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| University of Birmingham  School of Psychology    Assessment Submission Form |  |

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| Module title: | **Current Research and Practice** |
| Assessment type: | **Research practical report** |

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| Title of your report: | **Cognitive mechanisms of visual search and the influence of temporal noise: A drift diffusion modelling study** |
| Word count: | **1904** |

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| I am happy for my assignment to be considered for inclusion as an anonymised exemplar in the Psychology Bank of Assessed Work. | Yes | No |

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*Write a brief comment about something that you have tried to implement in the current piece in response to previous feedback: e.g. "I have been told that I need to include an opening paragraph that identifies the purpose of the piece. I have tried to address this here."*

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**Request for particular attention to be paid (max. 60 words):**

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**Cognitive mechanisms of visual search and the influence of temporal noise: A drift diffusion modelling study**

**Cognitive mechanisms of visual search and the influence of temporal noise: A drift diffusion modelling study**

**Introduction**

Visual selective attention refers to the process by which cognition filters out unnecessary, irrelevant or distracting information, in order to focus on stimuli of interest within the visual field. In the context of experimental research, examinations of this process have commonly employed the visual search task (Treisman & Gelade, 1980; Wolfe, 1989; Wolfe, 2021) – a paradigm in which participants are presented with sets of items and are tasked with identifying distinct targets among other distractor stimuli. By manipulating the visual features of the presented stimuli, researchers can examine the resulting effects to search efficiency (speed and accuracy of responses) and draw inferences about the nature of visual selective attention from these observed changes.

Given that dynamic visual noise constitutes an inherent feature of the natural environment, a number of studies have investigated visual search efficiency under conditions of moving targets (e.g. Dick, Ullman & Sagi, 1987; Roitman & Shadlen, 2002). Despite the ecological prevalence of indiscriminate temporal noise, however, there appears to be only one empirical study looking at visual search under conditions where both the targets and distractors feature movement. In this study, conducted by Heinke et al. (2019), stimuli were operationalised as random dot kinematograms (RDK) – shapes containing dots that move in a given direction. Participants were tasked with detecting the presence or absence of distinct target RDKs, while the number of presented stimuli, coherence of motion and target presence were manipulated. Findings from this novel methodology revealed significantly greater search efficiency in conditions where the target was present and where RDK coherence was higher, as well as an interaction between target-presence and set size – showing increased efficiency as set size increased within target-present conditions, and reduced efficiency as set size increased within target-absent conditions. Given these pertinent effects of temporal noise in different visual search conditions, as well as the overall lack of investigation that has taken place surrounding this research question, we decided to conduct our own investigation based on Heinke et al.’s (2019) data.

While the aforementioned literature has focused on the ways in which visual selective attention is influenced by the physical features of items in the visual field, more recent computational research acknowledges the significance of internal cognitive functions to this process. In particular, the drift diffusion model (Ratcliff & McKoon, 2007) offers a comprehensive means of measuring these internal cognitive factors (Matzke & Wagenmakers, 2009; Forstmann, Ratcliff & Wagenmakers, 2016). As a sequential sampling model, this concept assumes that binary perceptual decisions are made by accumulating evidence from the visual field until the threshold for a given decision is reached – at which point a corresponding response is initiated (Ratcliff, 1978). The simplest form of the drift diffusion model is defined by three parameters: drift rate, decision boundary and non-decision time. The rate at which evidence is accumulated, as it approaches a response threshold, is the drift rate. The amount of evidence required to reach a decision is the decision boundary. The total time taken to execute a response, excluding the time taken to reach that decision, is the non-decision time. In contrast to methodologies studying the nature of visual selective attention through the use of scores of performance (e.g. response time and/or accuracy), this procedure of modelling from estimated parameters that represent the definitive cognitive processes of visual search offers a comprehensive means of examining the effect of different visual search conditions, including conditions of motion among targets and distractors, on the functioning of these internal processes.

Considering the empirical potential of this methodology in its application to the study of these implicit cognitive processes, in addition to the evidently limited base of existing literature surrounding the influence of indiscriminate temporal noise on visual search, therefore, our study employed drift diffusion modelling to computationally examine this effect of target and distractor motion on these processes, under different conditions of the visual search task.

**Method**

***Design***

In using the data from Heinke et al.’s (2019) research, our study comprised the same 2x3x3 repeated-measures design. There were three independent variables: target presence (operationalised as either present or absent), RDK set coherence (operationalised as either 65%, 80% or 95% coherence), and set size (operationalised as either 5, 10 or 15 trial items presented). Our dependent variables were the estimated drift rates, decision boundaries and non-decision times.

***Participants***

Participants were recruited as part of Heinke et al.’s (2019) original study. For our modelling and analysis, data from 23 of these participants was used. Two were excluded due to their data being incomplete, ultimately leaving 21 included in our study.

***Procedure***

In generating the drift diffusion models for each participant, we employed the differential-evolution Markov Chain Monte Carlo (DE-MCMC) algorithm for the Bayesian estimation of our model parameters. As Bayes’ theorem states, the probability of event A, given event B, is proportional to the probability of event B, given event A, multiplied by the probability of event A.

𝑃(A|B) ∝ 𝑃(B|A) ⋅ 𝑃(A)

In order to estimate the probability of an unknown parameter, given some observed data, therefore, DE-MCMC computes a posterior distribution by updating a prior distribution, using the likelihood of the observed data. The prior is a distribution representing the prior beliefs about the probabilities of each possible unknown parameter value, while the likelihood is a distribution of the probabilities of each observed data point, given the possible unknown parameter values. By multiplying the prior by the likelihood, we produce a posterior distribution proportional to the two, comprising the probabilities of each sample parameter value, from which we can discern the best estimate for the parameter we are looking to approximate.

In the context of our drift diffusion models, we formed our priors under a number of assumptions. On the basis that the conditions of the visual search task would not affect the time taken to execute the motor response indicating the target’s detected presence or absence, we assumed that non-decision time would remain constant throughout all trials. We therefore computed one posterior distribution estimating this parameter, for each participant. On the basis that the decision boundary would be influenced by changes in the coherence of the presented RDK stimuli, we assumed that the decision boundary parameter would change across the three coherence levels. We therefore computed three posterior distributions, estimating this parameter at each coherence level for each participant. On the basis that drift rate would be influenced by changes in set size, coherence and target presence, we assumed that drift rate would vary across all conditions of the task. We therefore computed 18 posterior distributions (see Appendix A for an example), estimating this parameter for all combinations of the conditions of the three independent variables. 22 parameters were estimated in total for each participant.

Due to the extensive sampling required to perform this computation, we used the University of Birmingham’s BlueBEAR supercomputer to perform this updating of the priors and generation of our posterior distributions, and later to analyse the variance between these estimates.

***Data analysis***

After generating the drift diffusion models for each participant, a one-way analysis of variance (ANOVA) was used to test for any effects of coherence on decision boundary estimates. A three-way ANOVA was used to test for any effects or interactions between the three independent variables on drift rate estimates.

**Results & discussion**

***One-way ANOVA***

**Table 1.** One-way ANOVA results comparing decision boundary estimates between each coherence level condition.

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| --- | --- | --- | --- | --- | --- |
| **Condition** | **SumSq** | **DF** | **MeanSq** | **F** | **p** |
| (Intercept): coherence | 49.398 | 2 | 24.699 | 1.9178 | 0.16019 |
| Error (coherence) | 515.15 | 40 | 12.879 |  |  |

Our one-way ANOVA revealed no significant main effect of coherence on decision boundary estimates (*F*(2,40) = 1.92, *p* = 0.16). This was unexpected, as our logical hypothesis was that as the coherence of the presented stimuli increased, the distinction between the target and distractors would become more prominent, thus leading to a lower threshold for the target’s presence or absence to be detected. While we can see from figure 1 that the search slope across the coherence conditions indeed reflects this pattern, the differences in decision boundaries between these conditions was not significant. While this could be interpreted as indicating that the amount of evidence required to decide on the presence or absence of a stimulus is not significantly influenced by the amount of temporal noise in the visual field, the fact that previous literature has explicitly demonstrated a connection between the decision boundary and coherence of stimuli (Ratcliff & McKoon, 2007), questions the basis of this interpretation. Alternatively, therefore, we posit that this absence of a significant effect may in fact be due to insufficient statistical power, potentially due to the small number of participants from which we obtained our data. As demonstrated by Brysbaert (2019) for a range of research questions, comparisons between three levels of a within-subjects variable are likely to be underpowered if less than 100 participants are used. Future studies pertaining to our research question could therefore evidently benefit from this consideration.



**Figure 1.** Search slope of decision boundary estimates between coherence levels.

**Three-way ANOVA**

**Table 2.** Results from our three-way ANOVA comparing drift rate estimates between each coherence, set size and target presence condition.

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| --- | --- | --- | --- | --- | --- | --- |
|  | **SumSq** | **DF** | **MeanSq** | **F** | | **p** |
| **(Intercept): set size** | 0.000001 | 2 | 0.000001 | 0.024 | 0.976 | | |
| **Error (set size)** | 0.001073 | 40 | 0.000027 |  |  | | |
| **(Intercept): target presence** | 0.002667 | 1 | 0.002667 | 14.316 | 0.001 | | |
| **Error (target presence)** | 0.003726 | 20 | 0.000186 |  |  | | |
| **(Intercept): coherence** | 0.004120 | 2 | 0.002060 | 18.863 | 0.000 | | |
| **Error (coherence)** | 0.004368 | 40 | 0.000109 |  |  | | |
| **(Intercept): set size x presence** | 0.000214 | 2 | 0.000107 | 4.146 | 0.023 | | |
| **Error (set size x presence)** | 0.001032 | 40 | 0.000026 |  |  | | |
| **(Intercept): set size x coherence** | 0.000168 | 4 | 0.000042 | 2.299 | 0.066 | | |
| **Error (set size x coherence)** | 0.001461 | 80 | 0.000018 |  |  | | |
| **(Intercept): presence x coherence** | 0.000084 | 2 | 0.000042 | 0.382 | 0.685 | | |
| **Error (presence x coherence)** | 0.004380 | 40 | 0.000109 |  |  | | |
| **(Intercept): set size x presence x coherence** | 0.000114 | 4 | 0.000028 | 1.191 | 0.321 | | |
| **Error (set size x presence x coherence)** | 0.001908 | 80 | 0.000024 |  |  | | |

Note. SumSq = sum of squares, DF = degrees of freedom, MeanSq = mean of squares, F = F-value, p = p-value.

Our three-way ANOVA revealed a significant main effect of coherence on drift rate estimates (*F*(2,40) = 18.86, *p* < .001). Specifically, drift rate increased as stimuli coherence increased and decreased as stimuli coherence decreased. Conditions of minimal temporal noise (95% coherence) produced the fastest rates of evidence accumulation, conditions of moderate temporal noise (80% coherence) produced slightly slower rates of evidence accumulation, and conditions of high temporal noise (65% coherence) produced the slowest rates of evidence accumulation. This demonstrates that the rate at which individuals accumulate evidence, leading to the detection of a target’s presence or absence in visual search, is affected by the amount of temporal noise characterising the target and distractors.

We also established a significant main effect of target presence on drift rate estimates (*F*(1,20) = 14.32, *p* = .001). Specifically, drift rate estimates tended to be higher in target-present conditions and lower in target-absent conditions, suggesting that the rate at which evidence is accumulated, leading to the detection of a target’s presence or absence, tends to be faster in conditions where the target is presented and slower in conditions where the target is not presented.

**Figure 4.** Search slopes of drift rate estimates for each target presence, coherence and set size condition level.



Our final significant finding was an interaction between set size and target presence on drift rate estimates (*F*(2,40) = 4.15, *p* = .02). Specifically, we found that in target-present conditions, drift rates appeared to slightly increase with set size. Meanwhile, in target-absent conditions, drift rates appeared to slightly decrease with set size. This is an interesting observation, suggesting that when the target is present, the rate of evidence-accumulation increases as the number of stimuli presented increases. Meanwhile, when the target is absent, the rate of evidence-accumulation decreases as the number of stimuli presented increases.



**Figure 5.** Search slopes of drift rate estimates across target presence, coherence and set size conditions.



These findings contribute valuably to the base of understanding established by Heinke et al.’s (2019), research. While their experiments demonstrated similar effects of RDK coherence, set size and target presence on inverse efficiency score, our recruitment of drift diffusion modelling allowed us to examine the effects of these conditions on the internal cognitive processes integral to performance in the visual search paradigm. From analysing the resulting changes in drift rate and decision boundary, our study highlights that a key way in which temporal noise influences the detection of target presence is through interference to the rate at which evidence is accumulated towards the corresponding perceptual decision. While future research would benefit from closer examination of the potential explanations for why these effects occur, we feel that the phenomena observed from this investigation nonetheless provide a valuable foundation of understanding, upon which further knowledge about the nature of visual selective attention, and the cognitive processes that underpin it, may be effectively built.

**References**

Brysbaert, M. (2019) How many participants do we have to include in properly powered experiments? A tutorial of power analysis with reference tables. *Journal of Cognition, 2*(1), 16.

Dick, M., Ullman, S. & Sagi, D. (1987) Parallel and serial processes in motion detection. *Science, 236*(4813), 400-402.

Forstmann, B. U., Ratcliff, R., & Wagenmakers, E. J. (2016). Sequential sampling models in cognitive neuroscience: Advantages, applications, and extensions. *Annual review of psychology*, *67*, 641-666.

Heinke, D., Deakin, J., Standage, D. & Schofield, A. (2019) A new visual search paradigm with multiple random dot kinematograms (RDKs). *Journal of Vision, 19*(10), 233. <https://doi.org/10.1167/19.10.233a>.

Matzke, D., & Wagenmakers, E. J. (2009). Psychological interpretation of the ex-Gaussian and shifted Wald parameters: A diffusion model analysis. *Psychonomic bulletin & review*, *16*(5), 798-817.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85*(2), 59–108. <https://doi.org/10.1037/0033-295X.85.2.59>.

Ratcliff, R. & McKoon, G. (2007) The drift diffusion model: theory and data for two-choice decision tasks. *Neural Computation, 20*(4), 873-922.

Roitman, J. D. & Shadlen, M. N. (2002) Response of neurons in the lateral intraparietal area during a combined visual discrimination reaction time task. *Journal of Neuroscience, 22*(21), 9465 – 9489.

Treisman, A. M. & Gelade, G. (1980) A feature-integration theory of attention. *Cognitive Psychology, 12*(1), 97-136.

Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, 1-33.

Wolfe, J. M., Cave, K. R. & Franzel, S. L. (1989) Guided search: An alternative to the feature integration model for visual search. *Journal of Experimental Psychology: Human Perception and Performance, 15*(3), 419–433. <https://doi.org/10.1037/0096-1523.15.3.419>.

**Appendices**

**Appendix A**