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The effect of spatial frequency information and visual similarity in threat detection

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ABSTRACT

In the current research, we sought to examine the role of spatial frequency on the detection of threat using a speeded visual search paradigm. Participants searched for threat-relevant (snakes or spiders) or non-threat-relevant (frogs or cockroaches) targets in an array of neutral (flowers or mushrooms) distracters, and we measured search performance with images filtered to contain different levels (high and low) of spatial frequency information. The results replicate previous work demonstrating more rapid detection of threatening versus non-threatening stimuli [e.g. LoBue, V. & DeLoache, J. S. (2008). Detecting the snake in the grass: Attention to fear-relevant stimuli by adults and young children. *Psychological Science*, 19, 284–289. doi:10.1111/j.1467-9280.2008.02081.x]. Most importantly, the results suggest that low spatial frequency or relatively coarse levels of visual information is sufficient for the rapid and accurate detection of threatening stimuli. Furthermore, the results also suggest that visual similarity between the stimuli used in the search tasks plays a significant role in speeded detection. The results are discussed in terms of the theoretical implications for the rapid detection of threat and methodological implications for properly accounting for similarity between the stimuli in visual search studies.

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Threat detection; spatial frequency; visual similarity; visual search

Researchers have been studying humans' ability to rapidly detect threat-relevant stimuli in the environment for decades. A large body of behavioural data has demonstrated that adults, children, and even infants detect threat-relevant stimuli faster than neutral or benign stimuli in visual search tasks (see Öhman & Mineka, 2001; and LoBue & Rakison, 2013, for reviews). Neuroimaging studies have implicated the importance of low spatial frequency information in the processing of such threat-relevant stimuli, suggesting that a "fast" subcortical pathway transmits coarse information to the amygdala where the information is then evaluated (Alorda, Serrano-Pedraza, Campos-Bueno, Sierra-Vazquez, & Montoya, 2007; Vuilleumier, Armony, Driver, & Dolan, 2003).

Corroborating this view, behavioural studies have shown preferential attentional effects to threat-relevant

stimuli (e.g. fearful faces) at low spatial frequencies (Bocanegra & Zeelenberg, 2009; Holmes, Green, & Vuilleumier, 2005). Using speeded visual identification or classification tasks, previous studies have directly tested the low spatial frequency advantage in processing speed for threat-relevant stimuli. However, the findings are not clear-cut. While an earlier study found a faster reaction time in identifying negatively valenced contents carried by low spatial frequencies than by high spatial frequencies (Alorda et al., 2007), recent studies showed faster reaction time at high spatial frequencies in general in classifying both threat-relevant and non-threat-relevant visual stimuli, with a relative speed advantage in classifying threat-relevant stimuli at low spatial frequencies (Langner, Becker, Rinck, & van Knippenberg, 2015; Mermillod, Droit-Volet, Devaux, Schaefer, & Vermeulen, 2010).

Such a discrepancy among studies in the processing speed of threat-relevant stimuli carried by different spatial frequencies reflects an important factor that was not controlled for in these previous studies. It is well documented that the performance in visual object identification or categorisation is largely affected by the amount of information available in the visual stimuli (Schyns, 1998). However, none of the previous studies measured the information availability in the spatial frequency filtered images. Such information may provide the key to resolve the seemingly contradictory results among the previous studies. For example, faster reaction time and higher accuracy in classifying high-pass filtered images than low-pass filtered ones in Mermillod et al. (2010) may be a result of the fact that high spatial frequencies carry more diagnostic visual information than low spatial frequencies in the images used, as the authors pointed out. Even in Alorda et al. (2007), the fastest reaction time was indeed achieved with the full-spectrum images, which carry more visual information than the spatial frequency filtered images. Therefore, to elucidate the role of low spatial frequency information in the detection of visual threat, it is necessary to gauge the availability of diagnostic visual information in the filtered images.

Here, we investigated the role of spatial frequency in the detection of visual threat using a speeded visual search paradigm (LoBue & DeLoache, 2008; LoBue, 2014a), in which participants searched for threat-relevant (a snake or a spider) or non-threat-relevant (a frog or a cockroach) targets in an array of neutral (flowers or mushrooms) distracters. This paradigm allowed us to collect a measurement of attention to visual threat that is directly comparable to data in the majority of the extant literature. Since performance on a visual search task is largely influenced by target to non-target similarity (Duncan & Humphreys, 1989), image similarity provides an index of the availability of diagnostic information in the visual search task. To measure similarity of the images, we used a well-established algorithm: the Structural Similarity Index (SSIM, Wang, Bovik, Sheikh, & Simoncelli, 2004). This algorithm takes characteristics of the human visual system into account, including both luminance masking and contrast masking terms. Luminance masking adjusts for the perceptual phenomenon that image differences tend to be less visible in bright regions, while contrast masking adjusts for the perceptual phenomenon that image differences become less visible where there is a high

contrast or “texture” in the image. Unlike a direct pixel-by-pixel assessment of image similarity, the SSIM assumes that pixels have strong inter-dependencies when they are spatially close. These dependencies carry important information about the structure of the images. Therefore, the SSIM resembles visual similarity rather than a simple physical similarity. To our knowledge, our study is the first to take information availability into account in assessing the role of spatial frequency in threat detection.

Experiment 1

In Experiment 1, we investigated the role of high and low spatial frequency information in detecting threatening (snakes) versus non-threatening (frogs) stimuli. We measured task performance with a well-established visual search paradigm and examined the effect of visual similarity between the targets and distractors on performance in the task. Using a touch-screen visual search paradigm (LoBue & DeLoache, 2008; LoBue, 2014a), we presented adult participants with 3×3 matrices of photographs and asked them to touch a target on the screen as quickly as possible.

Methods

Participants

Participants were 64 university students, half female and half male ($M = 21.5 \pm 5.2$ years, gender counterbalanced with experimental conditions). The racial/ethnic representation was 26% White, 28% Hispanic, 19% African American, 11% Asian or Pacific Islander, 9% South Asian/Indian, and 7% mixed race or other. The sample size is similar to previous studies using the same paradigm. All participants were recruited from the Rutgers University human subjects' pool and received course credit for their participation. The Rutgers University Institutional Review Board approved all procedures and all participants signed an informed consent.

Materials

The photographs were modifications of those originally used in LoBue and DeLoache (2008), and consisted of 24 photographs of snakes, 24 photographs of frogs, and 24 photographs of flowers, each measuring 4.06×3.36 inches on the screen. We first converted all of the original colour images to greyscale

and replaced the amplitude spectrum of each image with the average amplitude spectrum across the whole image set. As a result, all of the greyscale images had the same mean luminance, contrast, and spatial frequency content. We then obtained 10 images from each greyscale image by low-pass filtering and high-pass filtering with the following cut-off frequencies: 5.6, 8, 11, 16, and 23 cycles per image width (c/iw , see examples in [Figure 1](#)). Image processing was carried out using Matlab (version 7.1, Mathworks, USA) with custom code. Filtering was done with low-pass and high-pass ideal filters. We added the mean luminance level of the unfiltered (full-spectrum) greyscale image to the high-pass filtered image, so that all of the filtered images (high-pass and low-pass) had the same mean luminance.

Apparatus

The MATRIX program was used to present participants with the visual search tasks (LoBue, 2014a). The MATRIX is a program designed to run a visual detection task on a touch-screen monitor or tablet with child or adult participants. It has been used successfully with participants ranging from 3 years of age to adult. The program automatically presents participants with matrices of photographs, and requires participants to select a single target among an array of distracters.

Design

Participants were randomly assigned to one of two target conditions—Snake Targets or Frog Targets. The flower photographs always served as the distracters for both the snake and frog target conditions. Participants were also randomly assigned to the high spatial frequency or low spatial frequency conditions. Within each condition, participants were given six visual search tasks in a random order. The tasks consisted of full-spectrum stimuli, and filtered stimuli with cut-off frequencies at 5.6, 8, 11, 16, and 23 (c/iw). Thus, snake versus frog target conditions and high versus low spatial frequency conditions were between-subjects variables, and cut-off frequency was a within-subjects variable.

Procedure

Each participant was seated in front of a Dell XPS 12 inch Ultrabook tablet computer (approximately 40 cm from the screen). First, a set of five practice trials

was given to teach the participant how to use the touch-screen tablet. On the first two trials, a single picture appeared on the screen. The first picture was from the target category and the second from the distracter category. Participants were asked to touch each picture on the screen. In the next three trials, participants were presented with full nine-picture matrices. Participants were told that for each trial, the task was to find the “X” (target) among “Y” (distracters) as quickly as possible, and touch it on the screen. All participants learned the procedure quickly.

Following the 5 practice trials, participants received 24 test trials, each of which consisted of a matrix containing 1 target and 8 distracters. Participants were instructed to find the target on each trial and touch it on the screen. The stimuli in each of the test trials were randomly selected from the photographs in the target and distracter stimulus sets. Participants completed the matrix task six times (once for each cut-off frequency) in a random order. For each task, latency was automatically recorded from the onset of the matrix to when the participant touched one of the images on the screen.

Results

Data from three participants were excluded from the analysis since they had zero accuracy in some experimental conditions. Therefore, reaction time of correct responses in these conditions was not available. For the remaining participants, an outlier removal procedure with a three-standard deviation criterion did not identify any outlier with either the accuracy data or the reaction time data. For each participant, we calculated the mean reaction time of the correct responses in each condition. Statistical analyses were performed with R (R Development Core Team, 2007). None of the measurements deviated from a normal distribution as suggested by Q-Q plot. When the equal variance assumption was violated, we used Welch's t -test and reported adjusted degree of freedom. When sphericity was violated in analysis of variance (ANOVA), we applied Greenhouse-Geisser correction and reported adjusted degree of freedom. We used Bonferroni correction to control the family-wise type I error in multiple t -tests and reported adjusted p values.

Accuracy

As shown in [Figure 2\(a\)](#), with full-spectrum images, participants' accuracies in searching for snakes and

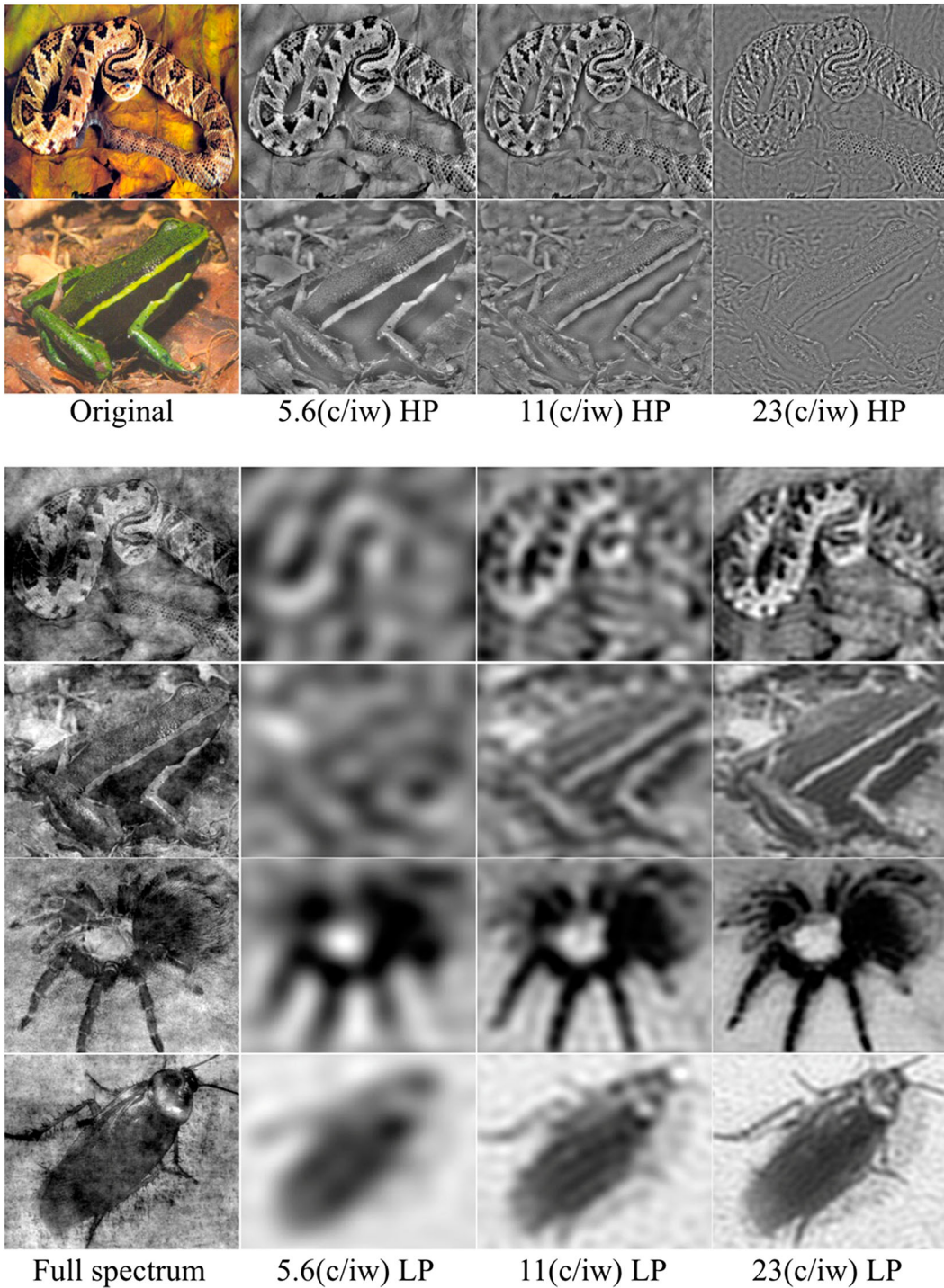


Figure 1. Examples of the greyscale and spatial frequency filtered versions of the original colour images. The original images were first converted to greyscale (full spectrum) and then low-pass (LP) and high-pass (HP) filtered with cut-off frequencies at: 5.6, 8, 11, 16, and 23 cycles per image width (c/iw). Snakes and frogs were used as targets in both Experiment 1 and 2. Spiders and cockroaches were used in Experiment 2 only.

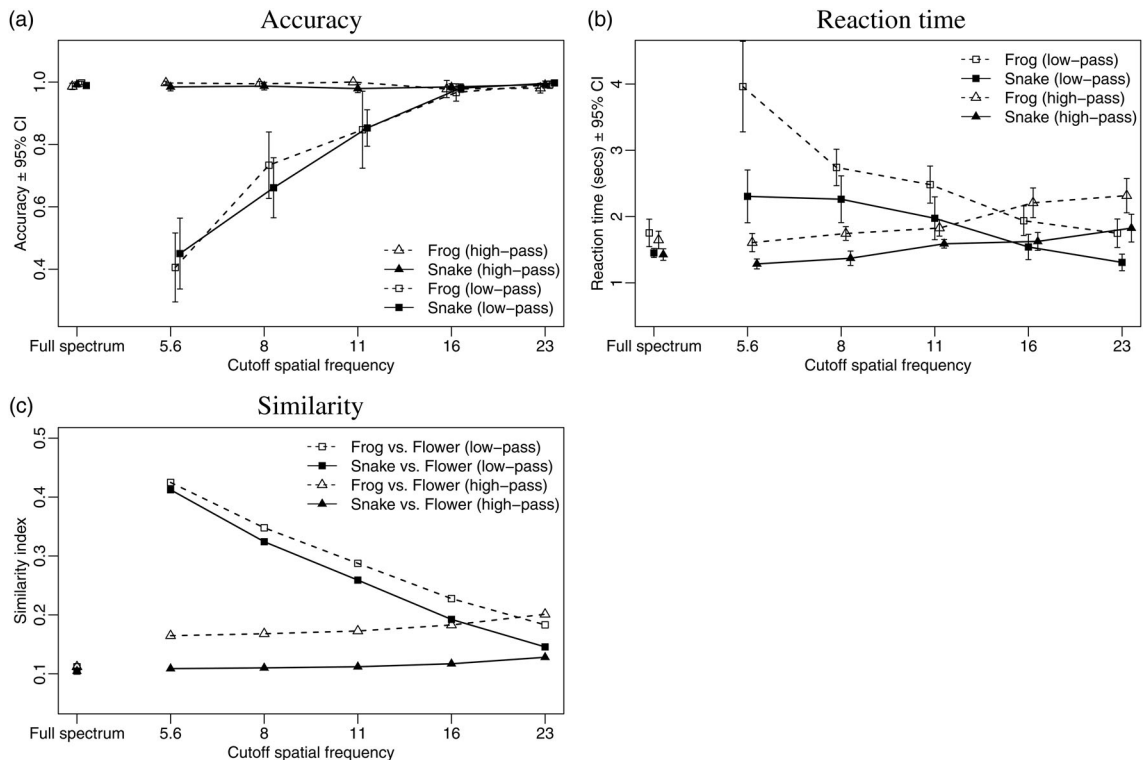


Figure 2. Experiment 1 results: (a) accuracy and (b) reaction time in detecting snakes (filled symbols/solid lines) or frogs (open symbols/dashed lines), and (c) visual similarity between snakes and flowers (filled symbols/solid lines) or between frogs and flowers (open symbols/dashed lines) in low-pass (squares) or high-pass (triangles) filtered conditions with different cut-off spatial frequencies (cycles per image width, c/iw).

frogs were both at ceiling and there was no difference between the two target types ($t(59.0) = 0.24$, $p = .81$). For the filtered images, a mixed-model ANOVA with target type (snake vs. frog) and filter type (low-pass vs. high-pass) as between-subject factors and cut-off frequency as a repeated measure revealed significant main effects of filter type ($F(1, 57) = 13.73$, $p < .001$, $\eta^2 = .19$) and cut-off frequency ($F(4, 228) = 2.72$, $p = .03$, $\eta^2 = .12$). The main effect of filter type suggests that the accuracy was lower with the low-pass filtered images than with the high-pass filtered images in general. For the high-pass filtered images, the accuracies were at ceiling across all the cut-off frequencies, while for the low-pass filtered images, accuracy was lower at lower cut-off frequencies. This difference is characterised by a significant interaction between filter type and cut-off frequency ($F(4, 228) = 7.17$, $p < .001$, $\eta^2 = .26$). To break down the interaction, we ran two mixed-model ANOVAs for the high-pass and the low-pass conditions separately, with target type as a between-subject factor and cut-off frequency as a repeated measure. There was no significant main

effect or interaction in the high-pass condition. In the low-pass condition, the only significant effect was the main effect of cut-off frequency ($F(4, 112) = 7.61$, $p < .001$, $\eta^2 = .44$). In all cases, the accuracies were not different between the snake condition and the frog condition.

Reaction time

Consistent with previous studies, for the full-spectrum images, participants were faster in detecting snakes than in detecting frogs ($t(40.2) = -3.83$, $p < .001$, two-tailed; Cohen's $d = 0.99$). For the filtered images, a mixed-model ANOVA with target type (snake vs. frog) and filter type (low-pass vs. high-pass) as between-subject factors and cut-off frequency as a repeated measure revealed a significant two-way interaction between target type and cut-off frequency ($F(4, 228) = 3.82$, $p = .01$, $\eta^2 = .14$) and a significant three-way interaction among target type, filter type, and cut-off frequency ($F(4, 228) = 7.22$, $p < .001$, $\eta^2 = .22$). There were no other significant effects. To

break down the three-way interaction, we ran two mixed-model ANOVAs for high-pass and low-pass conditions separately, with target type as a between-subject factor and cut-off frequency as a repeated measure. For the high-pass filtered images, there was only a significant main effect of target type ($F(1, 29) = 24.05, p < .001, \eta^2 = .45$), suggesting that snakes were detected more quickly than frogs in the high-pass condition across all the cut-off frequencies. For the low-pass condition, we found a significant main effect of target type ($F(1, 28) = 19.86, p < .001, \eta^2 = .42$), which was qualified by an interaction between target type and cut-off frequency ($F(4, 112) = 6.49, p = .001, \eta^2 = .30$). To analyse this interaction, we ran *t*-tests comparing the snake condition and the frog condition at each cut-off frequency. We found a snake advantage at the highest cut-off frequency (23 c/iw) ($t(23) = -3.47, p = .01$; Cohen's $d = 1.27$). This advantage was not significant at the intermediate cut-off frequencies (16 c/iw: $t(27) = -2.64, p = .06$; 11 c/iw: $t(27) = -2.33, p = .13$; 8 c/iw: $t(26) = -2.10, p = .22$). At the lowest cut-off frequency (5.6 c/iw), we saw a strong snake advantage ($t(23) = -4.1, p < .002$; Cohen's $d = 1.50$). As shown in Figure 2(b), in the low-pass filtered condition, the reaction time had a steep increase from 8 c/iw to 5.6 c/iw for detecting frogs, while it did not increase from 8 c/iw to 5.6 c/iw for detecting snakes. This pattern contributes to the snake advantage seen at the lowest cut-off frequency in the low-pass filtered condition.

Targets to non-targets similarity

It is well documented that performance in a search task is largely influenced by similarity of targets to non-targets (Duncan & Humphreys, 1989). To assess how stimulus similarity affected the performance in the current search task, we measured the similarity between the images of snakes and flowers, and between the images of frogs and flowers used in the current experiment. Specifically, we measured image similarity based on an algorithm that takes the characteristics of the human visual system into account (Wang et al., 2004).

Figure 2(c) shows the average similarity between snakes and flowers and between frogs and flowers in different spatial frequency filtering conditions used in the current study. It is striking that the pattern of stimulus similarity (Figure 2(c)) highly resembles the pattern of reaction time in the search task, where differences between snake condition

and frog condition were found (Figure 2(b)). We assessed the contribution of stimulus similarity (Sim) on reaction time (RT) in the search task using linear regressions. We also tested the contributions of two additional regressors: (a) a general threat advantage (T_{general} , binary variable, 1 for all the snake conditions, 0 for all the frog conditions), and (b) a specific threat advantage at the lowest spatial frequency (T_{low} , binary variable, 1 for the snake condition low-passed filtered at 5.6 c/iw, 0 for all the other conditions). We compared the following four models:

$$\text{Model I: RT} = \beta_0 + \beta_1 \text{Sim} + \varepsilon,$$

$$\text{Model II: RT} = \beta_0 + \beta_1 \text{Sim} + \beta_2 T_{\text{general}} + \varepsilon,$$

$$\text{Model III: RT} = \beta_0 + \beta_1 \text{Sim} + \beta_3 T_{\text{low}} + \varepsilon,$$

$$\text{Model IV: RT} = \beta_0 + \beta_1 \text{Sim} + \beta_2 T_{\text{general}} + \beta_3 T_{\text{low}} + \varepsilon.$$

Model I assumes stimulus similarity is the only contributing factor to reaction time. Model II assumes, in addition to stimulus similarity, there is a general snake advantage contributing to reaction time. Model III assumes, in addition to stimulus similarity, there is a specific snake advantage only at the lowest spatial frequency (low-pass filtered at 5.6 c/iw) that contributes to reaction time. Model IV assumes, in addition to stimulus similarity, there are both a general snake advantage, and a specific snake advantage at the lowest spatial frequency that contribute to reaction time.

As summarised in Table 1, in all cases, stimulus similarity played an important role in visual search performance. Stimulus similarity alone (Model I) explained 71% of the total variance in reaction time. Adding either a general threat advantage or a specific threat advantage at the lowest spatial frequency significantly improved the model fit (Model I vs. Model II, $p = .02$; Model I vs. Model III, $p = .01$). However, when both a general threat advantage and a specific threat advantage at the lowest spatial frequency are included in the model (Model IV), the effect of the general threat advantage was not significant ($p = .24$). While Model IV has a better fit than Model II ($p = .04$), the improvement in model fit of Model IV

Table 1 Coefficients of the linear regression models in Experiment 1.

	β_0	β_1 (Sim)	β_2 (T_{general})	β_3 (T_{low})	R^2
Model I	0.91***	5.10***			0.71
Model II	1.14***	4.74***	-0.32*		0.78
Model III	0.72***	6.35***		-0.78**	0.81
Model IV	0.89***	5.87***	-0.17	-0.60*	0.82

* $p < .05$, ** $p < .01$, *** $p < .001$.

over Model III is not significant ($p = .10$). Therefore, Model III is the best model for explaining reaction time in the visual search task as it is more parsimonious than Model IV, while the amounts of variance explained by the two models do not differ. Together, these results suggest that reaction time in the current search task is largely affected by similarity between targets and non-targets, and there is a substantial snake advantage at the lowest spatial frequency (cut-off at 5.6 c/iw), which accounted for 10% of the total variance in reaction time.

Experiment 2

In Experiment 1, we demonstrated that visual search performance is largely affected by the similarity between targets and distractors. In addition to visual similarity, images signalling threat (snakes) were detected faster than non-threatening images (frogs), especially at low spatial frequencies. In Experiment 2, we try to address two potential limitations of Experiment 1. First, the conclusions of Experiment 1 were limited by the fact that only a single type of threatening and non-threatening stimuli were used. It is possible that the snake advantage we found in Experiment 1 reflects differences in visual features between the two stimulus categories (e.g. no limbs, curvy shape of the snakes vs. rounded body of the frogs) rather than the differences in the level of threat signalled by the images. In Experiment 2, we investigated the threat detection advantage at low spatial frequencies with new sets of threatening (spiders) and non-threatening (cockroaches) stimuli, which share no common visual features with the previous set (snakes and frogs).

Second, in Experiment 1, target type (snake vs. frog) was a between-subject factor. Since different groups of participants were tested in the snake condition and in the frog condition, it remains possible that the difference between the two conditions may simply arise from the differences between the two samples of participants. To rule out this possibility, in Experiment 2, we assigned target type (threat vs. non-threat) as a within-subject factor. We tested the same set of stimuli (snakes and frogs) as used in Experiment 1 with a new group of participants ($n = 16$) and the new set of stimuli (spiders and cockroaches) with a second group of participants ($n = 16$) on the low-pass filtered conditions used in Experiment 1 since no difference between threat-relevant and non-threat-relevant targets was found with high-pass

filtered stimuli in Experiment 1. We kept the other aspects of Experiment 2 identical to Experiment 1.

Methods

Participants

Participants were 32 university students, half female and half male ($M_{age} = 23.7 \pm 7.2$ years, gender counter-balanced with experimental conditions). The racial/ethnic representation was 28% White, 19% Hispanic, 9% African American, 19% Asian or Pacific Islander, 6% South Asian/Indian, and 19% mixed race or other. All participants were recruited from the Rutgers University human subjects' pool and received course credit for their participation. The Rutgers University Institutional Review Board approved all procedures and all participants signed an informed consent.

Design

We tested 16 participants with the same stimulus set as used in Experiment 1 (snakes and frogs as targets, and flowers as distractors) but with target type as a within-subject factor. Target type was administered in a blocked manner with order of the blocks counter-balanced with gender of the participants, so that half of the participants in each gender searched for the threat targets first. Within the block of each target type, we tested six spatial frequency conditions in a random order. The spatial frequency conditions included a full-spectrum condition and five low spatial frequency conditions with cut-off frequencies at 5.6, 8, 11, 16, and 23 (c/iw). In total, each participant completed the matrix task 12 times. With the same design, we tested another group of 16 participants with a new set of stimuli (spiders and cockroaches as targets, and mushrooms as distractors).

Results

Data from one participant were excluded from the analysis because of zero accuracy in some experimental conditions. Therefore, reaction time of correct responses in these conditions was not available. For the remaining participants, an outlier removal procedure with a three-standard deviation criterion did not identify any outlier with either the accuracy data or the reaction time data. For each participant, we

calculated the mean reaction time of the correct responses in each condition.

Accuracy

Participants achieved ceiling level of accuracy with the full-spectrum images with no difference between threatening and non-threatening stimuli for either the snake–frog condition ($t(14) = 0.37, p = .72$) or the spider–cockroach condition ($t(15) = -0.81, p = .43$). For the low-pass filtered images, a mixed-model ANOVA with stimulus set (snake and frog vs. spider and cockroach) as a between-subject factor, and threat level (threat vs. non-threat) and cut-off frequency (5.6, 8, 11, 16, and 23 c/iw) as repeated measures revealed a significant main effect of stimulus set ($F(1, 29) = 18.79, p < .001, \eta^2 = .39$), a significant main effect of threat level ($F(1, 29) = 7.52, p = .010, \eta^2 = .21$) and a significant three-way interaction among stimulus set, threat level, and cut-off frequency ($F(4, 116) = 7.91, p < .001, \eta^2 = .69$). To break down the three-way interaction, we ran two separate ANOVAs for the two stimulus sets.

For the snake and frog condition, an ANOVA with threat level and cut-off frequency as repeated measures revealed a significant main effect of cut-off frequency ($F(4, 56) = 26.21, p < .001, \eta^2 = .79$) qualified by a significant interaction between cut-off frequency and threat level ($F(4, 56) = 3.19, p = .039, \eta^2 = .65$). Pairwise *t*-tests between the snake condition and the frog condition at each cut-off frequency did not reveal any significant results ($ps > .1$). We therefore replicated the findings of Experiment 1, showing that the participants had no differences on accuracy in the search task with snake or frog as targets.

For the spider and cockroach condition, an ANOVA with threat level and cut-off frequency as repeated measures revealed a significant main effect of cut-off frequency ($F(4, 60) = 8.29, p = .005, \eta^2 = .90$), a significant main effect of threat level ($F(1, 15) = 76.03, p < .001, \eta^2 = .84$), and a significant interaction between cut-off frequency and threat level ($F(4, 60) = 8.61, p < .001, \eta^2 = .94$). Pairwise *t*-tests revealed significantly higher accuracy in detecting spiders than in detecting cockroaches at cut-off frequencies of 5.6, 8, and 11 (c/iw, $t(15) = 4.80, 7.96, 3.45, p = .001, .000, .015$, Cohen's $d = 0.69, 2.78, 1.25$, respectively) but not at 16 and 23 (c/iw, $ps > 0.1$). As shown in Figure 3(a), the accuracy for detecting cockroaches dropped at lower cut-off frequencies, while the drop in accuracy at lower cut-off frequencies was

significantly smaller for detecting spiders. Such a pattern suggests a threat advantage on accuracy at low frequencies.

Reaction time

For the full-spectrum images, participants were faster in searching for threat-relevant targets in both the snake and frog conditions ($t(14) = -5.18, p < .001$, Cohen's $d = 1.10$) and the spider and cockroach conditions ($t(15) = -3.28, p = .005$, Cohen's $d = 0.87$). For the low-pass filtered images, a mixed-model ANOVA with stimulus set (snake and frog vs. spider and cockroach) as a between-subject factor, and threat level (threat vs. non-threat) and cut-off frequency (5.6, 8, 11, 16, and 23 c/iw) as repeated measures revealed a significant main effect of stimulus set ($F(1, 29) = 17.76, p < .001, \eta^2 = .38$) and a significant three-way interaction among stimulus set, threat level, and cut-off frequency ($F(4, 116) = 7.22, p < .001, \eta^2 = .38$). As with the accuracy data, to break down the three-way interaction, we ran two separate ANOVAs for the two stimulus sets.

For the snake and frog condition, an ANOVA with threat level and cut-off frequency as repeated measures revealed a significant main effect of cut-off frequency ($F(4, 56) = 19.56, p < .001, \eta^2 = .86$), a significant main effect of threat level ($F(1, 14) = 27.66, p < .001, \eta^2 = .66$) qualified by a significant interaction between cut-off frequency and threat level ($F(4, 56) = 4.67, p = .003, \eta^2 = .53$). Pairwise *t*-tests between the snake condition and the frog condition at each cut-off frequency revealed faster reaction time to snake targets at the lowest cut-off frequency (5.6 c/iw, $t(14) = -4.35, p = .003$, Cohen's $d = 1.04$) and the highest cut-off frequency (23 c/iw, $t(14) = -5.26, p < .001$, Cohen's $d = 1.06$), but not the intermediate cut-off frequencies (8 c/iw: $t(14) = -2.90, p = .06$; 11 c/iw: $t(14) = -1.89, p = .40$; 16 c/iw: $t(26) = -2.80, p = .07$). Such results (Figure 3(b)) were highly consistent with the findings in Experiment 1 (Figure 2(b)).

For the spider and cockroach condition, an ANOVA with threat level and cut-off frequency as repeated measures revealed only a significant main effect of cut-off frequency ($F(4, 60) = 6.02, p < .001, \eta^2 = .69$), suggesting increased reaction time at lower cut-off frequencies.

Thus, with the snake and frog stimulus set, we replicated the threat advantage at low spatial frequency on reaction time as seen in Experiment 1. With the new spider and cockroach stimuli, we also found a threat

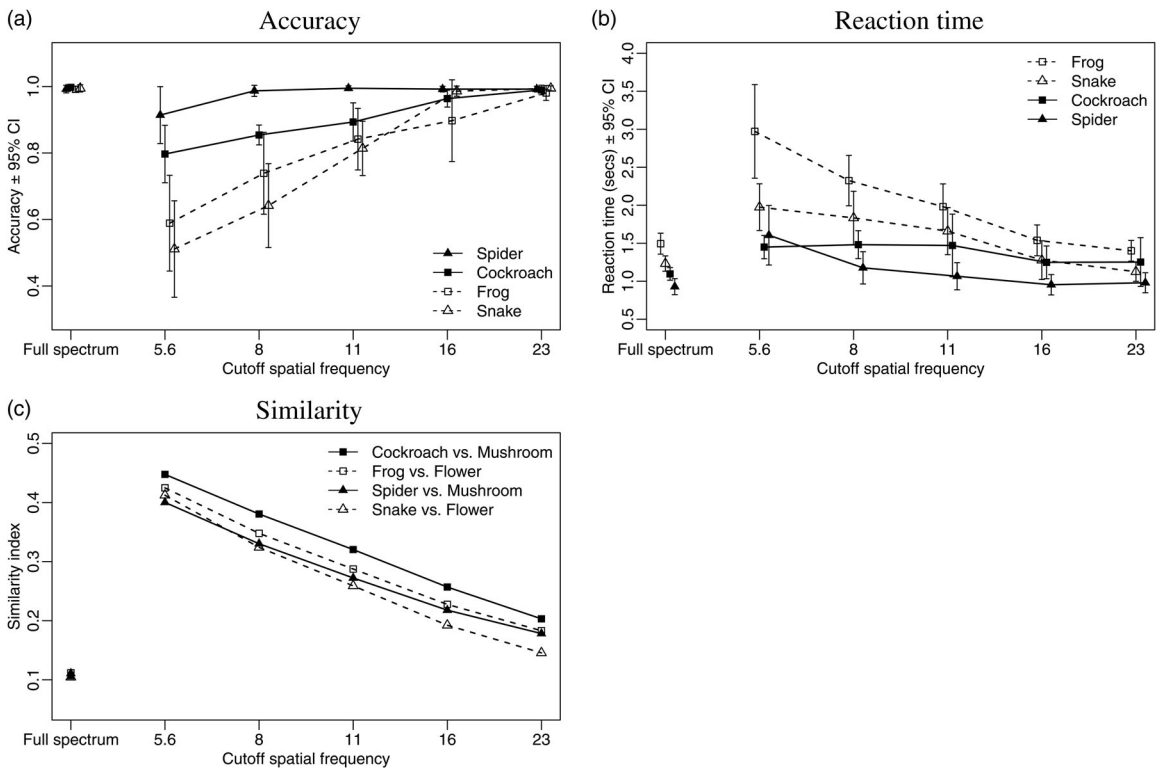


Figure 3. Experiment 2 results: (a) accuracy and (b) reaction time in detecting snakes (open triangles/dashed lines) and frogs (open squares/dashed lines) or in detecting spiders (filled triangles/solid lines) and cockroaches (filled squares/solid lines), and (c) visual similarity between cockroaches and mushrooms (filled squares/solid lines) or between frogs and flowers (open squares/dashed lines) or between spiders and mushrooms (filled triangles/solid lines) or between snakes and flowers (open triangles/dashed lines) in low-pass filtered conditions with different cutoff spatial frequencies (cycles per image width, c/iw).

advantage at low spatial frequency, although the threat advantage was on accuracy rather than on reaction time.

Targets to non-targets similarity

The results of Experiment 1 were best accounted for by a model assuming stimulus similarity and a threat advantage at the lowest spatial frequency (Model III in the results section of Experiment 1). Here we tested if the same model can offer a satisfactory explanation to the patterns we found in Experiment 2. More specifically, we tested Model III from Experiment 1 on reaction time in the snake and frog condition and on accuracy in the spider and cockroach condition in Experiment 2. In the snake and frog condition, reaction time is accounted for by stimulus similarity ($\beta = 5.03, p < .001$) and threat advantage at the lowest spatial frequency ($\beta = -0.50, p = .033$) with 85% of variance explained by the model. In the spider and cockroach condition, accuracy is accounted for by stimulus

similarity ($\beta = -0.60, p < .001$) and threat advantage at the lowest spatial frequency ($\beta = 0.07, p = .027$) with 81% of variance explained by the model. Therefore, consistent with the findings in Experiment 1, performance in visual search is largely affected by similarity between targets and distractors (Figure 3(c)). In addition, threat information carried by low spatial frequencies does facilitate visual search as well.

General discussion

In the current research, we sought to examine the role of spatial frequency in the detection of threat using a speeded visual search paradigm. Participants searched for threat-relevant (snakes or spiders) or non-threat-relevant (frogs or cockroaches) targets in an array of neutral (flowers or mushrooms) distracters, and we measured search performance with images filtered to contain different spatial frequency information. The results replicate previous work demonstrating more rapid detection of threatening versus

non-threatening stimuli (e.g. LoBue & DeLoache, 2008). We also take these results further by providing important information about the role of both spatial frequency information and similarity of the stimuli in visual detection of threat.

First, we found evidence that crude information is sufficient for the rapid/accurate detection of threat-relevant stimuli. In general, participants' accuracy in detecting threatening and non-threatening targets was not affected by cut-off frequency in the high-frequency conditions; in contrast, in the low-frequency conditions, participants were more accurate overall as the cut-off frequency became higher (so that more visual information was available). Likewise, images signalling threat were detected more quickly than non-threatening images in the high-frequency conditions regardless of differences in cut-off frequency. Most importantly, in the low-frequency conditions, while reaction times increased for frog (or accuracy dropped for cockroach) targets as less visual information became available, the advantage for snakes (or spiders) remained consistent. This finding suggests that low spatial frequency information might be particularly important for the processing of threat-relevant stimuli, and is consistent with previous behavioural work (Langner et al., 2015; Mermillod et al., 2010) and neuroimaging studies that implicate a "fast" subcortical pathway for the transmission of coarse information to the amygdala (Alorda et al., 2007; Vuilleumier et al., 2003).

Second, although there was an advantage for threat stimuli at the lowest frequency bands that was independent of the perceptual features of the stimuli, visual similarity between the photographs accounted for the majority of the variance in detection speed or accuracy. In other words, the search advantage for threat stimuli was mostly driven by the fact that the photographs signalling threat were perceptually more distinct from the neutral distracter photographs when compared to the non-threatening stimuli (Figures 2(c) and 3(c)). This suggests that similarity between the target and distracter stimuli in visual search studies has a large impact on adults' behavioural responses. Indeed, recent research has suggested that multiple interacting factors, even very subtle perceptual features of the target and distracter stimuli can influence the results of speeded detection studies (LoBue, 2014b; LoBue, Matthews, Harvey, & Stark, 2014). The current data thus have important implications for the design of future visual search studies, suggesting that researchers should

take great care to account for the similarity between their stimuli when probing the effect of threat-relevance in visual detection.

The conclusions of the current study are limited by the fact that during each run of the visual search task, only one target animal was used. Even though we have demonstrated the low-frequency advantage for detecting snakes or spiders, it does not necessarily mean that such an advantage is purely a result of their threat level. It remains possible that besides the high threat level snakes and spiders both signal, the search performance is also affected by the unique visual features of these two kinds of animals. It would be important for future research to implement a more stringent test where threat/non-threat targets in the same run do not share any visual or semantic features, leaving the only thing in common to be their threat level.

In summary, the current results provide evidence that low spatial frequency information is sufficient for the rapid (or more accurate, in the case of spiders) detection of threatening stimuli. This suggests that for the processing of living threats, detailed visual information might not be necessary for recognising and responding very quickly. Furthermore, although an advantage for threatening stimuli at the lowest frequency channels was found independent of the role of perceptual information, the majority of the variance in detection speed/accuracy could be accounted for by visual similarity between the target and distracter stimuli used in this study. This suggests that while threat-relevance does play a role in visual search, a large portion of the advantage might be driven by perceptual characteristics of the target and distracter stimuli typically used in these tasks.

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