Atten Percept Psychophys
DOI 10.3758/s13414-013-0562-6

Association and dissociation between detection and discrimination of objects of expertise: Evidence from visual search

Tal Golan · Shlomo Bentin · Joseph M. DeGutis · Lynn C. Robertson · Assaf Harel

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Abstract Expertise in face recognition is characterized by high proficiency in distinguishing between individual faces. However, faces also enjoy an advantage at the early stage of basic-level detection, as demonstrated by efficient visual search for faces among nonface objects. In the present study, we asked (1) whether the face advantage in detection is a unique signature of face expertise, or whether it generalizes to other objects of expertise, and (2) whether expertise in face detection is intrinsically linked to expertise in face individuation. We compared how groups with varying degrees of object and face expertise (typical adults, developmental prosopagnosics [DP], and car experts) search for objects within and outside their domains of expertise (faces, cars, airplanes, and butterflies) among a variable set of object distractors. Across all three groups, search efficiency (indexed by reaction time slopes) was higher for faces and airplanes than for cars and butterflies. Notably, the search slope for car targets was considerably shallower in the car experts than in nonexperts. Although the mean face slope was slightly steeper among the DPs than in the other two groups, most of the DPs' search slopes were well within the normative range. This pattern of results suggests that expertise in object detection is indeed associated with expertise at the subordinate level, that it is not specific to faces, and that the two types of expertise are distinct facilities. We discuss the potential role of experience in bridging between low-level discriminative features and high-level naturalistic categories.

Keywords Visual search · Face perception · Perceptual categorization · Developmental prosopagnosia · Perceptual expertise

T. Golan (✉) · S. Bentin
Interdisciplinary Center for Neural Computation, Hebrew University of Jerusalem, Jerusalem 91905, Israel
e-mail: tal.golan@alice.nc.huji.ac.il

S. Bentin
Department of Psychology, Hebrew University of Jerusalem, Jerusalem, Israel

J. M. DeGutis
Veterans Affairs Boston Healthcare System, Boston, MA, USA

L. C. Robertson
University of California, Berkeley, Berkeley, CA, USA

L. C. Robertson
VA Northern California Healthcare System, Martinez, CA, USA

A. Harel
Laboratory of Brain and Cognition, National Institute of Mental Health, Bethesda, MD, USA

J. M. DeGutis
Vision Sciences Laboratory, Harvard University, Cambridge, MA, USA

Human face perception is a striking example of visual expertise (Tanaka, 2001). Discriminating between and recognizing individual faces should be a difficult perceptual task, as faces form a highly homogeneous set of stimuli with a very similar spatial configuration of parts. Nonetheless, humans are extremely adept at recognizing individual faces (e.g., Moscovitch, Winocur, & Behrmann, 1997; Tanaka, 2001). This remarkable human skill in individuating faces is achieved through a number of specialized processing mechanisms, broadly termed "holistic" (for a review, see Maurer, Grand, & Mondloch, 2002).[1] Holistic processing implies the joint processing of the

[1] The terms "holistic" and "configural" are notorious in the face perception literature for their many definitions and associations. In the context of the present study, we use the terms in their most general, inclusive sense as defined by Maurer et al. (2002), subsuming first-order configural processing, second-order configural processing, and holistic (or integral) processing.

Published online: 12 December 2013

constituting parts of the object (including their relative location and metric distances) and is distinguished from the piecemeal processing of individual object parts that is more characteristic of standard object recognition (DeGutis, Wilmer, Mercado, & Cohan, 2013; Richler, Cheung, & Gauthier, 2011).

Although the hallmark of face expertise is enhanced within-category discrimination (also known as subordinate categorization), face recognition also entails a between-category advantage, that is, faces are more easily categorized relative to other object categories at the basic-level (i.e., "a face" relative to "a car"; Anaki & Bentin, 2009; Harel & Bentin, 2009; Harel, Ullman, Epshtein, & Bentin, 2007). This advantage is manifest in the categorization of single objects, as well as in more ecological and computationally demanding tasks, such as the detection of faces among other objects (Hershler, Golan, Bentin, & Hochstein, 2010; Hershler & Hochstein, 2005). However, relative to face individuation, much less is known about the mechanisms underlying the basic-level face advantage, in particular how it is related to within-category face individuation (for discussion, see Harel & Bentin, 2009). Specifically, the question is whether expertise in detecting faces is part of the greater expertise in face individuation (for example, by channeling the first-order feature information for later specialized second order processing), or whether the two aspects of advantageous face processing are independent perceptual phenomena acquired simultaneously with increasing experience. Indeed, given the vast experience that people have with faces, and with face individuation in particular,[2] the question of how the two manifestations of face expertise (detection and individuation) relate has implications for the broader field of visual perception, as they raise the question of how experience with the same type of visual input results in two putative distinct types of visual expertise. In other words, does general experience with faces similarly produce expertise in face detection and expertise in face individuation? And how independent are the two types of expertise? Does achieving expert performance in one type of expertise necessarily enhance performance in the other? Despite their importance, these questions are quite difficult to answer since nearly all adults are face experts, making it almost impossible to study the two types of face expertise in isolation. Further, given the social and biological importance of faces (Zebrowitz & Montepare, 2008), the two manifestations of face expertise may be a unique characteristic of face processing and may not generalize to other object categories. In the present study we aim to untangle these issues, by investigating face expertise from two complementary perspectives.

One way to address the challenge of studying the role of experience in face perception is by studying individuals with expertise in nonface object categories (e.g., cars). Similar to face expertise, expertise in visual object recognition is defined as the enhanced ability to distinguish between exemplars from a homogeneous object category (Tanaka & Taylor, 1991; Tarr & Gauthier, 2000), and some evidence supports the use of holistic processing, albeit generally less than is found with faces (Diamond & Carey, 1986; Gauthier & Tarr, 2002; Richler, Wong, & Gauthier, 2011; but see Harel & Bentin, 2013; Robbins & McKone, 2007, for an opposing view). Our current understanding of how expertise in discriminating objects impacts expertise in detecting objects is still limited, as the majority of research on expert object recognition has focused on within-category discrimination, and not on basic-level detection of objects of expertise, which emphasizes generalization across exemplars rather than differentiation among them (Bukach, Gauthier, & Tarr, 2006; Palmeri, Wong, & Gauthier, 2004; but see Harel, Ullman, Harari, & Bentin, 2011). Consequently, studying expertise with nonface objects allows a test of whether the enhanced advantage seen in faces is a general manifestation of expertise, or whether it is a unique characteristic of face perception. Expertise in object recognition has been demonstrated for many object categories, including cars (Bukach, Phillips, & Gauthier, 2010; Gauthier, Skudlarski, Gore, & Anderson, 2000), dogs (Diamond & Carey, 1986; Robbins & McKone, 2007), birds (Johnson & Mervis, 1997), (Rhodes, Byatt, Michie, & Puce, 2004), X-rays (Evans et al., 2011; Harley et al., 2009), and fingerprints (Busey & Vanderkolk, 2005). In the present study, we chose to focus on expertise in car recognition, as it is one of the most extensively studied domains of visual object expertise and has been shown to have distinct behavioral (Bukach et al., 2010; Gauthier et al., 2000; Harel & Bentin, 2013; Harel et al., 2011; Rossion & Curran, 2010) and electrophysiological (Gauthier, Curran, Curby, & Collins, 2003; Rossion, Collins, Goffaux, & Curran, 2007) markers, as well as functional (Gauthier et al., 2000; Harel, Gilaie-Dotan, Malach, & Bentin, 2010; Xu, 2005) and structural (Gilaie-Dotan, Harel, Bentin, Kanai, & Rees, 2012) neuroimaging markers. Specifically, we examined whether, as with faces, expertise with cars (i.e., expertise in car discrimination) is also accompanied by an advantage in detecting cars among other objects with which the participants are not experts. We then asked how independent these two types of expertise are by looking at a case in which face expertise is missing—namely, in developmental prosopagnosia (DP).

With typically intact low-level vision and normal object recognition, developmental prosopagnosics (DPs) frequently fail to identify people by looking at the face, and their ability to distinguish or match individual faces is impaired (for a review, see Duchaine & Nakayama, 2006). Like visual object expertise, developmental prosopagnosia (DP) manifests primarily at the individual exemplar level and therefore provides

[2] Please note that, although experience clearly plays a role in face perception, several lines of research have suggested that face perception also has a strong innate element (Kanwisher, 2010; Sugita, 2008; Wilmer et al., 2010).

an opportunity to study how separate within-category face discrimination is from basic-level face detection. The majority of DP studies seem to suggest that the absence of one expertise does not entail the absence of the other, as almost all DPs can distinguish between faces and nonface control stimuli (de Gelder & Rouw, 2000; Duchaine, Nieminen-von Wendt, New, & Kulomäki, 2003; Lee, Duchaine, Wilson, & Nakayama, 2010; Le Grand et al., 2006). However, when faces are presented in clutter, DPs were found to be slower, on average, than control participants in detecting a face among nonface objects as well as in detecting a two-tone face among jumbled face-like stimuli (Garrido, Duchaine, & Nakayama, 2008). These findings suggest that difficulties with face detection in DP may exist, but they may be revealed only by more demanding tasks than simple object recognition, particularly tasks in which difficulty can be adjusted. This can be accomplished by employing visual search paradigms, allowing for a wide range of performance. Note that the interpretation of the Garrido et al.'s study was limited by the use a fixed array size that precludes the calculation of search slopes. Search slopes yield information about performance as a function of perceptual complexity operationalized by search array size and are often considered a better measure of perceptual processing than raw reaction times. Reaction times are affected not only by the requirements of target detection but also by target processing and response selection (Wolfe & Horowitz, 2004).

To examine the nature of the basic-level advantage in face detection, the present work uses visual search methods in two distinct subpopulations, object experts and DPs, thereby integrating the different approaches outlined above. We aimed to characterize expertise in face detection by asking two questions: First, how common is the co-occurrence of expert basic-level detection and skill in subordinate categorization? Is it unique to faces or can it also be found when individuals become experts with a non-face object category (e.g., cars)? Second, can enhanced basic-level face detection (measured using visual search slopes) be demonstrated in the absence of the ability to discriminate individual faces? To answer these two questions, we studied expertise in face detection expressed in visual search for faces among object distractors in relation to two other distinct instances of expertise. In Experiment 1, we contrasted face expertise with real-world object expertise (car expertise) to ask whether we see enhanced search performance for nonface objects of expertise. In Experiment 2, we examined how DPs, who by definition have not gained expertise with faces (and hence may be considered "face novices") search for faces among nonface object distractors. The underlying rationale of combining these two distinct groups of experts and "novices" to study basic-level face detection is that both groups are defined on the basis of their within-category discrimination ability, leading to the question of how general the presence or absence of this ability for basic-level detection might be.

Experiment 1

The goal of this experiment was to test whether the association between subordinate and basic-level face expertise can be generalized and is equivalent to other types of object expertise. We compared the efficiency of visual search for four target categories (faces, airplanes, cars, and butterflies) in a group of car experts relative to a control group of novice participants. Participants searched in separate blocks for face, car, airplane, or butterfly targets among object distractors from a wide range of object categories. To discourage within-category processing, all targets were explicitly defined at their basic level. A specific advantage for car experts in detecting car targets among object distractors would demonstrate an influence of expertise on visual search, consistent with the notion that the face detection advantage reflects the effect of experience. The search for face targets was expected to be efficient, in line with previous reports (Hershler et al., 2010; Hershler & Hochstein, 2005). The other two object target categories of butterflies and airplanes were used as controls, and hence were expected to be searched equally less efficiently than faces, since neither of these categories had particular relevance to the participants.

Method

Participants The car experts were 12 individuals (22–40 years old, $M = 27.5$, all males) with self-declared lifelong interest in cars. They were recruited from among volunteers who responded to messages posted in car forums on the Internet and had been selected for a previous study (Harel et al., 2010). Critically, the experts were selected on the basis of their performance in a subordinate same–different matching task: In each trial, candidates had to report whether a pair of sequentially displayed car images portrayed cars of the same model (e.g., both Honda Civics) or cars of the same make but of different models (e.g., a Honda Civic and a Honda Accord). The specificity of the candidates' expertise with cars was verified by an equivalent task with civil airplanes, relative to the performance of a group of novice participants tested in that study. The experts were more accurate by far with cars than were the novices, but no group difference emerged in performance accuracy with airplanes (for more details, see Harel et al., 2010).

The control group consisted of 24 undergraduate students at the Hebrew University (20–34 years old, $M = 24.6$; 15 males, nine females). A subset of 12 of the control participants was matched to the experts for gender and experimental blocks orders. Since the results derived from this matched subset were qualitatively indistinguishable from those derived from the entire control group, we will report the latter in order to allow for better comparison with the results of Experiment 2.

Fig. 1 Examples of stimuli representing each of the four target categories

All participants reported normal or corrected-to-normal visual acuity and were free of any neurological or psychiatric condition. They signed an informed consent approved by the Hebrew University Institutional Review Board. The car experts were compensated for their participation, and the control participants received either monetary compensation or course credit.

Stimuli Images from 20 object categories were collected from the World Wide Web. Four of the categories—faces, butterflies, airplanes, and cars—were used as targets (see examples in Fig. 1).

The 16 categories used as distractors were sofas, fish, dogs, painted eggs, hats, shirts, apples, flowers, shoes, watches, potatoes, trousers, wardrobes, jackets, balls, and computer mice (Fig. 2). We presented 48 different exemplars for each target category and 32 different exemplars for each distractor category. All images were converted to grayscale, resized to fit a square of 100 × 100 pixels, and the background of each image was removed using Adobe Photoshop. The objects were edited to a uniform size by equating the size of each object's convex hull and were centered in the square using each object's center of mass (average coordinates of the nontransparent pixels). The mean luminance was equated across objects by a nonlinear point operation. To ensure optimal visibility across categories, the RMS contrast of each image was enhanced by clipping the 0.5 % brightest and darkest pixels and remapping the remaining pixels to the full range. Search arrays were built from the single object images. Each array comprised 4, 8, 12, or 16 items with no more than one exemplar of a category. The items in a display were randomly placed over a 4 × 4 virtual grid and their exact locations within each grid entry were jittered by up to 15′ of visual angle. The whole array subtended a visual angle of 10°, with 2° per item.

Design and procedure The experiment consisted of four blocks, with a different target category used for each block. Each block consisted of 192 experimental trials with 48 trials per display set size (4, 8, 12, or 16 different items), presented in random order. Across all set sizes, half of the trials included a target from the predesignated category ("target-present" condition) and half did not include the target category ("target-absent" condition). The identity of the distractor categories, the specific exemplars used and the location of the images within the display matrix were randomly determined prior to each trial onset. The specific target exemplars presented in each display were determined by a pseudorandom "drawing-without-replacement" method, minimizing repetition.

All 24 possible orders of the four blocks were used across the 24 control participants, whereas a subset of 12 orders were used for the 12 car experts (analysis of the block order revealed no significant effects). A training session of eight trials depicting all Set Size × Target-Present/-Absent conditions preceded each experimental block.

Participants were seated in front of a 17-in. monitor positioned at eye level, 80 cm from the participant (a chinrest was used to ensure constant viewing distance). They were instructed to press as quickly as possible the "/" key when a target was detected and the "z" key for its absence. Speed and accuracy were equally emphasized. Each trial began with a fixation mark presented for 750 ms. The visual search array replaced the fixation mark and was exposed until response. Reaction time was measured from the onset of the display and stored along with the response type (target present/absent) and accuracy. An auditory "buzz" feedback was delivered when the response was incorrect. The fixation mark beginning the subsequent trial followed the response immediately. Stimulus presentations and data recordings were controlled by E-Prime software (Psychology Software Tools, 2000).

Data analysis The reaction time analysis was conducted only on correct trials (~98 % and ~97 % of the trials for control participants and car experts, respectively). These trials were subjected to an absolute (200 to 5,000 ms) reaction time filter (Wolfe & Myers, 2010). Across all participants, only 16 trials (less than 0.01 %) were rejected by this filter, with no more than four trials per participant. For each participant, a search slope was estimated independently for each target category by linear regression of reaction times over set size. For the present purposes, the estimation of search slopes was limited to target-present trials in order to reduce nonperceptual factors such as search strategies based on item or feature memory.[3] The resulting slopes were analyzed by repeated measures 2 × 4 ANOVAs with the between-subjects factor Group (two levels: car experts and controls) and the within-subjects factor Target Category (four levels: butterfly, car, face, and airplane). Post-hoc

[3] Since the slopes were calculated by regressing reaction times in the "target-present" trials only, they cannot be considered millisecond/item estimates, which are probably higher. The "target-absent" data are available from the corresponding author upon request.

Fig. 2 Example of a “target-absent” display presenting all 16 distractor categories

pair-wise comparisons were conducted using nonparametric tests, so the impact of potential non-Gaussian distributions was minimized.

Results

The mean reaction times across conditions (Fig. 3) and the mean search slopes for each target (Fig. 4) exhibited an overall comparable performance pattern between car experts and controls, with the exception of one noticeable car-related between-group difference. Both groups were most efficient at searching for faces and slightly less so at searching for airplanes. However, whereas the controls exhibited seemingly equally inefficient search for cars and butterflies, car experts searched for cars with an efficiency almost as high as for airplanes, leaving butterflies behind as the least efficient target category (for the distributions of individuals’ performance, see Fig. 5). These descriptive observations were supported by an ANOVA of the target-present search slopes, which showed significant effects of target category [$F(3, 102)$[4] = 41.5, $p < .001$, G-GE = .74, $\eta_p^2 = .550$], group [$F(1, 34) = 4.90$, $p < .05$, $\eta_p^2 = .126$], and critically, a significant Target Category × Group interaction [$F(3, 102) = 7.773$, $p < .01$, G-GE = .74, $\eta_p^2 = .186$]. Post-hoc within-group pair-wise comparisons showed significant search slope gradients: faces < airplanes < butterflies and cars in control subjects, whereas in experts no difference emerged between the slope to cars and airplanes, which were both steeper than the slope for faces and both shallower than that for butterflies ($p < .05$ for all relevant comparisons, Wilcoxon signed-rank test, Holm–Bonferroni corrected within each group). The critical planned contrast comparing the car target slope of car experts with the car target slope of controls was highly significant (Mann–Whitney test, $p < .001$), whereas the other between-group, within-category comparisons were not (ps = .608, .704, and .856 for faces, airplanes, and butterflies, respectively). To deal with the potential confound of expertise with participants’ sex, we repeated the above tests using only a subset of the control group consisting of 12 male nonexperts and found qualitatively equivalent results. The present expertise effects are not likely to reflect speed–accuracy trade-offs, as can be observed in Table 1, reporting accuracy data broken down by false alarms and hits. As a further test of the relation between expertise in within-category discrimination and expertise in detection, we estimated the correlations between car experts’ level of expertise and their performance in the between-category visual search task.

[4] For the Target Category factor and interactions, the degrees of freedom were corrected when Mauchly’s test revealed significant deviations from sphericity, by using the Greenhouse–Geisser epsilon (G-GE); for simplicity, the original values are presented along with the correction factor.

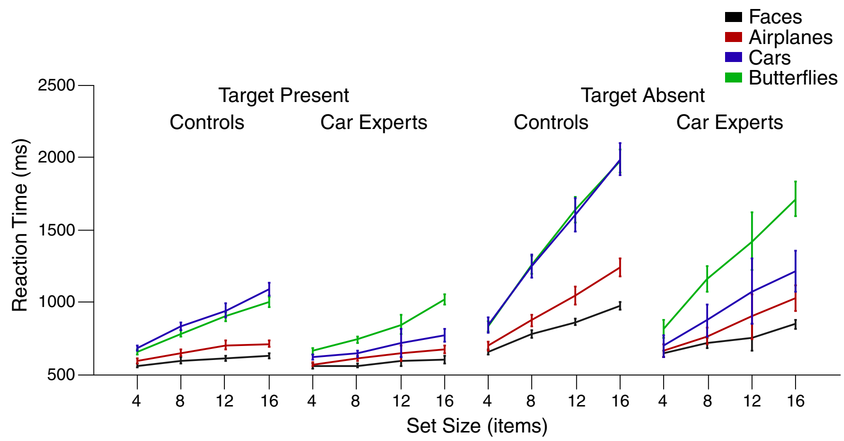

Fig. 3 Mean reaction times for correct trials. Error bars indicate 1 *SE*

The within-category expertise was indexed by the d' scores in the car discrimination task (see the "Method" section; due to a data archiving issue, the d's of two of the 12 experts were not available for this analysis), and the detection expertise was measured using the car detection search slopes. A nearly significant correlation between expert car discrimination and expert car detection was found, with greater car discrimination being associated with smaller search slopes (r = –.62, p < .06). In order to account for nonspecific interindividual variability in task performance (e.g., some participants are simply better than others at visual search, regardless of the target's category), we also correlated the difference between car d' and airplane d' with the difference between the car search slope and the airplane search slope, which was found to be significant (r = –.74, p = .014). These results strongly suggest that the two types of car expertise are highly related.

The relatively efficient search for airplanes was not a priori expected. Since this category had no particular experience-related status, this finding is most probably explained by low-level diagnostic features. In order to test whether the stimulus image statistics could account for this finding, we quantified how well the images' Fourier amplitude spectra (see VanRullen, 2006) could distinguish between the target categories and the distractors. We found that a measure of the Fourier amplitude spectrum collapsed across orientations predicted the behavioral results, suggesting that efficient search for airplanes can be accounted for, at least in part, by low-level image statistics (see the Appendix for further details).

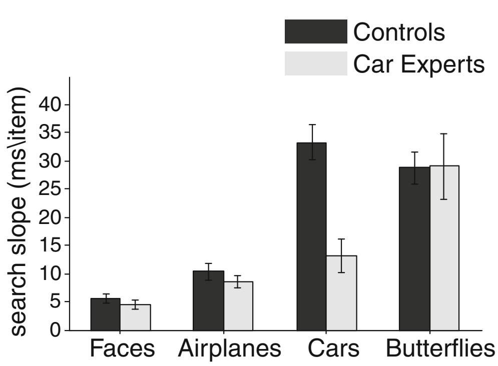

Fig. 4 Mean search slopes for correct, target-present trials among car experts versus control participants. Error bars indicate 1 *SE*

Previous studies showed that the face detection advantage over other categories is higher in the visual field periphery than in the parafovea (Hershler et al., 2010). Therefore, we calculated the slopes separately for trials on which the targets appeared in the four central locations and for those on which the targets appeared in the 12 more peripheral locations (Fig. 6). The search slopes were analyzed by repeated measures ANOVAs with Target Location (central or peripheral) and Target Category as within-subjects factors and Group as a between-subjects factor. This analysis showed that the main effect of target location was significant [$F(1, 34) = 42.226$, $p < .001$, $\eta_p^2 = .554$], with slopes being steeper for peripheral than for central targets. This main effect was modulated by an interaction with category [$F(3, 102) = 4.328$, $p < .05$, G-GE = 0.7, $\eta_p^2 = .113$]. We also found a significant Category × Group interaction [$F(3, 102) = 5.302$, $p < .01$, G-GE = 0.7, $\eta_p^2 = .135$] and a trend toward a Location × Category × Group interaction [$F(3, 102) = 3.038$, $p = .057$, G-GE = 0.7, $\eta_p^2 = .082$]. Subsequent Location × Group ANOVAs separately within each target category found significant location effects within all of the target categories ($p < .05$). A significant interaction of car expertise with target location was shown for car targets [$F(1, 34) = 6.230$, $p < .05$, $\eta_p^2 = .155$] but not for the other categories ($p > .3$). Comparisons of car search slopes between the experts and controls within each target location showed a highly significant advantage (shallower slopes) for experts in detecting car targets located in the periphery (Mann–Whitney test, $p < .001$) and a weaker, but still significant, advantage for experts in detecting car targets located centrally (Mann–Whitney test, $p = .049$). This finding seems to indicate that the detection advantage for objects of expertise is evident both for centrally and peripherally displayed targets, but it is significantly more accentuated in the periphery.

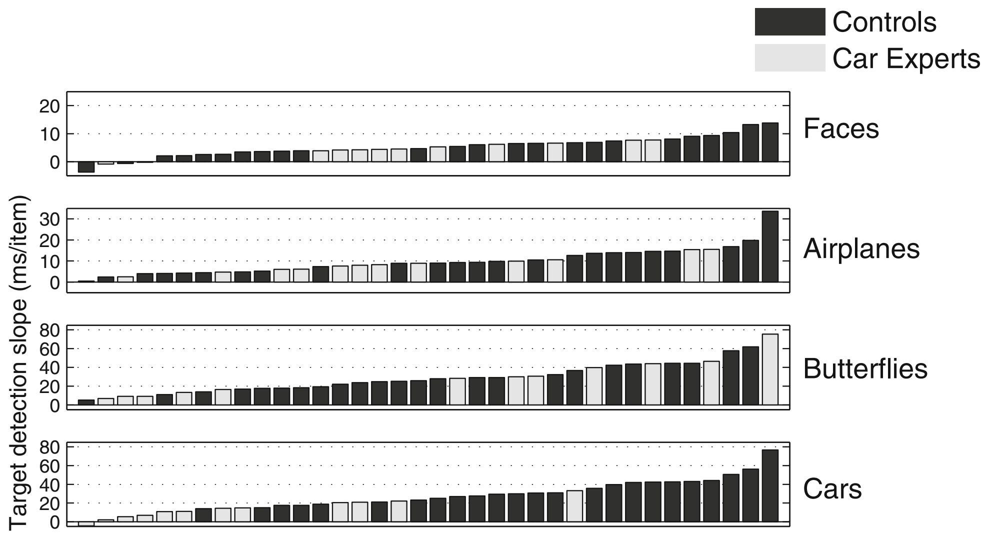

Fig. 5 Individual participant search slopes for correct target-present trials, ordered from shallow to steep within each target category. Note that, whereas performance in the two groups is evenly distributed for faces, airplanes, and butterflies, in the car category the majority of the car experts occupy the lower end of the distribution, representing their greater search efficiency for car targets relative to controls

Experiment 2

In this experiment, we compared the visual search efficiency of DPs with that of typical participants. In a way, DPs can be viewed as "face novices": They have a partial or complete deficit of the representation of individual human face identities (e.g., Palermo, Rivolta, Wilson, & Jeffery, 2011) that in typical individuals facilitates their superb subordinate categorization ability. It is not evident, however, that DPs have problems in face detection. As we reviewed above, some studies have suggested that the distinction between faces and nonface control stimuli (e.g. scrambled faces) is within the normative range in DPs (e.g., Le Grand et al., 2006), although it might be slower than normal, particularly when the face is presented among distractors (Garrido et al., 2008). In this sense, the relation between the DPs and controls was analogous to the relation between controls (who were defined as car novices) and car experts when viewing cars, and provided an opportunity to compare the processing of faces with that of objects. Thus, having observed an association in car experts between expertise in detection and expertise in subordinate categorization, we next asked how tightly related these two types of expertise might be by testing DPs. Examining the difference between car novices and experts may lead to the conclusion that the two types of expertise are highly related, as the car novices—who lacked the ability to distinguish between similar car models—detected cars less efficiently than did the car experts, who were defined by their superior within-category discrimination. Similarly, one might predict that DPs, who are deficient in their ability to distinguish between faces, would detect faces less efficiently than controls (considered face experts). In other words, if the face detection advantage in typical individuals is inseparable from their expertise in face individuation (i.e., expertise in detection is not independent of expertise in discrimination), DPs, who lack this facility, should display considerable deficiency in face detection, as well.

Table 1 Mean hit and false alarm rates for the control and car expert groups

Target	Set Size	Controls		Car Experts	
		Hit Rate	False Alarm Rate	Hit Rate	False Alarm Rate
Faces	4	.98	.01	.99	.02
	8	.98	.01	.97	.01
	12	.99	.01	.97	.02
	16	.98	.01	.96	.01
Airplanes	4	.98	.01	.97	.01
	8	.99	.01	.98	.01
	12	.96	.00	.97	.01
	16	.97	.01	.96	.01
Cars	4	.97	.01	.97	.01
	8	.94	.01	.97	.01
	12	.94	.00	.95	.00
	16	.91	.01	.93	.02
Butterflies	4	.98	.01	.97	.01
	8	.96	.01	.92	.01
	12	.94	.00	.90	.01
	16	.93	.01	.90	.02

Method

Participants The DP group included 12 individuals (Table 2). They all had normal or corrected-to-normal vision, had never been diagnosed with neurological or neuropsychiatric

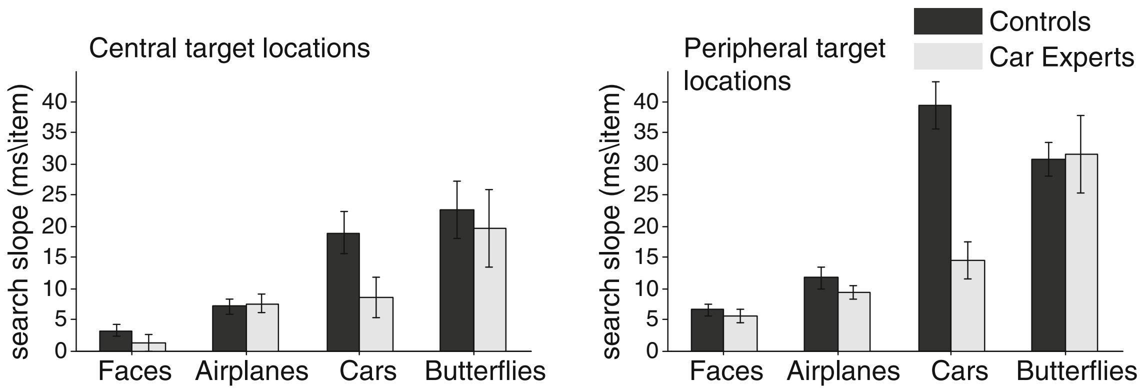

Fig. 6 Mean search slopes for correct target-present trials for the four central target locations versus the 12 peripheral target locations. Error bars indicate 1 *SE*

disorders or autistic spectrum disorder (possible borderline cases of autism were screened using the Autism Spectrum Quotient Questionnaire of Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001, and excluded if they scored >32). All participants gave informed consent in compliance with the Institutional Review Board of the VA Boston Healthcare System. To be considered a DP, each participant had to report a significant lifelong history of facial recognition deficits and answer "yes" to the following series of questions about everyday face recognition: (1) Do you find it hard to recognize someone you just met?, (2) Do you have difficulty recognizing casual acquaintances out of context?, (3) When you meet someone, do you pretend to recognize them until their identity is revealed?, (4) Do you have trouble recognizing people when they are in uniform?, (5) Do you find it hard to keep track of characters in TV shows and movies?, (6) Do you have trouble visualizing the faces of family and close friends?, (7) When trying to find an acquaintance, do you have trouble if they are in a room full of people?, and (8) Do you have trouble recognizing a close friend or family member in a photograph?

Additionally, each participant had to score 1.7 standard deviations worse than the healthy control mean on the Cambridge Face Memory Test (CFMT; Duchaine & Nakayama, 2006) or the Cambridge Face Perception Test (CFPT; Duchaine, Germine, & Nakayama, 2007). In addition to the detailed questionnaire, and considering that the CFMT and CFPT have some small amount of measurement error, we thought this to be a reasonable cutoff to identify DPs. Table 2 presents demographic details about the DPs and their performance on the relevant clinical diagnostic tests.

The controls were the same 24-participant group reported in Experiment 1. The experimental design and procedures were the same as in Experiment 1, with the exception of using only eight block orders for the DP participants (an analysis of block order revealed no significant effects). Since the control data had already been statistically tested in Experiment 1, only effects within the DP group and the differences between the DP and control groups will be reported and discussed.

Stimuli, design, and procedure The exact same stimuli and paradigm were used as in Experiment 1, with participants searching in separate blocks for face, car, airplane, or butterfly targets among object distractors from 16 categories.

Results

As is evident in Fig. 7, the reaction time pattern observed in the DP group was fairly similar to the pattern observed in the control group. A Group × Target category ANOVA of the search slopes (Fig. 8) supported this observation, showing no

Table 2 Demographic and diagnostic results of the developmental prosopagnosic (DP) participants

Participant	Age	Gender	CFMT*†	CFPT*
323	25	F	**44 (–1.87)**	70 (–2.73)
434	33	F	44 (–1.76)	68 (–2.57)
437	58	M	39 (–2.39)	68 (–2.57)
101	28	F	39 (–2.39)	58 (–1.75)
630	43	F	**47 (–1.50)**	78 (–3.39)
737	56	F	40 (–2.27)	58 (–1.75)
762	23	F	36 (–2.77)	68 (–2.57)
781	43	M	41 (–2.14)	60 (–1.91)
973	30	F	**47 (–1.50)**	58 (–1.75)
1024	25	M	37 (–2.64)	60 (–1.91)
1101	52	M	37 (–2.64)	68 (–2.57)
1226	53	M	41 (–2.14)	70 (–2.73)
Mean	39.1		41.0	65.3
SD	13.3		3.8	6.4

* For the Cambridge Face Memory Test (CFMT) and Cambridge Face Perception Test (CFPT), the raw scores are shown, with *z* scores in parentheses. † The bolded CFMT scores were from an alternate version of the CFMT with a slightly higher mean among the controls than the standard CFMT (mean alternate = 58.8, mean original = 57.9). This alternate form was used because these DPs were part of a training study in which they received the original CFMT after training.

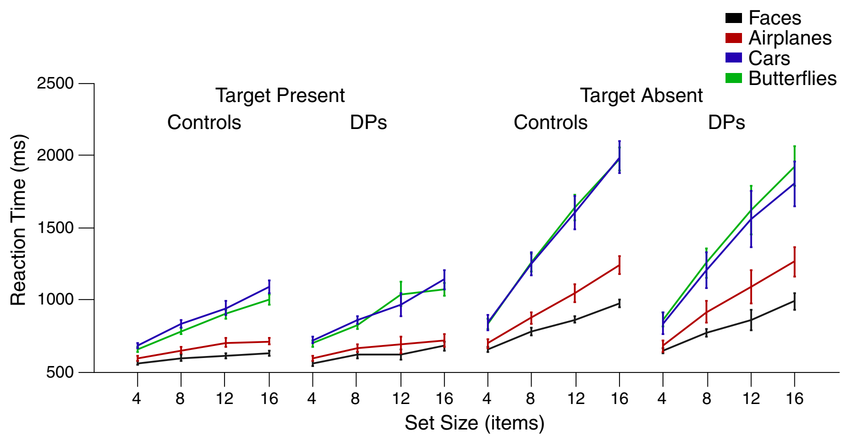

Fig. 7 Mean reaction times for correct trials, control participants versus developmental prosopagnosics (DPs). Error bars indicate 1 *SE*

main effect of group [$F(1, 34) < 1$] and no Group × Category interaction [$F(3, 102) < 1$]. Thus, by and large, we observed no overall significant differences between DPs and controls in detection efficiency for different object categories. It should be noted that directly testing the simple-effect prediction of higher search slopes in DPs than in controls showed that the mean target-present search slopes of the DP group were less efficient (9.00 ms) than those of controls (5.58 ms; Mann–Whitney test, $p < .05$). However, visual inspection of the individual search slopes (Fig. 9) revealed that although the DPs as a group were slightly less efficient at detecting faces among distractors, their individual performance was highly variable, with most DPs exhibiting face search slopes within the normal range spanned by the control group. This normal expertise in detection was dissociated from expertise in face discrimination, as revealed by a statistically nonsignificant correlation between face search slopes and the CFMT scores ($r = -.35$, $p < .255$). Furthermore, splitting the DPs on the basis of their face recognition performance (assessed by the median score in the CFMT) did not affect the present results. Accuracy data broken down by false alarms and hits (Table 3) provided no evidence of speed–accuracy trade-offs.

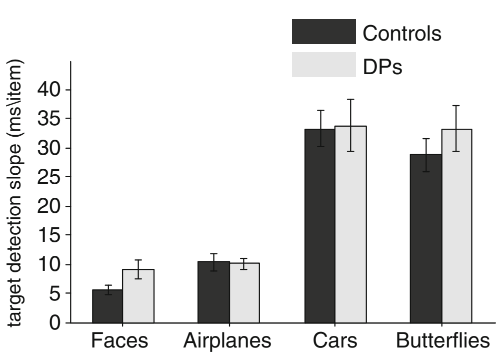

Fig. 8 Mean search slopes for correct, target-present trials. Error bars indicate 1 *SE*

Since the DP participants were, on average, older than the control group, we also analyzed the potential contribution of age to the observed differences between groups. As is shown in Fig. 10, this analysis demonstrated no significant correlation between the individual slopes in the face target conditions with age, either for the DPs [$r(10) = -.24$, $p = .45$] or for controls [$r(22) = .11$, $p = .62$].

In order to assess whether the face disadvantage of DPs was more pronounced at the periphery (as was the car advantage of car experts), we repeated the calculation of separate search slopes for central and peripheral targets (Fig. 11). The face slopes were analyzed in a Target Location × Group ANOVA. A tendency toward a Location × Group interaction [$F(1, 34) = 3.460$, $p = .072$, $\eta_p^2 = .092$] was further investigated by comparing the face slopes between the two groups. This analysis showed a trend toward a DP-related efficiency deficit when the face targets were presented in the periphery (Mann–Whitney test, $p = .062$), but not when they were central ($p = .908$).

Discussion

The aim of the present study was to elucidate the nature of the relation between expertise in within-category recognition and expertise in between category object detection. To achieve this aim, we focused on the one of the best examples of visual expertise, face expertise. Specifically, we aimed to characterize the basic-level advantage in face detection by asking two questions. First, is the co-occurrence of basic-level detection skill and subordinate categorization skill found in faces a general characteristic of expertise or is it a unique property of faces? Second, if a general association exists between the two types of expertise, how strong is this association? Specifically, can enhanced basic-level face detection exist independently of the ability to discriminate individual faces? To answer these questions, we investigated how car experts and

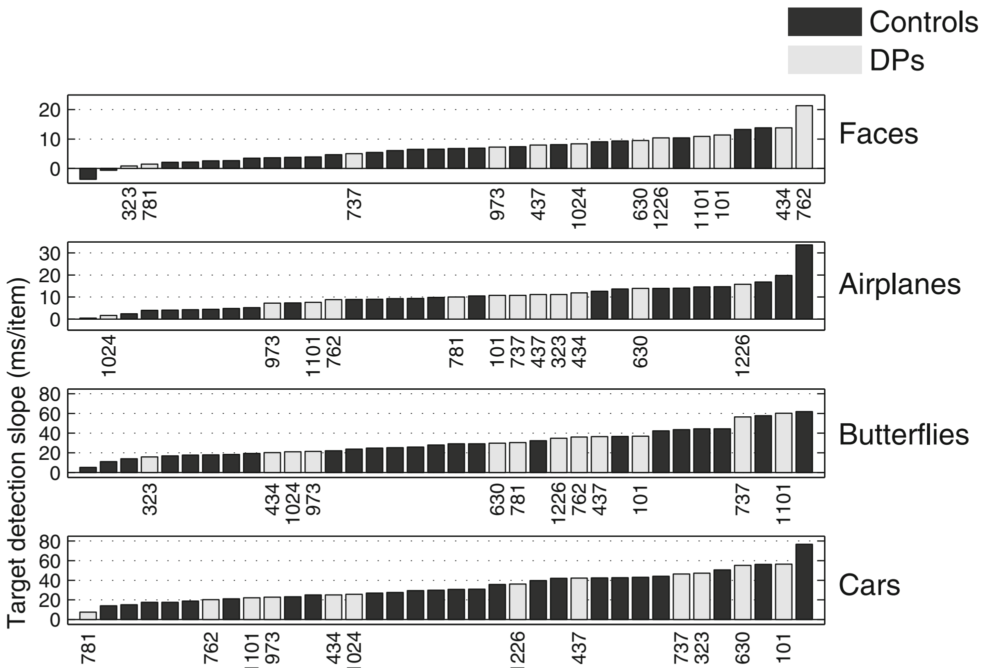

Fig. 9 Individual participant search slopes for correct target-present trials, ordered from shallow to steep within each target-category. Labels denoting individual developmental prosopagnosic (DP) participants (see Table 2) are listed below their corresponding data points

DPs, two distinct groups defined by improved or reduced performance, respectively, in *within-category* object recognition, would perform in a *between-category* object detection task—namely, in a visual search paradigm using real-world naturalistic objects.

Three key findings were revealed by the present study. First, car experts were much better than controls in detecting cars, showing considerably shallower search slopes, yet steeper than those of faces, which were efficiently detected and similar to controls. Second, whereas the DPs, as a group, were significantly worse than the controls in detecting faces, with search efficiency comparable to their search rate for airplanes, they were still better than with the other target categories (cars or butterflies). Indeed, the majority of DPs exhibited normative face detection performance. Finally, an unpredicted finding of the present study was unexpected search efficiency for airplanes, a target category with which none of the groups was expert, but one that contained spectral properties (different from those of the other categories) that could be used by low-level visual

Table 3 Mean hit and false alarm rates for the developmental prosopagnosic group

Target	Set Size	Hit Rate	False Alarm Rate
Faces	4	.98	.02
	8	.98	.00
	12	.97	.01
	16	.94	.01
Airplanes	4	.97	.02
	8	.97	.02
	12	.97	.01
	16	.94	.01
Cars	4	.94	.01
	8	.92	.00
	12	.88	.00
	16	.88	.03
Butterflies	4	.97	.01
	8	.91	.01
	12	.93	.01
	16	.86	.01

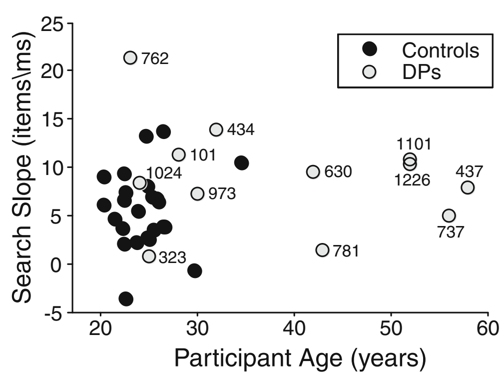

Fig. 10 Individual face search slopes for correct target-present trials as function of age. Labels denoting individual developmental prosopagnosic (DP) participants (see Table 2) are listed next to their corresponding data points. No evidence was apparent of significant correlations between age and search slope within the groups (p = .62 for controls, p = .45 for DPs)

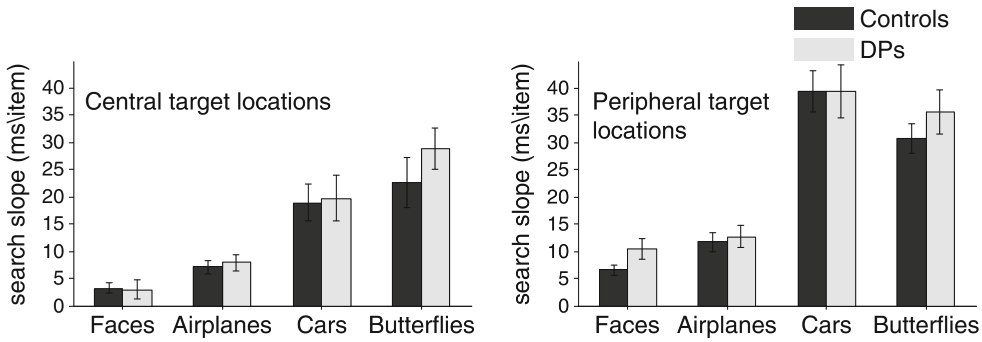

Fig. 11 Mean search slopes for correct target-present trials, for the four central target locations versus the 12 peripheral target locations. Error bars indicate 1 *SE*

mechanisms. For all groups, airplane targets produced nearly as efficient search as did human faces.

Together, these findings suggest that expertise in visual recognition is not specific to within-category discrimination and may generalize to basic-level object detection. Notably, the association between the two types of expertise is seen not only for faces, but also for other objects of expertise. This association suggests that the basic-level advantage for faces is not unique to face perception, but reflects a general effect of experience. Whereas these two expressions of expertise are closely linked, they are nonetheless independent, as is evidenced by a preserved basic-level face advantage (i.e., normative search performance for faces) in DPs, who by definition lack the expertise needed to individuate faces. In other words, one instance of expertise can exist without the other. Finally, the findings of the present study are not only relevant for visual expertise, but they also highlight the interactive nature of visual search for real-world objects, integrating categorical specialization and low-level, stimulus-driven processing.

Previous studies of expertise in object recognition have shown that expertise is highly specific to task (Harel et al., 2010; Wong, Folstein, & Gauthier, 2012) and stimulus (Bukach et al., 2010; Diamond & Carey, 1986; Tanaka, Curran, & Sheinberg, 2005). Task, in particular, plays a central role in constraining the neural and behavioral manifestations of visual expertise. For example, training participants to perform two different tasks on identical artificial stimuli results in separate cortical representations: Whereas a combination of orientation discrimination with a visual search task elicited activations primarily in early retinotopic visual cortex, a naming task elicited activations in various category-selective regions in high-level visual cortex (Wong et al., 2012). Given these distinct task-dependent manifestations of visual expertise, it is not self-evident how experience with a particular task, such as face individuation, might facilitate a totally different task, such as visual search, or whether the lack of face individuation expertise might reduce visual search efficiency. Furthermore, it has been suggested that the human expertise with faces can generalize to other objects of expertise if they share the same characteristics for processing (Bukach et al., 2006; but see McKone, Kanwisher, & Duchaine, 2007). Thus, cars and faces may tap the same neural and perceptual mechanisms in car experts, since both of these categories are homogeneous and involve holistic processing, which emerges following extensive training in subordinate categorization (Bukach et al., 2010; Gauthier et al., 2003; Rossion & Curran, 2010). However, if the shared process in face and car expertise is subordinate categorization supported by holistic processing, it is not obvious why a basic-level detection advantage would also emerge in car expertise. What is shared, then, by basic-level expertise with faces and basic-level expertise with nonface objects?

One factor common to the different types of basic-level expertise is the increased level of engagement that experts have with their category of expertise (Harel et al., 2010). Unlike experts trained in the laboratory, real-world voluntarily acquired expertise is the result of increased interest that experts have in their category of expertise, and therefore they are more likely to allocate covert and overt attention toward these objects in daily life (for a similar conclusion using an object fragment detection paradigm, see Harel et al., 2011). The suggestion that both face expertise and object expertise affect the deployment of attention is consistent with the observation that faces selectively affect the allocation of attention, demonstrated in a multitude of experimental paradigms, including the attentional blink (Awh et al., 2004; Landau & Bentin, 2008), change blindness (Ro, Russell, & Lavie, 2001; but see Palermo & Rhodes, 2003, for a different interpretation), and inattentional blindness (Devue, Laloyaux, Feyers, Theeuwes, & Brédart, 2009). In line with this proposal, a recent study showed that car distractors selectively hindered visual search for faces in car experts (McGugin, McKeeff, Tong, & Gauthier, 2011). This finding suggests that at least a partial overlap might exist between the top-down mechanisms that facilitate face detection and the mechanisms that are involved with processing of nonface objects of expertise.

As we discussed above, the present findings strongly suggest that expert car detection and (expert) face detection utilize similar top-down attentional mechanisms. Nonetheless, it is important to note that expert car detection and face detection differ in at least one critical aspect: the time course of development. Infants preferentially direct their attention to faces (or face-like stimuli) within minutes after birth (for a review, see Mondloch, Le Grand, & Maurer, 2010), and monkeys raised in a lab without any exposure to faces showed a strong preference for faces over other objects (Sugita, 2008). In contrast, real-world expertise with objects such as cars develops over many years of practice and training. This dramatic difference in the time courses of acquisition of expertise in detection might imply that expert car detection utilizes different mechanisms, relative to face detection (note that this is independent of the question of the innate bias for faces). This possibility resonates with the distinction made by Harel et al. (2010) between natural expertise (i.e., with faces) and acquired expertise (i.e., with objects). Whereas the former is likely to be automatic, stimulus-driven, and effortless, the latter is considered a controlled and intentional process reflecting the direct interest and engagement of the observer (Harel et al., 2010). Nonetheless, car expertise has been shown to be highly related to face processing, as has particularly been demonstrated in event-related potential studies of the N170 component (Gauthier et al., 2003; Harel & Bentin, 2007; Rossion et al., 2007). Notably, the N170 component has been suggested to reflect the early perceptual stage, at which faces are detected in the visual field and submitted to further face-characteristic analysis (Bentin, Golland, Flevaris, Robertson, & Moscovitch, 2006), and addition training studies have shown that the N170 reflects nonspecific effects of expertise, such as the expert's interest. Thus, expert car detection is clearly related to expert face detection, but the nature of the relations between them has yet to be determined.

The finding of an advantage of car experts in detecting cars is consistent with the notion that expertise in within-category discrimination is associated with an advantage in the detection of objects of expertise (see also Hershler & Hochstein, 2009). However, the normative face detection performance of many of the tested DPs suggests that expertise in between-category detection is independent from expertise in within-category recognition. Thus, visual expertise can be composed of at least two task-specific components: one dealing with the detection of category members, and the other with within-category discrimination (Wong et al., 2012). Accordingly, the association between these two modes of expertise observed in car experts should not necessarily be attributed to a common perceptual process (e.g., holistic processing of homogeneous objects) and may reflect the operation of multiple processes, including attention and memory. In the case of DPs, the preserved expertise in face detection might stem from the utilization of low-level features for attentional guidance toward faces. Such features might render faces an easy target category, even for a participant who has no *subordinate* expertise with faces. The fact that the disadvantage of DPs with faces tends to be more conspicuous at the periphery of the visual field supports this interpretation, as such low-level features are arguably more difficult to resolve in the periphery, relative to the center of the visual field. The present findings support the idea that expertise in basic-level categorization involves knowledge of the particular diagnostic features, and then selectively attending to these features, culminating in a better utilization of the existing discriminative information and a more efficient search (Biederman & Shiffrar, 1987; Goldstone, 1998). Finally, this interpretation is also compatible with the results of Garrido et al. (2008), who reported a small deficit for DPs relative to controls in the detection of face photographs, but a larger deficit in the detection of two-tone faces, which may carry less low-level discriminative information. It should also be noted that, whereas research on attention to faces in DPs is scarce, some studies have suggested that DPs show little difficulty in allocating their attention to faces or face features in the visual field (in contrast, e.g., to individuals with autism spectrum disorder, who avoid fixating faces or certain face features under natural viewing conditions; see, e.g., Klin, Jones, Schultz, Volkmar, & Cohen, 2002), which arguably allows them later to utilize diagnostic low-level features for further processing (DeGutis, Cohan, Mercado, Wilmer, & Nakayama, 2012; Kimchi, Behrmann, Avidan, & Amishav, 2012).

An alternative account of the advantage of faces in visual search is that faces are efficiently detected simply because of the unique presence of discriminative low-level stimulus properties, such as their Fourier amplitude spectra (VanRullen, 2006; but see Hershler & Hochstein, 2006). Relatedly, the efficient search for airplanes, a category that had no a-priori behavioral significance for the participants, suggests that nonface categories can be detected as well by utilizing discriminative low-level features (see also Cave & Batty, 2006). Can a constellation of such low-level features explain the pattern of results demonstrated by the controls in the present study, showing efficient search for faces and airplanes, and inefficient search for cars and butterflies? Our computational analysis of the stimuli (see the Appendix) revealed that both faces and airplanes displayed highly informative Fourier amplitude spectra. Interestingly, unconstrained utilization of these features predicted equally highly efficient search for all four target categories (see Fig. 12a). Indeed, only by further restricting the feature set (using Fourier amplitude spectra collapsed over spatial orientations) could a consistent prediction of human search efficiency be achieved (Fig. 12c). Thus, it is evident that the mere existence of low-level stimulus properties does not necessarily entail their successful utilization in visual search. We suggest that, at least in some detection tasks, the successful utilization of low-level stimulus properties requires the top-down deployment of knowledge of the diagnostic information. Whereas in some cases these diagnostic features may be evident through common knowledge (e.g., airplane detection), for other categories the knowledge of the diagnostic features is probably acquired through experience and training (e.g., car detection). Additional research systematically contrasting image statistics with human detection performance would be required in order to define exactly which low-level image properties might guide attention and how they interact with higher-level, experience-based, category-specific mechanisms to guide the detection of naturalistic objects.

Author note One of the authors, Shlomo Bentin died unexpectedly shortly after receiving the first reviews of this article. We dedicate this article to his memory. Without his hard work, creativity, insight, and collaborative spirit, this research would not have been possible. This study was funded by NIMH Grant No. R01 MH 064458 to L.C.R. and S.B. L.C.R. has a Senior Research Career Scientist award from the Veterans Administration and is affiliated with the VA Clinical Sciences Research Service, Department of Veterans Affairs Medical Center, Martinez, CA.

Appendix: Image analysis

In order to quantify how well each target category could be detected among the distractors solely by means of low-level stimulus properties, we turned to a classification approach. We chose to quantify the category-related information carried by the Fourier amplitude spectrum[5]. This image property has been put forward as an explanation of the advantage of faces in visual search with real-life images (VanRullen, 2006). In general, each image used in the experiments described in the main text was characterized by three separate measures, or 'binning strategies', derived from their Fourier amplitude spectra (orientation-frequency bins, orientation bins, and frequency bins). Each one of these measures was then evaluated separately by assessing their contribution to the performance of the classification of target versus distractor image categories.

All images were first normalized to have a zero mean and unit variance, and then were Fourier transformed; all of the following procedures were implemented by custom-made Matlab (The MathWorks, Natick, MA) scripts. The absolute value of each Fourier coefficient was computed. In order to reduce the high dimensionality (5000 coefficients), the Fourier plane was divided into logarithmic-radial bins, using 18 orientations (every 10º between 0º and 180º) and six scales. The values within each bin were averaged, transforming each image into a 108 (18 × 6) feature long vector. This representation is based on the texture histogram used by Neumann and Gegenfurtner (2006), which was shown to significantly predict human similarity ratings. Two modifications of their method were made: First, to compress the wide range of Fourier amplitude coefficients, a log-transform of the entire Fourier plane was applied prior to averaging. Second, the transitions between the different bins were graded, using a log-cosine function to define scale rings (as in Peli, 1990) and a cosine function to define orientation sectors. This allowed

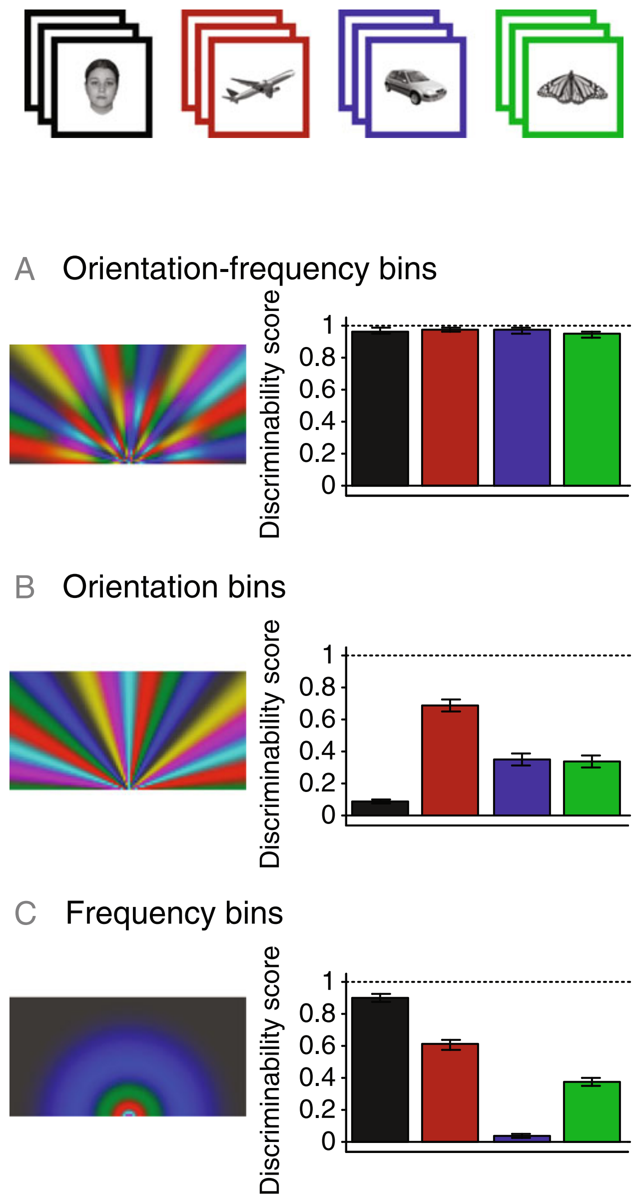

Fig. 12 Discriminability analyses of the four different target categories, conducted using three different Fourier amplitude spectrum binning strategies. On the left, the binning strategies of the Fourier plane are illustrated. The coloring of the bins has no relation to the color code of the bar charts; it is used only to demonstrate the ways that the Fourier plane was softly divided. On the right, the mean discriminability scores for each target category are charted. The error bars depict one standard error of the mean across 100 random training-test splits

[5] We have tested a few other image properties as well. These were found to be either too poor (object orientation and length) or too informative [Silhouette Distance (Cutzu & Tarr, 1997) and Coarse Footprint Difference (Sripati & Olson, 2010)] to drive the observed behavior. We focused our report on Fourier amplitude based measures due to their theoretical significance, but the analyses of the other measures are available by demand.

for equal representation of each Fourier coefficient while avoiding arbitrary hard bin limits. In addition to the radial-logarithmic binning ('orientation-frequency bins'), two additional binning strategies were applied: one using only orientation sectors (collapsed across frequencies) and the other using only frequency rings (‘radial average’, collapsed across orientations). These two binning strategies transformed each image into an 18- or six-feature-long vector, respectively.

Once the feature vectors were produced by a given binning strategy, they were used to train four different linear classifiers (support vector machines) to discern between each of the target categories and the distractors. For example, for face targets, a classifier was trained to classify feature vectors derived from the face images as class +1 and feature vectors derived from the 16 distractor categories as class −1 (a ‘one vs. all’ approach). Similarly, this was repeated with the three other target categories, each resulting in its own trained linear classifier.

In order to test the performance of the classifiers in the task of detecting a particular target category out of 16 search items (as was required from the human participants in the largest set size condition), we assembled groups of 16 images, each consisting of 15 distractors from different categories and a single target. In order to ensure unbiased classification, the images used in the training phase were excluded from this testing phase. Next, the degree of ‘targetness’ of each image was defined as the inner product of its feature vector with the weight vector corresponding to the trained classifier. We then checked whether each actual target received the highest ‘targetness’ score among its group of search items. If the actual target was indeed ranked first, that was considered a successful detection. By repeating this procedure over 16 different allocations of search item groups and 100 training and test subset splits, we estimated the probability of a successful detection, which we will refer as the ‘discriminability score’. In the case of no relevant information in the Fourier spectra, this score would be expected to equal 1/16 (chance performance). In the case that a specific target category could be always discerned from the distractors on the basis of its Fourier amplitude spectra, this measure would be expected to equal 1. The discriminability scores for each spectral binning strategy are depicted in Fig. 12. The least constrained binning of the Fourier power spectrum (Fig. 12a, ‘orientation-frequency bins’) was found to be highly informative of the object’s basic-level category in general, and not only for faces. Since the search for faces by humans was significantly more efficient than those for cars and butterflies, the Fourier amplitude spectra per se cannot account for the most efficient search for faces in the present study (cf. Hershler & Hochstein, 2005). The detection of targets by this procedure can be considered a coarse equivalent of selective top-down gain of different subpopulations of V1 complex cells, enhancing the responses to spatial frequencies of particular orientations and wavelengths. However, if such unconstrained top-down gaining of V1 subpopulations was a reality, human participants would have been expected to efficiently detect all four of the target categories tested. Since our behavioral results showed otherwise, this result indicates that, whereas naturalistic basic-level categories are confounded by typical amplitude spectra, this information is not necessarily utilized for guiding attention.

The discriminability scores based on the Fourier power spectrum collapsed across frequencies (Fig. 12b) were more consistent with human performance, in the sense that they predicted that airplanes should be discriminated better from the distractors than would either cars or butterflies. Note, however, that the discriminability of airplanes was higher than that of faces, which contrasts with the human search performance.

The discrimination scores based on the Fourier power spectrum averaged across orientations (Fig. 12c), were ordered in a fashion consistent with the human data: Faces were the most distinguishable, followed by airplanes, butterflies, and cars. Whereas these scores did not perfectly match the pattern of human results, they were strongly negatively correlated with the control group's search slopes across the four target categories ($r = -.95$, as compared with $r = -.26$ for the orientation frequency bins and $r = -.01$ for the orientation bins).

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