**The CASPER Model**

**Core Theoretical Claims**

The CASPER model (Concurrent Attention: Serial and Parallel Evaluation and Rejection) makes several core theoretical claims. The claims are summarized in Table 1. One of the most important theoretical claims in CASPER is that visual search does not follow a two-stage process, where items are supposed to undergo a parallel processing stage followed by a serial processing stage (e.g., Treisman & Gelade, 1980; Wolfe & Gray, 2007; Lleras et al., 2020). Instead, CASPER assumes that something is always the focus of attention, even while parallel processing is occurring. In CASPER, the serial search for the target occurs from the beginning of search, while all distractors are still in contention and undergoing parallel processing. CASPER provides a computational account of how serial processing can proceed concurrently with parallel processing during search, with the parallel process influencing the course of serial item selection.

CASPER makes a second core theoretical claim that parallel processing is faster than serial processing and that parallel processing necessarily more error prone. CASPER assumes high accuracy in the evaluation of a search item under attentional scrutiny, but the parallel evaluation process in CASPER is lower in accuracy. CASPER also assumes that parallel processing has a greater effect on an item when it is close to fixation, as opposed to the far periphery.

In CASPER, items can be permanently accepted or rejected as the search target under attentional selection only. Although parallel processing can change the likelihood of an item being selected for attentional scrutiny, the parallel process does not permanently remove items from contention. Similarly, the parallel process cannot determine that a search item is the target item. Items can be severely deprioritized or highly prioritized for selection, but selection and attentional scrutiny must occur before a final decision is made about that item.

The representations in CASPER are simplified and preliminary, but the theoretical framework assumes that visual representations are hierarchical in nature (see Palmer 1977; Hummel & Biederman, 1992), and that all levels of representation can contribute. For example, some representations in CASPER are simple color and shape features (e.g., oriented lines, vertices, or hues) that might correspond to visual areas V2 or V4. However, the representational scheme assumes that features from higher visual areas (e.g., surfaces or parts) would also contribute to visual processing if the model were extended to support them.

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| Claim #1 | *Serial and parallel processing occur concurrently and not in successive stages* |
| Claim #2 | *Parallel processing is faster and more error prone than serial processing* |
| Claim #3 | *Visual processing near fixation has a greater impact on the evaluation of search items than processing in the periphery* |
| Claim #4 | *Items are only accepted or rejected as the search target under attentional scrutiny* |
| Claim #5 | *Visual representations are hierarchical in nature and all levels of representation (after V1) can contribute to item evaluation during search* |
| Claim #6 | *Item selection is neither purely random nor deterministic, but is instead governed by a Luce’s choice axiom, where items most similar to the target are more likely, but not guaranteed, to be selected for attentional scrutiny* |

Table 1The core theoretical claims in the CASPER model of visual search

**Overview of the Model**

CASPER uses concurrent serial and parallel processing to find the target in a visual search display, rather than the more typical two-stage sequence in which a parallel process proceeds before a serial one. In CASPER, a serial process attends to a single search item at a time, comparing it to a *target template*. While this is happening, all the search items in the display update their priority for attentional selection in parallel.

At the beginning of search, all items in the display are set at a high priority for attentional selection. However, items immediately begin to decay in selection priority with each iteration. At the same time, items are be adjusted in selection priority in proportion to their similarity to the search target. Consistent with theoretical claim #2 that parallel processing is more error prone, similarity calculation for this parallel processing includes a stochastic component. Specifically, rather than comparing all features of every search item to the search template during each iteration of parallel processing, CASPER compares only a probabilistically chosen selection of target features to the search items, mimicking noise in parallel processing.

The contribution of parallel processing to the model’s performance is not instantaneous; items are differentiated in priority via the parallel process over time as the model runs. Decay and boosting of selection priority occur continuously in parallel for all items in the display during search, except during eye movements. Items do not decay out of contention completely via the parallel process, but they can become extremely unlikely to be selected for attentional scrutiny if they have a very low selection priority.

Items are accepted or rejected as the target via the serial process. When an item is selected for attentional scrutiny, the model compares the features of the target template to all the features of the selected search item. If the item is an exact match to the target template, the target is found and the search terminates. If the item is not an exact match to the target template, the item is rejected and a new item is selected for scrutiny, until there are no candidate items remaining in the display.

As the number of distractors in the display increases, there is more opportunity for items to decay out of practical contention via the parallel process before they are selected for attentional scrutiny. When this happens, CASPER produces negatively accelerating functions of response time (RT) vs set size.

**Representation of Shape and Color in CASPER**

CASPER encodes both the target template and the search items as vectors that contain features that represent aspects of color and shape. As described in theoretical claim #5, CASPER assumes that relevant features can be represented as early as area V2, but no earlier. The model further assumes that the visual system will utilize all levels of representation (i.e., line segments and junctions in V2, color and surfaces in V4, and object parts and objects in lateral occipital complex (LOC) and higher areas) that are appropriate to the task. In the current version of the model, all the representations of shape and color are a hybrid of low and mid-level features that are known to be diagnostic of shape. However, no claims are made about their completeness or correctness. They are better viewed as a first approximation and a work in progress that is extensible to more sophisticated representational schemes in the future.

The representations of shape in the current model include oriented line segments, diagonal segments, L-vertices, T-junctions, and X-junctions. These can be combined to create typical visual search stimuli, such as Ts, Ls, X’s, O’s, and so forth. CASPER represents color using an opponent color system like that of the primate visual system. Color is coded according to red-green opponency, blue-yellow opponency, and black-white opponency.

Each feature is represented as a trinary (1, 0, -1) encoding of presence (1), absence (0), or opposition (-1) in either the target template or search items. Some features are coded by multiple vector entries, allowing CASPER to encode the strength of a color feature’s presence (e.g., a saturated red vs an unsaturated red). Extra representational resolution is also given to vertical and horizontal oriented line segments. The representations of color and shape in the current version of model are shown in Tables 2 and 3, respectively.

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| **Color** | **White/Black** | **Red/Green** | **Blue/Yellow** |
| White | 1, 1, 1,-1,-1,-1 | 0, 0, 0, 0, 0, 0 | 0, 0, 0, 0, 0, 0 |
| Black | -1,-1,-1, 1, 1, 1 | 0, 0, 0, 0, 0, 0 | 0, 0, 0 ,0, 0, 0 |
| Red | 0, 0, 0, 0, 0, 0 | 1, 1, 1,-1,-1,-1 | 0, 0, 0 ,0, 0, 0 |
| Green | 0, 0, 0, 0, 0, 0 | -1,-1,-1, 1, 1, 1 | 0, 0, 0 ,0, 0, 0 |
| Blue | 0, 0, 0, 0, 0, 0 | 0, 0, 0 ,0, 0, 0 | 1, 1, 1,-1,-1,-1 |
| Yellow | 0, 0, 0, 0, 0, 0 | 1, 1, 1, 1, 1, 1 | -1,-1,-1, 1, 1, 1 |
| Orange | 0, 0, 0, 0, 0, 0 | 1, 1, 0,-1,-1, 0 | -1, 0, 0, 1, 0, 0 |
| Pink | 1, 1, 0,-1,-1, 0 | 1, 0, 0,-1, 0, 0 | 0, 0, 0 ,0, 0, 0 |

Table 2 Representations of color in CASPER. Color is represented using an opponent encoding scheme with white/black, red/green, and blue/yellow channels. Each of the six basic color categories used to encode opponent color have three bits of information, and can take on three values: 1, 0, and -1. For example a strongly red value would be encoded as {1, 1, 1,-1,-1,-1} on the red/green channel to indicate maximum red activity and the absence of green activity. An orange stimulus has a red/green channel encoding of {1, 1, 0, -1, -1, 0} to indicate the presence of some red information without the presence of green, and a blue/yellow encoding of {-1, 0, 0, 1, 0, 0} to indicate the presence of some yellow without the presence of blue.

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|  | **Orientation coding in units of Pi/8 radians** | | | | | | | | **L-**  **vertex** | **T-junction** | **X-**  **junction** |
| **Shape** | **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| Vertical | 1, 1, 1 | 1, 0 | 0, 0 | 0, 0 | 0, 0, 0 | 0, 0 | 0, 0 | 1, 0 | 0, 0, 0, 0 | 0, 0, 0, 0 | 0 |
| Horizontal | 0, 0, 0 | 0, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 1, 0 | 0, 0 | 0, 0 | 0, 0, 0, 0 | 0, 0, 0, 0 | 0 |
| T1 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 0, 0, 0, 0 | 1, 0, 0, 0 | 0 |
| T2 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 0, 0, 0, 0 | 0, 1, 0, 0 | 0 |
| T3 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 0, 0, 0, 0 | 0, 0, 1, 0 | 0 |
| T4 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 0, 0, 0, 0 | 0, 0, 0, 1 | 0 |
| L1 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 0, 0 | 0, 0 | 1, 0 | 1, 0, 0, 0 | 0, 0, 0, 0 | 0 |
| L2 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 0, 0 | 0, 0 | 1, 0 | 0, 1, 0, 0 | 0, 0, 0, 0 | 0 |
| L3 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 0, 0 | 0, 0 | 1, 0 | 0, 0, 1, 0 | 0, 0, 0, 0 | 0 |
| L4 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 0, 0 | 0, 0 | 1, 0 | 0, 0, 0, 1 | 0, 0, 0, 0 | 0 |
| Pi/4 Diagonal | 0, 0, 0 | 1, 0 | 1, 1 | 1, 0 | 0, 0, 0 | 0, 0 | 0, 0 | 0, 0 | 0, 0, 0, 0 | 0, 0, 0, 0 | 0 |
| 3Pi/4Diagonal | 0, 0, 0 | 0, 0 | 0, 0 | 0, 0 | 0, 0, 0 | 1, 0 | 1, 1 | 1, 0 | 0, 0, 0, 0 | 0, 0, 0, 0 | 0 |
| X | 0, 0, 0 | 1, 0 | 1, 1 | 1, 0 | 0, 0, 0 | 1, 0 | 1, 1 | 1, 0 | 0, 0, 0, 0 | 0, 0, 0, 0 | 1 |
| O | 1, 0, 0 | 1, 0 | 0, 0 | 1, 0 | 1, 0, 0 | 1, 0 | 1, 0 | 0, 0 | 0, 0, 0, 0 | 0, 0, 0, 0 | 0 |
| Q | 1, 0, 0 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 1, 0 | 1, 0 | 0, 0 | 0, 0, 0, 0 | 1, 0, 1, 0 | 1 |
| Pomerantz  (1997) Exp 5  ‘Poor’ Shape1 | 1, 1, 1 | 1, 1 | 1, 1 | 1, 1 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 0, 1, 0 | 0, 0, 0, 0 | 1 |
| Pomerantz  (1997) Exp 5  ‘Poor’ Shape2 | 1, 1, 1 | 1, 0 | 0, 0 | 1, 0 | 1, 1, 1 | 1, 1 | 1, 1 | 1, 0 | 1, 0, 1, 0 | 0, 0, 0, 0 | 0 |

Table 3 The simplified representations of shape in CASPER. In the current version of the model, shape is represented using four basic elements of shapes: oriented line segments in increments of Pi/8 radians, L-vertices, T-junctions, and X-junctions. Orientation is coded with multiple bits to capture strength of the representation, where all bits on is a strong representation and all bits off is the absence of a feature. Horizontal and vertical segments have an extra bit to capture bias toward horizontal and vertical. Oriented segments can have overlap in orientation. For example, a diagonal corresponding to orientation Pi/4 might also have weak activity in pi/8 and 3pi/8 orientations as well. L-vertices and T-junctions correspond to four orientations. X junctions have only one orientation.

**Item Selection in CASPER**

Unlike some other models of visual search, (e.g, TCTS; Lleras et al., 2020), candidate search items in CASPER are not selected strictly at random for attentional scrutiny. Search items are instead selected for serial scrutiny in CASPER according to Luce’s (1959) Choice Axiom, where the probability of an item being selected from the set of remaining items is given by:

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| --- | --- | --- |
|  |  | (1) |

whereis the selection priority of a given item as determined by the parallel processing mechanism described below. This means that the item with the highest selection priority is not necessarily selected as the next scrutinized target.

By default, CASPER simulates probabilistic eye movements to the attended search item with a higher probability of an eye movement the closer the item is to current fixation. The probability of an eye movement occurring is given by a distance weight, , where

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|  |  | (2) |

where is the distance of the item from fixation, and is a parameter that describes the distance at which an item is considered too distant for an eye movement to occur.

Eye movements can be turned off by setting a parameter. Eye movements incur a time cost of three simulation iterations, during which time parallel processing does not proceed. Item selection priorities are retained across eye movements (see Lleras et al., 2005). Once an item has been selected, attentional scrutiny occurs concurrently with parallel processing, meaning that additional parallel processing does not wait until serial scrutiny has occurred to proceed.

As items are rejected via serial scrutiny, the set of items becomes progressively smaller until either the target is found, or all items have been selected and rejected.

**Parallel Processing in CASPER**

Parallel processing occurs continuously during search, and its primary function is to set the priority for selection of an item for attentional scrutiny. Search items’ priorities update on every iteration of a simulation run. The change is based on two components. The first component is a decay factor that is uniformly applied over all items on every iteration of the model. The second component is an adjustment to the selection priority that is applied to each item that either offsets or reinforces the rate of decay in an item’s selection priority. The adjustment is based on a probabilistic match between the target template and the search item and can either boost the item’s priority or further reduce the item’s priority.

The change in the selection priority, , of item is given by:

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|  |  | (3) |

where is a decay rate, is the effect of distance from fixation, is the similarity of the item to the template (see Eq. 3 below), and is a random number taken from a uniform distribution between 0 and 1 that approximates noise in the system. is not permitted to fall below a minimum selection priority, .

The model assumes that the closer an item’s location is to fixation, the greater the ability to compare that item to the target template during parallel processing. The weight of distance on the comparison to the target, , is given by equation (2), and is the same term used to determine the probability of an eye movement. The ratio in equation (2) is the proportion of the maximum distance at which an item can receive an adjustment, resulting in a linear falloff of adjustment activity with distance from fixation.

The similarity match in the model is governed by a probabilistic sampling of feature dimensions in both the target template and the search items. At the beginning of a simulation, all possible feature dimensions are categorized as either relevant, irrelevant, or absent. Features are considered relevant if there is a mismatch on that feature between the target template and any search item. Features are deemed irrelevant if they are present in the template and the search items, but there is a match between the target template and the values of the features in the search items. Features that are deemed relevant are sampled with greater probability (probability = 0.9) than features that are not relevant (probability = 0.15). Features that are absent are not sampled.

The feature match during parallel processing is the sum of the match quality across all sampled features divided by the total number of relevant features, given by:

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|  |  | (4) |

where = 1 if feature was sampled, and 0 if was not, and = 1 if feature is relevant, and 0 if it is not. The feature weight in the match calculation, = 3.0 if the feature is present in the search template. If a feature is absent in the target templae but present in the search item, =1.0. The accumulation term, , is +1 if the value of in the search template matches the value of in item , and -1 if they mismatch. Recall that in the current version of the model, all features k are trinary, with a value of 1 if they are present, 0 if they are absent, and -1 if they are opposed by a present feature (e.g., in the way that green is opposed by red).

In other words, if a feature is sampled and there is a match between the target template and the search item, positive evidence is accumulated. If there is not a match, negative evidence is accumulated. If the sampled feature is present in the target template, it will count more toward the match calculation between the target template and the selected item than if the feature were not in the search template.

Figure X illustrates the parallel search process. At the beginning of search all item priorities begin to decay. Items that are near fixation will undergo greater adjustment than items that are far from fixation. Over time, items that are a better match to the target template retain higher priority compared to items that are worse matches. Some items that are not good matches and are far from fixation will rapidly lose selection priority so that they become unlikely to be a target of attentional scrutiny.

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| **A** | **B** | **C** | **D** |
|  |  |  | A picture containing clock  Description automatically generatedA picture containing object, clock  Description automatically generatedA picture containing clock  Description automatically generatedA picture containing diagram, design, graphics  Description automatically generated |

Figure 1 A) UPDATE THIS FIGURE At the beginning of search, all items are high priority for selection for focused attentional scrutiny B) Selection priority immediately begins to decay for all items C) Item priority is stochastically adjusted in proportion to each item’s similarity to the search target D) Decay and adjustment occur continuously in parallel across all items during search.

**Serial Processing in CASPER**

CASPER focuses attentional scrutiny on one item at a time. The serial process of selecting items for attentional scrutiny is depicted in Figure X. The match between the target template and a search item does not have a probabilistic component like in the parallel process. Instead, the match under attentional scrutiny is computed as a strict match on all the features between the target template and the search item . If an item is not an exact match for the target template, then the item is rejected and permanently removed as a candidate (Figure 3 B). It will no longer be selected by the model for attentional scrutiny, nor will it be updated via the parallel process. If the target is found, the search terminates (Figure 3 D). If all the items are rejected, the search also terminates.

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| --- | --- | --- | --- |
| **A** | **B** | **C** | **D** |
| **A picture containing diagram, design, graphics  Description automatically generated** | **A picture containing diagram, design, circle  Description automatically generated** | **A group of rectangles on a white background  Description automatically generated with low confidence** | **A picture containing graphics, diagram, screenshot, design  Description automatically generated** |

Figure 2 A) UPDATE THIS FIGURE While the parallel process continues, items are serially selected for focused attention by Luce’s choice axiom (depicted by the dotted circle) B) Selected items are matched to target or rejected by strict comparison across all feature dimensions. Rejected items are depicted in grey.  C) Rejected items are removed from contention for future selection D) When the search target is selected and matched via focused attention (indicated by the purple circle), the search terminates.

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