline for analyzing ERP components. First, the raw EEG signal for each participant was filtered with a 30Hz low-pass filter. Next, we segmented the continuous EEG into 1000ms epochs using stimulus markers inserted into the EEG record during the recording session. We used each marker to identify a single epoch that began 100ms before the stimulus was presented and extended 900ms after stimulus onset, yielding a one second long segment for each trial at each of our 64 channels. The 100ms-long pre-stimulus baseline period was used to correct each individual segment for DC offset due to drift, local movement or other factors that could result in a shifted signal. We calculated the average value measured during the baseline period and subtracted this value from each timepoint across the entire waveform to obtain a baseline-corrected signal. Next, we applied routines for artifact detection and removal that included thresholds for identifying eye movements (saccades), eye blinks, and individual channels that could be identified as "bad" due to extreme values. Following this artifact detection stage, we applied routines for bad channel replacement that used interpolation methods to replace missing data at problematic sensors with a weighted average of neighboring sensor values. At this stage, we would typically average individual trials within each stimulus condition to obtain an average ERP we could use to identify individual components, but for the present analysis we did not implement this step to preserve the individual trials within each condition for each participant.

Single-trial classification of ERP signals

Following the pre-processing routines described above, the dimensionality of each single-trial ERP is quite high: We have measurements of 225 post-stimulus onset timepoints at each of 64 channels for a total of 14400 values for trial. To reduce this dimensionality somewhat and also provide us with a more global representation of the ERP signal across the entire scalp, we chose to describe each trial using the *Global Field Power* rather than retaining data for each individual sensor. The Global Field Power (or GFP) is a function of time (Eqn. 1) that describes the standard deviation of the ERP signal across the entire sensor array. It is thus non-negative everywhere and condenses the topographic information in the ERP signal to a single measure of how large voltage fluctuations are across the entire scalp. We lose all spatial

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sensitivity by representing the raw ERP signal this way, but retain the temporal sampling from the original signal.

$$GFP(t) = \sqrt{\frac{\sum_{1}^{k}(V_i(t) - V_{mean(t)})^2}{k}} \quad (1)$$

Equation 1 – The expression for the Global Field Power across the sensor array (GFP) as a function of time. In the above expression, 'k' signifies the number of sensors in the array, and V(t) signifies the voltage measured at an individual sensor (indexed by i) over time.

We continued by training and testing a linear SVM classifier for each participant using the *svmtrain.m* and *svmclassify.m* functions implemented in Matlab. Specifically, we determined how separable the upright and inverted ERP trials were for face and chair images by using a leave-one-out procedure. Each participant thus yields two values, one describing our accuracy at classifying upright vs. inverted face ERPs and a second one describing our accuracy at classifying upright vs. inverted chair ERPs.

The first question we examined was whether or not we were able to reliably classify upright vs. inverted image orientation using single-trial ERPs at above-chance levels as a function of image category (face vs. chairs) and experience with faces (small-town vs. large-town experience). Given the set of leave-one-out accuracy values we calculated for each condition, we estimated 99% confidence intervals of the mean accuracy in each condition by carrying out a bootstrap sampling procedure with 1000 iterations. We found that these intervals included zero for the chair condition in both participant groups as well as for the face condition in our small-town sample. However, the interval did not include zero for the face condition in our large-town sample (Figure 3), suggesting that we were only able to reliably classify image orientation from single-trial ERP data obtained from large-town observers viewing face images.

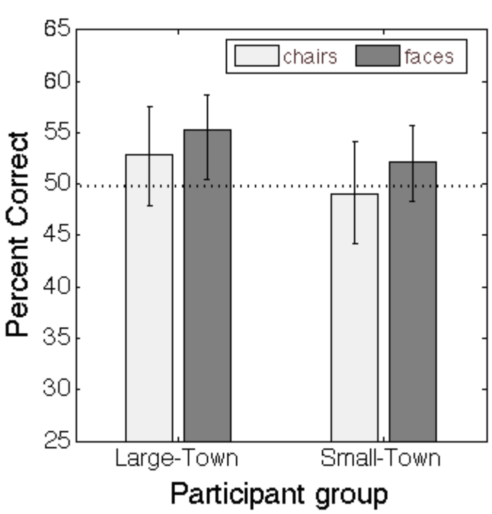

Figure 3 – Bootstrapped estimates of our mean SVM classification for both participant groups and both image categories. Error bars depict 99% confidence intervals of the mean. Critically, only the classification rate for face images viewed by the large-town group is significantly above chance.

Next, we examined whether the CFMT scores we measured for small- and large-town participants were related to either the upright/inverted classifier accuracy for faces or chairs. In each case, we computed the correlation coefficient between the values we obtained for SVM classification in each condition. In no case did we observe a significant correlation, suggesting that there is no clear relationship between the separability of upright vs. inverted ERPs responses and participants' actual face recognition abilities as indexed by the Cambridge Face Memory Test.

We note that in prior work we have also found relatively limited relationships between performance on the CFMT and individual component characteristics. CFMT performance thus does not seem to be clearly related to neural measures of face processing, whether local or global representations of the ERP signal are used.

Discussion

These analyses extend our prior results obtained from this unique participant population, specifically with regard to the possibility that individuals from relatively impoverished face environments may actually process faces in qualitatively different ways. Specifically, our classifier results suggest that the face inversion effect may be to some extent less clearly reflected in the visual ERPs of small-town observers. This outcome is largely consistent with the hypothesis that face expertise leads to subsequent changes in the mechanisms applied to face stimuli such that so-called configural [23] and holistic processing are applied to face images. Further, compared to our prior results with this population that relied heavily on standard analyses of ERP components, the use of a single-trial classifier made it possible to reveal features of the ERP signal we were not sensitive to in our original analysis. For example, we have found that when we consider only the amplitude and latency of the P100 and N170 components, there is no evidence that the inversion effect manifests differently across object categories for small-town or large-town observers [12]. The fact that we do observe a difference in classifier accuracy across image category and participant groups here may indicate that later parts of the ERP signal carry information about face orientation differently as a function of group experience.

One important limitation of our current analysis is that by collapsing across sensor locations via the Global Field Power we are unable to make any statement about which sensors carried diagnostic information. An obvious extension of this work would thus be to either re-do our classification procedure using the entire sensor array, or selectively choose subsets of electrodes to use as the basis for classification and characterize the diagnosticity of spatial and temporal subsets of the ERP data. Recent work on the neural basis of material categorization [24] has employed techniques like this to reveal the timecourse of material recognition using ERPs, for example, and application of these techniques to our data set could be similarly informative. Overall, understanding both where and when diagnostic information for image orientation emerges for small-town and large-town observers would help us more closely characterize the differences in neural processing between these two groups.

There are also some key limitations of both our participant groups and our design that are important to point out. First, we made no real attempt to verify or quantify participant experience with faces in either of our two participant groups, meaning that there may be substantial heterogeneity in both samples. While

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naively we might think this should only compromise our ability to measure differences between the two groups, overall we argue that understanding how individual experience may shape perception ultimately requires that we make better efforts to establish exactly what the visual experience of our observers might be. Here, we do not know how frequently our participants may have traveled to more densely populated cities, how frequently they watched television, or any of a number of other factors that may have modulated the representations they use for face recognition and their subsequent capability to recognize the people around them. Such rich descriptions of visual experience have been useful in interpreting the nature of experience-dependent effects in infancy [25,26], and in future work it would be invaluable to obtain similar descriptions of adult face exposure. We also do not know given the present data set whether the behavioral difference we observed for face memory as a function of participant group might extend to other visual tasks. Do these participants have any deficits for non-face object recognition, for example? While our neural results offer a compelling case that one key difference between small-town and large-town observers may be a category-selective response to image orientation, behaviorally we cannot say if there is perhaps a more general effect of face experience on the perception of complex (or even simple) visual stimuli.

Overall, we regard these results as an important demonstration that not only do variations in face experience impact how well faces are remembered and recognized, these variations may also affect how faces are represented for recognition. These effects are not just relevant when we consider face recognition within different categories, but they extend to faces of all categories, implying a broad impact of overall face exposure. Important extensions of this work would include other characterizations of holistic face processing beyond the inversion effect and the inclusion of other behavioral markers of face-specific processing. For example, employing recently developed standardized assessments of holistic processing [27] would be a powerful way to compare small-town observers' performance to a typical population, and look for relationships between neural responses to faces, other behavioral descriptors of face recognition ability, and holistic representations of appearance. Examining how face adaptation and aftereffects [28] manifest in small-town and large-town observers would also be a powerful means of understanding the relationship between behavioral performance and the neural representations that underlie face processing. Continued examination of how varying statistics of face exposure lead to variation in face processing in the absence of impairment or deprivation will offer insights into the nature of visual learning and the plasticity of higher levels of the visual system.

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Corey Grant received his BS degree in 2007 from Salem State University and subsequently received Master's degrees in Experimental Psychology (2013) and Computer Science (2015) from Rivier College. He is currently a PhD student at North Dakota State University. His research interests include visual social perception, including the influence of experience on judgments of trustworthiness from face images.