

The Alejandro Project: Testing the Target Contrast Signal Theory

Replication and Generalisation

Anna Hughes · Anna Nowakowska · Alasdair
D. F. Clarke

Received: date / Accepted: date

Abstract Insert your abstract here. Include keywords, PACS and mathematical subject classification numbers as needed.

Keywords First keyword · Second keyword · More

1 Introduction

Background Visual search, where participants are asked to find a target within a cluttered scene, has been extensively studied within psychology. Several models have been developed that can generate testable predictions about how different types of distractors and targets affect search efficiency.

The two most studied families of models of visual search include bottom-up models (also known as visual saliency models) and top-down models. Saliency models rest on the assumption that fixations are directed to objects or locations that are most dissimilar to the background or other objects in the visual display Itti and Koch (2000); Itti et al. (1998); Koch and Ullman (1987). While the original saliency model was able to predict fixation allocation in a visual search task above chance Parkhurst et al. (2002), further research demonstrated that a comparable level of performance could be achieved using a simple central fixation bias heuristic Tatler (2007). The saliency models have since been extended and improved (see for example Zhang et al. (2008)); however, the main issue with this family of models remains their limited usability in complex real-life search arrays Tatler et al. (2011); Koehler et al.

ESRC grant?

F. Author
first address
Tel.: +123-45-678910
Fax: +123-45-678910
E-mail: fauthor@example.com

S. Author
second address

(2014). In addition, in most instances of visual search, the target is clearly defined (i.e. the goal is to find a specific object) and inspecting the most salient areas of the display may in these cases be inefficient.

Another class of models are based around Feature Integration Theory Treisman and Gelade (1980), which has been modified and extended by Wolfe in the Guided Search Model Wolfe et al. (1989); Wolfe (2014). These models combine top-down influences (how closely an item resembles the observer's goal) with bottom-up image properties. For example, if one's goal (top-down processing) is to find a red horizontal bar, all the red and horizontal items in a visual search display will be given greater weight than distractors (e.g. vertical and blue items) in the model. The salience of a given object in the display (how distinctive it is from the surrounding objects) also activates bottom-up processing. For instance, a blue item among red items is ranked higher than red among orange items. Combining bottom-up and top-down sources of activation generates an activation map which generates a prediction of the order in which stimuli are processed in visual search. Thus, these models aim to produce a representation of the visual properties of the distractors at each location in the visual field.

However, more recent work has taken a different approach, focusing solely on representing the difference between targets and distractors. For example, in work on eye movement patterns, it has been proposed that performance in inefficient (serial) visual search is mostly determined by the size of the 'functional viewing field', whose size varies as a function of target-distractor similarity Hulleman and Olivers (2017). One recent model, the Target Contrast Signal (TCS) Theory Lleras et al. (2020) aims to provide a unifying, quantitative framework that can make behavioural predictions based on this general assumption.

Theoretical intro to TCS TCS proposes that behaviour is determined by comparing the target template (held in memory) with every element present in the scene in parallel. This allows the visual system to reject peripheral non-targets quickly; the speed at which items are evaluated is determined by how different the item is from the template through an evidence accumulation process (formally, the slope of the logarithmic function is assumed to be inversely proportional to the overall magnitude of the contrast signal between the target and distractor). The model thus focuses on an initial, efficient processing stage of search; if sufficient evidence is not accumulated during this process, the model posits that a second stage is entered, where attention is deployed serially. TCS has been successful in predicting a number of empirical results, including search performance in heterogeneous scenes based on parameters estimated in homogeneous scenes, both with artificial stimuli Buetti et al. (2016); Lleras et al. (2019) and with real-world objects visualised on a computer display Wang et al. (2017).

Limitations, and extending basic stimuli While results to date for TCS appear promising, they remain relatively preliminary, being tested by only one research group so far. There remains a great deal of scope for extending beyond the parameters tested to date (such as the number of distractors) in order to test the robustness and generalisability of the model. In addition, there are some predictions of the model, including

its ability to explain search asymmetries, that have yet to be empirically confirmed Lleras et al. (2020).

Within subjects In addition, in all implementations of TCS so far, predictions of search efficiency (e.g. in heterogeneous scenes) have been made on the average of a group of participants, using data from a different group performing a different task (e.g. searching in homogeneous scenes). Thus, we know that TCS can replicate group-level averages between subjects in search well, but we do not know whether it is also able to make predictions at the individual level. This is particularly important given that conclusions based on aggregate data can be different from those that take individual differences into account; in one study where participants searched for a target in an array of randomly oriented line segments, aggregating the data suggested that participants were using a stochastic search model. However, when considering each participant individually, it became clear that there was a high level of heterogeneity in responses, with some participants performing close to optimally, and others actually performing worse than chance Nowakowska et al. (2017). Similarly striking variability has also been reported in other search studies Irons and Leber (2016, 2018).

Conclusion to introduction In the current manuscript, we focus on replicating and extending findings from Buetti et al. (2019). Here, participants searched for a target in a scene of homogeneous distractors. First, parallel search efficiency (measured by the logarithmic search slope) was estimated for cases where the distractors varied from the target in one dimension: either colour (e.g. a cyan target being searched for in either yellow, blue or orange distractors) or shape (e.g. a semicircle target in either circle, diamond or triangle distractors). New participants then searched for the same targets in displays where the distractors were compounds, differing from the target in both colour and shape (e.g. searching for a cyan semicircle in either blue circles, orange diamonds or yellow triangles). Figure 1 shows example stimuli from their paper. The logarithmic search slopes in the initial experiments were then used to predict the logarithmic slopes and reaction times using a number of models. The authors found that the best model was a 'collinear contrast integration model' where the distinctiveness scores were summed along each attribute in the unidimensional experiments, creating an overall contrast score that was used for compound stimuli predictions.

Overview of the current study We first run a replication of Buetti et al. (2019), in an online, within-subjects study. This design allows us to extend the modelling, both incorporating a multi-level design to predict within-subjects effects and by utilising a Bayesian generalised linear model framework to better represent the distribution of responses (e.g. avoiding predicting negative reaction times, accounting for uncertainty in model predictions). We also carry out a direct analytical replication using the same methods as in Buetti et al. (2019) allowing us to ask whether the choice of analysis affects the results.



Fig. 1 Example stimuli from Buetti et al. (2019) Top left: Expt 1A. Here, the target is a blue semicircle within a set of homogeneous (yellow semicircle) distractors. Top right: Expt 1B. The target is a grey semicircle in circular grey distractors. Bottom left: Expt 2A. The target is a blue semicircle in orange diamond distractors. Bottom middle: Expt 2B. The target is a blue semicircle in dark blue triangle distractors. Bottom right: Expt 2C. The target is a blue semicircle in yellow circular distractors.

2 The Target Contrast Model

We first describe the original Target Contrast Model (and verify that we can replicate the original analysis - see Supplementary Materials). This is followed by our proposed extension.

2.1 TCS modelling overview

In Experiment 1a of Buetti et al. (2019), participants searched for a cyan semicircle target among blue, yellow or orange semicircular distractors i.e. they searched for a target that differed from the distractors by a *single* feature (colour). The experiment was then repeated (1b) using a different single feature (shape, with participants searching for the semicircular target within triangle, circle or diamond distractors). In Experiments 2a, 2b and 2c, participants again searched for a cyan semicircle, but this time, the distractors differed in both shape and colour. We will refer to these conditions as *double features*. Note, unlike in standard conjunction searches, in this paradigm, the distractors are all identical (i.e. orange triangles).

The *Target Signal Contrast* theory allows us to predict the value of the logarithmic slope, D_{overall} , in this condition based on the corresponding D_j in the single feature search experiments.

2.1.1 Calculating the logarithmic slope parameter, D_i

In both experiments, the number of distractors varied, allowing the data to be used to fit a log-linear model for reaction times, where reaction times increase linearly with $\log(N_T)$ (the log of the number of distractors) 1. In the original model the error distribution was assumed to be normal.

$$\hat{RT} = D_i \log(N_T + 1) + a \quad (1)$$

Thus the results of Experiment 1 were used to calculate the logarithmic slope, for each type of distractor. When colour varied, we will refer to D_c , for $c = 1, 2, 3$. Similar for shape (D_s), and the compound features ($D_{c,s}$). As a represented the intercept in our model, it is independent of both shape and colour, as it represented how long observers take to find a target when $N_T = 0$, i.e., there are no distractors.

2.1.2 Estimating $D_{c,s}$, the logarithmic slope parameter for compound features

The core of the idea in the TSC theory is that we estimate the logarithmic slope parameter for a double feature visual search from the slopes parameters in the two independent single feature searches. I.e., $D_{c,s} = f(D_c, D_s)$.

Buetti et al. (2019) tested three different models for predicting D for compound colour-shape stimuli. The best feature guidance model (Equation 2) suggests that when the target and lures differ in two dimensions, participants will choose to attend to whichever feature dimension is the most discriminable (i.e. has the smallest D value):

$$D_{\text{overall}} = \min(D_{\text{colour}}, D_{\text{shape}}) \quad (2)$$

The orthogonal contrast combination model instead suggests that independent feature dimensions comprise a multidimensional space, where an object can be described by the overall vector in this space, and thus D_{overall} can be represented as:

$$D_{\text{overall}} = \frac{1}{\sqrt{\frac{1}{(D_{\text{colour}})^2 + (D_{\text{shape}})^2}}} \quad (3)$$

Which simplifies as:

$$D_{\text{overall}} = (D_{\text{colour}})^2 + (D_{\text{shape}})^2 \quad (4)$$

Finally, the collinear contrast integration model also assumes independence of feature dimensions, but assumes that while the visual features create a multidimensional space, the contrast between them is unidimensional. As D is assumed to be inversely proportional to contrast, the equation can be written as follows:

$$\frac{1}{D_{\text{overall}}} = \frac{1}{D_{\text{colour}}} + \frac{1}{D_{\text{shape}}} \quad (5)$$

Buetti et al. (2019) found that with their dataset, the collinear contrast integration model was best able to predict their empirical RT results with an $R^2 = 93.27\%$. We

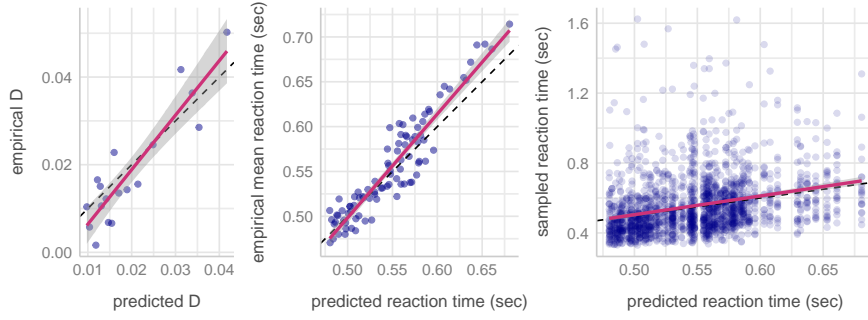


Fig. 2 (left) The collinear method for calculating D offers a good prediction. (right) Using the TSC to predict reaction times.

verified we were able to replicate the results of Buetti et al. (2019) using the dataset available on OSF (<https://osf.io/f3m24/>)¹ and using the exclusion criteria originally applied²; see *Supplementary Materials* for details. See Figure 2(left).

2.1.3 Estimating mean Reaction Times

According to TCS, Equation 6 allows us to predict mean reaction times:

$$RT = a + \beta \sum_{j=1}^L \left((D_j - D_{j-1}) \log \left(\left(N_T - \sum_{i=1}^{j-1} N_i \right) 1_{[2,\infty](j)} + 1 \right) \right) \quad (6)$$

Where L is the number of distractor types present in the display, N_T is the total number of distractors, N_i is the number of distractors of type i and D_j is the logarithmic slope parameters associated with distractors of type j (from smallest D_1 to largest D_L). The constant a represents the reaction time when no distractors are present and β represents inter-item interactions. When $L = 1$ (all lures are identical), as in the current experiment, the equation simplifies to:

$$RT = a + D_1 \log(N_T + 1) \quad (7)$$

These predictions are shown in Figure 2(right).

2.1.4 Discussion

While the TCS theory offers a good prediction of search slopes and corresponding mean reaction times for compound feature search, there are two related limitations. Firstly, it is unable to account for individual differences between observers, only the changes to the sample average. Secondly, it cannot account for the distribution of reaction times over multiple trials. To address these issues, we propose a second version of the TCS that makes use of multi-level modelling techniques

¹ downloaded on 28th August 2020

² We also applied some additional exclusion crit!

Fig. 3 The shaded regions show the model’s predicted D values for each of the conditions in Expt 1 and Expt 3.

Fig. 4 Correlation between empirical D and the predicted D using (*top*) normal and (*bottom*) log-normal distributions.

2.2 A multi-level TCS

Switching from a linear regression model to a multi-level model will allow us to compute D for each participant, while simultaneously estimating the trial-to-trial variance. We also switch from a frequentist to Bayesian framework, as this allows us to naturally account for the uncertainty in the model’s predictions.

However, switching from linear regression to a multi-level model raises the problem of which distribution to use for modelling reaction times. Using a normal distribution is unlikely to be satisfactory, as it is unable to account for the skew frequently seen in rt distributions, and also allows the possibility of negative reaction times! We can account for both of these problems by using a log-normal distribution, $rt \sim \text{lognormal}(\mu, \sigma)$. We will also test whether a slightly more complex extension of this model, the *shifted lognormal* model offers any improvement in model fit.

2.2.1 Fitting the single feature search data

We proceed in a similar fashion to section 2.1.1, although this time, we fit each model three times using a (i) normal, (ii) lognormal, and (iii) shifted lognormal distribution. Please see Supplementary Materials for full details of our modelling approach, including prior predictive checks and model fit diagnostics. The three models were compared using leave-one-out cross validation, and the results showed that the shifted-lognormal model (illustrated in Figure 3) was given 100% of the weight. Therefore, we will only use this model for the rest of the analysis.

2.2.2 Measuring D

As we are using a Bayesian framework, rather than D representing the best fit in equation 8, it is now represented as a probability distribution over possible values (see Figure 3). We can then estimate D in the compound feature distractor cases using the three methods detailed above and compare the predicted values to the empirical values (see Figure 4). We additionally calculated a fourth prediction method, the ‘mean method’ which simply takes the averages of the collinear contrast and orthogonal contrast models.

$$\hat{y} = a + D \log(N_T + 1) \quad (8)$$

[NEED TO COMPARE BEST MODELS HERE - EXPLAIN HOW WE DO IT.]

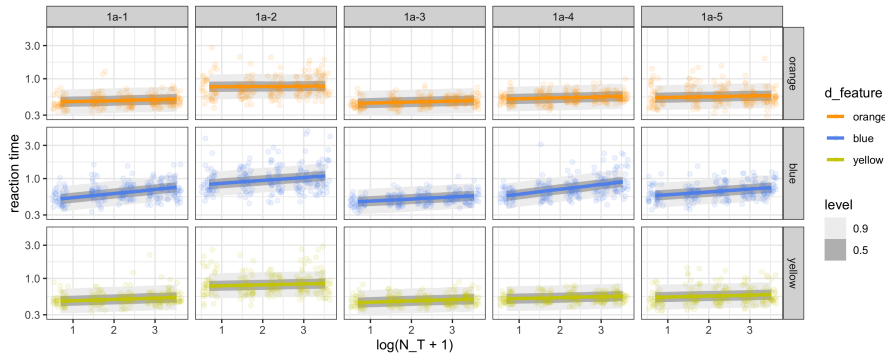


Fig. 5 Example results from the first five participants of Experiment 1a Buetti et al. (2019). We can see considerable between-subjects variation.

2.2.3 Estimating D for compound distractors

2.2.4 Reaction Time Model

2.3 Extension: Individual Differences

While we can't generate within-participant reaction time predictions from the original data, we can present data on the uncertainty around the individual differences in D for each condition (see Figure 5).

2.4 Power Analysis

To estimate the required sample size for future experiments, we repeatedly reran the above analysis on smaller subsets of the data from Buetti et al. (2019). (Full details are given in the *Supplementary Materials*.) Based on this, we found that $n =$ per observer and condition was enough to reliably estimate D .

2.5 Discussion

While we replicate the good predictions using the collinear method if we use a normal distribution, we do not find this that this is the best method if we use a log-normal distribution, and instead, we find the orthogonal contrast method is slightly better. This suggests that (seemingly small) analytical decisions may have important implications for the conclusions drawn.

3 Hypotheses

We plan a number of experiments to test the extent to which the original results in Buetti et al. (2019) replicate and generalise. As well as following the original,

between-subjects, experiment design, in which data from one group of observers in one task is used to predict behaviour of a second group of participants in a different task, we will allow for within-subject comparisons. Specifically, we will ask: to what extent do the individual differences in the homogeneous task explain the differences in the heterogeneous task?

1. **Replication of Buetti et al (2019) with online data collection.** Specifically, that the *collinear contrast ingratiation model* outperforms the *best feature guidance*, and *orthogonal contrast combination models*. Furthermore, the $R^2 = (99\% \text{ HPDI} = [,])$ between predicted and observer reaction times.
2. **Larger number of distractors (or targets further in periphery?)** Add an extra ring
3. **Search asymmetries** test O in Qs and Q in Os

4 General Methods

4.1 Participants

Based on the power analysis 2.4, we will recruit ...

4.2 Stimuli

4.3 Procedure

4.4 Data Pre-processing

incorrect trials? Poorly behaved participants? RTs that are far too short? Or far too long?

4.5 Analysis Plan

We will follow the analysis given in Section ??.

5 Experiment 1

5.1 Results

– blank –

5.2 Discussion

– *blank* –

6 Experiment 2

6.1 Methods

Same as Experiment 1? Perhaps we should have a *General Methods* section for both experiments?

6.2 Results

– *blank* –

6.3 Discussion

– *blank* –

7 General Discussion

Is discriminating between the different models one of our aims? Or is this a discussion point i.e. it's quite hard to do? And therefore maybe a follow up paper?

Acknowledgements Thank you to AL for help and encouragement!

Conflict of interest

The authors declare that they have no conflict of interest.

References

- Simona Buetti, Deborah A Cronin, Anna M Madison, Zhiyuan Wang, and Alejandro Lleras. Towards a better understanding of parallel visual processing in human vision: Evidence for exhaustive analysis of visual information. *Journal of Experimental Psychology: General*, 145(6):672, 2016.
- Simona Buetti, Jing Xu, and Alejandro Lleras. Predicting how color and shape combine in the human visual system to direct attention. *Scientific reports*, 9(1):1–11, 2019.
- Johan Hulleman and Christian NL Olivers. On the brink: The demise of the item in visual search moves closer. *Behavioral and Brain Sciences*, 40, 2017.
- Jessica L Irons and Andrew B Leber. Choosing attentional control settings in a dynamically changing environment. *Attention, Perception, & Psychophysics*, 78(7):2031–2048, 2016.
- Jessica L Irons and Andrew B Leber. Characterizing individual variation in the strategic use of attentional control. *Journal of Experimental Psychology: Human Perception and Performance*, 44(10):1637, 2018.

- Laurent Itti and Christof Koch. A saliency-based search mechanism for overt and covert shifts of visual attention. *Vision research*, 40(10-12):1489–1506, 2000.
- Laurent Itti, Christof Koch, and Ernst Niebur. A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on pattern analysis and machine intelligence*, 20(11):1254–1259, 1998.
- Christof Koch and Shimon Ullman. Shifts in selective visual attention: towards the underlying neural circuitry. In *Matters of intelligence*, pages 115–141. Springer, 1987.
- Kathryn Koehler, Fei Guo, Sheng Zhang, and Miguel P Eckstein. What do saliency models predict? *Journal of vision*, 14(3):14–14, 2014.
- Alejandro Lleras, Zhiyuan Wang, Anna Madison, and Simona Buetti. Predicting search performance in heterogeneous scenes: Quantifying the impact of homogeneity effects in efficient search. *Collabra: Psychology*, 5(1), 2019.
- Alejandro Lleras, Zhiyuan Wang, Gavin Jun Peng Ng, Kirk Ballew, Jing Xu, and Simona Buetti. A target contrast signal theory of parallel processing in goal-directed search. *Attention, Perception, & Psychophysics*, pages 1–32, 2020.
- Anna Nowakowska, Alasdair DF Clarke, and Amelia R Hunt. Human visual search behaviour is far from ideal. *Proceedings of the Royal Society B: Biological Sciences*, 284(1849):20162767, 2017.
- Derrick Parkhurst, Klinto Law, and Ernst Niebur. Modeling the role of salience in the allocation of overt visual attention. *Vision research*, 42(1):107–123, 2002.
- Benjamin W Tatler. The central fixation bias in scene viewing: Selecting an optimal viewing position independently of motor biases and image feature distributions. *Journal of vision*, 7(14):4–4, 2007.
- Benjamin W Tatler, Mary M Hayhoe, Michael F Land, and Dana H Ballard. Eye guidance in natural vision: Reinterpreting salience. *Journal of vision*, 11(5):5–5, 2011.
- Anne M Treisman and Garry Gelade. A feature-integration theory of attention. *Cognitive psychology*, 12(1):97–136, 1980.
- Zhiyuan Wang, Simona Buetti, and Alejandro Lleras. Predicting search performance in heterogeneous visual search scenes with real-world objects. *Collabra: Psychology*, 3(1), 2017.
- Jeremy M Wolfe. Approaches to visual search: Feature integration theory and guided search. *Oxford handbook of attention*, pages 11–55, 2014.
- Jeremy M Wolfe, Kyle R Cave, and Susan L Franzel. Guided search: an alternative to the feature integration model for visual search. *Journal of Experimental Psychology: Human perception and performance*, 15(3):419, 1989.
- Lingyun Zhang, Matthew H Tong, Tim K Marks, Honghao Shan, and Garrison W Cottrell. Sun: A bayesian framework for saliency using natural statistics. *Journal of vision*, 8(7):32–32, 2008.