Face information sampling in super-recognizers

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Abstract

Perceptual processes underlying individual differences in face recognition ability remain poorly understood. We compared visual sampling of 37 super-recognizers – individuals with superior face recognition ability – to typical viewers by measuring gaze position as they learned and recognized unfamiliar faces. In both phases, participants viewed faces through ‘spotlight’ apertures that varied in size, with face information restricted in real-time around their point of fixation. We found higher accuracy in super-recognizers at all aperture sizes – showing their superiority does not rely on global sampling of face information, but is also evident when forced to adopt piecemeal sampling. In addition, super-recognizers made more fixations, focused less on the eye region and distributed their gaze more broadly than typical viewers. These differences were most apparent when learning faces, and were consistent with trends we observed across the broader ability spectrum, suggesting that they are reflective of factors that vary dimensionally in the broader population.

Statement of Relevance

We asked why some people – known as ‘super-recognizers’ – can recognize faces far better than average people, by focusing on the visual information they sample when learning and recognizing faces. Using eye-tracking technology, we manipulated the amount of visual information available to participants by varying the size of ‘spotlight’ apertures that were centered on where they looked. Super-recognizers performed better than average people at all aperture sizes, even when just 12% of the face was visible at once through the aperture. This result dispels the notion that individual differences in face recognition ability can be explained by ‘holistic’ processing alone. We also show differences in how super-recognizers sample information. These differences were especially apparent when they initially learned faces, suggesting that super-recognizers are better described as *super-learners*.

Faces provide fundamental social information, but people's ability to recognize faces varies to a surprising extent. Ability ranges from people with Congenital Prosopagnosia (CP) who are unable to recognize friends and family and perform at chance on standardised tests (Duchaine & Nakayama, 2006), to 'super-recognizers' that are capable of remarkable feats of recognition in their daily life and achieve the highest scores attainable on standardised tests (see Noyes et al., 2017; Ramon, 2021 for reviews; Russell et al., 2009).

This wide-ranging spectrum of ability is believed to be a result of a stable and specific cognitive trait. Support for this comes from the stability of performance across repeated testing (Bobak et al., 2016; Dunn et al., 2020; White et al., 2021), genetic heritability (Wilmer et al., 2010), resistance to training effects (Towler et al., 2019; Towler et al., 2021) and independence from general object recognition (Richler et al., 2017; Shakeshaft & Plomin, 2015; c.f. Geskin & Behrmann, 2017). Representing the top of the distribution, super-recognizers are individuals who have obtained visual expertise for a task that we all perform many times each day. Studying the basis of their skill can therefore help us to understand not only face recognition, but perhaps visual intelligence more broadly.

A useful starting point in understanding super-recognizer superiority is by examining the information they rely on for face recognition. Initial work aiming to understand individual differences in face recognition was inspired by the finding that people, in general, tend to process faces as gestalts, rather than the more piecemeal part-based processing that characterises other types of object processing (Farah et al., 1998; Richler & Gauthier, 2014). This led to the hypothesis that inter-individual differences in face processing ability could be explained by differences in the extent to which they use 'holistic' processing (DeGutis et al., 2013; Wang et al., 2012). Although this hypothesis received some initial support from studies of the full ability spectrum, the association between holistic processing and face recognition ability were found to be weak (DeGutis et al., 2013; Wang et al., 2012) and other studies showed no association (Konar et al., 2010; Rezlescu et al., 2017; Richler et al., 2015; Sunday et al., 2017).

Another approach to studying individual differences has been to compare people at extremes of the face recognition ability spectrum to typical viewers. There is some indirect evidence from these studies of an association between holistic processing and face recognition ability. For example, studies have reported a reduced face composite effect for people with congenital prosopagnosia (Avidan et al., 2011; Palermo et al., 2011), as well as smaller inversion effects for faces (Malaspina et al., 2017). At the opposite extreme, larger face inversion effects have been reported super-recognizers compared to typical viewers (Bobak et al., 2016; Russell et al., 2009; c.f. Towler et al., in prep). When viewing scenes containing faces, super-recognizers spent longer fixating on nose regions (Bobak et al., 2017), which may also indicate a global processing strategy (but see Mielliet et al., 2013).

On the other hand, there is emerging evidence pointing to differences in part-based processing being important in explaining individual differences in face recognition ability. Royer and colleagues (2015) found that better face recognizers required less visual information to maintain accurate recognition, suggestive of enhanced *local* processing at higher levels of face recognition ability. While this result has not been shown in super-recognizers, there is preliminary evidence that super-recognizers can process visual information more efficiently

than typical viewers (Nador et al., 2021; Tardif et al., 2019)

Exactly how an individual's face recognition ability is supported by initial perceptual processing is unclear. Here, we address this question by manipulating the amount of global versus local information available to viewers when they performed a face recognition task. We restrict face information using gaze-contingent "Spotlights" – viewing apertures of varying size that are centered on the participants' fixated location (Caldara et al., 2010; Miellet et al., 2013; Papinutto et al., 2017; for example see Fig. 1; demonstration video available at: <https://osf.io/xtjzh/>). This enables us to examine active exploration of face information during face learning and recognition, while also having control over the information available to viewers on a given fixation.

In Experiment 1, we measured the visual information sampling of 34 super-recognizers and compared it to typical viewers. Super-recognizers were more accurate than typical viewers across all spotlight aperture sizes, contrary to the notion that differences in holistic processing drive differences in accuracy. We also find reliable differences in the amount of information they sample from faces, the extent to which they distribute their sampling across the face, and their viewing patterns. These differences were most apparent when learning faces. In Experiment 2, we examined whether these differences in visual information sampling are reflective of trends across the full spectrum of face recognition ability, to address whether perceptual processing in super-recognizers represents an extreme version of normal face processing, or whether they rely on qualitative different processing strategies (Noyes et al., 2017; Tardif et al., 2019).

Experiment 1

Method

Sample size estimation

To estimate sample size we performed a statistical power analysis using GPower 3.1 (Erdfeider et al., 1996). Based on the only previous comparison of eye-movement strategies in super-recognizers and typical viewers (Bobak et al., 2017), we expected large to very large effect sizes ($\eta^2 > .13$). Taking the smallest effect size estimate, which corresponds to Cohen's $f = 0.39$, a projected total sample size of 58 participants was needed to detect an effect of this size ($\alpha = .05$, power = 0.8). Consequently, we aimed to recruit at least 29 super-recognizers and typical viewers once accounting for exclusions.

Participants

Forty super-recognizers were recruited to participate in the study based on their scores on three standardized face identification tests completed before beginning the study: the Cambridge Face Memory Test-long form (CFMT+: Russell et al., 2009), Glasgow Face Matching Test short form (GFMT: Burton et al., 2010), and the UNSW Face Test (Dunn et al., 2020) (see supplementary materials for a description of screening tests; Table S1 shows super-recognizers individual scores on each screening test). All super-recognizers satisfied the criteria for super-recognition by having a mean Z score above 1.7 SDs across these tests. This is a strict criteria relative to selection thresholds used in this field (see Ramon, 2021), and the requirement to show repeated high performance over subsequent tests limits any influence of chance or transient factors on performance. Twenty-eight 'typical viewers' were recruited

from a research participation site hosted by the School of Psychology at UNSW Sydney and paid \$20 AUD for their participation. All participants had normal or corrected to normal vision.

Six super-recognizers and two typical viewers were excluded from analysis due to technical difficulties with the eye-tracker (N=2), incomplete data (N=3) or excessive data loss (>20% of trials were removed; see data cleaning parameters below; N=3). The final group consisted of 34 super-recognizers (14 females, 20 males) aged between 26 and 51 years old (mean = 37.8, SD = 7.4) and 26 typical viewers (15 females, 10 males, 1 non-binary) aged between 18 and 61 years old (mean = 27, SD = 8.6).

This research was approved by the Human Research Ethics Advisory Panel at UNSW Sydney. All participants gave their informed consent either digitally or in writing.

Apparatus

Participants' eye movements were recorded with Tobii Pro Spectrum (with chin rest). This tracker has an average gaze position error of about 0.25° and a spatial resolution of 0.01°. Only the dominant eye was tracked. The experiment was coded in MATLAB using the Psychophysics toolbox (Brainard, 1997). Calibrations for eye fixations were conducted at the beginning of the experiment using a nine-point fixation procedure using MATLAB software and repeated until the optimal calibration criterion was reached.

Stimuli

Stimuli were obtained from the Lifespan Database of Adult Facial Images (Minear & Park, 2004). We used a total of 144 identities with different genders, ethnicities, facial expressions and ages. Face stimuli were aligned by the eye and mouth positions to ensure they appeared at a standard size on the screen. To operationalize the aperture viewing, spotlight viewing apertures were created using a method described by Papinutto and colleagues (2017). We used aperture sizes of 5°, 10°, 15°, 20°, and 25° of visual angle. To determine the preserved information in the Gaussian aperture, Papinutto and colleagues carried out a data-driven reconstruction of the Facespan based on the convolution of a retinal filter (Targino Da Costa & Do, 2014), computation of the Structural SIMilarity index (Wang et al., 2004) and use the pixel-test (Chauvin et al., 2005; based on Random Field Theory). Their analysis showed that a 17° Gaussian aperture corresponds to 7° or 45% of the total face information being preserved. Thus, assuming linearity, in the present study, 5°, 10°, 15°, 20°, and 25° apertures correspond to 2°, 4°, 6°, 8°, and 10° of preserved information. To provide a clearer description of the amount of information available at each aperture size, here we will report the angular representations of the faces (5°, 10°, 15°, 20°, and 25°) in terms of their respective preserved face information (12%, 24%, 36%, 48% and 60%), with the natural view (NV) providing 100% of the face.

Procedure

Participants completed a recognition memory procedure where they studied faces displayed on a screen and were later tested on their memory for the faces. There were six blocks each involving a presentation of a series of faces to be learned and subsequently recognized. In each of these blocks, participants viewed 12 faces in one of six viewing conditions (natural viewing and each aperture size condition, see demonstration video available at: <https://osf.io/xtjzh/>). Faces were each presented for 5 seconds, which randomly displayed neutral or happy facial expressions. At the beginning of each trial, participants were instructed to fixate a cross at the center of the screen. Faces were presented at random locations on the computer screen to avoid anticipatory oculomotor strategies. Each learning phase was immediately followed by a recognition phase where 24 faces were presented (12 faces from learning and 12 new faces). Participants were instructed to indicate as quickly and accurately as possible whether each face had been presented in the face learning phase via keypress. Typical viewers completed the CFMT+ after the experimental task, and super-recognizers had completed the CFMT+, GFMT and UNSW Face Test as part of pre-screening (see Participants).

Eye movement classification and cleaning parameters

Fixations were coded based on a threshold of 30° of visual angle/sec, where adjacent samples that were below the velocity threshold were coded as a single fixation and adjacent samples that above this threshold were coded as saccades. Fixation data was then cleaned using the following parameters: 1) fixations that were within 0.5° visual angle and 75ms were merged; 2) fixations shorter than 50ms were removed; 3) fixations longer than 3SD from the mean fixation duration of each participant were removed. For trial-level analyses, trials were removed if there were no valid fixations or if response latency was greater than 3SD from the mean latency for each participant. Participants were excluded from analysis if more than 20% of the total trials were excluded after cleaning.

Statistical Analyses

Our primary measure of interest was face recognition accuracy across gaze aperture conditions, which provided a test of whether super-recognizers rely on global sampling of information for face learning and recognition. We also carried out a more exploratory analysis of fixation patterns. Given the preliminary nature of this work, we opted for data-driven analysis methods that did not rely on experimenter intervention, for example by pre-defining region of interests (Bobak et al. 2019). All statistical analyses were conducted with Linear mixed models using the GAMLj module package in JAMOVl (The jamovi project, 2021). Participants' intercept was included as a random effect in all models and all continuous factors were analyzed with Z-Score scaling. To control for variability in the difficulty of remembering specific faces, trial-level analyses also included stimuli as a random effect. The specific factors included in each analysis is specified below. For brevity, full analyses for each model are reported in supplementary materials.

Face recognition accuracy. We measured participants performance in the face recognition task using A prime (A'; Stanislaw & Todorov, 1999) with preserved face information (Continuous: 100%, 60%, 48%, 36%, 24%, 12%) and group (super-recognizers, typical viewers) as factors. Analysis of response latency was also conducted using the same factors and is reported in supplementary materials.

Fixation count and gaze dispersal. Analyses of the number of fixations were conducted at the trial-level with phase (face learning, face recognition), aperture size (Continuous: 100%, 60%, 48%, 36%, 24%, 12%), group (super-recognizers, typical viewers), and all interactions as fixed factors. To control for the impact of trial duration on the number of fixations, trial duration was also included as a fixed factor in the model (without any interaction terms) using study time (5s) as the duration for Study Phase trials.

The dispersal of gaze across the face was measured using the Gini coefficient. The Gini coefficient is a measure of statistical dispersion that represents the inequality among values in a distribution (Lorenz, 1905). When analyzing gaze maps, higher Gini coefficients will correspond to fixations occurring in concentrated regions, while lower Gini coefficients will correspond to fixations dispersed over greater areas (for example see the left panel in Fig. 2). To quantify and compare the dispersion of eye movements across the face between super-recognizers and typical viewers, we computed the Gini coefficient for each trial-level gaze map (using the MATLAB ‘Gini coefficient and the Lorentz curve’ package; see Lengwiler, 2020). Analysis of Gini coefficients was conducted at the trial-level with phase (face learning, face recognition), preserved face information (Continuous: 100%, 60%, 48%, 36%, 24%, 12%), group (super-recognizers, typical viewers), and all interactions as factors. To control for the impact of trial duration on the Gini coefficient, trial duration was also included as a factor in the model (without any interaction terms) using study time (5s) as duration for Study Phase trials.

Gaze pattern analysis. To capture the major differences in gaze patterns across participants we conducted a Principal component analysis (PCA) using trial-level gaze patterns. PCA is data-driven, in the sense that it does not rely on experimenter input in the form of pre-defined regions of interest and so is well suited to exploratory analysis of eye-tracking data (see Varela et al., 2018; Wegner-Clemens et al., 2019). To conduct this analysis we first normalized, then resized, the gaze maps — from 891x656 pixels to 209*182 pixels — and converted each to a single vector. Separate PCAs were conducted for trials from face learning and face recognition phases with PC loadings reported as a Z-score (i.e., SD units from mean). After applying the PCA, we created visual reconstructions of the first five components (PC1-5) and compared the loadings for super-recognizers and typical viewers on these PCs.

Analysis of PC1, representing the major source of differences in gaze patterns, was conducted at the trial-level with phase (face learning, face recognition), preserved face information (Continuous: 100%, 60%, 48%, 36%, 24%, 12%), group (super-recognizers, typical viewers), and all interactions as factors. This same analysis was repeated for PCs 2-5, but these are reported in supplementary materials.

Results

Face recognition accuracy

For accuracy, Linear mixed models show super-recognizers superior face recognition accuracy was maintained under increasingly restricted viewing conditions (Figure 1). This is shown by a significant main effect of group for A' , $b = 0.069$, $CI = [0.035, 0.102]$, $t(58) = 4.05$, $p < .001$, and non-significant interaction with aperture size, $b = 0.017$, $CI = [-0.005, 0.039]$,

$t(298) = 1.52, p = .129$. There was a significant main effect of aperture size, with both groups showing similar decreases in A' with small aperture sizes, $b = 0.123$, $CI = [0.112, 0.134]$, $t(298) = 21.74, p < .001$.

Fig. 1. Super-recognizers are more accurate than typical viewers even with only 12% of face information available on each fixation. Diamond shows group mean and 95% confidence intervals, while violins and boxplots show the distribution and interquartile range respectively. Images below the x-axis show the face information that is preserved at each aperture size when fixated on the left eye.

Analysis of fixation counts and dispersal

Linear mixed models show super-recognizers made more fixations especially during face learning. This was evident from a significant interaction between group and phase, $b = 0.67$, $CI = [0.43, 0.91]$, $t(11519.8) = 5.44, p < .001$, with simple effects showing a larger group difference in number of fixations during face learning ($b = -1.28$, $t(61.0) = -2.49, p = .016$) but this difference was not significant during recognition ($b = -0.61$, $t(58.9) = -1.2, p = .234$). We also observed a significant interaction between group and aperture size, $b = -0.19$, $CI = [-0.31, -0.06]$, $t(10564.6) = 2.93, p = .003$, due to a larger group difference at larger aperture sizes. These interactions show that super-recognizers sampled more face information, especially when they learned faces in a limited study period, suggesting that they are able to extract face information more efficiently on each fixation.

Although super-recognizers made more fixations than typical viewers, it is not clear whether they also sampled more face information. It is possible that they focused their study on the

same regions on each fixation. To examine whether they also engaged in more exploratory fixations, we analyzed participants dispersal of gaze using the Gini coefficient. The Gini coefficient is a measure of statistical dispersion that represents the inequality among values in a distribution and was originally used to study the distribution of wealth (Lorenz, 1905). When analyzing gaze maps, higher Gini coefficients index higher concentration of fixations to specific regions, while lower Gini coefficients index greater dispersal of fixations across the face (for example see the left panel in Fig. 2).

In line with the interactions on number of fixations between group and aperture size, and between group and phase, linear mixed models revealed a significant three-way interaction between group, phase and aperture size, $b = .004$, $CI = [.001, .007]$, $t(11503.5) = 2.82$, $p = .005$. Simple effects show that during learning, super-recognizers have a lower Gini coefficient (i.e. more exploration) at larger aperture sizes than typical viewers ($b = -.013$, $t(63.6) = -1.73$, $p = .089$), but this difference decreases with smaller aperture sizes ($b = -.003$, $t(63.7) = -0.41$, $p = .683$). During recognition, the difference between groups is less affected by aperture size and smaller in magnitude (b 's between $-.001$ to $-.002$). Together, this pattern of effects shows that the largest differences in face information sampling between super-recognizers and typical viewers are during face learning with larger aperture sizes.

Fig. 2. Differences in fixation counts and dispersal between typical viewers and super-recognizers. Super-recognizers made more fixations (a), and this difference was driven mostly by face learning (top) rather than recognition (bottom). Gini coefficients (b) were used to measure the statistical dispersion of gaze across the face, with lower values corresponding to higher dispersion. Example trial gaze maps show those with highest (top), median (middle) and lowest (bottom) Gini coefficients. Super-recognizers had lower Gini coefficients than typical viewers, signaling greater visual exploration. Again, this was driven mostly by face learning (top right) rather than recognition (bottom right). In all data figures, diamond shows group mean and 95% confidence intervals; boxplots show interquartile range of mean.

Gaze pattern analysis

To capture the key differences in eye movement behavior across participants we conducted a Principal Component Analysis (PCA) of gaze patterns on each trial separately for face learning and recognition phases. Figure 3 shows the reconstruction of PC1 in both face learning and recognition phases (reconstruction of first 5 principal components are shown in supplementary materials, Fig. 4). We found remarkable stability in the first principal component (PC1) that emerged in both learning and recognition phases despite being independent models. PC1 consistently coded participants tendency to fixate the eye-region (left-side of the continuum) versus their tendency to distribute fixations more broadly across central regions of the face (right-side of the continuum) and accounted for between 15% and 18% of the variance in gaze patterns across trials (for more information see supplementary materials).

Figure 3 also shows the mean PC1 loadings across conditions for each group. Linear mixed

models show a significant interaction between phase and group, $b = -.101$, $CI = [-.154, -.048]$, $t(1151.6) = 3.72$, $p < .001$, with simple effects showing that the difference between groups was larger during face learning ($b = .225$) than face recognition ($b = .125$). As can be seen from visual inspection of Figure 3, this difference reflected a more negative loading in typical viewers relative to super-recognizers, which is reflective of a stronger bias to fixate on the eye-regions in typical viewers (Figure 3). This difference was larger at smaller apertures ($b = .229$) than with larger apertures ($b = .121$; see supplementary materials for full analysis model).

Fig. 3. Visualisation of first principal component that emerges from PCA of trial-level gaze maps during face learning and recognition in Experiment 1 (a). PCA1 loadings show differences in gaze patterns between super-recognizers and typical viewers (b). Diamond shows mean and 95% confidence intervals while boxplots show interquartile range of mean PC1 loadings (in SD units) for each condition. Consistent with all our eye-tracking analyses, differences between super-recognizers and typical viewers are most consistent during face learning. Boxplots and mean distribution of PC1 loading across trials for each participant (c). Visual inspection shows substantial inter-trial variability in PC1 for each participant. Participants' data are ordered from top to bottom in both learning (left) and recognition phases (right) based on mean loading on PC1 on the learning phase (left). Consistent ordering between learning and recognition shows remarkably strong stability in an individual's idiosyncratic gaze patterns. Probability distributions at the top show aggregates of trial-level PCA loadings, with the vertical lines showing the group means.

Fig. 3 shows intra-individual differences in processing strategy across trials, with the width of boxplots showing the extent of inter-trial variability for individual participants' PC1 loadings. In addition to the group difference aggregated across aperture size (top), two main observations can be made from visual inspection. First, there are large intra-individual differences, suggesting that sampling strategy is influenced at least as much by the individual trial as by the individual observer. Second, there appears to be a strong relationship between participants' PC1 loadings for learning and recognition phases. This relationship indicates that,

despite large intra-individual variation, there is also consistency in participants modal strategy between learning and recognition ($r_{58} = .954$, $p < .001$). Interestingly, there was also stability in the standard deviation of these boxplots between learning and recognition ($r_{58} = .686$, $p < .001$) suggesting that the extent to which individual participants shift their sampling pattern from trial to trial is also a stable individual difference. Both patterns were consistent across aperture sizes, and their consistency is especially striking given that learning and recognition eye-gaze data were used to produce separate PCA models (see supplementary materials).

Discussion

Super-recognizers were more accurate than typical viewers in all aperture conditions. Previous estimates of the perceptual span for face recognition in typical viewers correspond to 45% preserved face information (Papinutto et al., 2017). We also found a sharper drop-off of performance in both groups after this threshold, but critically the magnitude of super-recognizers superiority remained relatively unchanged down to as little as 12% of face information per fixation. This suggests that super-recognizers are equally adept at piecemeal as they are more global sampling and can draw on either type of processing to support face learning and recognition.

In addition, number of fixations and fixation dispersal analyses show that super-recognizers sample information more efficiently than typical viewers, and distribute their gaze more widely across a face. We also found differences in the gaze patterns of super-recognizers, who were less focused on the eye region relative to typical viewers. Unexpectedly, all of these differences were found most strongly during face learning.

Experiment 2

An important question for understanding the nature of individual differences in face recognition ability is whether perceptual processing in super-recognizers represents an extreme version of normal face processing, or whether they rely on qualitative different processing strategies (Noyes et al., 2017; Tardif et al., 2019). Do the information sampling differences between super-recognizers and typical viewers found in Experiment 1 reflect qualitative processing differences? To address this, we recruited a larger group of typical viewers to examine whether the group differences we observed can be explained by linear changes in processing as a function of face processing ability across the ability spectrum. We also recruited three additional super-recognizers, to test whether their performance fitted the linear models derived from the broader population.

Method

Participants

Forty-three typical viewers were recruited to participate from the UNSW Sydney and the University of Wollongong. One was excluded from analysis for excessive data loss following the same data cleaning procedures as Experiment 1. The final group consisted of 35 females and 7 males aged between 18 and 44 years old (mean = 21.2, SD = 5.0). Three super-recognizers were recruited based on their scores on the CFMT+, GFMT and UNSW Face Test (see supplementary materials, Table S1). All participants had normal or corrected to normal vision.

This research was approved by the Human Research Ethics Advisory Panel at UNSW Sydney and the Department of Psychology ethics committee at University of Wollongong. All participants gave their informed consent either digitally or in writing.

Apparatus and Procedure

Participants' eye movements were recorded with the SR-Research EyeLink Portable Duo (with chin rest only) at UNSW Sydney and with the SR-Research EyeLink 1000+ (with a chin and forehead rest) at the University of Wollongong. Critically, the angular size of the stimuli was the same in both recording sites and matched Experiment 1, at approximately 16.5° of visual angle. Both devices had an average gaze position error of about 0.25° and a spatial resolution of 0.01° . Only the dominant eye was tracked. The experiment was completed in MATLAB using the same procedure as Experiment 1 using the EyeLink toolbox (Cornelissen et al., 2002).

Statistical Analyses

Analyses were conducted using linear mixed models with the same parameters as Experiment 1 except the continuous variable of CFMT+ score replaced the categorical variable of group as a factor in all models. Scores were z-score normalized before analysis.

Results

Face recognition accuracy

A-prime scores are shown as a function of gaze aperture conditions in Figure 4, and correlations between accuracy and CFMT+ score for each aperture size are shown in Figure 4. As in Experiment 1, Linear Mixed Models show that face recognition ability did not interact with aperture size. This is shown by a significant main effect of CFMT+ score for A' , $b = 0.042$, $CI = [0.023, 0.060]$, $t(43) = 4.42$, $p < .001$, and non-significant interaction with aperture size, $b = -0.004$, $CI = [-0.015, 0.007]$, $t(223) = -0.69$, $p = .492$. There was again a significant main effect of aperture size, with both groups showing similar decreases in A' with small aperture sizes, $b = 0.091$, $CI = [.080, .101]$, $t(223) = 16.61$, $p < .001$.

To examine whether super-recognizer's performance was consistent with the linear models at each aperture size, in Figure 4 we plotted their accuracy on linear trends established from the broader population. Visual inspection of these plots clearly shows that super-recognizer's performance is closely predicted by broader patterns of individual differences. This pattern is confirmed by goodness of fit statistics for a linear models trained on typical viewers, as it predicts super-recognizer's A' scores with high accuracy (typical viewers: $RMSE = 0.107$, $R^2 = 0.48$; super-recognizers: $RMSE = 0.072$, $R^2 = 0.60$; see supplementary materials for more

details).

Fig. 4. Distributions of A' for each aperture size in Experiment 2 (left). Diamond shows group mean and 95% confidence intervals, while violins and boxplots show distribution and interquartile range respectively. Data from three super-recognizers collected as part of this experiment are shown as yellow dots. Scatterplots and correlations (right) show that CFMT+ scores predict A' for most aperture sizes. Linear models and coefficients were produced without including the super-recognizers (yellow dots), which appear to also fit onto the same trendlines.

Analysis of fixation counts and dispersal

Linear mixed models replicate the findings of Experiment 1, showing that participants with higher CFMT+ scores made more fixations, and distributed these fixations across wider regions of the face. Again, these differences were most apparent at face learning. Scatterplots of the relationships between CFMT+ scores and fixation data are shown in Figure 5.

Fig 5. Scatterplots showing mean fixation count (left) and gaze dispersal (mean Gini coefficient; right) as a function of CFMT+ scores in Experiment 2. Typical viewers used to generate linear models (dashed lines) are shown in purple, with super-recognizers shown as yellow dots.

For number of fixations, the main effect of CFMT+ score was significant, $b = -0.55$, $CI = [0.24, 0.86]$, $t(43.2) = 3.44$, $p = .001$, with higher CFMT+ participants tending to make more fixations per trial than lower CFMT+ participants. There was also a significant main effect of aperture size, $b = 1.04$, $CI = [0.93, 1.15]$, $t(1553.8) = 18.28$, $p < .001$, with fewer fixations being made at smaller aperture sizes. These effects were qualified by a significant three-way interaction

between CFMT+, phase and aperture size, $b = -0.14$, $CI = [-0.24, -0.03]$, $t(9160.6) = 2.60$, $p = .009$. Simple effects suggest that the main effects of CFMT+ scores and aperture size are seen in both phases, these effects are larger in face learning (b 's = 0.7 - 0.9) than face recognition (b 's = 0.26 - 0.34). Goodness of fit statistics show that a linear model trained on typical viewer data predicted super-recognizer's fixation counts with comparable fit to the typical viewer data (typical viewers: $RMSE = 2.4$, $R^2 = 0.58$; super-recognizers: $RMSE = 4.6$, $R^2 = 0.42$; see supplementary materials for more details).

Gaze dispersal analysis also replicated Experiment 1. Linear mixed models of Gini coefficient show a significant main effect of CFMT+ score, $b = -.008$, $CI [-.014, -.002]$, $t(43.0) = -2.44$, $p = .019$, with higher CFMT+ scores leading to lower Gini coefficients. This effect was characterized further by a significant interaction between CFMT+ and Phase, $b = .007$, $CI [.005, .008]$, $t(9141.6) = 10.44$, $p < .001$, with simple effects showing an effect of CFMT+ scores during face learning ($b = .011$) but not during face recognition ($b = .004$). Again, goodness of fit statistics show that a linear model trained on typical viewer data predicted super-recognizer's Gini coefficients with comparable fit to the typical viewer data (typical viewers: $RMSE = 0.031$, $R^2 = 0.15$; super-recognizers: $RMSE = 0.052$, $R^2 = 0.27$; see supplementary materials for more details). Together with accuracy analysis, these results are consistent with differences in super-recognizers viewing behavior observed in Experiment 1 being due to dimensional – rather than qualitative and categorical – differences across the ability spectrum.

Gaze pattern analysis

PCA was conducted in the same way as Experiment 1 and appeared to replicate the same first component (Fig. 6). PC1 again appeared to code participants tendency to fixate the eye-region (left-side) versus their tendency to distribute fixations more broadly across central regions of the face (right side) and accounted between 19-20% of the variance in gaze patterns across trials (for more information see supplementary materials).

Fig 6. Visualisation of first principal component (a) that emerges from PCA of trial-level gaze maps during face learning and recognition in Experiment 2. Scatterplots (b) show the poor predictiveness of super-recognizers eye gaze patterns based on linear models trained on only typical viewers data (dashed red line). A U-shaped function provided a closer fit to the data (solid blue line).

As in experiment 1, we explored the relationship between PC1 loading and face recognition ability. Scatterplots of this relationship are shown separately for learning and recognition in Figure 6. Critically for our research question, linear mixed models of PC1 show no significant main effect of CFMT+ score, $b = 0.02$, $CI = [-0.18, 0.23]$, $t(43.0) = 0.2$, $p = .844$. There was a significant three-way interaction between CFMT+ score, phase and aperture size, $b = 0.03$, $CI [0.00, 0.06]$, $t(9157.4) = 2.17$, $p = .030$, which was peripheral to the motivation of Experiment 2 and is described in supplementary materials. Goodness of fit statistics suggests that linear models trained on typical viewers poorly predict *both* super-recognizers and typical viewers gaze patterns (typical viewers: $RMSE = 0.732$, $R^2 = 0.05$; super-recognizers: $RMSE = 1.264$, $R^2 = 0.07$; see supplementary materials for more details). As in Experiment 1, we found a strong relationship between participants' PC1 loadings for learning and recognition phases in both modal strategy ($r_{43} = .926$, $p < .001$) and variability of strategy across trials ($r_{43} = .719$, $p < .001$; see supplementary materials for analysis separately by aperture size).

This suggests that individual differences in gaze patterns, while present, are not linearly related to face recognition across the ability spectrum. Differences observed in super-recognizers gaze patterns, which were less fixated on eye regions in both Experiment 1 and 2, raises the question of whether there is a non-linear relationship between CFMT+ scores

and gaze pattern differences. Visual inspection of data points shown in Figure 6 was suggestive of a U-shaped relationship. Given evidence showing that people with Congenital Prosopagnosia also show less fixation on eye regions (DeGutis et al., 2012; Towler et al., 2016), we conducted a formal analysis of quadratic fit. Comparison of information criteria showed a better quadratic than linear fit for both learning and recognition for typical viewers (RMSE = 0.722, $R^2 = 0.05$; Model comparison Likelihood ratio = 14.03, $p < .001$) and super-recognizers (RMSE = 0.638, $R^2 = 0.26$; see supplementary materials for more details). Both linear and quadratic regressions are displayed in Figure 6 for purposes of visual comparison.

Discussion

In Experiment 2 we replicated key differences between super-recognizer and typical viewers from Experiment 1 in the broader ability spectrum. Face recognition ability was a significant predictor of face recognition accuracy, and this did not interact with aperture size. Likewise, differences in the number and dispersal of fixations observed in Experiment 1 were predicted by differences observed in Experiment 2 across the spectrum of face recognition ability, showing that higher performance in face recognition is associated with more fixations and a more distributed sampling of face information.

We also examined whether linear trends in participants sampled from the broader ability spectrum predicted the performance and sampling strategies observed in a smaller group of super-recognizers. Consistent with previous work (Tardif et al., 2019), most of the differences between super-recognizers and typical viewers found in Experiment 1 were predicted by linear trends in the broader ability spectrum. Notably, however, our analysis of gaze patterns showed that these differences were not explained by linear trends in the broader ability spectrum. Instead, we observed a U-shaped function whereby gaze patterns in super-recognizers were more similar to participants with low ability than for participants with average ability.

General Discussion

Across two experiments we made three consistent observations about face information sampling in people with superior face identification ability. First, high performers retain their performance advantage even when only able to sample very small regions of the face on each fixation. Second, they sample more information from across the face. Third, these differences are observed most when they initially learn faces.

Reducing the amount of global information available to super-recognizers in a single fixation did not reduce their performance advantage. Initial work aiming to understand perceptual processes underlying individual differences in face processing ability had examined the association between measures of holistic processing ability to face identification performance (e.g. DeGutis et al., 2013). While this work sometimes reported an association (e.g. Wang et al., 2012), more recent studies have not (e.g. Sunday et al., 2017). The findings we report here extend recent reports that underline the importance of local-processing. For example, people with superior face recognition ability require less local image information for accurate recognition (Royer et al., 2015; c.f. Tsantani et al., 2020). Together, this evidence appears to dispel the notion that individual differences in face identity processing can be explained by differences in holistic processing alone. To the extent that super-recognizers face recognition ability is related to 'holistic' processing, face researchers will need to re-evaluate what is meant

by this term (e.g. Farah et al., 1998) — because it is not contingent on being able to view the whole face at any one time.

We also found differences in the face information sampled by super-recognizers compared to typical viewers. The greater number of fixations and greater dispersal across the face suggests that super-recognizers extract face information more efficiently than typical viewers, which in turn allows them to sample more information in the face. Interestingly, we found that these differences were most clearly and consistently observed in information sampled during face learning. This result suggests that understanding superior face recognition abilities might first require understanding the process of face learning. Notably, we observed these differences despite limiting participants to studying a single image of each unfamiliar face on a computer screen for just 5 seconds. In everyday experience, visual information sampling is far less constrained. The degrees of freedom for visual exploration – for example through interacting with people, or changes in viewpoint – are increased exponentially, potentially enabling the discovery of richer identity signatures in the face (Butcher & Lander, 2017; Butcher et al., 2011; Yovel & O'Toole, 2016). Understanding how super-recognizers encode faces into memory in more realistic settings may therefore help to understand how they construct robust memory representations of familiar faces.

In Experiment 2, we found that most differences in information sampling of high performers were consistent with linear trends across the broader ability spectrum. This extends recent studies examining information use in high performers in face identification tasks (Chuk et al., 2017; Royer et al., 2018; Schyns et al., 2002; Tardif et al., 2019), and appears to show that super-recognizers abilities are not supported by qualitatively different processing (see Noyes et al., 2017). However, there were two important differences to this prior work. First, in our analysis of gaze-patterns, super-recognizers appeared to fixate eye regions less than typical viewers, despite the prior implication of greater eye region use in high performers (e.g. Tardif et al., 2019). This difference is likely because we enabled participants to actively explore the face information, rather than the information available being constrained by the experimenter (as in the Bubble technique, Schyns et al., 2002). Second, we did not observe a linear trend of information sampling patterns across the ability spectrum. Instead, the U-shaped association suggests both low and high performers fixated less on the eye region. This is consistent with studies of people with congenital prosopagnosia, who also show more visual exploration and less attention to eyes compared to typical viewers (for reviews see Avidan & Behrmann, 2021; Towler et al., 2016). This is an intriguing pattern, and may suggest that additional information obtained via visual exploration both compensates for reduced function in low performers, and facilitates normal function in high performers.

Overall, these findings highlight the importance of studying extreme face recognition abilities in the context of the broader ability spectrum. As yet, there is no clear evidence of qualitative differences in super-recognizers perceptual and cognitive processing, suggesting that the study of super-recognizers is simply an alternative approach to studying individual differences, we have shown that these are linked to differences in visual sampling and exploration during face learning. Understanding individual differences in the construction of face identity representations during learning is, therefore, a critical avenue for future work.

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