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Running Title: average set identity

Viewers extract mean and individual identity from sets of famous faces

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18 **Abstract**

19 When viewers are shown sets of similar objects (for example circles), they may extract
20 summary information (e.g., average size) while retaining almost no information about the
21 individual items. A similar observation can be made when using sets of unfamiliar faces:
22 Viewers tend to merge identity or expression information from the set exemplars into a
23 single abstract representation, the set average. Here, across four experiments, sets of
24 well-known, famous faces were presented. In response to a subsequent probe, viewers
25 recognized the individual faces very accurately. However, they also reported having
26 seen a merged 'average' of these faces. These findings suggest abstraction of set
27 characteristics even in circumstances which favour individuation of the items. Moreover,
28 the present data suggest that, although seemingly incompatible, exemplar and average
29 representations co-exist for sets consisting of famous faces. This result suggests that
30 representations are simultaneously formed at multiple levels of abstraction.

31

32 **Keywords:** set representation, ensemble coding, face, identity, averaging

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35

Introduction

36 “Set representations” have recently attracted increasing research interest. When
37 seeing groups of perceptually similar objects, information such as size, or motion, may
38 be coded via summary statistics in terms of a mean value across exemplars (Albrecht &
39 Scholl, 2010; Chong & Treisman, 2003). Whenever observers can capitalize on
40 redundancy of information – a common observation in structured sets – they can
41 compress this information into a single representation such as the set average (Alvarez,
42 2011). In a seminal investigation, Ariely (2001) investigated size representations from
43 sets containing differently sized circles. Critically, participants tended to identify a test
44 circle as having been presented when it had a similar size to the mean of the whole set,
45 even when such an item had not been present. Moreover, participants were near
46 chance when they had to choose which of two circles had been presented. Taken
47 together, these findings suggest that i) mean size information was computed and
48 retained for the set and ii) size information of individual set members was unavailable.
49 There are different potential explanations for weak exemplar representations. First,
50 encoding of precise exemplar representations may not routinely occur, or may simply
51 contain too much noise, perhaps due to the lack of focal attention to set exemplars.
52 Alternatively, an individual representation may initially be computed but may then be
53 discarded extremely fast.

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Recently, statistical representations have been demonstrated for sets of
perceptually complex stimuli, such as faces. When asked to compare the emotional
intensity of a single image with that of a set (up to 16 face photographs varying in
emotional intensity), participants performed highly accurately (Haberman & Whitney,

58 2007, 2009). Performance was actually comparable to a control “exemplar” condition, in
59 which participants compared an image with a homogeneous set with constant emotional
60 intensity. Beyond extraction of mean emotion (and gender, see Haberman & Whitney,
61 2007) information from sets of faces, a similar mechanism may compute the mean
62 *identity* from sets of *unfamiliar* faces. In one recent study (de Fockert & Wolfenstein,
63 2009), participants initially saw sets containing photographs of 4 unfamiliar faces from
64 different individuals. In a “match” condition, a subsequent single image could either be
65 an exemplar image from the previous set, or an average morph created from the four set
66 images. Strikingly, the set averages (which had never been seen) received more
67 ‘present’ responses than the (seen) exemplars. The authors concluded that averaging
68 identity information might serve as the “default mode” for generating mental
69 representations from groups of faces.

70 Given that facial representations should serve person recognition, this is a
71 surprising finding, since mean identity representations should actually *prevent*
72 identification of a specific person in a group. It is relatively straightforward to understand
73 how superficial averaging of abstract shapes might take place in the visual system, but
74 much harder to account for averaging over such high-level characteristics as someone’s
75 identity. For this reason, it is important to note that the authors used unfamiliar faces.
76 Crucially, unfamiliar face recognition is strongly image-dependent and sensitive to
77 superficial picture similarity (Bruce et al., 1999), and is thus based on very different
78 mechanisms than familiar face recognition. For example, viewers are very good at
79 matching different images of a familiar person, but very poor at matching unfamiliar
80 faces (Bruce, Henderson, Newman, & Burton, 2001; Burton, Bruce, & Hancock, 1999;

81 Kemp, Towell, & Pike, 1997; Clutterbuck & Johnston, 2004). This discrepancy suggests
82 a qualitative difference in perception of familiar and unfamiliar face identities (Hancock,
83 Bruce, & Burton, 2000), which may also have consequences for the interpretation of the
84 identity set averaging data. Accordingly, increased percentages of “present” responses
85 to matching averages in the study of de Fockert and Wolfenstein (2009) could reflect
86 *image* averaging across similar pictures, rather than *identity* averaging. If viewers are
87 failing to differentiate between the unfamiliar people shown to them, they might plausibly
88 construct a set average combining these images. So, while this study certainly
89 demonstrates set averaging for a class of high-level stimuli (faces), we argue that
90 evidence for *identity* set averaging would be much more compelling if it could also be
91 shown to exist for familiar faces sets.

92 Another important characteristic of previous studies examining set averaging for
93 faces was relatively small image variability within sets. For instance, set averaging for
94 facial expressions was generally investigated by assembling sets from a single identity,
95 using slightly different emotional intensities from a morph continuum between two
96 veridical expressions (Haberman, Harp, & Whitney, 2009; Haberman & Whitney, 2007,
97 2010). One study on set *identity* averaging actually involved 4 true set photographs, but
98 had sets deliberately arranged to comprise similar identities (de Fockert & Wolfenstein,
99 2009). Therefore, low recognition rates for set exemplars may have originated from
100 participants being unable to differentiate between exemplars at encoding. It is important
101 to see if the use of more naturally diverse sets could increase exemplar memory, and
102 whether this would in turn affect the quality and strength of set representations.

103 In sum, previous studies have investigated set averaging using face sets that
104 varied little on either identity or image properties. In the present study, we tested facial
105 identity averaging by using diverse pictures from highly familiar identities, for which
106 participants have rich pre-existing mental representations. We further encouraged
107 identity processing for half of the participants by instructing them to indicate whether a
108 specific *person* had been seen in a set of faces, while the other half indicated whether a
109 specific *image* had occurred. We expected that set averaging would be strongly reduced
110 or absent for highly familiar faces, and that performance would reflect accurate
111 representation of exemplars instead; Since viewers know these identities, and faces in
112 the set were quite diverse, there appears to be no advantage in averaging across them.

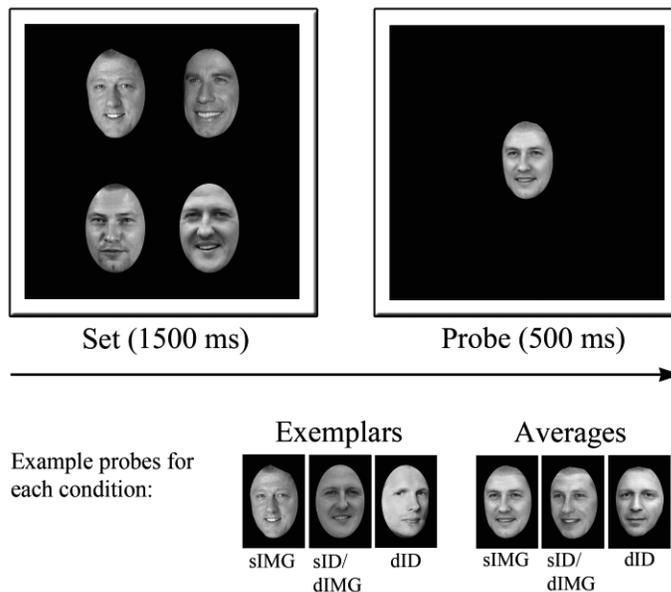
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114

Material and methods

115 The present article includes 4 experiments that share the following aspects.
116 Stimuli were 240 original faces collected from various internet sources, 10 each from 24
117 well-known celebrities (12 German and 12 International). Sixty gender-homogeneous
118 sets were created from these photographs, each containing 4 images of different
119 identities. Images contributing to a set were chosen to be roughly similar with respect to
120 head angle and gaze direction. Five sets from 12 different identity combinations were
121 assembled. Note that as a result of obtaining the images from the internet, image
122 variation within the sets was large. All images were taken under entirely non-
123 standardized conditions, causing considerable variation on image parameters such as
124 lighting. Additional *set averages* were created for each of the 60 sets by morphing
125 across the respective 4 set images. Image size was 247 x 387 pixels, all images were
126 presented grey-scaled and fitted in an oval mask, excluding most of the hair.

127 Set displays contained 4 images randomly assigned to 4 specified positions on
128 the screen (cf. Fig. 1), and were presented for 1500 ms. Immediately following the set
129 display (ISI = 0), probe images were displayed for 500 ms, in smaller size than the set
130 images (200 x 300 pixels). Participants used both index fingers to indicate via button
131 press (“f” and “j” on a standard German keyboard) whether or not the probe image had
132 been present in the previous S1 set. Probe images were: i) a set exemplar (i.e., an
133 image from the previous set); ii) a new exemplar of one of the 4 identities of the previous
134 set; iii) a new exemplar of a different familiar identity; iv) the average of the 4 set
135 images; v) the average of 4 different images of the set identities; or vi) the average of 4
136 images of different familiar identities.



137

138 **Fig. 1: Example of a set, followed by a probe (sIMG average). Sets were presented simultaneously in**
 139 **Experiments 1-3, and sequentially in Experiment 4. Celebrities in the example set depict (top left to bottom**
 140 **right): Bill Clinton, John Travolta, Till Schweiger (German actor), and Michael Schumacher (German race car**
 141 **driver). Examples for all probe conditions of this set are given below.**

142 In each of these six conditions, 60 trials were presented, with 10 trials per
 143 condition in each of 6 experimental blocks. Response button assignment for “present”
 144 and “absent” was counterbalanced across participants. A blank screen for 2200 ms
 145 allowed for a total response window of 2700 ms.

146 Experiments were run in two versions, varying in task requirements. Version a)
 147 required participants to indicate whether a particular *image* had been a set member,
 148 whereas version b) required participants to match *identity* (i.e., whether a person had
 149 been a set member). Participants in version a) were explicitly informed that a different
 150 image for one of the set identities could occur as a probe stimulus and were instructed
 151 to respond “absent” in this case. Overall, 84 young adult participants (mean age = 22.01,
 152 $SD = 3.38$; 19 male) were tested and received monetary compensation or course credit.
 153 Participants gave written informed consent and reported normal or corrected-to-normal

154 visual acuity. Experiments 1a and 1b each comprised 18 participants, and all remaining
155 experiments (2a, 2b, 3a, 3b, 4a, 4b) comprised 8 participants each.

156 **Experiment 1 - main study**

157 **Method**

158 Experiments 1a and 1b followed the procedure laid out above, differing only in
159 the response required by participants (image-present, or person-present). These and
160 subsequent experiments followed a 2 (Probe Type) x 3 (Match Type) design. Probe
161 types were either exemplars (i.e., original images), or set averages. Match Type referred
162 to the relation of the probe face to the set images in that it involved either one, or an
163 average of all i) image(s) from the set (sIMG), ii) different image(s) from the same set
164 identities (sID/dIMG), or iii) image(s) of different identities (dID).

165 Prior to the experiment proper, participants were given 24 practice trials, and
166 provided with trial-by-trial feedback on accuracy. Note that the correct answer to
167 average probes is always “absent”. In order to prevent participants from learning this
168 association, averages were not presented in the practice phase. In order to assess
169 familiarity of the identities used, new pictures of the 24 celebrities were shown following
170 the main procedure in Experiment 1b. Participants were presented images consecutively
171 in the middle of the screen for an unlimited duration, and for each face they indicated by
172 button press whether or not they were familiar with the person. For a “familiar” response,
173 participants were additionally asked to indicate the name, or if they were unable to do
174 so, some identifying semantic information for that person (i.e., occupation, nationality).

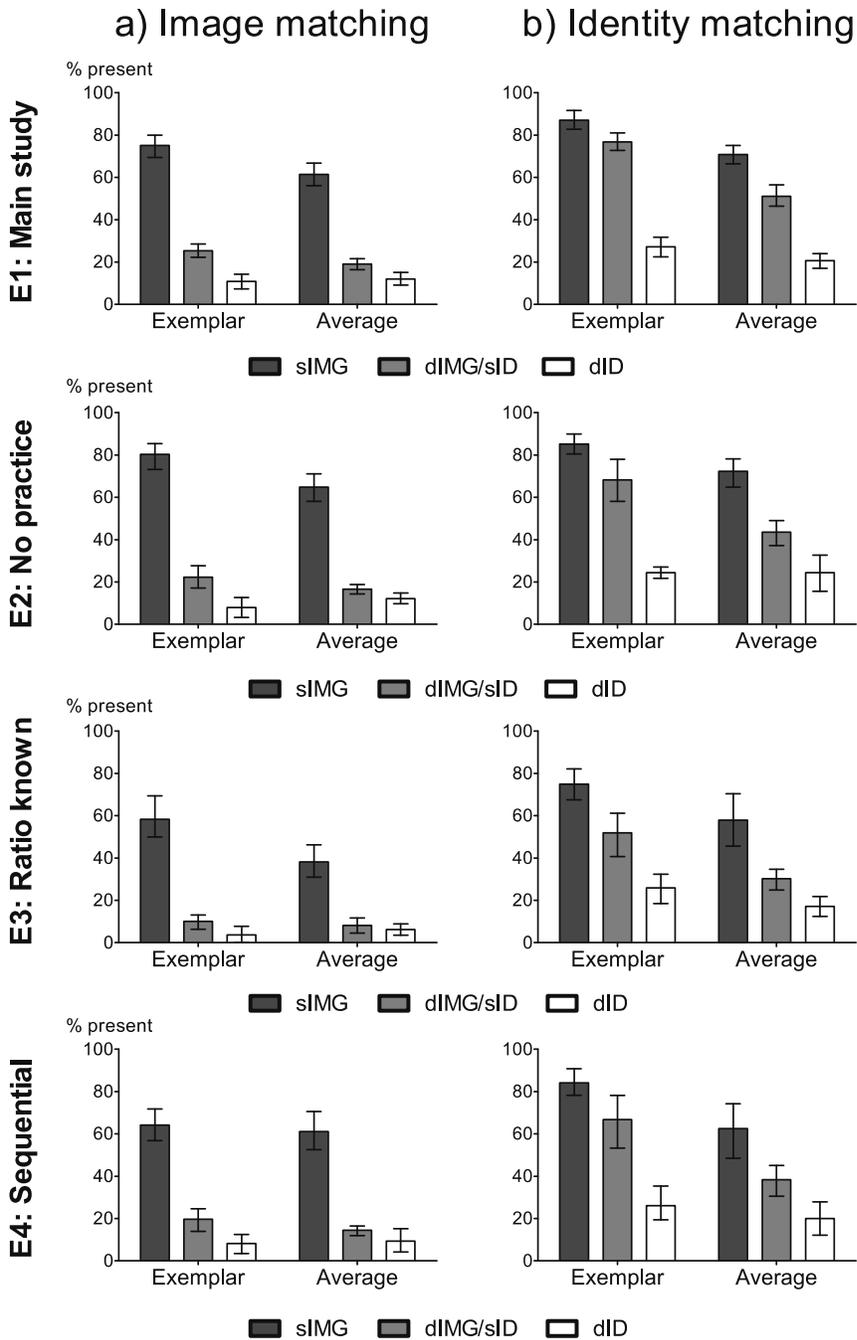
175

176 Results**177 Face familiarity task**

178 Written responses from one participant were unavailable. Overall, recognition
179 performance was high, and nearly all the celebrities used in the Experiment could be
180 spontaneously named. On average, celebrities were successfully identified by unique
181 semantic information or name in 92.4% of the cases.

182 “Present” responses to probe faces

183 Figure 2 (row 1) shows the proportion of present responses for each of the probe
184 types in Experiment 1 for the image matching (left) and the identity matching group
185 (right). First, and as expected, participants performed very accurately on probe
186 exemplars. Proportions of “present” responses during both tasks were clearly largest for
187 sIMG conditions, indicating good matching performances when a probe image was
188 identical to one of the set images. New identities in dID conditions received few
189 “present” responses overall, i.e., false positives were rare. During image matching, new
190 images from one of the set identities (sID/dIMG) were rejected quite accurately, but less
191 well than dID images. During identity matching, “present” hits to sID/dIMG images were
192 frequent, though reduced compared to present responses to identical images (sIMG).



193

194 **Fig. 2: Percentage “present” responses to probe images in all 4 Experiments. Left column: image**
 195 **matching; Right column: identity matching. Error bars represent 95% CI based on normalized data**
 196 **(see Cousineau, 2005). $N = 18$ in Experiments 1a and 1b, $N = 8$ in all control Experiments 2a,b;**
 197 **3a,b; and 4a,b, respectively.**

198 Unexpectedly, a strikingly similar pattern was elicited by set average images.
199 sIMG averages elicited remarkably large proportions present responses, indicating that
200 participants erroneously identified the set average as an actual set member. This was
201 not because averages per se tended to elicit responses (e.g., due to inflated typicality),
202 since averages of different identities (dID) were reliably rejected. During image
203 matching, averages across 4 new images from the set identities (sID/dIMG) were
204 rejected - correctly - almost as accurately as averages from new identities (dID). By
205 contrast, a much larger and intermediate level of incorrect present responses occurred
206 during identity matching (incorrect, because an average *never* represented an identity
207 from a set).

208 Statistical analyses were performed by entering data from both experiment
209 versions to separate 2 by 3 ANOVAs. These revealed reliable main effects of Match
210 Type and Probe Type (all $F > 8$, all $p < .011$, all $\eta^2_P > .320$), and significant interactions
211 of both factors, $F(2, 34) = 9.55$, $p < 0.01$, $\eta^2_P = .360$; $F(2, 34) = 17.50$, $p < 0.01$, $\eta^2_P =$
212 $.507$, for Experiments 1a and 1b, respectively. Accordingly, present responses were
213 most frequent for sIMG, intermediate for sID/dIMG, and infrequent for dID conditions. In
214 addition, while present responses occurred overall more often for exemplar than
215 average probes, the amount of the difference varied with Match Type, and was rather
216 small (Exp. 1b) or absent (Exp. 1a) in dID conditions. Critically, even when averages
217 were analysed separately, Match Type was still highly significant (both $F > 170$, $p <$
218 $.001$, $\eta^2_P > .810$), as were all pairwise contrasts between sIMG and sID/dIMG, and
219 between sID/dIMG and dID conditions in both tasks (all $t(17) > 3.81$, all $p < .002$).
220 Importantly, this confirms that averages were more often selected not only when created

221 from the identical set images (sIMG), but also when created from different images of the
222 set identities (sID/dIMG), compared to averages from new identities (dID). More detailed
223 descriptions of all 2 by 3 ANOVAs and follow-up paired comparisons are detailed in
224 Table 1 in the appendix.

225 In a second step, we examined differences between task conditions by including
226 Task as between-subjects factor in an ANOVA on combined data from Experiments 1a
227 and 1b. The 3-way interaction of Task by Probe Type by Match Type, $F(2, 68) = 6.88$, p
228 $< .01$, $\eta^2_p = .360$ was significant, indicating differences in patterns elicited during image
229 and identity matching, respectively. Fig.2 suggests that a main source for this interaction
230 were large differences in sID/dIMG exemplar conditions in both tasks. This was
231 unsurprising, because a “present” response had been the correct answer during identity
232 matching, but the incorrect response during image matching.

233 Of greater theoretical interest were differences in present responses elicited by
234 average probes across the two tasks. ANOVA on data from average probes with Match
235 Type and Task revealed a significant interaction, $F(2,68) = 20.34$, $p < .001$, $\eta^2_p = .374$).
236 Independent sample t-tests carried out on corresponding Match Type conditions
237 between the two tasks indicated comparable proportions present responses for sIMG
238 averages in image and identity matching, $t(34) = 1.670$, $p = .104$, and slightly more
239 present responses during identity than image matching for dID conditions $t(34) = 2.619$,
240 $p = .014$. Most importantly, sID/dIMG present responses differed substantially between
241 task conditions, $t(34) = 6.460$, $p < .001$, with more present responses given in the
242 identity than in the image matching task. Thus, sID/dIMG averages were not easily
243 mistaken as a *set image*, but were frequently mistaken as a *person* occurring in a set.

244

Control Experiments 2-4

245 Considering that set averaging was typically observed in combination with
246 impaired exemplar memory, the finding from Experiment 1 is particularly challenging,
247 because it suggests that viewers are extracting identity-average information from a set,
248 while simultaneously representing individual exemplar information. Moreover, while it
249 seems reasonable to suppose that viewers might code a set of circles using summary
250 statistics, or even a set of unknown faces, there seems no reason why one should
251 extract an average of, for instance, Bill Clinton and John Travolta. In the following
252 control experiments, we tested for a number of possible alternative explanations for this
253 effect.

254 Method

255 Experiments 2-4 were identical to Experiment 1 except as follows. Experiment 2
256 did not include practice trials. During practice in Experiment 1, the ratio of correct
257 “present” responses was larger than in the actual experiment, such that one might be
258 concerned that participants developed exaggerated expectations about the required
259 ratio of present responses. To exclude this possibility, practice trials were omitted in
260 Experiment 2 and all further experiments. In Experiment 3, participants were additionally
261 informed, correctly, that present responses were required in 16.6 % (Exp. 3a), or 33.3 %
262 (Exp. 3b) of the trials. In Experiment 4, set images were presented sequentially rather
263 than at the same time (order: top left, top right, bottom left, bottom right). Each image
264 was shown for 375 ms, such that total presentation duration was equivalent to
265 Experiments 1-3 (i.e., 1500 ms).

266 **Results**

267 Control Experiments 2-4 yielded results completely consistent with Experiment 1
268 (cf. Fig. 2, rows 2-4). Most importantly, performance in sIMG conditions was in each
269 case quite accurate for exemplars, and very inaccurate for averages, with large
270 proportions present responses to both sIMG exemplars and, only slightly reduced, to
271 sIMG averages.

272 Separate 2 by 3 ANOVAs for each experiment corroborated the pattern of
273 Experiment 1. Again, more present responses were given to exemplars than to
274 averages (except for Experiment 3a, where the main effect of Probe Type only
275 approached significance, $p = .076$, and in Experiment 4a, $p = .334$). Main effects of
276 Match Type indicated more present responses to sIMG vs. sID/dIMG conditions, and to
277 sID/dIMG vs. dID conditions throughout. Probe Type interacted with Match Type in all
278 experiments except for Experiment 3b and 4a. Further descriptions of 2 by 3 ANOVAs
279 for all control experiments are detailed in Table 1 in the appendix.

280 Experiments 2 and 3 controlled for possible expectation effects in Experiment 1a
281 regarding the correct proportion present responses. Such expectations could either
282 originate from practice trials, or from a more general expertise with psychological
283 experimentation methods. However, Experiment 2 replicated all key results of
284 Experiment 1 in virtually identical form, despite excluding practice trials (cf. Fig. 2).
285 Similarly, informing participants about the correct ratio of present trials in Experiment 3
286 did not differentially affect responses to set averages, although it led to an overall
287 decrease in present responses, indicating that this information successfully induced a

288 more conservative response criterion. We conducted additional ANOVA on combined
289 data from Experiments 2 and 3, and included “Ratio Information” (Experiment 2: not
290 informed, Experiment 3: informed) as an additional between-subjects factor. No
291 significant 4-way interaction was found, $F < 1$, and no other interaction including Ratio
292 Information, all $p > .05$, except for an interaction of Match Type by Ratio Information,
293 $F(2, 56) = 8.09$, $p = .002$, $\eta^2_P = .224$. The latter interaction simply reflects the fact that
294 informing participants about correct ratio led to a greater reduction of present responses
295 in SIMG matching (18.3%) conditions (critically, both for exemplars and averages), and
296 less reduction in the other two conditions (sID/dIMG = 12.6%; dID = 4.0%), in which
297 present responses were already less frequent. Importantly, Experiment 3 provides no
298 evidence that the ratio of present responses might explain the remarkably large
299 proportions of present responses to “matching” set averages.

300 Experiment 4 addressed a different possibility. Specifically, when presented
301 simultaneously, set images could have been processed to a different extent (e.g., with a
302 focus on the top two faces, and only brief inspection of the bottom faces). By presenting
303 the set faces sequentially for the same amount of time, participants are encouraged to
304 process all faces equivalently. Note that simultaneous presentation is not essential for
305 statistical processing (Chong & Treisman, 2005b; Haberman & Whitney, 2009). In the
306 ANOVA on combined data from Experiments 4a and 4b, the 3-way interaction only
307 approached significance, $F(2, 28) = 2.75$, $p = .086$, $\eta^2_P = .164$, possibly due to relatively
308 low power. However, interactions of Task by Probe Type, $F(2, 28) = 4.66$, $p = .049$, η^2_P
309 = .250, and Task by Match Type, $F(2, 28) = 8.75$, $p = .002$, $\eta^2_P = .385$, were revealed.
310 Overall, the pattern of results strikingly resembles the previous findings. Most

311 importantly, sequential presentation caused no selective reduction in present responses
312 to sIMG set averages compared to Experiment 2. If anything, sIMG *exemplar* detection
313 was slightly compromised during image matching in Experiment 4a: Exemplars received
314 comparable proportions present responses as averages, and neither the main effect of
315 Probe Type, $F(1, 7) = 1.08$, $p = .334$, $\eta^2_P = .134$, nor the interaction of Probe Type and
316 Match Type $F(1, 7) = 2.62$, $p = .111$, $\eta^2_P = .273$ were significant.

317

318

General Discussion

319 We examined set averaging for identity information in face sets. In contrast to
320 previous work, sets in the present study involved both familiar faces, and large image
321 variability. Compared to earlier work, we used an extended experimental procedure by
322 including both an image-change condition (SID/dIMG) and an additional task (identity
323 matching) to promote identity processing of sets exemplars. Across four experiments,
324 we consistently received two key results that extend the current knowledge regarding
325 set representations for complex stimuli, and that can be summarized as follows.

326 First, and as predicted, the use of familiar faces in briefly presented sets
327 produces good memory for set exemplars. Second, and surprisingly, viewers
328 nevertheless show clear and consistent evidence for averaging identity information in
329 faces, even across highly familiar set exemplars. Three control studies ruled out
330 alternative explanations based on participants' expectations, or a potential selective
331 processing of a subgroup of set items. We will first discuss these novel findings in the
332 context of our specific approach to create variable sets from familiar faces, and then
333 relate these results to the concepts of set averaging and individual face recognition
334 more generally.

335 Previous studies had used low image variability within sets. Set images were
336 either taken from standardized databases and set identities were chosen to resemble
337 each other (de Fockert & Wolfenstein, 2009), or – more commonly – sets comprised
338 perceptually similar levels from a morph continuum (e.g. happy to neutral expression,
339 see Haberman & Whitney, 2007, 2009). One reason why participants in previous studies

340 were almost unable to recall individual set exemplars may have been simply because
341 when presented in the set, they all looked alike. By contrast, sets in the present study
342 employed images from different internet sources, and therefore varied more naturally on
343 various dimensions including lighting, viewing angle, head posture, and expression. We
344 expected that set exemplars would consequently be easier to discriminate and that this
345 would lead to improved exemplar memory, which was the pattern we observed in the
346 present study. However, we also assumed that increased exemplar memory would
347 coincide with little if any evidence for set average representations. This assumption was
348 based on our understanding of set averages as an efficient process to capture the
349 essential information from a set in situations where accurate encoding of the set
350 constituents is impossible, for instance by short presentations of crowded displays. Such
351 an idea seemed intuitively plausible and was supported by many previous studies using
352 both simple and complex stimulus material (for a recent review, cf. Alvarez, 2011).

353 Here we observed a strikingly different pattern: Despite the expected good
354 performance in exemplar memory, set averaging was remarkably robust. In actual fact,
355 present response rates for sIMG averages of about 60% in the present study were even
356 higher when compared to a analogous condition of a different study, where unfamiliar
357 faces had been used (approximately 40%, de Fockert & Wolfenstein, 2009).
358 Accordingly, set averaging of facial identity appears robust to substantial image
359 variability within sets, at least for familiar faces.

360 Importantly, the use of familiar faces enabled us to address alternative low level
361 explanations for this identity set averaging effect, which previous work could not
362 completely rule out. Specifically, it was unclear whether participants generated average

363 *identity*, or rather *average image* representations from sets. Here, we tested separate
364 groups of participants either with an image matching task as in previous work (e.g., de
365 Fockert & Wolfenstein, 2009), or with an identity matching task. Such a task should have
366 promoted identity processing for the set exemplars, and participants could not simply
367 rely on matching certain low-level aspects of an image due to the potential image
368 change in sID/dIMG conditions.

369 Critically, we found clear evidence for set averaging in the identity matching
370 group. This suggests that the abstraction of identity information into a summary statistic
371 is not simply a low-level stimulus-driven process, but includes averaging of actual
372 identity information from several faces. This argument receives further support when
373 taking into account the results from sID/dIMG conditions, where participants of the
374 identity matching group often misinterpreted an average across 4 different identities as
375 an actual person from the previous set, even though the probe average involved
376 different images of these identities! Note that this was not a result of inaccurate person
377 memory due to the rather short presentation duration: Identity recognition for exemplars
378 was generally accurate even across the image change in the present experiments:
379 Participants in the identity matching group very accurately accepted sID/dIMG
380 exemplars, while the very same sID/dIMG exemplars were rejected – again very
381 accurately – by participants from the image matching group.

382 We had expected that both using familiar faces and more variable images would
383 increase exemplar recognition, but reduce or abolish set averaging. By contrast, while
384 accurate exemplar recognition was indeed observed, set averaging for facial identity
385 was also robust. This is remarkable since **compelling evidence for set averaging was**

386 previously associated with absent or noisy memory for instances, irrespective of
387 stimulus type (Ariely, 2001; Chong & Treisman, 2005b; Alvarez & Oliva, 2008;
388 Haberman & Whitney, 2007, 2009). Accordingly, average set processing has been
389 thought of as an effective and efficient method to extract only the most important
390 information from a complex visual scene (Alvarez, 2011). Supporting this idea, it has
391 been shown that abstractive representations are more precise under distributed than
392 under focused attention (Chong & Treisman, 2005a), and summary coding of high-level
393 information can proceed even in the near absence of attention (Alvarez & Oliva, 2009).
394 In fact, set averaging seems to be so efficient that it can be performed almost as
395 accurately as coding of a single exemplar (Chong & Treisman, 2003). This research
396 suggests that precise exemplar and set average representations are incompatible to the
397 extent that only one representation is extracted at a time, according to task needs. Most
398 research on set averaging employs settings in which it is difficult for viewers to extract
399 precise exemplar representations for their experience. Sets were usually quite crowded
400 or perceptually very similar. Here, task conditions (distinct, familiar faces) allowed
401 forming of precise exemplar representations, accompanied with strong set average
402 representations. To our knowledge, this is the first demonstration of robust simultaneous
403 exemplar and average representations.

404 In our experiments, “present” responses for exemplars exceeded those for sIMG
405 averages, a pattern that contradicts the commonly described preponderance of average
406 over exemplar representations. This is clearly not reflecting weak average
407 representations in the present study, but rather a consequence of increased recognition
408 of familiar face exemplars (approximately 80%, compared to 30-35% for unfamiliar faces

409 in de Fockert & Wolfenstein, 2009). Our data demonstrate that robust set average
410 representations can co-exist with precise exemplar representations.

411 Given that ensemble coding is supposed to foster efficient extraction of
412 information, as suggested by previous studies, a simultaneous extraction of exemplar
413 and set average representations does not appear to be particularly efficient. The extent
414 to which exemplar and average representations may draw upon identical or distinct
415 resources is a matter of current debate. Of particular interest, a recent study suggested
416 that hierarchical representations in working memory may simultaneously be formed on
417 multiple levels of abstraction (Brady & Alvarez, 2011). In this study, participants
418 remembered the size of an individual circle at clearly above-chance precision, but size
419 judgements were consistently biased towards the average size in the set. Accordingly,
420 items in working memory could be represented via a combination of set ensemble
421 statistics and individual exemplar information, with statistical representations increasing
422 accuracy in situations of inaccurate exemplar memory. Data from the present
423 experiments are in line with the general idea of a hierarchical representation system.

424 In the experiments reported here, there seems no obvious advantage to be
425 gained from constructing a representation that merges the individuals. For example,
426 when interacting with groups, there is no communicative advantage to forming a single
427 visual representation of all faces. A tentative suggestion is that set averaging could
428 serve compensatory purposes. For instance, while impaired at recognizing individuals,
429 participants with developmental prosopagnosia nevertheless showed preserved identity
430 and expression set averaging for unfamiliar faces (Leib et al., 2012). Additionally, face
431 recognition performance did not correlate with set averaging performance in that study,

432 suggesting that both tap into distinct processes. While this is an important finding, it
433 remains unclear how set averaging could compensate for poor *individual face*
434 recognition. Further research is needed to clarify the relation between the different
435 coding mechanisms (individual exemplars versus set averages) and their respective
436 relevance for typical and impaired identity processing of both unfamiliar and familiar
437 faces.

438 It remains to be seen whether the accurate simultaneous computation of
439 exemplar and average representations – which were expected to be incompatible – is a
440 feature of categories beyond faces. These have made a good starting-point, because it
441 is simple to manipulate familiarity without affecting stimulus structure, and because there
442 are well-understood technical mechanisms for combining different images. However,
443 even within the class of faces, a thorough understanding of this phenomenon will require
444 further investigation into the role of encoding time to test efficiency of set
445 representations, set characteristics (e.g., male vs. female, own-race vs. other-race) and
446 other operational variables.

447

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Appendix

Exp.	Effect	F-statistics	Effect size (partial η^2)	Description
E1a	ProbeType	$F(1,17) = 8.28, p = .010$	$\eta^2_p = .328$	Exemplars ($M = 37.0\%$) > Averages ($M = 30.8\%$)
	MatchType	$F(2,34) = 303.84, p < .001$	$\eta^2_p = .947$	sIMG ($M = 68.2\%$) > sID/dIMG ($M = 22.2\%$) > dID ($M = 11.4\%$)
	ProbeType x MatchType	$F(2,34) = 9.67, p = .003$	$\eta^2_p = .363$	Exp _{sIMG} > Avg _{sIMG} $t(17) = 3.24$ $p = .005$ Exp _{sID/dIMG} > Avg _{sID/dIMG} $t(17) = 2.86$ $p = .011$ Exp _{dID} = Avg _{dID} $t(17) = -0.70$ $p = .493$
E1b	ProbeType	$F(1,17) = 37.16, p < .001$	$\eta^2_p = .686$	Exemplars ($M = 63.6\%$) > Averages ($M = 47.5\%$)
	MatchType	$F(2,34) = 244.53, p < .001$	$\eta^2_p = .935$	sIMG ($M = 78.9\%$) > sID/dIMG ($M = 63.9\%$) > dID ($M = 23.9\%$)
	ProbeType x MatchType	$F(2,34) = 17.51, p < .001$	$\eta^2_p = .507$	Exp _{sIMG} > Avg _{sIMG} $t(17) = 4.88$ $p < .001$ Exp _{sID/dIMG} > Avg _{sID/dIMG} $t(17) = 6.31$ $p < .001$ Exp _{dID} > Avg _{dID} $t(17) = 3.26$ $p = .005$
E2a	ProbeType	$F(1,7) = 6.24, p = .041$	$\eta^2_p = .471$	Exemplars ($M = 36.8\%$) > Averages ($M = 31.1\%$)
	MatchType	$F(2,14) = 224.48, p < .001$	$\eta^2_p = .970$	sIMG ($M = 72.5\%$) > sID/dIMG ($M = 19.4\%$) > dID ($M = 10.0\%$)
	ProbeType x MatchType	$F(2,14) = 10.42, p = .006$	$\eta^2_p = .598$	Exp _{sIMG} > Avg _{sIMG} $t(7) = 3.41$ $p = .011$ Exp _{sID/dIMG} = Avg _{sID/dIMG} $t(7) = 2.09$ $p = .075$ Exp _{dID} = Avg _{dID} $t(7) = -1.67$ $p = .134$
E2b	ProbeType	$F(1,7) = 7.11, p = .032$	$\eta^2_p = .504$	Exemplars ($M = 59.2\%$) > Averages ($M = 46.7\%$)
	MatchType	$F(2,14) = 111.43, p < .001$	$\eta^2_p = .941$	sIMG ($M = 78.7\%$) > sID/dIMG ($M = 55.9\%$) > dID ($M = 24.3\%$)
	ProbeType x MatchType	$F(2,14) = 18.26, p < .001$	$\eta^2_p = .723$	Exp _{sIMG} > Avg _{sIMG} $t(7) = 2.77$ $p = .028$ Exp _{sID/dIMG} > Avg _{sID/dIMG} $t(7) = 3.70$ $p = .008$ Exp _{dID} = Avg _{dID} $t(7) < 0.01$ $p > .999$
E3a	ProbeType	$F(1,7) = 4.33, p = .076$	$\eta^2_p = .382$	Exemplars ($M = 24.0\%$) = Averages ($M = 17.5\%$)
	MatchType	$F(2,14) = 109.16, p < .001$	$\eta^2_p = .940$	sIMG ($M = 48.2\%$) > sID/dIMG ($M = 9.1\%$) > dID ($M = 4.9\%$)
	ProbeType x MatchType	$F(2,14) = 10.50, p = .010$	$\eta^2_p = .600$	Exp _{sIMG} > Avg _{sIMG} $t(7) = 2.89$ $p = .023$ Exp _{sID/dIMG} = Avg _{sID/dIMG} $t(7) = 0.78$ $p = .460$ Exp _{dID} = Avg _{dID} $t(7) = -1.84$ $p = .108$
E3b	ProbeType	$F(1,7) = 6.94, p = .034$	$\eta^2_p = .498$	Exemplars ($M = 50.9\%$) > Averages ($M = 35.0\%$)
	MatchType	$F(2,14) = 57.55, p < .001$	$\eta^2_p = .892$	sIMG ($M = 66.4\%$) > sID/dIMG ($M = 41.0\%$) > dID ($M = 21.5\%$)
	ProbeType x MatchType	$F(2,14) = 3.14, p = .077$	$\eta^2_p = .310$	
E4a	ProbeType	$F(1,7) = 1.08, p = .334$	$\eta^2_p = .134$	Exemplars ($M = 30.7\%$) = Averages ($M = 28.3\%$)
	MatchType	$F(1,7) = 78.58, p < .001$	$\eta^2_p = .918$	sIMG ($M = 68.2\%$) > sID/dIMG ($M = 22.2\%$) > dID ($M = 11.3\%$)
	ProbeType x MatchType	$F(2,14) = 2.62, p = .111$	$\eta^2_p = .273$	
E4b	ProbeType	$F(1,7) = 6.77, p = .035$	$\eta^2_p = .492$	Exemplars ($M = 59.0\%$) = Averages ($M = 40.2\%$)
	MatchType	$F(2,14) = 63.82, p < .001$	$\eta^2_p = .901$	sIMG ($M = 73.2\%$) > sID/dIMG ($M = 52.6\%$) > dID ($M = 23.0\%$)
	ProbeType x MatchType	$F(2,14) = 6.42, p = .013$	$\eta^2_p = .478$	Exp _{sIMG} = Avg _{sIMG} $t(7) = 2.33$ $p = .052$ Exp _{sID/dIMG} > Avg _{sID/dIMG} $t(7) = 3.17$ $p = .016$ Exp _{dID} = Avg _{dID} $t(7) = 1.12$ $p = .301$

513 Table S1: Results from all four Experiments' 2x3 ANOVAs and, where applicable, post-hoc comparisons.

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