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An Attentional Bias for LEGO® People Using a Change Detection Task: Are LEGO® People Animate?

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Animate objects have been shown to elicit attentional priority in a change detection task. This benefit has been seen for both human and nonhuman animals compared with inanimate objects. One explanation for these results has been based on the importance animate objects have served over the course of our species' history. In the present set of experiments, we present stimuli, which could be perceived as animate, but with which our distant ancestors would have had no experience, and natural selection could have no direct pressure on their prioritization. In the first experiment, we compared LEGO® "people" with LEGO "nonpeople" in a change detection task. In a second experiment, we attempt to control the heterogeneity of the nonanimate objects by using LEGO blocks, matched in size and colour to LEGO people. In the third experiment, we occlude the faces of the LEGO people to control for facial pattern recognition. In the final 2 experiments, we attempt to obscure high-level categorical information processing of the stimuli by inverting and blurring the scenes.

Keywords: attention, change detection, change blindness, animacy

Animacy is a distinct and important category that is easily identifiable by humans. This distinction has become ubiquitous across several streams of psychological research. For example, observers can use simple motion cues to perceive bipedal (Johansson, 1973) and quadrupedal walking (Chang & Troje, 2008), gender (Kozlowski & Cutting, 1977), identity (Cutting & Kozlowski, 1977), and categories of animals (Mather & West, 1993). Moreover, attributing self-propelled motion to animacy has been shown in infants (Poulin-Dubois, Lepage, & Ferland, 1996), children scoring high on the autism spectrum (Rutherford, Pennington, & Rogers, 2006), and nonhuman primates (Hauser, 1998). Even apparent self-propelled motion of single objects elicits percepts of animacy (Pratt, Radulescu, Guo, & Abrams, 2010; Tremoulet & Feldman, 2000).

Motion, however, is not necessary for the rapid and accurate identification of animate objects. When simultaneously presented with two static scenes, observers will orient to the scene containing an animal in as little as 120 ms (Crouzet, Joubert, Thorpe, & Fabre-Thorpe, 2012; Kirchner & Thorpe, 2006). This rapid scene categorisation is not a product of colour or brightness (Elder & Velisavljević, 2009), partial or full view of the animal, or perspective (e.g., side vs. front view; Delorme, Richard, & Fabre-Thorpe, 2010). Static faces and animals are processed at similar speeds compared with distractors (Rousselet, Mace, & Fabre-Thorpe, 2003; although see VanRullen & Thorpe, 2001 for an example of nonliving, but animate-like advantages for modes of transportation; see also Bae & Kim, 2011). Considered together, it appears that humans are sensitive to objects that can be perceived as animate, even when they are not in motion.

One explanation of these types of findings comes from New, Cosmides, and Tooby (2007), who also show an attentional advantage for animate objects using static images. Here, participants were presented with natural scenes containing a target object from one of five categories: animals, people, moveable objects, fixed objects, and plants. These scenes were presented within the flicker paradigm (Rensink, O'Regan, & Clark, 1997), wherein an image containing the target object alternated with a second image containing only the background until observers detected the change. Animate objects were detected 1 to 2 s faster and 21% to 25% more accurately than inanimate objects. The authors interpret these results as evidence for the animate monitoring hypothesis (AMH), which states that an attentional bias toward animate objects has developed over the course of our phylogeny. New et al. argue that animate objects—being allies, enemies, sources of food, or dangerous predators—were critical to our ancestors' survival. Those who paid closer attention to animate objects would have a better chance of passing on their genetic material, selecting for an attentional bias over evolutionary time. It is important to note that the authors also tested change detection performance for objects that could be perceived as animate or that contain animate-like characteristics (e.g., directed motion). When testing change detection for static images of animate objects to static images of vehicles, New et al. continued to find performance benefits for animate

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objects, leading to the conclusion that an attentional bias exists for ancestral, not modern, priorities.

The purpose of the present experiments was to investigate the extent to which the animacy effect reported by New et al. (2007) might generalise beyond objects that are animate. To this end, we presented scenes constructed from LEGO® in the flicker paradigm. We chose LEGO stimuli because they are inherently inanimate, but may semantically represent animate objects. In the first experiment, we compared change detection for LEGO people with other LEGO objects (e.g., LEGO trees). In the second experiment, we compared change detection for LEGO people with a homogeneous control group made up of LEGO blocks, matched in size and colour to the LEGO people. In the third experiment, we occluded the faces of the LEGO people to control for face detection, and compared performance on these items with matched control blocks. Finally, in the last two experiments, we attempt to disrupt preferential processing of the LEGO people by inverting (Experiment 4a) and blurring (Experiment 4b) the images. Given that our stimuli are inanimate and did not serve as an ancestral priority, we should find no difference in change detection performance across our target category in any of our experiments. Alternatively, as is clear from the literature reviewed at the beginning of the introduction, characteristics of animacy can be generalised to inanimate objects; accordingly, we may find increased performance for our LEGO people compared with LEGO nonpeople.

If it is the case that we find no difference in performance across our target category, this result can be taken as an indication that the animacy effects reported by New et al. (2007) do not generalise beyond static images of animate objects, at least not to static images of LEGO people. If, however, we do find superior change detection performance for our LEGO people, this result can be taken as an indication that the effects reported by New et al. can be generalised to inanimate yet animate-like objects. Either result would serve as an important step forward in determining how and to what objects the category of animacy is applied.

Experiment 1

In the first experiment, we compared change detection performance for LEGO people with LEGO nonpeople (e.g., LEGO trees). According to the AMH, our species' interaction with animate objects, coupled with their importance to our survival, resulted in an innate attentional bias for animate objects. The stimuli we use in the present experiment are not inherently animate and, therefore, we should find no difference in change detection performance across our target stimuli. However, if the category of animacy can be generalised to inanimate objects, perhaps because of feature overlap, then we might find better change detection performance for the LEGO people compared with the LEGO nonpeople.

Method

Participants. Twenty undergraduates from McMaster University participated in exchange for partial course credit. Data from two participants were excluded from the final analyses for failure to complete the experiment.

Stimuli. Eighty black-and-white image pairs were created from four distinct LEGO scenes. Black-and-white images were used to avoid the influence of colour on change detection performance across our target category (e.g., the consistent yellow head of LEGO people). Images were standardized to 1,037 pixels × 692 pixels, appearing as 26.7 cm × 16.5 cm on the computer screen. At the viewing distance of 51 cm, each scene subtended 29.4° × 18.4° visual angle. Each scene had 20 associated target objects, 10 of which were LEGO people and 10 were LEGO nonpeople objects (e.g., LEGO tree). Within each scene, half the LEGO people targets and half the LEGO nonpeople targets appeared on the left side of the image, with the other halves appearing on the right side of the image. The LEGO people averaged 2.0° wide (range 1.0° to 2.7°) and 3.9° tall (range 3.1° to 4.5°), whereas the LEGO nonpeople averaged 2.2° wide (min 0.9°, max 3.4°) and 3.1° tall (min 1.2°, max 6.9°). Each pair of images contained a background-plus-target image (A′) and a background-only image (A). Figure 1 provides examples of the four LEGO scenes.

Materials and procedure. Stimuli were presented on a 17-in. iMac G5 monitor with a resolution of 1,440 × 900 pixels, using MATLAB with the Psychophysics and Video toolboxes (Brainard, 1997; Pelli, 1997). Participants made manual responses using a standard keyboard.

Each trial began with a fixation cross, presented for 1 s in the middle of the screen. Next, the background-plus-target image (A′) was presented for 250 ms, followed by a blank interstimulus interval (ISI) for 80 ms. The second image (A), containing the background only, was then presented for 250 ms, followed by another 80-ms ISI. This sequence continued to alternate until a response was made (see Figure 2). Each image pair was presented only once, for a total of 80 experimental trials. Upon detecting the change, participants pressed the "A" button if the change was perceived on the left side of the screen and the "L" button if it was perceived on the right side of the screen. Both scene type (1, 2, 3, 4) and target type (people vs. nonpeople) were presented in a random order.

Results

This experiment contained two dependent variables: mean response times (RTs) from correct-response trials and proportion of localization errors (see Figure 3). RTs were measured from the onset of the first image (A′) until button press on correctly responded to trials. Localization errors were calculated for trials in which a response was made, but the incorrect location was given. A repeated measures ANOVA with factors of Target Category (people vs. nonpeople) and Scene (1, 2, 3, 4) was applied separately to both dependent variables.

RT. There was a significant main effect of target category, $F(1, 17) = 49.07$, *mean square error (MSE)* $= 49.32$, $p < .001$, $\eta_p^2 = .74$, with changes to people targets (6.45 s) detected significantly faster than nonpeople targets (14.64 s). Scene number had no significant effect, $F(3, 51) = 1.13$, $MSE = 38.36$, $p = .35$, $\eta_p^2 = .06$, and did not interact with target category, $F(3, 51) = .27$, $MSE = 67.74$, $p = .84$, $\eta_p^2 < .02$.

To assess the influence of learning, either of the task or the stimuli, over the course of the experiment, we also compared RTs in the first half of the experiment with the second half across target category. We failed to find a main effect of experimental block, $F(1, 17) = .07$, $MSE = 8.41$, $p = .79$, $\eta_p^2 < .01$. However, we did find a main effect of target category, $F(1, 17) = 36.23$, $MSE =$

Figure 1. The background-plus-target scenes (1–4) used in Experiment 1. Each scene had 10 LEGO® people target objects and 10 LEGO nonpeople target objects, for a total of 80 unique changes.

42.68, $p < .001$, $\eta_p^2 = .68$, with changes to people targets (6.52 s) detected significantly faster than nonpeople targets (15.79 s). There was no interaction between experimental block and target category, $F(1, 17) = .29$, $MSE = 21.93$, $p = .6$, $\eta_p^2 = .02$.

Localization errors. There was a significant main effect of target category, $F(1, 17) = 34.43$, $MSE = 26.66$, $p < .001$, $\eta_p^2 = .67$, with fewer errors on people trials (0.42%) than nonpeople trials (5.47%). There was also a significant main effect of scene, $F(1, 17) = 4.37$, $MSE = 27.28$, $p = .01$, $\eta_p^2 = .20$, and a significant interaction of scene and target category, $F(3, 51) = 5.84$, $MSE = 26.27$, $p = .002$, $\eta_p^2 = .02$. We therefore analysed the effect of target category separately for each scene. For Scenes 1 and 4, participants made significantly fewer localization errors on people trials (0.56% and 0%, respectively) than nonpeople trials (5.28% and 10.56%, respectively, $t(17) = 2.36$, $p = .03$, $\eta_p^2 = .29$, $t(17) = 8.30$, $p < .001$, $\eta_p^2 = .80$. For Scene 2, there was no significant difference in the number of localization errors between people and nonpeople trials, $t(17) = .59$, $p = .56$, $\eta_p^2 = .02$. For Scene 3, there was a marginally significant difference in the proportion of localization errors, $t(17) = 1.93$, $p = .07$, $\eta_p^2 = .19$, with fewer localization errors on people (0.56%) than nonpeople trials (4.92%).

Also to assess learning, of either the task or stimuli, we compared localization errors in the first half of experimental trials with the second half. There was a significant main effect of experimental block, $F(1, 17) = 26.33$, $MSE = .19$, $p < .001$, $\eta_p^2 = .61$, with fewer errors in the second half of the experiment (0.89%) compared with the first (2.21%). There was also a significant main effect of target category, $F(1, 17) = 39.97$, $MSE = .43$, $p < .001$, $\eta_p^2 = .70$, with fewer errors on people trials (0.21%) than nonpeople trials (2.89%). We also found a significant interaction between block and target category, $F(3, 51) = 32.29$, $MSE = .27$, $p < .001$, $\eta_p^2 = .66$. Therefore, we analysed the effect of target category separately for each half of the experiment. For the first half, participants made significantly fewer localization errors to people targets (0%) than nonpeople targets (4.42%), $t(17) = 8.81$, $p < .001$, $\eta_p^2 = .82$. In contrast, for the second block, there was no significant difference in the number of localization errors participants made for people targets (0.42%) compared with nonpeople targets (1.36%), $t(17) = 1.33$, $p = .2$, $\eta_p^2 < .09$.

Discussion

The main result from this experiment was faster change detection speed and higher localization accuracy for LEGO® people compared with LEGO nonpeople. In addition, participants made fewer localization errors as the experiment progressed, although RTs remained stable. One concern regarding these findings is the

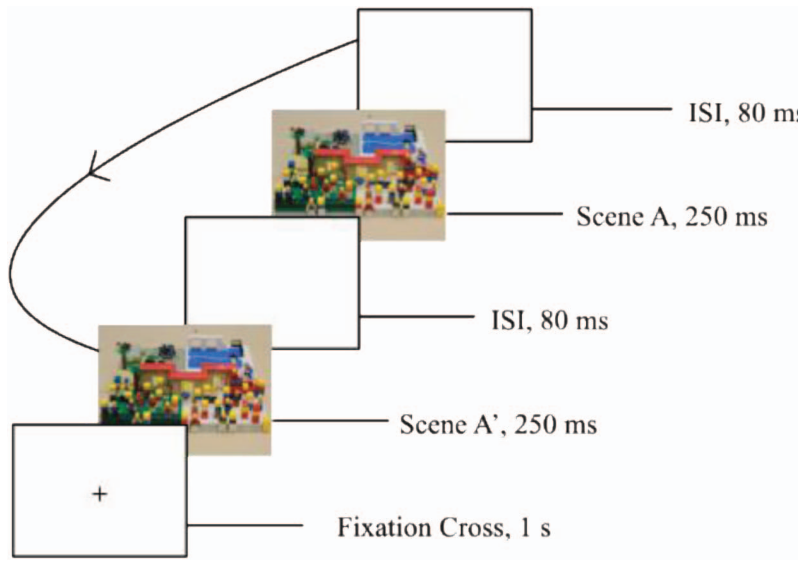

Figure 2. Flicker task used for all experiments. Each trial began with a fixation cross, which remained on the screen for 1 s. Next, the first image (A′) was presented for 250 ms. This image included both the background and the target object. The first image was followed by a white interstimulus interval (ISI) for 80 ms. Next, the second image (A), containing the background only, was presented for 250 ms. Finally, a second ISI was presented for 80 ms. In the first experiment, this sequence, from the first image to the second ISI, continued until a response was made. In subsequent experiments, this sequence continued for 30 s or until a response was made. See the online article for the color version of this figure.

relative homogeneity of our categories (see Figure 1). The LEGO® people were always the same size, shape, and consisted of only three colours (i.e., the legs, body, and head), whereas the non-people targets consisted of a variety of sizes, shapes, and colours. Our second experiment was designed to better control the heterogeneity of the nonpeople stimuli.

Experiment 2

In the second experiment, we compared change detection performance for LEGO people with standardized LEGO blocks. The blocks were matched in both size and colour to the corresponding LEGO people, and all blocks were of the same shape. If the

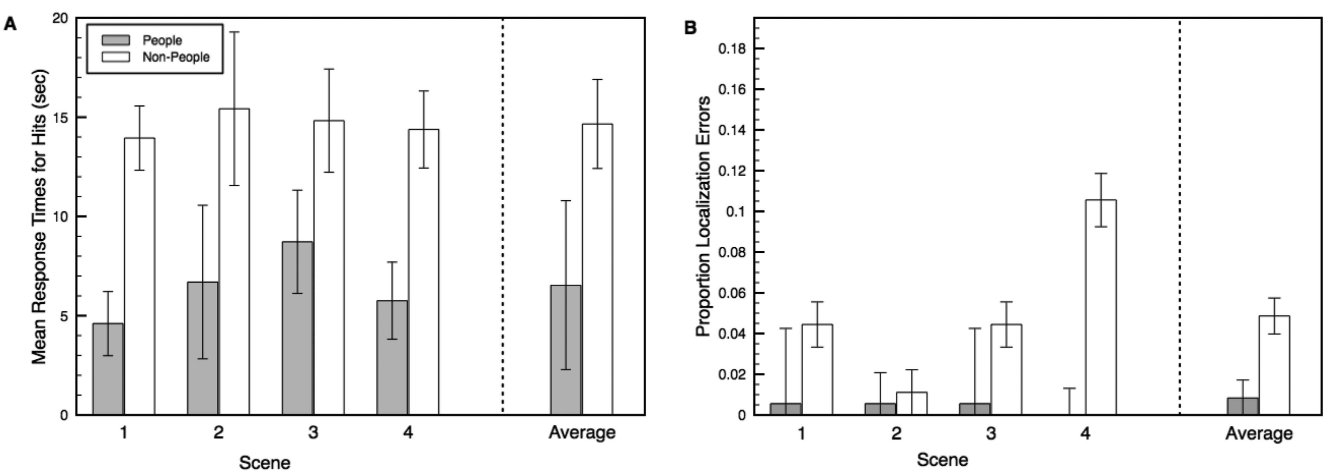

Figure 3. (A) Mean response time for correctly detected changes of LEGO® people and LEGO nonpeople in each scene (1, 2, 3, 4) and averaged across all scenes in Experiment 1. Response time was measured as the latency between onset of the first presentation of image A′ (background + target) and initiation of the key press indicating detection of the change. (B) Mean proportion of location errors for LEGO people and LEGO nonpeople in each scene (1, 2, 3, 4) and averaged across all scenes in Experiment 1. Location errors were defined as trials in which a change detection response was made, but an incorrect location was given. Error bars indicate standard errors of within-subject variation (Morey, 2008).

performance advantage for LEGO® people in the first experiment was because of the homogeneity of that category relative to the heterogeneity of the LEGO nonpeople category, we should find no difference in performance across categories in the second experiment. However, if category homogeneity did not contribute to the performance benefit for LEGO people in the first experiment, then we should again find a performance benefit for this target category in the second experiment.

Method

Participants. Twenty undergraduates from McMaster University participated in exchange for partial course credit, none of which had participated in the first experiment. Data from one participant was excluded for not following task instructions.

Stimuli. Forty colour image pairs were created from one LEGO scene. Images were standardized to 1,037 pixels × 478 pixels, appearing as 28.7 cm × 13.2 cm on the screen. At a viewing distance of 51 cm, each scene subtended 31.43° × 14.75° visual angle. Each pair included a background-plus-target image (A′) and a background-only (A) image. There were 20 LEGO people (10 on the left side of the image and 10 on the right) and 20 matched LEGO blocks in each A′ image. The LEGO people measured 2.02° × 3.03° visual angle, and the LEGO blocks measured 1.25° × 3.25° visual angle. The LEGO blocks were built to match the LEGO people in both colour and size. Figure 4 provides an example of the LEGO scene.

Materials and procedure. Stimuli were presented on a 24-in. BENQ LCD monitor with a resolution of 1,920 × 1,080 pixels, using MATLAB with the Psychophysics and Video toolboxes (Brainard, 1997; Pelli, 1997). The procedure was similar to the first experiment, but in this case, the images were presented in two blocks in order to match the number of experimental trials used in Experiment 1, as well as to assess learning over the course of the experiment. All 40 image pairs were presented in a random order within each block, creating a total of 80 experimental trials. Also, unlike the first experiment, the sequence of images stopped alternating after 30 s or when a response was made.

Results

This experiment contained three dependent variables: mean RT, misses, and errors. Mean RT was computed using only correct responses. Misses were defined as trials that expired before a response was made, presumably because the change was not detected. Errors were calculated for those trials in which an incor-

Figure 4. The background-plus-target scene used in Experiment 2, containing 20 LEGO® people target objects and 20 LEGO nonpeople target objects, for a total of 40 unique changes. See the online article for the color version of this figure.

rect response was given (see Figure 5). Mean RTs, misses, and errors were each submitted to repeated-measures ANOVAs with the factors of Block (first vs. second) and Target Category (people vs. nonpeople).

RT. There was a significant main effect of block, $F(1, 18) = 17.07$, $MSE = 8.18$, $p = .001$, $\eta_p^2 = .49$, with changes to targets in the second block (6.78 s) detected significantly faster than in the first block (9.09 s). We also found a main effect of target category, $F(1, 18) = 9.86$, $MSE = 3.97$, $p = .01$, $\eta_p^2 = .35$, with people targets (7.49 s) detected significantly faster than nonpeople targets (8.92 s). There was no interaction between block and target category, $F(1, 18) = .05$, $MSE = 1.88$, $p = .8$, $\eta_p^2 < .01$.

Localization errors. There was a significant main effect of block, $F(1, 18) = 10.79$, $MSE = 5.97$, $p = .004$, $\eta_p^2 = .37$, with participants making significantly fewer localization errors in the second block (2.76%) than the first block (11.97%). There was also a main effect of target category, $F(1, 18) = 12.42$, $MSE = .95$, $p = .002$, $\eta_p^2 = .41$, with participants making significantly fewer localization errors for people (5.40%) than nonpeople targets (9.34%). The interaction between block and target category was significant, $F(1, 18) = 12.65$, $MSE = 10.32$, $p = .002$, $\eta_p^2 = .41$. Therefore, we analysed the effect of target category separately for each block. For the first block, participants made significantly fewer localization errors to people targets (8.16%) than nonpeople targets (15.79%), $t(18) = 4.32$, $p < .001$, $\eta_p^2 = .51$. In contrast, for the second block, there was no significant difference in the number of localization errors participants made for people targets (2.63%) compared with nonpeople targets (2.89%), $t(18) = .21$, $p = .84$, $\eta_p^2 = .01$.

Misses. There was a significant main effect of block, $F(1, 18) = 6.57$, $MSE = 31.29$, $p = .02$, $\eta_p^2 = .27$, with participants missing significantly more changes to targets in the first block (5.40%) than the second block (2.11%). There was also a main effect of target category, $F(1, 18) = 11.91$, $MSE = 26.54$, $p = .003$, $\eta_p^2 = .40$, with participants missing significantly fewer changes to people targets (1.71%) than nonpeople targets (5.79%). There was no significant interaction between block and target category, $F(1, 18) = .10$, $MSE = .003$, $p = .75$, $\eta_p^2 < .01$.

Discussion

We observed superior change detection performance for LEGO® people compared with LEGO nonpeople. The advantage in speed of response (~2 s) is comparable with the results observed by New et al. (2007) using static images of real animate objects. Moreover, we continued to observe performance advantages for our target category in terms of both localization error rate and miss errors (degree of change blindness). With these controlled stimuli, the difference cannot be attributed to differences in the homogeneity of size, colour, or shape across our categories. We did uncover better performance on each of our dependent measures in the second block of the experiment. This is possibly related to participants becoming more proficient at the task; however, in the second block of the experiment, participants were exposed to a second instantiation of each target change. As such, performance increases over time in this case is more likely related to memory. It is important to note that despite overall better performance in the second block, we continued to find faster RTs and fewer misses for the LEGO people compared with the LEGO nonpeople.

Experiment 3

Despite controlling the homogeneity of our nonpeople category in the second experiment, we continued to find a change detection benefit for LEGO people. One salient difference between the two stimulus categories was the presence of a facial pattern on the LEGO people. Humans are generally considered to be face per-

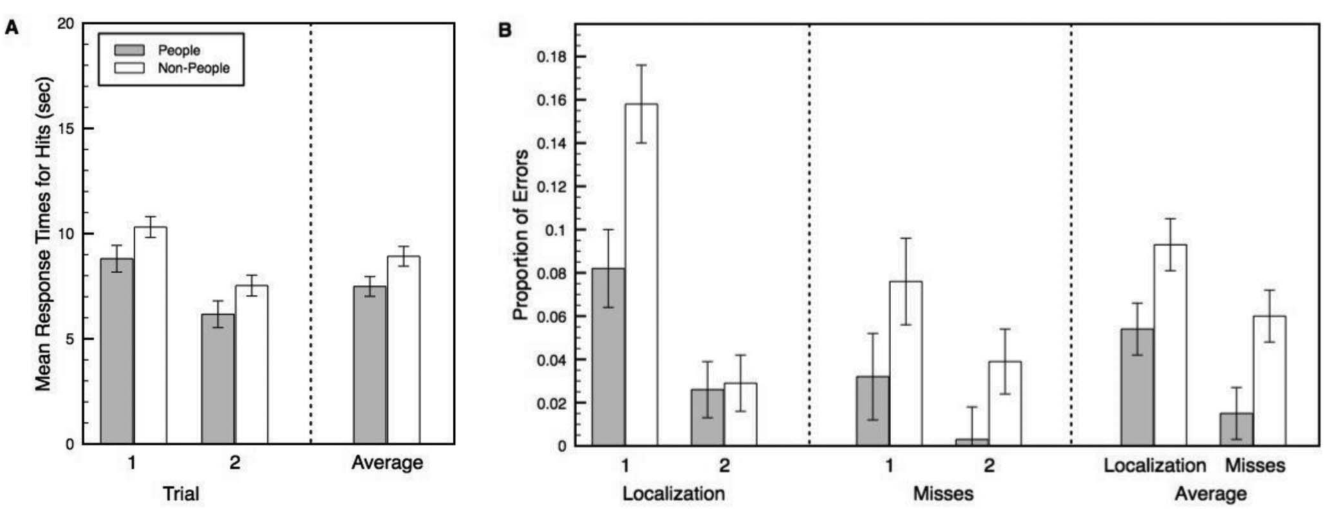

Figure 5. (A) Mean response time for correctly detected changes in each block of trials and averaged across both blocks in Experiment 2 for LEGO® people and LEGO nonpeople. (B) Mean proportion of localization errors for LEGO people and LEGO nonpeople in each block of trials and averaged across both blocks in Experiment 2. Mean proportion of changes missed in each block of trials and averaged across both blocks for Experiment 2. Misses were defined as trials in which no response was made over the course of a 30-s trial.

ception experts (Diamond & Carey, 1986). Indeed, human brains contain a specialized area preferentially recruited in the processing of faces, aptly called the *fusiform face area*, located within the fusiform gyrus (Kanwisher, McDermott, & Chun, 1997). Of specific interest, Wilford and Wells (2010) report better change detection performance with face stimuli compared with images of houses. Given the expertise humans have in face processing, the results of first two experiments may have been driven by the presence of facial patterns.

In the third experiment, we compared change detection performance for LEGO® people with faces occluded with the standardized LEGO blocks used in the second experiment. If the change detection advantage for LEGO people observed in the first two experiments was because of a sensitivity to face patterns, we should find no difference in performance across our target categories in the current experiment. However, if the performance benefit for LEGO people in the first two experiments was because of something other than face availability, we should continue to find better change detection for this category in the current experiment.

Method

Participants. Twenty-four undergraduates from McMaster University participated in exchange for partial course credit, none of which had participated in either of the first two experiments.

Stimuli. Forty image pairs were created from the same LEGO scene used in the second experiment, however, the heads of the LEGO people were turned around, eliminating the face pattern from the stimuli. Again, each pair included a background-plus-target image (A′) and a background-only (A) image. And, again, the target objects were either a LEGO person with the face occluded or a LEGO block, matched in size and colour with the LEGO people.

Materials and procedure. The materials and procedure were the same as those used in the Experiment 2.

Results

Experiment 3 contained the same three dependent variables as those measured in the second experiment: mean RT, misses, and errors. Again, mean RT was computed using only correct responses, misses were defined as trials that expired before a response was made, and errors were calculated for those trials in which an incorrect response was given (see Figure 6). Mean RTs, misses, and errors were each submitted to repeated-measures ANOVAs with the factors of Block (first vs. second) and Target Category (people vs. nonpeople).

RT. There was a significant main effect of block, $F(1, 23) = 86.25$, $MSE = 1.94$, $p < .001$, $\eta_p^2 = .79$, with changes to targets in the second block (6.50 s) detected significantly faster than the first block (9.14 s). We also found a main effect of target category, $F(1, 23) = 35.37$, $MSE = 2.74$, $p < .001$, $\eta_p^2 = .61$, with changes to people targets (6.82 s) detected significantly faster than nonpeople targets (8.83 s). There was no interaction between block and target category, $F(1, 23) = .79$, $MSE = 1.49$, $p = .38$, $\eta_p^2 = .03$.

Localization errors. There was no significant main effect of block, $F(1, 23) = 1.79$, $MSE = .003$, $p = .19$, $\eta_p^2 = .07$. However, there was a significant main effect of target category, $F(1, 23) = 16.85$, $MSE = .003$, $p < .001$, $\eta_p^2 = .42$, with participants making significantly fewer localization errors for people (2.8%) than nonpeople targets (7.1%). There was no significant interaction between block and target category, $F(1, 23) = .65$, $MSE = .002$, $p = .43$, $\eta_p^2 = .03$.

Misses. There was a significant main effect of block, $F(1, 23) = 34.24$, $MSE = .005$, $p < .001$, $\eta_p^2 = .60$, with participants missing significantly fewer changes to targets in the second block (2.5%) than the first block (10.5%). There was also a main effect

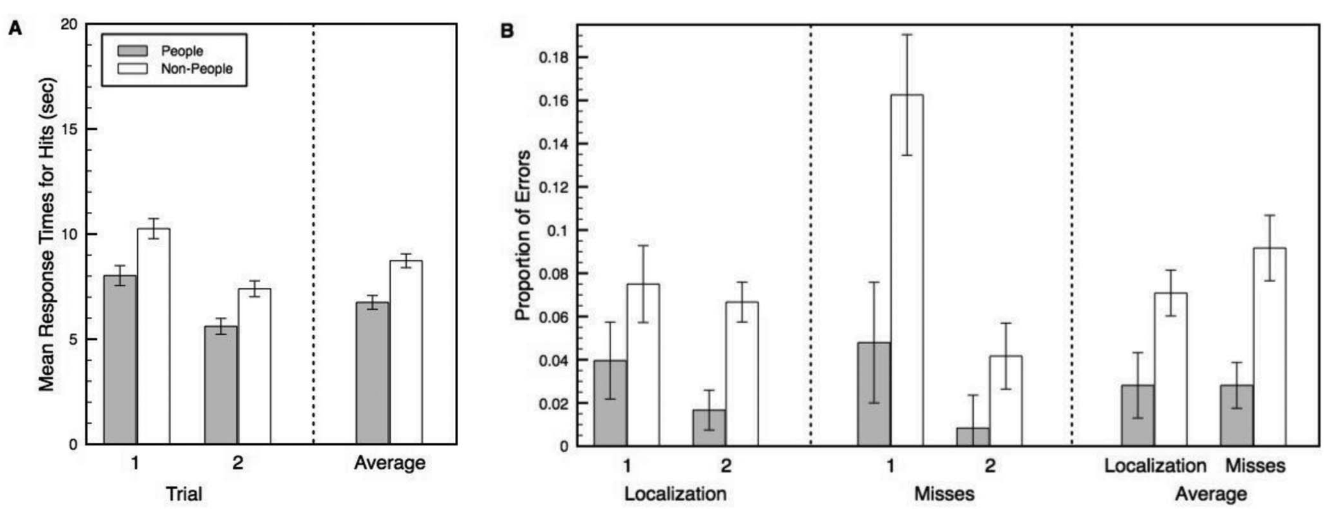

Figure 6. (A) Mean response time for correctly detected changes to LEGO® people and nonpeople in each block of trials and averaged across blocks in Experiment 3. (B) Mean proportion of localization errors for LEGO people and nonpeople in each block of trials and averaged across both blocks in Experiment 3. Mean proportion of changes missed in each block of trials and averaged across both blocks for Experiment 3. Misses were defined as trials in which no response was made over the course of a 30-s trial.

of target category, $F(1, 23) = 14.60$, $MSE = .009$, $p = .001$, $\eta_p^2 = .39$, with participants missing significantly fewer changes to people targets (2.8%) than nonpeople targets (10.2%). The interaction between block and target category was significant, $F(1, 23) = 14.93$, $MSE = .003$, $p = .001$, $\eta_p^2 = .39$. Therefore, we analysed the effect of target category separately for each block. For the first block, participants missed significantly fewer changes to people targets (4.79%) than nonpeople targets (16.25%), $t(23) = 4.19$, $p < .001$, $\eta_p^2 = .43$. For the second block, participants also missed significantly fewer changes to people targets (0.83%) than nonpeople targets (4.17%), $t(23) = 2.23$, $p = .04$, $\eta_p^2 = .18$. The interaction was caused by a much smaller effect in the second block (4.17 – 0.83 = 3.34) compared with the first block (16.25–4.79 = 11.46), $t(23) = 3.86$, $p < .001$, $\eta_p^2 = .39$.

Discussion

Despite eliminating the faces of the LEGO® people, we continued to uncover a change detection benefit for these objects compared with LEGO nonpeople. Although human observers are experts with face stimuli, such expertise does not appear to underlie the change detection benefits we observed in Experiment 2. The current results mimic those found in Experiment 2: We continue to find faster RTs, fewer localization errors, and less change blindness for LEGO people compared with LEGO nonpeople. And despite increases in performance over the course of the experiment, as indicated by better performance in the second block, this does not eliminate the target category effect.

Experiment 4a and 4b

Experiments 4a and 4b were intended as replications of the third and fourth experiments presented by New et al. (2007); each was intended to disrupt the processing of the categorical features of the target objects and, thus, disrupt the attentional prioritizing of LEGO people.

In their third experiment, New et al. (2007) rotated each image 180° before presenting them in the flicker paradigm. Inverting faces has been shown to have severe effects on recognition (Farah, Tanaka, & Drain, 1995; Valentine, 1988; Yin, 1969). However, inverting objects or scenes has had varying effects on change detection (Kelley, Chun, & Chua, 2003; LaPointe, 2011; Shore & Klein, 2000), visual array (Ro, Russell, & Lavie, 2001), and visual search tasks (Rieger, Köchy, Schalk, Grüschow, & Heinze, 2008; Rousselet et al., 2003; Vuong, Hof, Bülthoff, & Thornton, 2006). Kelley et al. (2003) found that when presenting changes that were highly significant to the scene, viewers noticed the change 81% of the time. When the scenes were rotated 180°, viewers noticed the highly significant changes only 69% of the time. Kelley et al. argued that inverting the images sufficiently disrupts the global properties of the scene. Moreover, New et al. found that when their images were rotated 180°, there was no difference in the rate at which animate and inanimate objects were detected. New et al. took this finding as support for the assumption that preferential animate monitoring relies on the categorical information contained in the objects.

In their fourth experiment, New et al. (2007) obscured their images using a Gaussian blur, under a similar assumption that once the features associated with the categorical information of the objects was disrupted, preferential attention to animate objects would be eliminated. Change detection performance in this experiment dropped considerably for both animate and inanimate objects and no difference in performance across these categories was reported. It is difficult to know whether this result was due to participants being unable to access the categorical information of the target objects or whether they simply had trouble naming the target objects once the change was detected. Because we had our participants locate the change, rather than name the object that was changing, this was not a concern for the present experiment.

Experiment 4a

Method.

Participants. Twenty undergraduates from McMaster University participated in exchange for partial course credit, none of which had participated in any of the previous experiments.

Stimuli. The same 40 image pairs used in Experiment 2 were used in the current experiment, however, each image was rotated 180°.

Materials and procedure. The materials and procedure were the same as those used in the second experiment.

Results. Again, we measured three key dependent variables: mean RTs for correctly responded to trials, misses, and errors (see Figure 7). Each of these dependent measures was submitted to repeated-measures ANOVAs with the factors of Block (first vs. second) and Target Category (people vs. nonpeople).

RT. There was a significant main effect of block, $F(1, 19) = 56.58$, $MSE = 2.79$, $p < .001$, $\eta_p^2 = .75$, with changes to targets in the second block (7.92 s) being detected significantly faster than changes to targets in the first block (10.72 s). We also found a main effect of target category, $F(1, 19) = 22.37$, $MSE = 4.59$, $p < .001$, $\eta_p^2 = .54$, with people objects (8.19 s) being detected significantly faster than changes to nonpeople objects (10.45 s). There was no significant interaction between block and target category, $F(1, 19) = .08$, $MSE = 2.27$, $p = .78$, $\eta_p^2 < .01$.

Localization errors. We failed to uncover main effects of either block, $F(1, 19) = 1.14$, $MSE = .01$, $p = .30$, $\eta_p^2 = .06$, or target category, $F(1, 19) = .00$, $MSE = .00$, $p = 1.00$, $\eta_p^2 = .00$. We also failed to uncover a significant interaction, $F(1, 19) = .33$, $MSE = .005$, $p = .57$, $\eta_p^2 = .02$.

Misses. There was a significant main effect of block, $F(1, 19) = 6.62$, $MSE = 31.09$, $p = .02$, $\eta_p^2 = .26$, with participants missing significantly more changes to targets in the first block (7.83%) compared with the second block (4.63%). There was also a main effect of target category, $F(1, 19) = 16.93$, $MSE = 86.18$, $p = .001$, $\eta_p^2 = .47$, with participants missing significantly fewer changes to people objects (1.96%) compared with nonpeople objects (10.50%). There was no significant interaction between block and target category, $F(1, 19) = .36$, $MSE = .004$, $p = .56$, $\eta_p^2 = .02$.

Experiment 4b

Method.

Participants. Twenty-nine undergraduates from McMaster University participated in exchange for partial course credit, none of which had participated in any of the previous experiments.

Stimuli. The same 40 image pairs used in the second experiment were used here, but with a circular Gaussian blur applied to

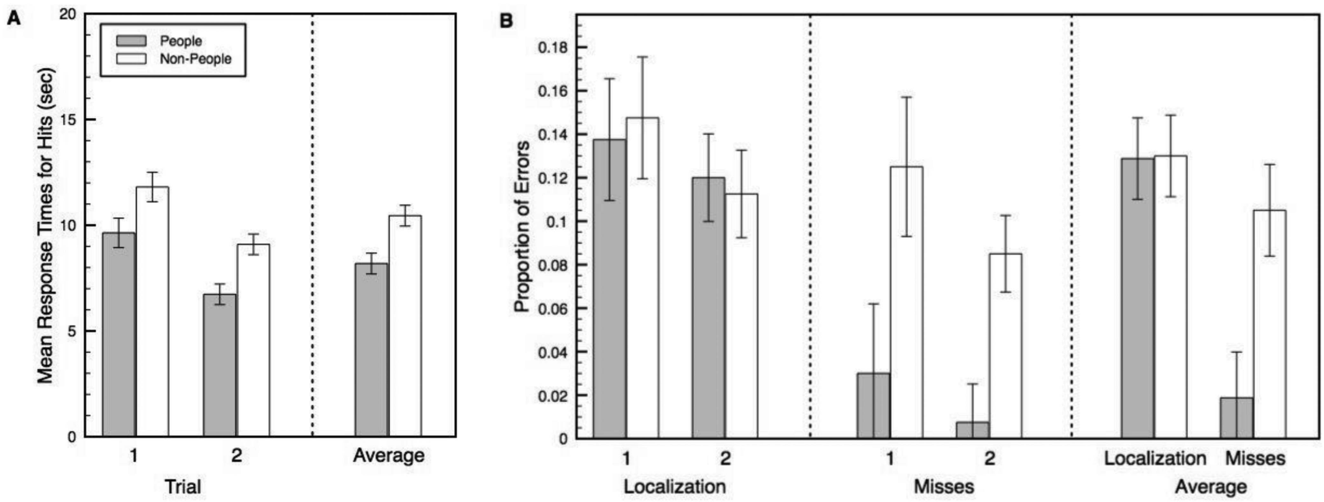

Figure 7. (A) Mean response time (s) for correctly detected changes in each block of trials and averaged across both blocks in Experiment 4a for LEGO® people and LEGO nonpeople. (B) Mean proportion of localization errors in each block of trials and averaged across both blocks in Experiment 4a for LEGO people and LEGO nonpeople. Mean proportion of changes missed in each block of trials and averaged across both blocks for Experiment 4a. Misses were defined as trials in which no response was made over the course of a 30-s trial.

each target location ($\sigma = 4°$). Some of the blurred regions did overlap (e.g., for targets in close proximity); however, the effect of the blurring was not additive. Figure 8 provides an example of the LEGO® scene.

Materials and procedure. The materials and procedure were the same as those used in the second experiment.

Results. The same three dependent variables measured in the Experiments 2, 3, and 4a were used in the current experiment (see Figure 9). Again, each of these dependent measures was submitted to repeated-measures ANOVAs with the factors of Block (first vs. second) and Target Category (people vs. nonpeople).

RT. There was a significant main effect of block, $F(1, 28)$, = 84.98 $MSE = 2.02$, $p < .01$, $\eta_p^2 = .75$, with changes to targets in the second block (6.53 s) being detected significantly faster than changes to targets in the first block (8.96 s). We also found a main effect of target category, $F(1, 28) = 6.98$, $MSE = 2.10$, $p = .01$, $\eta_p^2 = .20$, with people objects (7.39 s) being detected faster than nonpeople objects (8.10 s). There was no significant interaction between block and target category, $F(1, 28) = .28$, $MSE = 1.40$, $p = .60$, $\eta_p^2 < .01$.

Localization errors. There was a significant main effect of block, $F(1, 28) = 31.57$, $MSE = .0007$, $p < .001$, $\eta_p^2 = .53$, with fewer localization errors occurring in the second block (1.00%) compared with the first block (4.00%). However, we did not uncover a main effect of target category, $F(1, 28) = 3.25$, $MSE = .0008$, $p = .08$, $\eta_p^2 = .10$, or a significant interaction between block and target category, $F(1, 28) = .00$, $MSE = .0004$, $p = 1.00$, $\eta_p^2 = .00$.

Misses. There was a significant main effect of block, $F(1, 28) = 41.40$, $MSE = .0004$, $p < .001$, $\eta_p^2 = .60$, with fewer changes missed in the second block (1.00%) compared with the first block (4.00%). However, we did not uncover a main effect of target category, $F(1, 28) = 1.75$, $MSE = .001$, $p = .20$, $\eta_p^2 = .06$, nor did we uncover an interaction between block and target category, $F(1, 28) = 3.5$, $MSE = .0004$, $p = .07$, $\eta_p^2 = .11$.

Discussion

Despite inverting our images, we continued to find a performance benefit for LEGO people, in terms of both RTs and misses, but no difference in terms of localization error rate. This finding is contradictory to the results described by New et al. (2007), wherein inverting their natural scenes disrupted change detection benefits for animate objects. Although inverting faces produces robust effects on processing (Farah et al., 1995; Valentine, 1988; Yin, 1969), the effect of inversion on scene processing is less conclusive. For example, Shore and Klein (2000) presented participants with pairs of images that contained a change either in a central or marginal area of interest (Rensink et al., 1997). The image pairs were either side-by-side or flickered using parameters similar to the current experiment. Shore and Klein observed significant performance benefits for changes that occurred centrally compared with marginally in both the side-by-side and flicker conditions. Interestingly, this difference in performance was eliminated when the images were inverted, but only when the images were presented side-by-side. When the images were presented using the flicker paradigm, the area of interest performance differences remained. Contrasting the results of Shore and Klein with those reported by New et al., it is clear the influence of inversion on scene processing is still an issue of debate. Although the results from the current experiment do not replicate those reported by New et al., our failure to disrupt categorical processing when inverting the scenes is nonetheless an important and interesting contribution to the literature.

It is important to note that we did find some decrements in performance when we inverted the images. RT performance in Experiment 4a was slower than that reported in the first three experiments. Moreover, when inverting the images, we failed to uncover any differences across our target categories in terms of localization error rate. That is, when the images were inverted,

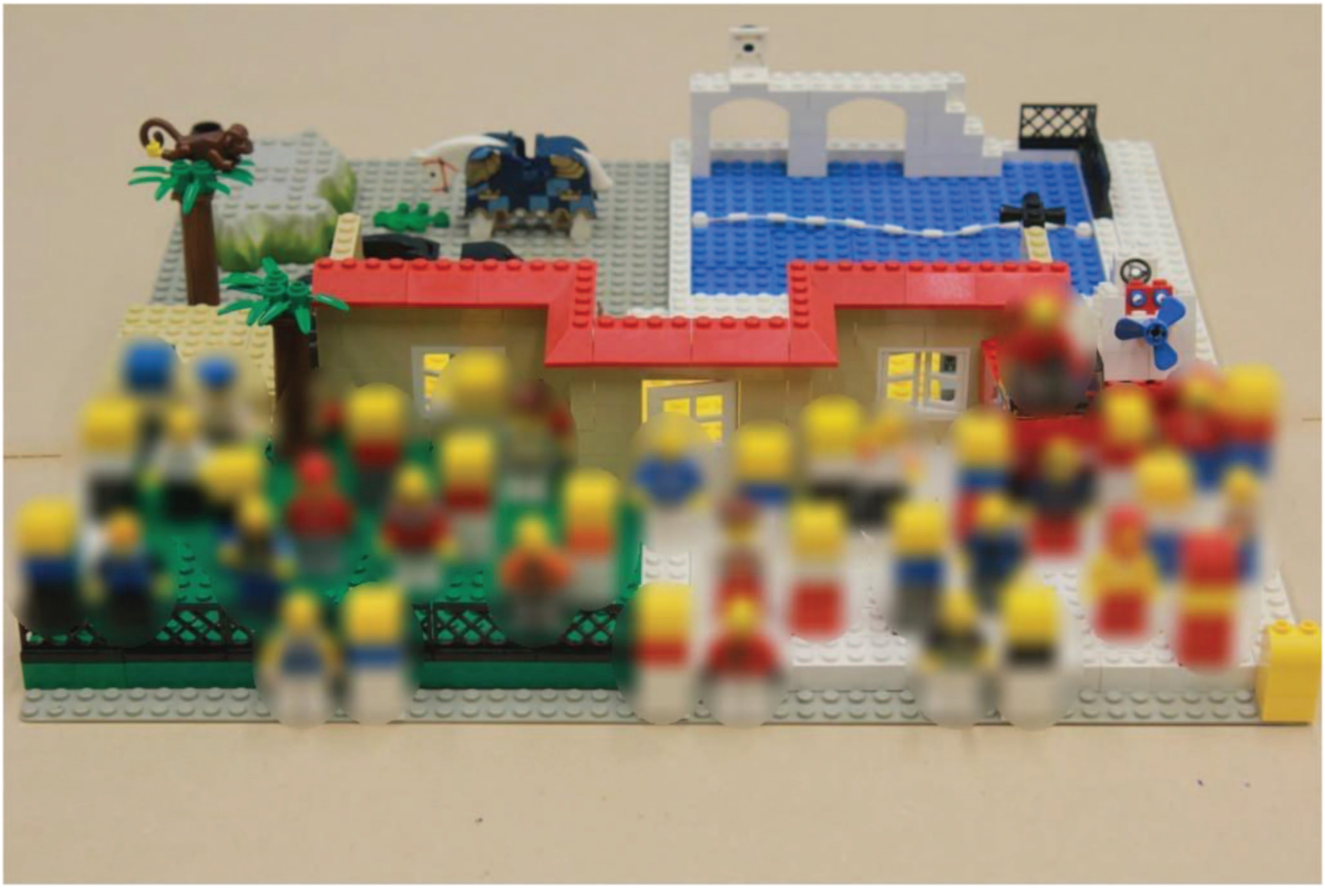

Figure 8. The background-plus-target scene used in Experiment 4b with a circular Gaussian blur applied to each target location (σ = 4°). See the online article for the color version of this figure.

participants were equally likely to make a localization error when the target was a LEGO® person or a LEGO block.

In Experiment 4b, we further disrupted the performance benefit for LEGO people by using Gaussian blur, which presumably abolished categorical information of the target objects. Despite this manipulation, we uncovered a RT benefit for LEGO people compared with LEGO nonpeople, which may be related in part to blurring only the target objects, leaving the contextual information intact (although, see LaPointe, 2011, Experiment 3). However, we failed to uncover any such benefit in terms of either the proportion of changes missed or the proportion of localization errors. It is important to note that in each of the dependent measures, we consistently uncovered better performance in the second block of the experiment compared with the first. These finding suggests memory benefits to performance, regardless of target type.

General Discussion

Over the course of five experiments, we have demonstrated a change detection benefit for objects that could be perceived as animate, but with which our distant ancestors had no experience. New et al. (2007) have shown similar results using a similar task, but with images of real-world animate objects. In fact, the difference in change detection RTs we report here (~2 s, Experiment 2 and 3) are comparable with those measured by New et al. (1s to 2 s, Experiments 1 and 2). The performance benefit we uncovered for LEGO people does not appear to be a consequence of stimulus complexity (Experiment 1), homogeneity (Experiment 2), of face detection (Experiment 3). However, note the RT difference we uncover in Experiment 1, in which the homogeneous animate category was compared with a heterogeneous inanimate category, was approximately 8 s, whereas in Experiments 2 and 3, in which we controlled the homogeneity of the inanimate group, the RT difference was approximately 2 s. Moreover, the performance benefit is at least partially disrupted by obscuring the categorical features of the objects (Experiments 4a and 4b). In this case, we assume our participants attributed animacy to the LEGO people, thereby producing superior change detection for those objects.

According to the AMH, attending to animate objects was an important skill for our ancestors, facilitating the passing of genetic material to subsequent generations, and thereby leaving an attentional imprint on our modern cognitive system to selectively monitor animate objects. New et al. (2007) validated this assumption by showing better change detection performance for images of animate objects than inanimate objects. Further, the AMH claims that the extraction of properties from animate objects triggers the concept of animacy, producing an attentional priority to these

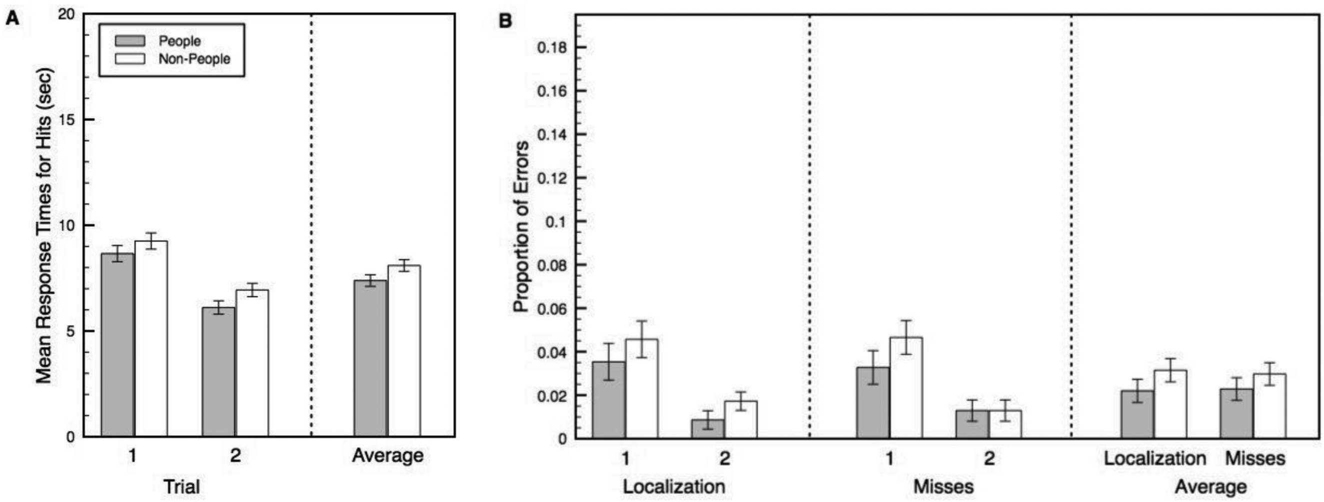

Figure 9. (A) Mean response time (s) for correctly detected changes in each block of trials and averaged across both blocks in Experiment 4b for LEGO® people and LEGO nonpeople. (B) Mean proportion of localization errors in each block of trials and averaged across both blocks in Experiment 4b for LEGO people and LEGO nonpeople. Mean proportion of changes missed in each block of trials and averaged across both blocks for Experiment 4b. Misses were defined as trials in which no response was made over the course of a 30-s trial.

objects. However, this prioritization does not generalise to inanimate objects (e.g., vehicles) containing animate characteristics (e.g., motion). New et al. validated this assumption by showing better change detection performance for images of animate objects compared with images of vehicles. Our results provide an important contribution to the literature by showing generalisation of animate prioritization to inanimate objects in a change detection task.

From the experiments we report, it is clear that our participants treated LEGO® people differently than LEGO nonpeople. The explanation that we favour for this difference in performance is that the animate category was generalised to the LEGO people, perhaps because the LEGO people contain some feature overlap with animate objects. The same interpretation might also explain the results summarised in the introduction. For example, despite not belonging to the category of animacy, point-light displays were treated as animate objects when they mimicked a particular animate feature such as bipedal motion (Chang & Troje, 2008; Cutting & Kozlowski, 1977; Johansson, 1973; Kozlowski & Cutting, 1977; Mather & West, 1993). The feature overlap between the LEGO people and real-animate objects that might spur generalisations of animacy remains unclear, although it does not appear to be the homogeneity of the category or facial pattern.

Further, whether such generalisations and the consequent attention benefits are a product of a phylogenetic interaction with animate objects is also unclear. With the current set of results, we are unable to distinguish whether such generalisations occur because of a phylogenetic residual in our modern cognitive system tuned to the prioritization of animate objects, as suggested by the AMH, or whether the preferential allocation of attention to these objects is because of a life history of interaction with this important category. Moreover, with the current results, we can only speculate on whether the flicker task is a sufficient tool for measuring adaptive behaviours. It is clear from previous research that change detection tasks are sensitive tools for measuring experience-based differences in performance (Curran, Gibson, Horne, Young, & Bozell, 2009; Jones, Jones, Smith, & Copley, 2003; Werner & Thies, 2000). For example, Werner and Thies (2000) presented expert and novice football players images of football scenes with target objects either appearing or disappearing across image presentations. They showed greater change detection performance for the expert football players compared with the novices. These results are an indication of attentional sensitivities accrued over the lifetime and driven by experience. Again, the current set of experiments does not specifically address the origins of preferential attention for animate or animate-like objects.

Finally, although we assume the performance benefit for LEGO people is due to a generalisation of animacy, it is important to note that there are several other perceptual and semantic differences across our target category that we have not accounted for, but may nonetheless explain the performance differences we report. In the experiments described above, we have attempted control for several perceptual characteristics across our target category (i.e., colour, homogeneity, and facial pattern); however, we cannot rule out other distinct perceptual qualities of the LEGO people. For example, despite controlling the shape of our target objects within our target categories across Experiments 2 through 4b, the LEGO people have round heads, whereas the LEGO blocks are rectangular. This is less of a concern in Experiment 1, in which the inanimate objects consisted of different shapes; it is possible, in Experiments 2 to 4, that participants used the simple strategy of looking for roundness, set against the rigid LEGO background. Equally, we cannot account for several semantic differences other than a generalisation of animacy across our target category. For example, level of interest or meaningfulness likely varies across our target category and could conceivably produce performance differences we report here. We should note that many of these unaccounted-for perceptual and semantic differences are equally likely to be potential confounds in the stimuli used by New et al. (2007).

In summary, we have demonstrated performance benefits for animate-like objects using a change detection task. We believe this is an important contribution to the literature—while using the same paradigm, and despite using a stimulus set comprised entirely of inanimate objects, we show similar results to those reported in a previous study that used images of animate objects. The difference we uncover between LEGO® people and LEGO nonpeople does not seem to be a consequence of stimulus complexity, homogeneity, or facial pattern. The difference, however, may be accounted for by a generalisation of animacy to inanimate objects related to feature overlap. Future research is required to determine the specific featural overlap required for such generalisations to occur, and to tease apart the contributions of phylogenetic and/or ontogenetic pressures underlining attentional prioritization of animate and animate-like objects.

Résumé

Il a été démontré que les objets animés déclenchent la priorité attentionnelle lors d'une tâche de détection des changements. Cet avantage a été constaté tant chez les animaux humains que chez les animaux non humains en comparaison avec des objets inanimés. Ces résultats peuvent s'expliquer par l'importance que les objets animés ont eu à travers l'histoire de notre espèce. Dans le cadre de la présente série d'expériences, nous présentons des stimuli, qui pourraient être perçus comme étant animés, mais avec lesquels nos lointains ancêtres n'auraient eu aucune expérience et sur lesquels la sélection naturelle n'aurait aucune influence directe par rapport à l'établissement des priorités. Dans la première expérience, nous comparons des « personnes » LEGO® à des « non-personnes » LEGO au cours d'une tâche de détection des changements. Lors de la deuxième expérience, nous tentons de contrôler l'hétérogénéité d'objets non-animés au moyen de blocs LEGO agencés en termes de grosseur et de couleur auprès de personnes LEGO. Au cours de la troisième expérience, nous cachons le visage des personnes LEGO afin de contrôler la reconnaissance des traits faciaux. Et lors des deux dernières expériences, nous tentons de masquer le traitement d'informations catégoriques de haut niveau du stimulus en inversant et en brouillant les scènes.

Mots-clés : attention, détection des changements, cécité au changement, animéité

References

Bae, J. E., & Kim, M. S. (2011, May). Selective visual attention occurred in change detection derived by animacy of robot's appearance. In V. W. Smari & G. C. Fox (Eds.), *Collaboration Technologies and Systems (CTS), 2011 International Conference* (pp. 190–193). Philadelphia, PA: IEEE.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision, 10,* 433–436. http://dx.doi.org/10.1163/156856897X00357

Chang, D. H. F., & Troje, N. F. (2008). Perception of animacy and direction from local biological motion signals. *Journal of Vision, 8*(5), 3.1–3.10. http://dx.doi.org/10.1167/8.5.3

Crouzet, S. M., Joubert, O. R., Thorpe, S. J., & Fabre-Thorpe, M. (2012). Animal detection precedes access to scene category. *PLoS ONE, 7,* e51471. http://dx.doi.org/10.1371/journal.pone.0051471 (Correction published 2013, *PLoS ONE, 8,* http://dx.doi.org/10.1371/annotation/9cc5295b-d8b7-482a-8940-eaa4c8b53a1e)

Curran, T., Gibson, L., Horne, J. H., Young, B., & Bozell, A. P. (2009). Expert image analysts show enhanced visual processing in change detection. *Psychonomic Bulletin & Review, 16,* 390–397. http://dx.doi.org/10.3758/PBR.16.2.390

Cutting, J. E., & Kozlowski, L. T. (1977). Recognizing friends by their walk: Gait perception without familiarity cues. *Bulletin of the Psychonomic Society, 9,* 353–356. http://dx.doi.org/10.3758/BF03337021

Delorme, A., Richard, G., & Fabre-Thorpe, M. (2010). Key visual features for rapid categorization of animals in natural scenes. *Frontiers in Psychology, 1,* 21.

Diamond, R., & Carey, S. (1986). Why faces are and are not special: An effect of expertise. *Journal of Experimental Psychology: General, 115,* 107–117. http://dx.doi.org/10.1037/0096-3445.115.2.107

Elder, J. H., & Velisavljević, L. (2009). Cue dynamics underlying rapid detection of animals in natural scenes. *Journal of Vision, 9*(7), 7. http://dx.doi.org/10.1167/9.7.7

Farah, M. J., Tanaka, J. W., & Drain, H. M. (1995). What causes the face inversion effect? *Journal of Experimental Psychology: Human Perception and Performance, 21,* 628–634.

Hauser, M. D. (1998). A nonhuman primate's expectations about object motion and destination: The importance of self-propelled movement and animacy. *Developmental Science, 1,* 31–37. http://dx.doi.org/10.1111/1467-7687.00009

Johansson, G. (1973). Visual perception of biological motion and a model for its analysis. *Perception & Psychophysics, 14,* 201–211. http://dx.doi.org/10.3758/BF03212378

Jones, B. T., Jones, B. C., Smith, H., & Copley, N. (2003). A flicker paradigm for inducing change blindness reveals alcohol and cannabis information processing biases in social users. *Addiction, 98,* 235–244. http://dx.doi.org/10.1046/j.1360-0443.2003.00270.x

Kanwisher, N., McDermott, J., & Chun, M. M. (1997). The fusiform face area: A module in human extrastriate cortex specialized for face perception. *The Journal of Neuroscience, 17,* 4302–4311.

Kelley, T. A., Chun, M. M., & Chua, K. P. (2003). Effects of scene inversion on change detection of targets matched for visual salience. *Journal of Vision, 3*(1), 1–5. http://dx.doi.org/10.1167/3.1.1

Kirchner, H., & Thorpe, S. J. (2006). Ultra-rapid object detection with saccadic eye movements: Visual processing speed revisited. *Vision Research, 46,* 1762–1776. http://dx.doi.org/10.1016/j.visres.2005.10.002

Kozlowski, L. T., & Cutting, J. E. (1977). Recognizing the sex of a walker from a dynamic point-light display. *Perception & Psychophysics, 21,* 575–580. http://dx.doi.org/10.3758/BF03198740

LaPointe, M. (2011). *Testing the animate monitoring hypothesis* (Unpublished master's thesis). University of Lethbridge, Lethbridge, Alberta, Canada.

Mather, G., & West, S. (1993). Recognition of animal locomotion from dynamic point-light displays. *Perception, 22,* 759–766. http://dx.doi.org/10.1068/p220759

Morey, R. D. (2008). Confidence intervals from normalized data: A correction to Cousineau (2005). *Tutorials in Quantitative Methods for Psychology, 4,* 61–64.

New, J., Cosmides, L., & Tooby, J. (2007). Category-specific attention for animals reflects ancestral priorities, not expertise. *PNAS Proceedings of the National Academy of Sciences of the United States of America, 104,* 16598–16603. http://dx.doi.org/10.1073/pnas.0703913104

Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision, 10,* 437–442. http://dx.doi.org/10.1163/156856897X00366

Poulin-Dubois, D., Lepage, A., & Ferland, D. (1996). Infants' concept of animacy. *Cognitive Development, 11,* 19–36. http://dx.doi.org/10.1016/S0885-2014(96)90026-X

Pratt, J., Radulescu, P. V., Guo, R. M., & Abrams, R. A. (2010). It's alive! animate motion captures visual attention. *Psychological Science, 21,* 1724–1730. http://dx.doi.org/10.1177/0956797610387440

Rensink, R. A., O'Regan, J. K., & Clark, J. J. (1997). To see or not to see: The need for attention to perceive changes in scenes. *Psychological Science, 8,* 368–373. http://dx.doi.org/10.1111/j.1467-9280.1997.tb00427.x

Rieger, J. W., Köchy, N., Schalk, F., Grüschow, M., & Heinze, H. J. (2008). Speed limits: Orientation and semantic context interactions constrain natural scene discrimination dynamics. *Journal of Experimental Psychology: Human Perception and Performance, 34,* 56–76. http://dx.doi.org/10.1037/0096-1523.34.1.56

Ro, T., Russell, C., & Lavie, N. (2001). Changing faces: A detection advantage in the flicker paradigm. *Psychological Science, 12,* 94–99. http://dx.doi.org/10.1111/1467-9280.00317

Rousselet, G. A., Macé, M. J. M., & Fabre-Thorpe, M. (2003). Is it an animal? Is it a human face? Fast processing in upright and inverted natural scenes. *Journal of Vision, 3*(6), 440–455. http://dx.doi.org/10.1167/3.6.5

Rutherford, M. D., Pennington, B. F., & Rogers, S. J. (2006). The perception of animacy in young children with autism. *Journal of Autism and Developmental Disorders, 36,* 983–992. http://dx.doi.org/10.1007/s10803-006-0136-8

Shore, D. I., & Klein, R. M. (2000). The effects of scene inversion on change blindness. *Journal of General Psychology, 127,* 27–43. http://dx.doi.org/10.1080/00221300009598569

Tremoulet, P. D., & Feldman, J. (2000). Perception of animacy from the motion of a single object. *Perception, 29,* 943–951. http://dx.doi.org/10.1068/p3101

Valentine, T. (1988). Upside-down faces: A review of the effect of inversion upon face recognition. *British Journal of Psychology, 79,* 471–491. http://dx.doi.org/10.1111/j.2044-8295.1988.tb02747.x

VanRullen, R., & Thorpe, S. J. (2001). Is it a bird? Is it a plane? Ultra-rapid visual categorization of natural and artifactual objects. *Perception, 30,* 655–668.

Vuong, Q. C., Hof, A. F., Bülthoff, H. H., & Thornton, I. M. (2006). An advantage for detecting dynamic targets in natural scenes. *Journal of Vision, 6*(1), 87–96. http://dx.doi.org/10.1167/6.1.8

Werner, S., & Thies, B. (2000). Is "change blindness" attenuated by domain-specific expertise? An expert–novices comparison of change detection in football images. *Visual Cognition, 7,* 163–173. http://dx.doi.org/10.1080/135062800394748

Wilford, M. M., & Wells, G. L. (2010). Does facial processing prioritize change detection? Change blindness illustrates costs and benefits of holistic processing. *Psychological Science, 21,* 1611–1615. http://dx.doi.org/10.1177/0956797610385952

Yin, R. K. (1969). Looking at upside-down faces. *Journal of Experimental Psychology, 81,* 141–145. http://dx.doi.org/10.1037/h0027474

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