Model Predictions and Implications for Chasing Subtlety

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Abstract

Chase detection involves tracking objects and comparing their locations over time. What is it about the relative spatial relations of two objects that helps you perceive one as chasing the other rather than, say, merely moving in the general direction of the other object? A recent model of chase detection provided an explanation in terms of an attentional strategy. However, it is unclear if this model generalizes or has predictive power since it was fit to experimental data. Here we examine whether this model explanation extends to and predicts a frequently studied chasing cue: chasing subtlety—the degree to which the chaser deviates from the most direct path to its target. To test the model, we made preregistered model predictions from simulations run *prior* to data collection. We then conducted two experiments where chasing subtlety varied. Overall, the model did a good job predicting response time and accuracy patterns across most conditions. Additionally, it predicted specific videos that had the highest error rates. Thus, we show that the model explanation extends to chasing subtlety and, more broadly, that the model can be used to generate a falsifiable theory of chase detection.

Keywords: chase detection; chasing; relations; dynamic scenes

Introduction

Humans possess an impressive capacity for understanding complex visual scenes, including identifying the actions of agents and the intentions behind those actions. One task developed to study this understanding is *chase detection*, in which an individual observes objects moving through a scene and determines whether one object is chasing another. Chase detection requires tracking objects and comparing their locations and motion patterns over time to identify subtle differences between, e.g.,"following", where the intention is to maintain some distance between agents, and "pursuing", where the intention is to close the gap. Many questions remain about how people infer the correct intention.

Recent work has investigated possible cues for determining whether agents are involved in a chase, including distance between the chaser and its target (Meyerhoff, Schwan, & Huff, 2014a,b), the direction that the chaser faces (Gao, McCarthy, & Scholl, 2010; Gao, Newman, & Scholl, 2009), the number of objects in a scene (Gao et al., 2019; Kon et al., 2024; Meyerhoff et al., 2013), and *chasing subtlety*, the degree to which the chaser can deviate from the most direct path to its target (Gao et al., 2019; Gao et al., 2009; Meyerhoff et al., 2013).

We recently developed a cognitive model for the chase detection task, to aid in exploring problem-solving strategies and stimulus factors that may influence performance (Kon, Khemlani & Lovett, 2024). The core claim of the model was that chase detection, like other demanding visual tasks, depends on strategically projecting spatial attention onto a visual scene. To determine whether one object is in pursuit of another, the model tracks the object, determines its motion trajectory, and then projects spatial attention along that trajectory to identify another object that may be a potential target of pursuit. This process is engaged repeatedly, and if a prospective pursuer is consistently moving towards the same prospective target, then it is likely that a chase is occurring.

We evaluated our model on a novel chase detection task, in which the possible pursuer was always a red circle and the possible targets were circles of unique colors. This color-coding simplified detection and tracking in a way that isolated specific factors that contribute to chase detection. The task utilized a two-stage design in which participants first pressed a button to indicate whether a chase was occurring (Stage 1) and then indicated the circle being chased (Stage 2), allowing for measures of response time and accuracy. After gathering human data on the task, we presented the same trial videos to the model and found an overall close fit to the human data.

Although the modeling results were promising, they suffered from several limitations. 1) The human data was gathered first, and free parameters in the model were selected to maximize the fit to this data. Additionally, there was only a small set (20) of stimulus videos. Thus, it remains unclear how well the model will generalize to other situations. 2) The study looked at the core chase detection task and varied only set size, without considering other factors that are believed to contribute to detection performance.

To overcome these limitations, we present a new pair of studies with the following changes. 1) Before the study was given to human participants, the model was run on the study with specific parameter values, and the resulting model predictions were preregistered on OSF. 2) A larger set of videos (180) was used. In these videos, we varied chasing subtlety, the degree to which the pursuing red circle moves directly towards the target, to explore how this factor affects the model's performance and fit to the human data. While there are other studies that measure the effect of chasing subtlety on speed and accuracy of chase detection (Gao et al., 2019; Gao et al., 2009; Meyerhoff et al., 2013), these studies used small sample sizes, ranging from 12-22. So, we also wanted to see whether some of these results are replicable with a larger sample size within this experimental paradigm.

Experiment Design

As in Kon et al. (2024), the present experiment used a two-stage chase detection task (Figure 1).

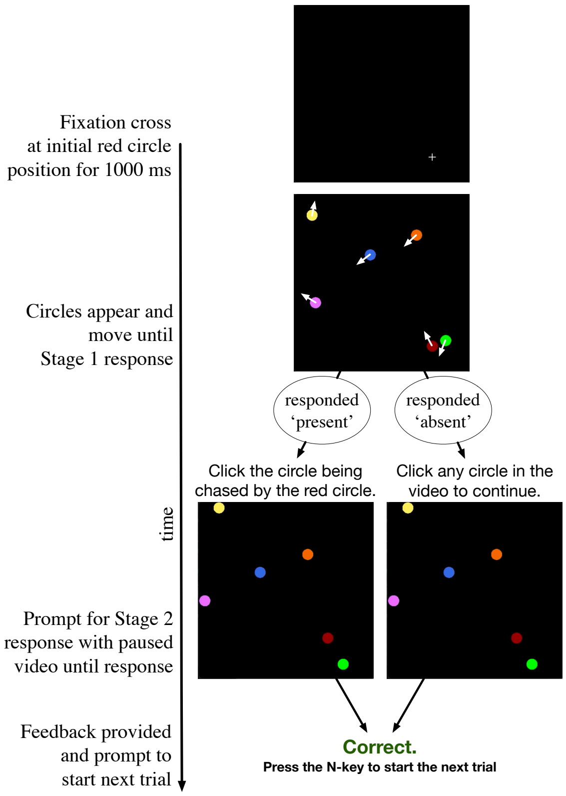

Figure 1: Schematization of an experimental trial in Experiment 1. After seeing a fixation cross at the initial position of the red circle, participants saw video of moving circles (motion is represented in this figure by the white arrows). When participants indicated whether a chase is present or absent, the video paused and a prompt to click on a circle appeared. Feedback was provided after each trial.

Each trial began with a fixation cross at the initial location of the red circle. Next, the red circle appeared with either one other circle (set size 2, including the red circle) or five other circles (set size 6). The initial location and initial trajectory of each circle was randomized with the constraint that no circles overlapped. All circles traveled at the same fixed speed. The red circle moved along a straight path toward the center of the chased circle with its direction updated every 50 ms. The circles moved until participants responded by pressing a key to indicate whether a chase was present or absent (Stage 1), or until the video ended after 22 seconds. Next, if participants indicated there was a chase present, they clicked on the circle they believed was being chased (Stage 2).

The trials in which the red circle was engaged in a chase (*chase-present* trials) varied in their chasing subtlety, which is the extent to which the chaser moves directly towards the target. We followed Gao et al. (2009) and Meyerhoff et al. (2013) by operationalizing subtlety as the difference in degrees between the direction the chaser travels and the direct path (0°) to the target. For 0° chase-present trials, the red circle updated its position towards the center of the target, whereas for 30° chase-present trials, it could deviate anywhere from -30° to 30° from that path.

For the study, four factors were varied: set size (2 or 6), chasing condition (present or absent), chasing subtlety (0°, 30° or 60°), and target color (one of five possible colors). We provide an example video for each condition here: osf.io/8cefh/. Three videos were generated for each combination of conditions, yielding 180 total videos. Chase-absent trials were generated exactly the same as chase-present trials, except that the target was an invisible circle. Thus, the red circle's motion patterns did not differ depending on whether it was chasing a visible circle or not.

The Model and Predictions

We developed a computational model of chase detection (see Kon et al., 2024, for details) based on the idea that an observer directs spatial attention to task relevant locations (Posner, 1980; Ullman, 1984). The model evaluates whether a red circle is chasing another by (1) finding and tracking the red circle over time to estimate its future trajectory based on past motion; (2) scanning along that trajectory; and (3) identifying what, if any, circle lays within a scan window traversing the trajectory. The more times a particular object is found along the expected path of the red circle, the more evidence the red circle is chasing this object.

The model is built within the ARCADIA framework, which was designed to explore attention's role in perception, cognition, and action (Bridewell & Bello, 2016). ARCADIA models are implemented as a set of components that process information and generate output; and an attentional strategy is used to select one piece of output as the focus of attention, which drives further processing. To these components, the chase detection model adds a set of stopping rules for determining when sufficient evidence has accumulated before producing a response on a trial.

Each ARCADIA processing cycle works as follows. On each cycle, components have access to: the output from all components on the previous cycle, a single output element that was selected as the focus of attention on the previous cycle, and data generated by sensors—typically, this grabs frames from a video, such as the chase detection stimuli. Components are essentially functions that process this information to generate new output elements that will be available on the following cycle. Depending on their purpose, different components will respond to different information.

The chase detection model relies on five key components. The **image segmenter** processes the images coming from the sensor, performing figure-ground segmentation (Palmer & Rock, 1994) to pick out segments corresponding to the colored circles in the video. These segments are used by the remainder of the model (Figure 2). The **color highlighter** identifies each segment's color and puts it forward as a candidate for attention. In the current model, the attentional strategy prioritizes attending to the red circle since it is always the potential pursuer. While attention is focused on the red circle, its positional information is used to calculate its motion trajectory (Figure 2, cyan line). After this trajectory information

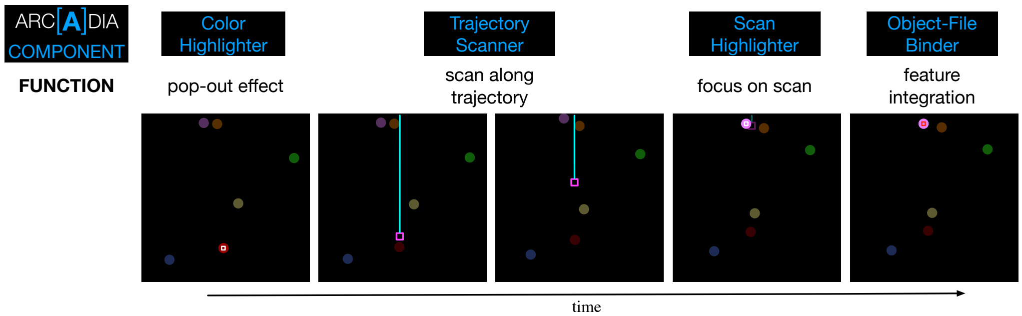

Figure 2: Example illustrating the function of each model component. Areas not grayed out indicate the focus of attention at a given time.

is available, the **trajectory scanner** projects a small window of spatial attention along that trajectory (the *scan window*, represented by the magenta box in Figure 2; see Gerstenberg et al., 2017). If that scan window intersects another circle, the **scan highlighter** highlights that circle as a candidate for attention (Bello et al., 2018). Finally, the **object file binder** generates a representation of this object (Treisman & Gelade, 1980), and its intersection count is incremented.

The model's stopping rules codify different strategies for determining when to respond on the chase detection task. The strategies can be varied based on four free parameters to the model. The stopping rules are as follows. 1) If the intersection count for a circle reaches the *intersection counter threshold*, then the model responds that this circle is being chased by the red circle. 2) If no intersection count reaches this threshold but *maximum time* is reached, then the model responds that it detects no chase. 3) If at *initial time check* no intersection count is at least at the value of the *initial intersection threshold*, then the model responds that there is no chasing detected. This third stopping rule can generate a quick response when there is minimal evidence of chasing.

A fifth free parameter is *scan window size* (diameter of the scan window). Our prior modeling work suggested that varying it could explain how differences in set size affect performance. In this study, there were either 2 or 6 objects in each video. We got the best fit to human data when the model used a small scan window with a large set size (6), and large scan window with a small set size (2). Intuitively, this makes sense: when the scene is cluttered with a large number of objects, one would want to focus in on a small area to avoid being distracted by irrelevant objects. But when there is only a single candidate for the target, a large scan window can maximize the chances of hitting that circle when scanning.

Model Results and Predictions

We ran several sets of simulations where we varied scan window size (with widths 71-182% of a circle diameter, in increments of approximately 12%), intersection counter threshold (4-11 in integer increments) and maximum time values (7-21 seconds, in increments of 2), while we fixed the initial time check (6 seconds) and initial intersection threshold (1) across simulations. The full results of these simulations and detailed discussion of them are beyond the scope of this paper; however, they are provided in the preregistration (osf.io/59gkc/). Based on the assumption that a human observer should make fast yet accurate responses, we made predictions about performance on this task based on the results of parameter values that produce both low response times and low error rates across all conditions. In other words, rather than fitting the model to data, we made predictions about performance prior to collecting data by examining model performance for parameter values that resulted in both the lowest mean response times and the highest mean accuracy rate across conditions.

In line with our past findings, such performance with low response times and high accuracy occurs for set size 2 when larger scan window sizes are used and for set size 6 with smaller scan window sizes. We also identified a subset of parameters that reflected a speed-accuracy tradeoff. It is characterized by larger scan window sizes for set size 2, smaller scan window sizes for set size 6, an intersection counter threshold of 5 or 6, and a maximum time from 15-17 seconds.

Figure 3A shows representative model results given these parameters. The several qualitative predictions about human performance based on model results are summarized below.

1. On chase-present trials (blue lines in Figure 3), response times will increase with chasing subtlety.
2. On chase-absent trials (red lines), response times will be unaffected by chasing subtlety.
3. All response times will increase with set size.
4. On chase-present trials, Stage 1 accuracy will be near ceiling for 0° and 30° subtlety, but will decrease for 60°.
5. On chase-present trials at 60°, performance will be lower for set size 2 than set size 6. This surprising prediction is the only case where set size 6 is easier.

The model also identifies particular videos that may result in lower accuracy and predicts the response times for these videos and which incorrect target circle will tend to be chosen. These are videos for which the model has a high error rate even when it uses parameter values that resulted in overall low speed and high accuracy. We discuss some of these videos, which are in our preregistration, in the *Error-Prone Videos* section below.

Experiment 1

To test model predictions about human performance on a larger stimulus set, we conducted an experiment after preregistering the predictions, using the same task and stimulus set

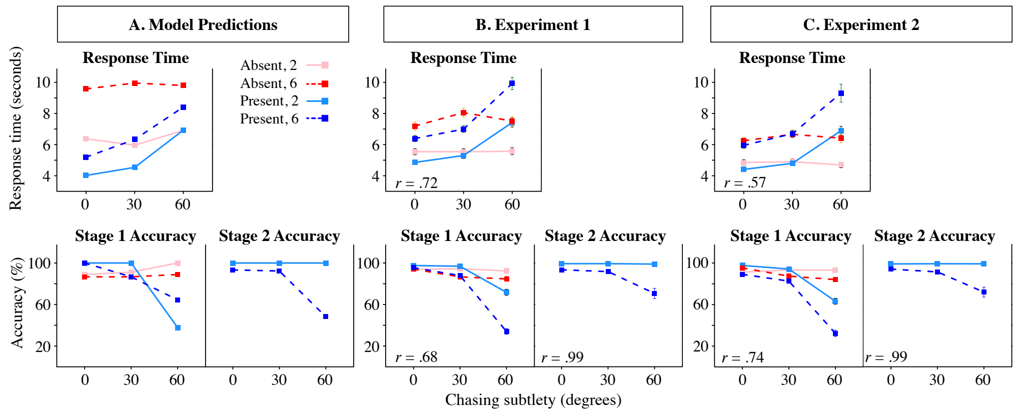

Figure 3: Model predictions and experimental results, with correlations between model results and data for each experiment. Mean response times were calculated from correct trials only. Error bars represent one standard deviation of the mean.

used in model simulations. Various chasing subtleties were used in the stimuli to investigate whether the model strategy generalizes to this frequently studied cue (Gao et al., 2019; Gao et al., 2009; Meyerhoff et al., 2013) and whether some of the key results of past chasing subtlety studies replicate with a larger sample.

Method

Participants 102 participants (mean age = 42.05 years; 56 females, 44 males, 1 other, 1 prefer not to answer) completed the study on the Amazon Mechanical Turk online platform in exchange for US$3.75. We excluded data from 5 participants with mean accuracy $<$ 2 standard deviations from pooled mean accuracy (82%). All but 3 participants reported normal color vision, with 2 reporting suspected colorblindness and 1 who did not respond; however, each yielded 82%, 81% or 89% accurate responses, so we retained their data. We analyzed the remaining data from $n = 97$ participants.

Materials, Procedure and Design The study used custom JavaScript and HTML code within the nodus-ponens package (Khemlani, 2022). After navigating to the webpage with the study, participants saw instructions that described the task, informed them that the red circle was always the potential chaser, stated the purpose of the fixation cross, and presented a few example videos and interactive example trial. Participants initiated each trial by pressing a key, which resulted in a video playing that showed a fixation cross followed by moving circles. Participants responded with the *F*- and *J*-keys on their keyboard to indicate whether there was a chase present or not (Stage 1 response), with key assignment counterbalanced across participants. The key press paused the video, and participants saw a prompt to click one of the circles (Stage 2 response) using their mouse. Specific feedback was provided after each trial, i.e., "Correct."; "Incorrect – red was chasing"; "Incorrect – no chasing"; "Incorrect circle", in addition to a warning if the Stage 1 response was too fast ($<$ 500 ms) or too slow ($>$ 20 s).

Each participant saw 4 practice trials with chasing subtlety 0°, which was followed by 32 experimental trials in randomized order, yielding a 2 (chase present vs. absent) × 2 (2 circles or 6 circles) × 3 (chasing subtlety 0°, 30° or 60°) repeated-measures design with these 12 total conditions repeated 3 times. For each trial a video was chosen randomly from the subset of videos in the pool of 180 videos that had a specified set of the independent variables of interest, e.g., chase-present, set size 6, chasing subtlety 30°, with a randomized target color and version number.

Results and Discussion

Figure 3B shows the mean response times and Stage 1 and Stage 2 accuracies for each condition. Analyses for response times were run on correct trials only. We fit the data to a linear mixed model using the nlme package (Pinheiro et al., 2021) in R (version 4.3.1; R Core Team, 2023). We found a significant effect of set size ($\chi^2(2) = 401.63$, $p < .001$) and of chasing subtlety ($\chi^2(2) = 117.16$, $p < .001$) on response time, but the presence of a chase did not reliably impact response times ($\chi^2(2) = 0.14$, $p = .707$). Pairwise contrasts with Tukey adjustment indicated that response time significantly increased with chasing subtlety (0° v. 30°: $b = 440.63$, $t(2799) = 4.48$, $p < .001$; 0° v. 60°: $b = 1181.27$, $t(2799) = 11.06$, $p < .001$, 30° v. 60°: $b = 741.27$, $t(2799) = 6.89$, $p < .001$) and with set size ($b = 1764.14$, $t(2799) = 20.84$, $p < .001$).

The pattern of response time data (Figure 3B, top plot) generally matches the pattern predicted by the model (Figure 3A, top plot; $r = .72$). As predicted, when there is a chase, response times for set size 2 are lower than for set size 6, and response times increase with chasing subtlety. And, as predicted, response times are relatively flat across chasing subtlety for chase-absent trials. However, the model performs worse than humans for these trials; people are much faster to indicate correctly that there is no chase.

How does our data compare to other studies? For chase-present conditions, only Gao et al. (2019) measured responses across chasing subtlety conditions, and the results from Experiment 1 generally matches: lower response times for smaller set sizes with a large increase in response time at 60°. No study provides chase-absent trial response times.

Full analyses of Stage 1 and Stage 2 accuracy are available at `osf.io/8cefh`; here we compare qualitative results and model predictions against the results of other studies. For Stage 1 accuracy (Figure 3B), chase-present performance is near ceiling except for 60°, and accuracy is lower for set size 6 than set size 2. Although the pattern for 0° and 30° resembles that of the model (Figure 3A), the model's prediction for 60° (performance should be worse for set size 2 than for 6) does not match the data, resulting in a lower correlation (r = .68). Only Gao et al. (2009) measure Stage 1 accuracy (detection accuracy) and for set size 4 chase-present trials only, making it difficult to directly compare our Stage 1 results with existing studies.

Stage 2 accuracy (Figure 3B) strongly resembles ($r = .99$) the model's predictions (Figure 3A), with set size 2 performance at ceiling. There is also a drop-off in accuracy for set size 6 with chasing subtlety of 60°, although people are more accurate than the model for this condition. Additionally, the pattern for set size 6 mirrors the results for accuracy reported by Gao et al. (2009, 2019) and Meyerhoff et al. (2013).

Experiment 2

Experiment 1 gave feedback on each trial. We were curious about the role of feedback on performance for two related reasons. First, the model does not receive feedback. So, we wanted to ascertain whether a version of the experiment without feedback would better approximate model results, particularly for the 60° subtlety condition. Second, it may be argued that chases with high chasing subtleties are not really chases at all. Although they may be defined in the generation of stimuli as a chase, they might not be considered chases by participants. Receiving feedback on each trial may cause participants to learn to classify videos with higher chasing subtleties as chases, even though outside of the experiment, these videos would not be regarded as chases. If this is the case, we would expect accuracy for 60° chase-present trials to be much lower when no feedback is given. To examine the impact of feedback on performance, we conducted a second experiment with the same design as Experiment 1 except that feedback did not follow experimental trials.

Method

Participants 102 naïve participants (mean age = 19.54 years; 65 females, 36 males, 1 other) were recruited from Purdue University in exchange for course credit. Data from 4 participants with mean accuracy less than 2 standard deviations from the mean (81%) were excluded. Two participants did not have self-reported normal color vision, and the data from one of these participants was among the 4 excluded for having a low accuracy rate. We retained the data from the other (92% accurate). We also excluded data from: 3 participants who chose not to report their age, 1 who reported being younger than 18, and 7 due to technical issues. We analyzed the remaining data from $n = 87$ participants.

Materials, Procedure and Design This experiment was identical to Experiment 1 except for the following. Participants received no feedback after each experimental trial. Since we had more time with this subject pool, each participant saw more experimental trials: we repeated the 12 total conditions (2 (chase present vs. absent) × 2 (2 circles or 6 circles) × 3 (chasing subtlety 0°, 30° or 60°)) 5 times resulting in 60 randomly interleaved experimental trials per participant.

Results and Discussion

Experiment 2 yielded results similar to those of Experiment 1 (see Figure 3C) with a significant effect of set size ($\chi^2(2)$ = 472.72, $p < .001$) and chasing subtlety ($\chi^2(2)$ = 120.16, $p < .001$) on response time, but, unlike Experiment 1, the impact on response time of whether a chase is present was also significant ($\chi^2(2)$ = 29.70, $p < .001$). Pairwise contrasts with Tukey adjustment indicated that response time significantly increased with chasing subtlety (0° v. 30°: $b = 387$, $t(4157) = 4.64$, $p < .001$; 0° v. 60°: $b = 1008$, $t(4157) = 11.03$, $p < .001$, 30° v. 60°: $b = 741.27$, $t(4157) = 6.89$, $p < .001$), set size ($b = 621$, $t(4157) = 22.36$, $p < .001$), and when a chase was present rather than absent ($b = 399$, $t(4157) = 5.46$, $p < .001$).

Thus, we have replicated the results from Experiment 1 from a different population, providing stronger support for the conclusions drawn from Experiment 1. Additionally, it seems that feedback does not have much impact on accuracy.

Error-Prone Videos

The model makes specific predictions about which videos are likely to receive incorrect responses. We focus on the three videos with 0° chasing subtlety for which the model, with parameters values that led to good overall performance, had a 100% error rate. Our preregistration provides details about these parameter values and how we made these predictions. Each of these videos can be found at `osf.io/8cefh`. Because the results from Experiments 1 and 2 were similar, we pooled the responses from these experiments to identify videos with high error rates.

Figure 4 compares model performance with empirical results for each of these videos. Video 1 is a chase-absent video with a red circle and a green circle, with the red moving towards the green circle at times during the first half of the video. The model predicted that people would tend to incorrectly respond that the red circle is chasing the green circle, with a response time in the range of 7.42-9.70 seconds. The gray bar of Figure 4A, left plot, shows the percent of incorrect Stage 2 responses expected for each color. So, the model predicts that 100% of the incorrect responses will indicate that the green circle was being chased. In line with the model's prediction, the same video was the most difficult at Stage 1 for humans across all 0° subtlety videos. Humans had a Stage 1 error rate of 34% on this video (shown in the title of Figure 4A, right plot). Additionally, all participants who responded incorrectly indicated that the green circle was being chased, with a mean response time of 7.92 seconds (Figure 4A, right plot).

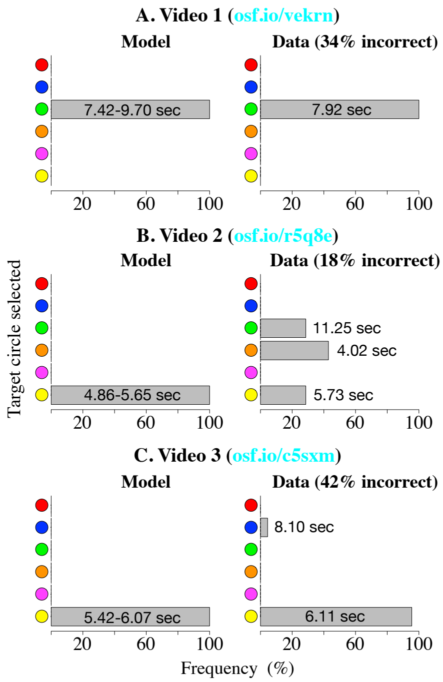

Figure 4: Left column: Model predictions for three videos with the highest simulated error rates, which show the response time associated with an incorrect response and what color will be chosen. Right column: Data for incorrect responses for these videos, indicating how frequently a particular color was chosen and the mean Stage 1 response time for that color. 'XX% incorrect' in the titles indicates the percent of video views with an incorrect response. Each plot shows information for incorrect responses for a particular video, i.e., what circle was thought to be chased (each bar indicates the percent of incorrect responses (x-axis) where a particular circle (y-axis) was selected) and the mean response time for the Stage 1 response on these trials (indicated by the number on/beside a bar).

Video 2 is a chase-absent video with set size 6. At different points in the video, the red circle moves towards a subset of the circles for a short time. The model predicts that people should tend to respond incorrectly that the yellow circle is being chased, with a response time in the range of 4.86-5.65 seconds (Figure 4B, left plot). For humans, however, this video did not rank among the top error-prone 0° chasing subtlety videos, with only 18% of participants responding incorrectly. Further, those that did respond incorrectly were not unanimous in indicating that the yellow circle was being chased (Figure 4B, right plot), yet their mean response time (5.73 sec) falls near the range predicted by the model.

Video 3 is a set size 6 chase-present trial where the orange circle is chased. However, the yellow circle seems to follow the orange circle for a short time at the beginning of the video. The model predicts the people will tend to provide a correct Stage 1 Response and, thus, respond that there is a chase around 5.42-6.07 seconds. However, that model also predicts that people will tend to make a Stage 2 error, indicating that yellow, rather than orange, is the circle being chased (Figure 4C, left plot). In line with the prediction, this video had the highest Stage 2 error rate (42%) among those with a 0° chasing subtlety, with the vast majority indicating that the yellow circle was being chased at around 6.11 seconds.

Overall, the model predicted the 0° chasing subtlety video with the highest Stage 1 error rate (Video 1), and the video with the highest Stage 2 error rate (Video 3). Additionally, in these cases, the model made accurate predictions about when people who made these errors tended to respond and what circle they tended to select. However, the model was not a good predictor regarding Video 2. Most people seemed to wait long enough to correctly identify there was no chase.

General Discussion

Previous research has identified a number of factors that influence chase detection in humans. The present work builds on that body of research while focusing on one key factor, chasing subtlety. Compared to prior studies, the present study uses larger sample sizes and provides an explanation, via a computational model, for why performance degrades when a pursuing object does not move directly towards its target.

More broadly, the present work explains chase detection by combining a) a model, based on the claim that participants direct spatial attention towards potential chase targets to perform the task, and b) a strategy for assigning values to the model's free parameters before human data has been gathered, based on finding a balance between low response times and high accuracy across conditions. We found the model parameter values that best achieved this balance result in a model that focuses attention on a narrow area when the scene is more crowded and a larger area when there are few objects. This provides support for and an explanation of our claim that the size of the focus of attention differs depending on the number of distractors in a scene (Kon et al., 2024): a narrow focus (wider focus) when there are many (few) objects tends to lead to lower response times but also higher accuracy. The result is a model capable of both predicting overall human performance and identifying videos that will be especially difficult for humans.

While the pattern of model results generally matches empirical results, humans outperform the model when there is no chase, responding faster across all set sizes and chasing subtlety conditions. This implies that the model stopping rules do not reflect those used by humans on this task. Future work should systematically survey plausible alternative cognitive stopping rules. For example, an earlier initial check may be afforded by having a dynamic scan window that gets larger as it moves away from the potential chaser.

We have demonstrated that this computational model can be used to make empirically testable predictions about human performance on chase detection tasks *prior* to data collection. This shows that the model allows us to develop a falsifiable theory of chase detection, one that we intend to expand and refine through future model development and empirical tests.

Acknowledgments

This work was supported by a National Research Council Associateship Award to MK and funding from the Naval Research Laboratory to SK. Data for Experiment 1 were collected by Knexus Research Corporation. The views expressed in this paper are solely the authors' and should not be taken to reflect any official policy or position of the United States Government or the Department of Defense.

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