Can we perceive two colors at the same time? A direct test of Huang and Pashler's (2007) Boolean map theory of visual attention

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Published online: 25 January 2019
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Abstract

Can observers access two spatially separated color targets (e.g., red and green) at the same time (i.e., in parallel)? According to the Boolean map theory of visual attention (Huang & Pashler, *Psychological Review*, 114(3), 599–631, 2007), access to two different features that belong to the same dimension (e.g., red and green targets) is limited and therefore can be held only in a serial fashion. The current study proposes a strong test of the Boolean map theory of attention through the application of two of the most rigorous stochastic approaches to response times modeling—the *system factorial technology* (Townsend & Nozawa, 1995) and the *logical rule models* (Fifić, Little, & Nosofsky, *Psychological Review*, 117, 309–348, 2010). These approaches allowed identification of serial, parallel, and coactive architectures in the processing of multicolor targets. The results showed that multiple-color targets are processed serially when observers are required to process all the targets in the display (i.e., an exhaustive stopping rule), and in parallel or coactively when observers can terminate the search when one of the targets is found (i.e., self-terminating stopping rule). These results are generally inconsistent with predictions of the Boolean map theory. They highlight the role of stopping rules in multicolor visual search, as well as the flexibility of the attentional system in shifting between processing architectures.

Keywords Boolean map · Feature-based attention · Multiple-color search · Logical rule models

Attention is a fundamental ability that allows us to select small bits of information from the vast sensory input impinging on our senses according to predefined rules or templates (Desimone & Duncan, 1995; Fitousi, 2015, 2016, 2018; Fitousi & Wenger, 2011; Olivers, Peters, Houtkamp, & Roelfsema, 2011). An important question in the study of attention concerns the mechanisms by which observers select colored targets (Treisman & Gelade, 1980; Wolfe, 1994). Many situations in our daily life require color-based selection. For example, looking for a yellow taxi among other colored vehicles, or searching for a red apple embedded in a basket of green fruits. Can observers search for two different colored targets at the same time (e.g., a green and an orange fruit among red and yellow fruits)? The mechanisms and processes that govern multiple-color search are crucial for understanding central attentional phenomena, such as symmetry detection (Morales & Pashler, 1999), visual memory for objects (Fitousi, 2018; Vogel, Woodman, & Luck, 2001; Wheeler & Triesman, 2002), or color perception (D'zamura, 1991).

A basic issue in the study of multiple-color target search concerns the architecture by which multicolor targets are processed. Are two colored targets processed in serial or in parallel fashion? This issue has been in dispute over the past years. Several researchers have argued for serial processing (Houtkamp & Roelfsema, 2009; Woodman & Luck, 2003), while others have argued for parallel processing (Allport, 1971; Cavanagh, & Alvarez, 2005; Grubert & Eimer, 2015; Kyllingsbæk & Bundesen, 2007). A recent theory by Huang and Pashler (2007)—the *Boolean map theory of visual attention*—has been particularly influential. This theory raises strong theoretical and empirical claims for serial processing, based on the idea that logical operations are those that define the processing units in our visual field.

The goal of the present study has been to test various fundamental information processing characteristics of multicolor target search, and in particular to provide a strong test of the Boolean map theory (Huang & Pashler, 2007). This has been achieved by applying a rigorous stochastic modeling approach known as the *logical rule models of classification* (Fifić & Little, 2017; Fifić, Little, & Nosofsky, 2010; Little, Nosofsky, Donkin, & Denton, 2013) to a categorization task. The approach allows quantitative and qualitative tests of major information processing aspects such as architecture (serial,

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parallel, coactive) and stopping rule (self-terminating, exhaustive). To anticipate, the results were only partially consistent with predictions from the Boolean map theory. The current study found that when observers searched for two targets defined by two separate colors, both serial and parallel processing were involved, depending on the stopping rule adopted by the observer. Serial processing ensued when observers complied with an exhaustive stopping rule (i.e., processing stops when all items are accessed), whereas parallel processing emerged when observers used a self-terminating stopping rule (i.e., processing stops when the target item is found).

The Boolean map theory of visual attention

Huang and Pashler (2007) have recently proposed a *Boolean map theory of visual attention* that offers a principled account of attentional mechanisms. The theory addresses situations in which observers search for colored targets embedded in multicolor displays. A central prediction of the theory is that targets of different color (e.g., red or green) will be searched one at a time. In other words, observers cannot process in parallel spatially separated colored objects, but must do it in a serial manner. To understand why, consider first the notion of a Boolean map as outlined by the authors: “A Boolean map is a spatial representation that partitions a visual scene into two distinct and complementary regions: the region that is selected and the region that is not selected” (Huang & Pashler, 2007, p. 601). The Boolean map is constructed through the assignment of a single feature label from a single dimension. For example, a portion of space is tagged as “red”; now, if there is also a green color in this space, it will be tagged under a different location in the map—“green” (see Fig. 1). Three immediate implications of the theory are that (a) “only one feature value can be consciously accessed at one instant” (p. 607), (b) “feature-based selection can only be based on one feature value at one time (p. 607), and (c) visual search for a single feature—say, a green color—can be held simultaneously over multiple locations. The goal of the present study has been to provide a strong test of claim (b). This claim can be tested under conditions that require observers to look for two targets of different color.

Search for multiple-color targets: Serial or parallel?

Is search for multiple color targets serial or parallel? The evidence available is rather mixed. Support in serial processing comes from various behavioral studies. Houtkamp and Roelfsema (2009) asked observers to search for either one or two possible color targets in a rapid serial visual presentation stream (Experiment 2). Performance with two colors was

Fig. 1 Three possible Boolean maps according to Huang and Pashler (2007): (a) the map contains only the red circle and indicates its shape and color, (b) the map contains only the green square and indicates its shape and color, and (c) the map contains both the circle and square, but neither of the two colors. (Color figure online)

impaired compared to performance with a single color. Based on these results, and other experiments in which various types of features (e.g., shapes) were tested, these authors concluded that search for features (including color) is capacity limited and held in serial manner. Stroud, Menneer, Cave, Donnelly, and Rayner (2011) have shown similar impairment in tasks that simulated airport security checking. Participants were slower to find two different objects in different colors compared with a single object or two different objects that were defined by the same color. Their results demonstrate the limitations of multicolor search compared to single-color search, a limitation that supports serial processing with the former and parallel processing with latter.

Evidence for serial processing with multiple-colors targets has been presented by Huang and Pashler (2007) in support of their Boolean map theory. In a symmetry-detection task, Morales and Pashler (1999) asked participants to judge whether every square in a given color grid had the same color as the corresponding square located in the same distance across the axis of symmetry. The researchers found an increase in response latencies as a function of the number of colors (holding constant the size of the grid), a result that was taken by them as evidence for serial processing of color figures. Moreover, Morales and Pashler found faster response times (RTs) in a condition in which the difference between two grid displays involved four colors (ABCD) compared with a condition in which the difference involved only two colors (ABBA). These results were interpreted as evidence for serial scanning of subfigures. In another set of studies by Huang and Pashler (2002, 2007), color grids were presented in either a simultaneous or

successive mode. Then, participants were shown a test color and asked whether it was one of the colors of the displays. Performance was better in the successive condition compared with the simultaneous condition, a result that was taken as evidence for serial processing.

Evidence for parallel processing with multiple colors comes from behavioral and electrophysiological sources. D'zamura (1991) asked observers to search for one or two colored targets embedded among distractors of different colors (e.g., look for an orange or yellow target among green and red distractors). D'zamura tested for different target-distractor color values. He found a zero search slope for colors that were linearly separable in color space, but a steep slope for colors that were not linearly separable in color space. D'zamura argued that parallel processing is possible for color target (see also Bauer, Jolicoeur, & Cowan, 1996). More recently, Grubert and Eimer (2015) presented observers with two successive search arrays separated by either a short (10 ms) or relatively long (100 ms) stimulus-onset asynchrony (SOAs). Each of the displays consisted of two predefined target colors (e.g., red and green) and a distractor object in a different color (e.g., yellow and blue) on the opposite side. The targets appeared at different spatial locations. The participants' task was to indicate whether the two target-color items were of the same alphanumeric category. The N2p, an electrophysiological marker of selectivity (Luck & Hillyard, 1994), showed two independent components that exactly mimicked the presentation of each display in short or long SOAs. The signals were also of the exact size and overlapping in time. These results by Grubert and Eimer (2015) suggest that focal attention to each target color is allocated rapidly and in parallel, and that participants can attend to two different colored targets in parallel.

Mance, Becker, and Liu (2012) have used the simultaneous/sequential paradigm, asking participants to indicate whether a probe color matched one of two masked color targets that preceded it. The targets were presented either simultaneously or sequentially. Comparable performance was observed in the two conditions. Mance et al. argued that this result supports parallel processing and that it is at odds with the Boolean map theory (see also Miller, Becker, & Liu, 2014).

Testing serial-parallel processing: Problems and challenges

The brief literature review shows that research on multicolor search relies on three major procedures: (a) comparison of visual search performance for single and double color targets (Menneer et al., 2007), (b) comparison of simultaneous and successive displays (Duncan, 1980a, 1980b; Huang & Pashler, 2007), and (c) measurement of display set size effects

on RT slopes (Bauer et al., 1996; D'zamura, 1991; Morales & Pashler, 1999). Several problems challenge the conclusions drawn from these methods. First, methods (a) and (b) are suitable for probing capacity (i.e., limited, unlimited, super) but are only remotely associated with processing architecture (i.e., serial, parallel). Townsend and his colleagues (Townsend & Nozawa, 1995; Townsend & Wenger, 2004) have argued convincingly that processing capacity is defined by the change in a system efficiency when shifting from zero to one and two processing channels. Method (a) and (b) fit into this definition. Moreover, practitioners of these techniques often make the assumption that limited-capacity indicates serial processing, an inference that has been shown to be dubious (Townsend, 1972, 1990). A similar argument has been made recently by Howe and Ferguson (2017), who highlighted the limitations of the simultaneous-sequential paradigm in the study of binding: "While a finding of unlimited capacity is indicative, though by no means proof, of parallel processing (Townsend, 1972, 1990; Townsend & Wenger, 2004), a finding of limited capacity is much harder to interpret, as it is readily predicted by both parallel and serial models" (p.319).

A second problem concerns method (c), which uses search slopes patterns to make inferences regarding serial-parallel processing (D'zamura, 1991; Morales & Pashler, 1999). Townsend has shown mathematically that search slopes cannot distinguish serial from parallel search due to a mimicry problem (Townsend, 1990; Townsend & Wenger, 2004). For example, a steep search slope can be produced by a parallel processing system with limited capacity (Townsend, 1972).

A third problem with those methods is that they cannot probe *coactivation* (Miller, 1982; Townsend & Nozawa, 1995). In this type of architecture information from two or more targets coalesce together into a single accumulator and result in faster responses than for either of the targets due to the pooling of evidence. These methods are incapable of identifying coactive architecture.

Finally, none of these methods considers the strategy by which observers halt processing information, namely the *stopping rule* (Townsend, 1974). Observers can stop processing when all sources of information have completed (i.e., exhaustive stopping rule), or alternatively when only one of the sources has been completed (i.e., self-terminating stopping rule). The stopping rule is an important aspect of processing, but it is often overlooked in the literature on multicolor visual search. The logical rule models approach (Fifíć et al., 2010) can circumvent all of these problems. It is introduced next.

Logical rule models of classification response times

The logical rule models approach (Fifíć et al., 2010; Fifíć, Nosofsky, & Townsend, 2008; Fifíć & Townsend, 2010;

Little, Nosofsky, & Denton, 2011; Little et al., 2013) is becoming increasingly popular in recent years, with applications spanning over a wide range of research questions (for review, see Algom & Fitousi, 2016; Griffiths, Blunden, & Little, 2016). The approach allows researchers to distinguish among various architectures (serial, parallel, and coactive) and stopping rules (self-terminating, exhaustive) in the processing of multidimensional stimuli. The logical rule models approach builds on earlier major advances in the *system factorial technology* (SFT; Townsend & Nozawa, 1995), and marks an ingenious leap from SFT, as it combines the mathematical rigor and theoretical novelty of the SFT with parametric modeling of diffusion (Brown & Heathcote, 2008; Nosofsky & Palmeri, 1997; Ratcliff, 1978) and decision bound (Ashby, 2000; Ashby & Townsend, 1986) mechanisms.

The SFT (Townsend & Nozawa, 1995) and its offspring—the logical rule models (Fifich et al., 2010)—can distinguish among several basic processing architectures and stopping rules (see Fig. 2). In a *serial* architecture, the two sources of information (dimensions, features) are processed one after the other in sequence (Sternberg, 1969). In a *parallel* architecture, the two sources of information are processed simultaneously. Coactive processing (Fitousi & Wenger, 2013; Miller, 1982; Townsend & Nozawa, 1995; Townsend & Wenger, 2004) means that the two sources of information are processed in parallel, but are combined at some point downstream, coalescing into a single evidence accumulator. A decision is made when this accumulator exceeds a certain threshold.

The *stopping rule* is another important characteristic of human information processing (Townsend & Nozawa, 1995). It refers to the strategy by which observers halt processing before emitting their response. Processing of the two sources of information can be *self-terminating* (Townsend, 2001; Townsend & Colonius, 1997), such that observers halt when processing of only one of the informational sources has been completed. An *exhaustive* stopping rule refers to a strategy by which observers stop processing only after processing all sources of information, even when only one of the sources is necessary for response.

In combination, the reviewed architectures and stopping rules can give rise to five possible processing models¹: (1) serial self-terminating, (2) serial exhaustive, (3) parallel self-terminating, (4) parallel exhaustive, and (5) coactive (see Fig. 2).

Figure 3 illustrates a typical design in the application of the logical rule models. The stimuli are constructed by a full factorial combination of the two dimensions/features in question, with each dimension/feature varying on three discriminability levels. This yields nine stimuli that are divided into two categories: a *target* category and a *contrast* category. This division

Fig. 2 Five basic architectures that can be distinguished by system factorial technology and logical rule models

is dictated by the assignment of two decision bounds, one on each dimension/feature (see Fig. 3). As a result, the target category consists of the four upper stimuli, and the contrast category includes all of the five remaining stimuli. Correct categorization of an item as belonging to the target category requires that both values on dimension *x* AND on dimension *y* exceeds a criterial value (e.g., a requirement that enforces an exhaustive stopping rule). Correct categorization of an item as belonging to the contrast category requires that either dimension *x* OR dimension *y* exceeds a criterial value (e.g., a requirement that leaves the observer the opportunity to adopt either a self-terminating or an exhaustive stopping rule).

The items in the target category represent a factorial combination of low (L) and high (H) discriminability levels. In accordance with the general recognition theory approach (GRT; Ashby & Townsend, 1986) and similar decision bound theories (Ashby & Gott, 1988; Ashby & Townsend, 1986; Fitousi, 2018; Townsend, Houpt, &

¹ Other possible models include serial-parallel mixture models (Fifich et al., 2010) or, exemplar-based random walk models (Nosofsky & Palmeri, 1997)

Fig. 3 Stimuli space for the logical rule models: **(a)** items depicted by their dimensional structure **(b)**, items depicted by labels used in the numerical predictions **(c)**, and the same stimuli space along the

hypothesized normal distributions reflecting perceptual effects as assumed by decision boundary models (Ashby & Gott, 1988; Ashby & Townsend, 1986)

Silbert, 2012), it is assumed that the effect of each stimulus dimension/feature is associated with a normal distribution of perceptual effects. Participants establish a decision boundary to separate the target category (i.e., Category A) from the contrast category (i.e., Category B). To arrive at a categorization decision, the observer samples from the perceptual distributions using these samples to derive a random-walk (Fifić et al., 2010) processes toward a boundary. For example, a sample that falls in Category A will lead to a step toward the +A criterion.

These computational assumptions lead to testable predictions. For example, the items in the target category that are located farther from the decision boundaries should be easier to discriminate from the other category (Ashby & Gott, 1988). The qualitative model predictions are presented next.

Qualitative model predictions

Figure 4 presents the characteristic RT patterns predicted for stimuli from Category A (target category). The four stimuli in Category A (the target category) (LL, LH, HL, and HH) allow the computation of a mean interaction contrast (MIC) and the survivor interaction contrast (SIC; Townsend & Nozawa, 1995; for a review, see Algom, Eidels, Hawkins, Jefferson, & Townsend, 2015). In combination, these two functions are helpful in diagnosing various processing models. The MIC is computed as follows:

$$\text{MIC} = [\text{MRT}_{\text{LL}}(t) - \text{MRT}_{\text{LH}}(t)] - [\text{MRT}_{\text{HL}}(t) - \text{MRT}_{\text{HH}}(t)] = \text{MRT}_{\text{LL}}(t) - \text{MRT}_{\text{LH}}(t) - \text{MRT}_{\text{HL}}(t) + \text{MRT}_{\text{HH}}(t),$$

Fig. 4 Target Category (A): mean RTs (right panel) and survivor interaction contrast (SIC) predictions for serial exhaustive, parallel exhaustive, and coactive architectures (Townsend & Nozawa, 1995)

where MRT_{LL} , MRT_{LH} , MRT_{HL} , and MRT_{HH} refer to mean RTs for each of the four target category stimuli. Recall that correct categorization of the stimuli in the target category requires the observer to adopt an exhaustive stopping rule, and the predictions for the MIC follow the formal results proved by Townsend and Nozawa (1995) for this stopping rule. A serial architecture predicts an additive pattern with $MIC = 0$. The rational being that the difference in MRT when both features change from H to L should be equal to the sum of the difference MRT when only one of the features changes from H to L.

A parallel architecture predicts an underadditive pattern with $MIC < 0$. The actual RT in this architecture is dictated by the maximum processing time of the two features. Thus, processing is slower for any of the LL, LH, and HL stimuli

relative to the HH stimulus. A coactive architecture predicts an overadditive pattern with $MIC > 0$. Because in this architecture evidence from the two channels is summed up, having two slow components (LL) is more deleterious to overall performance than having only one slow component (L). All of these predictions do not rely on any distributional assumptions and hold as long as selective influence holds (Algom et al., 2015; Fitousi & Algom, 2018; Luce, 1986; Sternberg, 1969; Townsend & Nozawa, 1995).

The survival function, S , for a random variable, T (corresponding to time of processing), is the probability that T takes longer to complete than t , so that $S(t) = p(T > t)$. Note that $S(t) = 1 - F(t)$, with $F(t)$ denoting the distribution function for the same process. In a manner analogous to the calculation of the MIC, one calculates in each time bin, t , the values of the

survival function associated with each of the four types of target combinations, $S_{LL}(t)$, $S_{LH}(t)$, $S_{HL}(t)$, and $S_{HH}(t)$. The quantity known as the survivor interaction contrast (SIC) is then given by:

$$SIC(t) = [S_{LL}(t) - S_{LH}(t)] - [S_{HL}(t) - S_{HH}(t)] = S_{LL}(t) - S_{LH}(t) - S_{HL}(t) + S_{HH}(t),$$

where $S_{LL}(t)$, $S_{LH}(t)$, $S_{HL}(t)$, and $S_{HH}(t)$ are the survivor function for each of the four stimuli in the target category. Townsend and Nozawa, (1995) have proved formally that each architecture has a unique SIC function (see Fig. 4). For parallel exhaustive models, the predicted $SIC(t)$ function is negative for all values of t . For serial exhaustive models the predicted $SIC(t)$ is a negative function for small values of t , but becomes positive for larger values of t , with the areas below and under zero summing up to zero. For coactive architectures $SIC(t)$ is predicted to have an initial blip, followed by a positive part.

I turn now to the RT predictions for Category B (the contrast category). Note that for items in this category exhaustive processing is not mandatory, but in principle can be carried out. The items in the contrast category are designated by their location in the category space (see Fig. 3b). The interior I_x (I_y) stimuli are located near the boundary of the x (y) dimension. The exterior E_x (E_y) stimuli are located farther away from the boundary of the x (y) dimension. The redundant (R) is remote from both the x and y boundaries, and satisfies the disjunctive rule on both dimensions. Fifić et al. (2010) have shown that in the contrast category, each combination of architecture and stopping rule leads to a unique RT quantitative prediction² (see Fifić et al., 2010, p. 315, for detailed reasoning). Figure 5 presents the predictions of the logical rule models for each model. For example, it is predicted that in a fixed-order serial self-terminating model, all stimuli with the same value on the first-processed dimension (x_0v_0 , x_0v_1 , and x_0v_2) should have the same processing time. Thus, all stimuli, should produce equal mean RTs on the first processed dimension/feature, and slower mean RTs on the second processed dimension/feature. In the case that processing does not finish after the first dimension/feature (exhaustive stopping rule), response times will be shorter for the exterior stimulus compared with the interior stimulus because the former stimulus is farther from the decision bound. This will lead to situations in which the exterior stimulus on the second processed dimension/feature is processed faster than the interior.

Serial and parallel exhaustive models predict that the exterior items will be processed faster than the interior items and the redundant stimuli. The parallel self-terminating model predicts comparable performance for interior and exterior items. The coactive model predicts that the interior items will be

processed more efficiently than the exterior items. In sum, the contrast category can serve as a diagnostic tool for separating various classes of processing models (see Fig. 5).

Probing intradimensional (feature-based) attention with logical rule models

A fundamental distinction in cognitive psychology separates the visual world into two types of dimensions: *integral* and *separable* (Fitousi, 2015, 2016; Garner, 1974; Garner & Felfoldy, 1970; for review, see Algom & Fitousi, 2016). Integral dimensions (e.g., hue and brightness) are processed as a single unitary whole, cannot be attended selectively, and interfere with each other in Garner's speeded classification task (Garner, 1974). Separable dimensions (e.g., circle's diameter and the tilt of its radius), by contrast, are processed as independent entities, are easy to attend to selectively, and do not interfere with each in Garner's speeded classification task (Garner, 1974; Little, Wang, & Nosofsky, 2016). The distinction between integral and separable dimensions has proved valuable in validation of the logical rule models. In a landmark study, Fifić et al. (2008) have shown that separable dimensions (i.e., line orientation and the saturation of a spatially separated rectangle)³ were processed according to a serial or parallel architecture, whereas integral dimensions (i.e., hue and saturation) were processed according to coactive architecture. Later studies have extended the validity of these conclusions to other pairs of dimensions (Blunden, Wang, Griffiths, & Little, 2015; Little et al., 2011; Little et al., 2013; Little et al., 2016; Moneer, Wang, & Little, 2016).

Practitioners of the Garner and logical rule approaches have applied these methods successfully to research questions regarding *interdimensional* processing, providing new insights on how two dimensions (e.g., shape and color) are processed, and whether they interact in processing (Algom, Fitousi, Eidels, 2016; Algom & Fitousi, 2016; Fifić et al., 2010; Fifić et al., 2008; Fitousi & Wenger, 2013; Little et al., 2016; Moneer et al., 2016). Nothing in these methods precludes their application to *intradimensional* processing. These methods can be used to study how features from the same dimension are processed (e.g., color–color). The present effort employs the logical rule models (Fifić et al., 2010; Little et al., 2011) to unravel

² Note that the SIC functions are relevant only for the target category but are not diagnostic for the contrast category (Fifić et al., 2010; Griffiths et al., 2016).

³ Researchers who study dimensional interaction often assume that spatially separated dimensions are also separable dimensions. This conjuncture is incorrect. In a matter of fact, many integral dimensions are separated in space (cf. Algom & Fitousi, 2016). For example, Garner and Felfoldy (1970) have shown that dots separated in space but arranged in a “good configural form” are processed as integral dimensions (see also Hawkins, Houpt, Eidels, & Townsend, 2016). Fitousi and Algom (2006) have shown that numerical Stroop dimensions that are separated in space interfere with each other (see also Kahneman & Chajczyk, 1983). Thus, the fact that the components of the stimuli in the current investigation are located at different locations in space does not necessarily exclude coactive architecture.

Fig. 5 Predicted mean RTs for redundant, interior, and exterior stimuli in the contrast category for various processing models

fundamental intra-dimensional information processing characteristics in multicolor displays.

The current study

The logical rule models approach (Fifíc et al., 2010; Little, 2012; Little et al., 2011; Little et al., 2013) is employed here to assess fundamental information processing characteristics of multiple-color search. According to the Boolean map theory (Huang & Pashler, 2007), targets of different colors will be accessed one at a time. This claim has been translated into a set of qualitative and quantitative predictions derived from the SFT (Townsend & Nozawa, 1995), and logical rule models (Fifíc et al., 2010; Little et al., 2011; Little et al., 2013). The main hypothesis tested in the current study is that stimuli that are composed of spatially separated color patches (i.e., red and green squares) will be guided by two disjunctive Boolean maps, and therefore will be processed in either a serial self-terminating or serial exhaustive manner. A complementary hypothesis is that any parallel or coactive architectures (parallel self-terminating, parallel exhaustive, or coactive) found with these type of stimuli⁴ will necessarily refute the

Boolean map theory. Note that the Boolean map theory is not explicit about which stopping rule will be used by observers in each of the cases.

Methods

Participants

Four undergraduate students from Ariel University with normal or corrected-to-normal participated. They received course credit for their participation. All observers reported normal or corrected-to-normal vision.

Stimuli

There were nine stimuli in the experiment. Each stimulus was composed of two $1.83^\circ \times 1.83^\circ$ color squares arranged vertically, with a red square on top and a green square on bottom. The squares were separated by 5.0° from each other. The green and red hues were used because they are considered to be opponent colors (Hering, 1874/1964) that are processed by biologically distinct filters. As such, they allow the strongest test of the Boolean theory hypothesis. Each square varied on three levels of color typicality (Rosch, 1975), ranging from the most typical to the less typical. Different RGB values were used to create the Red color in high ($R = 255$, $G = 0$, $B = 0$),

⁴ Another hypothesis that can be derived from the Boolean map theory, but is not being tested here, is that stimuli composed of objects with the same color will be guided by a single conjunctive Boolean map, and therefore will be processed in either a parallel self-terminating, parallel exhaustive, or coactive manner.

medium ($R = 255$, $G = 199$, $B = 198$), and low ($R = 242$, $G = 134$, $B = 139$) levels of typicality. Different RGB values were used to create the Green color in high ($R = 0$, $G = 128$, $B = 0$), medium ($R = 215$, $G = 255$, $B = 255$), and low ($R = 166$, $G = 255$, $B = 166$) levels of typicality. The orthogonal manipulation of the color typicality levels resulted in the nine stimuli presented in Fig. 6. Stimuli names and their RGB values are presented in Table 1.

Procedure and design

Participants were seated in a dark room, approximately 56 cm from a desktop computer screen. The stimuli were presented over a white background at the middle of a computer screen. Each participant completed 22 blocks over 2 days. At the beginning of each session, the participants were presented with a diagram of the stimulus space, showing all nine items and the decision rule boundaries. The categories' structure and the decision rules were also carefully explained to the participants by the experimenter. Each session began with a practice block that consisted of 64 trials. The experimental session consisted of 11 blocks of 64 trials each. Blocks were separated by a short break. Stimuli presentation was randomized by the computer, with roughly similar frequency of presentation for items from Category A and Category B. Overall, each participant completed 2,816 trials. Each trial started by a fixation point that was presented for 500 ms, and then one of the nine stimuli was shown until response. Each category was assigned a key response. Participants pressed “M” if the item belonged to Category A (target category), and “z” if the item belonged to Category B (contrast category).

Fig. 6 Stimuli space for the system factorial technology rule-based task. Category A includes Items 1–4, whereas Category B included Items 5–9. O = very low; L = low; H = high

Table 1 RGB values used to construct the 9 stimuli

Stimulus	Top color (red)			Bottom color (green)			Salience	
	R	G	B	R	G	B	Red	Green
1	255	0	0	0	128	0	HH	
2	255	199	198	0	128	0	LH	
3	255	0	0	215	255	255	HL	
4	255	199	198	215	255	255	LH	
5	242	134	139	0	128	0	OH	
6	242	134	139	215	255	255	OL	
7	255	0	0	166	255	166	HO	
8	255	199	198	166	255	166	LO	
9	242	134	139	166	255	166	OO	

O = very low; L = low; H = high

Results

Trials with response times shorter than 150 ms or longer than three standard deviations from the mean of each participant (1.1%, 1.2%, 0.4%, and 1.5% for the four participants, respectively). Incorrect trials were excluded from the reaction time analyses (1.6%, 5.7%, 2.9%, 2%).

Target category

The mean response times for each of the four stimuli in the target category were computed for each observer. These are presented in left panel of Fig. 7. As can be noted, the effects of hue salience on the top and bottom colors were additive, a pattern that is most consistent with serial exhaustive processing (Sternberg, 1969; Townsend & Nozawa, 1995). A two-way ANOVA with top color and bottom color as factors confirmed the additive pattern in the data of all observers (see Table 2). Significant main effects were found for each of the factors, but none of the interactions was significant ($F < 1$ for all four observers). The outcome supported serial processing and is consistent with the hypothesis of the Boolean map theory (Huang & Pashler, 2007) that targets defined by different colors will be searched one at a time.

Next, consider the survivor interaction contrast functions SIC (t). These were computed separately for each observer, and can be seen in middle panel of Fig. 7. As can be noted, the functions were negative for small values of t and all positive beyond a certain large values of t . The total area spanned by the negative portion was equal to that spanned by the positive portion. This pattern is consistent with serial exhaustive processing.

For inferences from the MIC and SIC to be valid, SFT (Townsend & Nozawa, 1995) requires that selective

Fig. 7 Response time means (left panel), survivor functions (middle panel), and survivor interaction contrasts (right panel) for the four observers

influence (Dzhafarov, 2003; Luce, 1986) should hold. Selective influence entails that each factor was exclusively affecting one feature (top and bottom). One way of testing for the prevalence of selective influence in the data is by assessing the ordering of the survivor functions. If selective influence holds, then the four SIC functions should be separated from each other such that $S_{LL}(t) > S_{LH}(t)$, $S_{HL}(t) > S_{HH}(t)$, for any t . Both visual inspection (see Fig. 7) and statistical testing using Kolmogorov–Smirnov tests confirmed this ordering pattern (all $\hat{D}$ values were accompanied by $ps < .05$). This means that selective influence held in the data, and that the conclusions drawn from the MIC and SIC are valid.

Taken together, the results from the MIC and SIC analyses provide strong converging evidence for a serial exhaustive

processing of the two target colors. This result is in agreement with the predictions of the Boolean map theory (Huang & Pashler, 2007).

Contrast category

Mean RTs were computed per stimuli and per observer. These are presented in Fig. 8. Predictions for the contrast category are made with respect to the redundant, interior, and exterior stimuli. Table 3 gives the t -test outcomes of these predictions. A visual glimpse at the patterns of Observers 1 and 2 suggests roughly comparable RTs for the interior and exterior stimuli, and faster RT for the redundant stimulus, a pattern that is indicative of parallel self-terminating model (Fifić et al., 2010). The statistical analyses confirmed that there were no

Table 2 Results of ANOVA for each of eight individual observers in two experiments

Observe	Source	<i>MSE</i>	<i>F</i>	<i>p</i>
1	Top	1,854,914	43.17	.005***
	Bottom	3,383,039	78.74	.005***
	Top × Bottom	528	0.01	0.91
2	Top	482,138	18.45	.005***
	Bottom	2,583,425	98.88	.005***
	Top × Bottom	125	0.005	.90
3	Top	2,494,921	17.56	.005***
	Bottom	10,759,178	75.74	.005***
	Top × Bottom	10067	60.70	.40
4	Top	2,385,194	59.59	.005***
	Bottom	3,489,089	87.18	.005***
	Top × Bottom	21,137	0.52	.46

differences between the interior and exterior RTs for each feature, but the expected difference between the redundant stimulus and the interior and exterior stimulus of the first processed features was not significant. A visual inspection of the RTs pattern for Observer 3 suggested a coactive model with mean RTs of the exterior stimuli longer than those of the interior stimuli. The statistical tests supported only one of those differences. A visual inspection of the RT pattern of Observer 4 is consistent with a parallel self-terminating architecture. The statistical analyses confirmed this observation, but without an advantage of the redundant over the fastest of the features. Taken together, the qualitative RT results from the contrast category are most consistent with parallel self-terminating and coactive models rather than the serial exhaustive or serial self-terminating model, which were predicted by the Boolean map theory (Huang & Pashler, 2007), and other advocates of serial processing with multiple color targets (Houtkamp & Roelfsema, 2009).

To obtain greater confidence in these qualitative RT patterns, I apply a computational modeling approach, in which various parametric models are fitted to the RT data, and choose among the models with the best fit.

Contrast category: Computational modeling results

So far, the data were tested against qualitative nonparametric predictions derived from the SFT (Townsend & Nozawa, 1995) and logical rules (Fifíc et al., 2010) approaches. The logical rules models approach can be extended to quantitative modeling. Fifíc et al. (2010) showed that models can be fitted to the same data by incorporating concepts from decision bound (Ashby & Townsend, 1986) and random walk (Nosofsky & Palmeri, 1997) theories. This feat can extend

the validity of the conclusions drawn from the qualitative analyses (cf. Moneer et al., 2016). The modeling procedure performed here is comparable to the one performed by Fifíc et al. (2010), with a slight difference. The random-walk accumulator is replaced with linear ballistic accumulators (LBA; Brown & Heathcote, 2008).

A GRT-LBA⁵ version of the original random-walk model (Fifíc et al., 2010) is used here to fit five different models (serial exhaustive, serial self-terminating, parallel exhaustive, parallel self-terminating, and coactive) to the data of individual observers. The LBA is a multiple accumulator model with the assumption that within-trial evidence accumulation is a noise-free linear function of the input signal. A sample from the stimulus space that falls in Category A increases the evidence accrual toward threshold in Accumulator A, and similarly, a sample that falls in Category B, increases the evidence accrual toward threshold in Accumulator B.

I used a quantile-based maximum likelihood estimation method to fit the theoretical to the empirical correct and incorrect RT distributions (Heathcote, Brown, & Mewhort, 2002). Predictions were derived for each stimulus for the correct and incorrect RTs for five quantile bins. Fit was estimated using the multinomial log-likelihood function:

$$\ln L = \sum_{i=1}^n \ln(N_i!) - \sum_{i=1}^n \sum_{j=1}^{m+1} \ln(f_{ij}!) + \sum_{i=1}^n \sum_{j=1}^{m+1} f_{ij} \ln(p_{ij})$$

where N_i is the number of observations of stimulus i ($i = 1, n$), f_{ij} is the frequency with which stimulus i had a correct RT in the j th quantile ($j = 1, m$) or was accompanied by an error response ($j = m + 1$), and p_{ij} is the predicted probability that stimulus i had a correct RT in the j th quantile or was accompanied by error response. To balance for the different numbers of free parameters of each model, the log-likelihood values were transformed to the BIC (Schwarz, 1978), which takes into account the number of free parameters and the size of the sample to which the model was fit:

$$BIC = -2\ln L + n_p \ln(M)$$

where n_p is the number of free parameters in the model, and M is the total number of observations in the data set. The model that produces the smallest BIC is the winning model (Fifíc et al., 2010; Little et al., 2013).

Each one of the GRT-LBA models incorporated nine or 10 (depending on model) free parameters. The set of parameters included two parameters for the category decision bounds (D_x , D_y), two for the variance of the Gaussian distributions (θ_x^2 , θ_y^2), one for the intertrial variance of the drift rate (V_s), two for the barrier of the correct (b_c) and incorrect (b_{in}) LBA accumulators, one for the starting point of the accumulators (A), and one for the nondecision times (t_0). The drift rates (V_x and V_y)

⁵ I thank Dr. Daniel Little for sharing his code.

Fig. 8 Response time means for redundant (R), interior (I), and exterior (E) stimuli in the contrast category

were not free but were derived from the GRT space parameters. The drift rate for a given feature accumulator was computed from the mean, standard deviation, and the boundary for this feature by transforming the distance between the bound and mean of the distribution to a z score of a normal distribution, and then converting it into cumulative probability under this distribution. In this way, drift rates were proportional to

distance from bound, and reflected the evidence accrual rate by which sampling from the stimulus reached the bound. Hence, the drift rates were bounded between zero and one. Serial models (exhaustive, self-terminating) incorporated a 10th parameter (p) that reflected the probability of starting with the first feature or the second ($1 - p$) feature.

Fitting was performed by conducting a maximum likelihood search across a large parameter space. Each of the five models was fitted 100 times, starting each cycle with different random starting points of the parameter values. Each stimulus in a given model was simulated by sampling 10,000 samples. In total, there were 90,000 samples for a model. The winning models were those with the lowest $-\log$ maximum likelihood and BIC values. The $-\log$ likelihood and BIC values for each of the winning models are presented in Table 4. As can be noted, the lowest BIC values were generated by the parallel self-terminating model (Observers 1, 2, and 4), and the coactive model (Observer 3). The best-fitting parameters of this model can be seen in Table 5. The predicted and observed mean RTs for each stimulus for each observer can be found in Table 6. The degree of fit was quite good, and as can be seen in Fig. 9, the models accounted for the distributional aspects of the correct RTs quite well.

As can be seen in Table 4, the best-fitting models were the parallel self-terminating and coactive models, which yielded the lowest $-\log$ likelihood and BIC values. The coactive model was an apt competitor for the parallel self-terminating model. It was the preferable model for the data of Observer 3. The most important thing to note is the finding that serial models

Table 3 T -test results for the contrast category predictions

Observer	Stimuli	M	$-t$
1	E1–I1	2	0.03
	E2–I2	22	1.12
	E1–R	3	0.14
	I1–R	2	0.13
2	E1–I1	3	0.24
	E2–I2	9	0.58
	E1–R	10	1.08
	I1–R	13	1.32
3	E1–I1	56	1.78*
	E2–I2	40	0.96
	E1–R	57	1.62
	I1–R	1	0.04
4	E1–I1	28	1.78
	E2–I2	30	0.96
	E1–R	13	1.62
	I1–R	15	0.04

(self-terminating or exhaustive) provided a lower fit. The outcomes of the RT modeling are highly consistent with the quantitative findings from the contrast category. They support the parallel self-terminating processing found for Observers 1, 2, and 4, and coactive processing for Observer 3.

In sum, the quantitative and qualitative results from the target and contrast categories are highly consistent across observers. In the target category, items were processed serially, as indicated by the MIC and SIC analyses. In the contrast category, items were processed either in parallel self-terminating fashion, or in coactivation, as indicated by the qualitative RT patterns and model fits. The upshot is that the target category results are consistent with the Boolean map theory (Huang & Pashler, 2007), whereas the contrast category results are not.

General discussion

The goal of the present study was to probe the mechanisms that govern multicolor visual search. Another related goal was to put the Boolean map theory of visual attention (Huang & Pashler, 2007) under a rigorous scrutiny. The two aims have been accomplished through the application of the logical rule models of classification (Fifić & Little, 2017; Fifić et al., 2010; Little, 2012; Little et al., 2011; Little et al., 2013; Moneer et al., 2016) to a categorization task with multiple-color stimuli. The application has produced a wealth of qualitative and quantitative results at both the mean and the distributional levels of response times. These allowed a series of strong tests of the Boolean map theory of visual attention (Huang & Pashler, 2007).

Observers in the current study categorized stimuli into target and contrast categories. The categories were defined along two features, a red square on top and a green square on bottom. The red and green colors varied in typicality. Inclusion in the target category was dictated by a conjunctive rule (AND), whereas inclusion in the contrast category was dictated by a disjunctive rule (OR). The results showed that the items in the target category were processed in a serial exhaustive strategy, whereas items from the contrast category were processed in a

parallel self-terminating or coactive strategy. The model fitting of the contrast category showed a close competition between the parallel self-terminating and coactive models. It is therefore possible that a more elaborate version of the coactive model in which the drift rates vary separately for each stimulus, would have produced better fit than the parallel self-terminating model. In any case, it should be highlighted that the coactive model is a breed of the parallel model (Townsend & Nozawa, 1995).

To further elucidate the logical rule model results, I conducted an auxiliary experiment in which I collected similarity scaling data on the color stimuli set.⁶ The procedures and results of this experiment are presented in the Appendix. The multidimensional solutions of the similarity scaling are depicted in Fig. 10. As can be seen, the MDS solution roughly mimicked the general 3×3 factorial design, with the axes of the MDS solution possibly representing the a top and bottom color axes of the factorial design. The MDS solution shows that Stimuli 1–4 (the target category) preserved their factorial structure. They were equally spaced and placed in their right location. Stimuli 5–9 (the contrast category) mimicked the factorial structure to a lesser degree, mainly due to the dislocation of Stimulus 7. Therefore, the MDS solution suggests that at least in the contrast category, the top and bottom colors of the stimuli were not perceived independently of each other. This result might be consistent with the possibility that items in the contrast category were processed with a coactive architecture. This type of architecture was observed for at least one of the observers.

The Boolean map theory assumes that it is impossible to search for two colored targets in parallel. According to this theory, attention dissects the visual field into restricted regions by first labeling features inhering in these areas, and then assigning each with a region in a Boolean map. Features tagged with the same color are assigned to a single conjunctive area, whereas features tagged with different colors are assigned to separate disjunctive areas (see Fig. 1). Processing of a disjunctive map is held one at a time. The results of the current investigation are only partially consistent with the predictions of the Boolean map theory (Huang & Pashler, 2007) or with alternative accounts (Grubert &

Table 4 Best fitting parameters for the best fitting models. The $-\ln L$ and BIC values of the best fitting models appear in Bold

Serial self-terminating			Model type							
			Parallel self-terminating		Serial exhaustive		Parallel exhaustive		Coactive	
Obs.	$-\ln L$	BIC	$-\ln L$	BIC	$-\ln L$	BIC	$-\ln L$	BIC	$-\ln L$	BIC
1	688	1455	294	597	378	827	333	737	335	741
2	398	875	184	439	289	649	231	533	197	465
3	572	1,223	235	541	250	571	368	807	230	531
4	444	967	189	449	343	757	366	803	226	523

Table 5 Best fitting parameters for the best fitting models

Obs.	D _x	D _y	θ_x^2	θ_y^2	A	b _{correct}	b _{error}	vs	t ₀
1	0.56	0.55	1.85	0.99	67	380	10,000	0.18	10.23
2	0.60	0.63	1.00	0.46	180	464	17617	0.19	58.76
3	0.57	0.56	1.24	0.33	251	488	6.66×10^5	0.25	154
4	0.59	0.59	1.00	0.68	194	451	16,934	0.21	205

Eimer, 2015). How can they be reconciled with state-of-the-art theories of multiple-color search? One possibility is to discard the data from the target category and accept the conclusions drawn from the contrast category. Practitioners of the logical rule models (Little et al., 2011) have often claimed that the crux of the method is the qualitative and quantitative inferences derived from the contrast category (Little et al., 2011). If this option is chosen, then the results would be in complete disagreement with the Boolean map theory (Huang & Pashler, 2007), and in accordance with theories of parallel processing (Grubert & Eimer, 2015; Kyllingsbæk & Bundesen, 2007). However, it is difficult to justify the discarding of the data from the target category, especially given that the qualitative inferences from this category are based on solid formal proofs (Townsend & Nozawa, 1995), are not susceptible to known weaknesses of fitting procedures (Roberts & Pashler, 2000), and were highly reliable and consistent across observers.

A second possibility, and one that I endorse, is that the processing of multiple-color targets can be performed in either serial or parallel manner depending on the stopping rule adopted by the observer, and by implication the category membership of a given stimulus. This interpretation must assume some level of strategic flexibility in the observer's ability to switch between architectures and stopping rules within

the same block. Hence, a parsimonious explanation of the shift from serial to parallel search is that observers performed the task at two stages. At a first stage, participants were using some aspect of the stimuli, probably in a “preprocessing mode” to control such aspects as the operative architecture. At a second stage, they acted out their chosen architecture. An analogous phenomenon has been observed by Townsend and his colleagues, albeit in patterns of frequency rather than RTs, in a study on the perception of letter-like symbols constructed from line and curve features (Townsend, Hu, & Evans, 1984; Townsend, Hu, & Kadlec, 1988). They found that the sensitivity (measured by d') on individual features was a decreasing function of the number of features contained in the stimulus, a reasonable cause of limited capacity. However, the signal detection beta (β) for individual features also decreased as the number of the features in a stimulus increased. Such a result is impossible in the usual detection models. Hence, Townsend and colleagues hypothesized that a “preprocessing” stage in which an analysis of the overall complexity of the stimulus took place. A similar explanation applies to the current results, assuming an analogous preprocessor that can classify, with great uncertainty, the rough category of the stimulus pattern but must perform more operations to avoid serious error. If this account is true, then the Boolean map theory is correct in

Table 6 Observed and predicted mean RTs per stimulus per observer.

RT and error rate by participant									
Stimulus	1 X ₂ Y ₂	2 X ₂ Y ₁	3 X ₁ Y ₂	4 X ₁ Y ₁	5 X ₂ Y ₀	6 X ₁ Y ₀	7 X ₀ Y ₂	8 X ₀ Y ₁	9 X ₀ Y ₀
Observer 1									
RT observed	484	567	593	682	615	617	705	683	612
RT parallel self.ter	478	528	577	607	624	610	653	650	551
Observer 2									
RT observed	515	556	615	646	522	525	643	634	512
RT parallel self.ter	515	566	625	654	514	513	662	663	493
Observer 3									
RT observed	597	670	762	858	774	718	882	842	717
RT coactive	597	638	704	763	752	697	817	782	629
Observer 4									
RT observed	640	721	740	835	716	744	799	829	729
RT parallel self.ter	654	719	757	800	746	737	806	802	671

Fig. 9 Observed correct RT distributions (green histograms) for each of the nine stimuli and their predicted values (black lines) for the four observers. A = Observer 1; B = Observer 2; C = Observer 3; D = Observer 4

predicting serial processing for demanding tasks, those that employ complex displays and require multiple-features conjunction search (e.g., symmetry detection). The target

category of the current design is an example for such a demanding condition.

The current investigation highlights the importance of task complexity in determining the processing mode of observers. It also raises the possibility that observers can be flexible in choosing and carrying out their mode of processing. Although such flexibility seems implausible, it is supported by several findings in recent studies. Yang, Little, and Hsu (2014) examined the influence of an exogenous cue on the processing architecture in the Posner paradigm (Posner, 1980). They found that when the cue was 50% valid observers adopted a parallel self-terminating strategy, but when a cue was 100% valid the same observers switched to a serial self-terminating strategy. Yang et al. argued that participants are capable of exerting top-down control over their strategy by using the information from the cue. Specifically, when the cue is not informative, participants process the location in parallel, but when the cue is informative, observers narrow their attentional window and process the target in serial (see also, Yang & Chang, 2014). Mance et al. (2011) found that observers switched from parallel to serial processing when the display set size increased. Bushmakin, Eidels, and Heathcote (2017) revealed that observers could break the required stopping rule on a portion of the trials within the same block. Moneer et al. (2016) have found evidence for a mixture of parallel and serial strategies. Flexibility is therefore plausible even within the same block of trials.

Fig. 10 Multidimensional solution for the color stimuli used in the main experiment

A possible explanation to these changes in strategy may be related to capacity limitation exerted by the stimuli (Fitousi & Wenger, 2011). According to this explanation, capacity determines whether a serial or parallel strategy is used, and capacity itself is affected by the type of stopping rule adopted by the observer. In principle, the three informational characteristics of a system—capacity, architecture and stopping rule—are independent aspects of the human processor (Fitousi & Wenger, 2011; Townsend & Nozawa, 1995), but in certain cases these aspects can interact. For example, in tasks that require observers to process all the targets in a display (Morales & Pashler, 1999; Townsend et al., 1984; Townsend et al., 1988), observers may be limited in capacity and therefore choose to narrow their focus of attention (see Yang et al., 2014). This would necessarily lead to serial processing. However, when observers stop processing after one target (i.e., self-terminating stopping rule), they have more capacity at their disposal and therefore will use a parallel processing strategy (Fitousi & Wenger, 2011).

A similar argument regarding capacity and architecture has been made by Kyllingsbæk and Bundesen (2007). Their account is based on the computational reasoning of Bundesen's (1990) TVA model. According to this account, observers optimize their performance so that serial processing takes place when the time cost of shifting attention is outweighed by gain in speed of processing after attention is shifted. Kyllingsbæk and Bundesen (2007) showed that serial processing is optimal if the time to switch attention between objects is smaller than $1/C$, with C being the total amount of capacity.

The idea that capacity demands can lead to changes in the processing architecture of multicolor patches has also been suggested by Mance et al. (2012). They have used the sequential-simultaneous paradigm to test the consolidation of simple color features into working memory. In their experiments, a probe color patch followed two or more color patches. Participants indicated whether the probe matched one of the targets. The results showed that processing was parallel when the number of targets was small (i.e., 2), but serial when the number of targets was larger than 2 (i.e., 3, 4). Mance et al. (2012) attributed the effect of set size on processing architecture to capacity limits.

Categorical structures can guide attention to constituent features

Attention, memory, and categorization are often studied along separate research programs. This divide-and-conquer strategy has led researchers to adopt different perspectives regarding the same cognitive act. But the division is artificial. When you look for your car in a parking lot, you attend to cars and not to other objects, categorize these objects as cars, and use your memory to retrieve your own car. Logan (2002) has expressed

this idea succinctly: “To attend is to categorize; to categorize is to remember, to remember is to attend” (p. 376). The present study employed a categorization task to investigate the attention and memory processes that govern multicolor search. The results support Logan's claims. The response categories were instantiated as logical operations stored in memory. It turned out that these logical rules had fundamental influence on the attentional procedures, namely, the architecture by which the constituent features were processed. When the category was based on a conjunctive rule, processing was serial; when the category was based on a disjunctive rule, processing was parallel or coactive. These conclusions were supported by the results of qualitative and quantitative measures. The upshot of the current study is that perception and attention cannot be separated from categorization. To perceive a color is also to categorize it. This insight also lays at the heart of the Boolean map theory. The conjunctive and disjunctive maps proposed in the Boolean map theory assume that any act of cognition starts by categorization of the visual field. The Boolean rules are set by the observer at an early stage of processing and are determined by the nature of the features themselves. This conception is different from the current one, in which the logical rules are set up by the environment (e.g., the experimenter) and are independent of the stimuli structure.

Another contribution of the current study is in emphasizing the importance of stopping rules in intradimensional processing. Stopping rules play an important role in many cognitive tasks (Townsend, 1974), but rarely do they receive the consideration they deserve in research on attention (but see Bushmakin et al., 2017). The Boolean map theory (Huang & Pashler, 2007), for example, does not take into account the possibility that different tasks entail different stopping rules. Stopping rules are taken into consideration in the feature integration theory (Treisman & Gelade, 1980), which distinguishes between feature and conjunction search. But this theory does not address situations in which observers search for two color targets at once.

Finally, the current study demonstrates how the logical rule models can be extended to the domain of intradimensional processing. Many applications of the logical rule models concerned processing with pairs of integral or separable dimensions (Little et al., 2011; Moneer et al., 2016; cf. Algom & Fitousi, 2016; Algom, Eidels, & Fitousi, 2016). These dimensions were presented either at a single location in space and therefore as an integrated single object (Little et al., 2011; Moneer et al., 2016), or at two different locations as two separate objects (Fifit et al., 2010). The present study demonstrates the utility of such models in answering questions regarding the processing of features from the same dimension, addressing questions regarding feature-based attention (Treue & Trujillo, 1999), which are ubiquitous in many areas of attention research.

Acknowledgements I am grateful to Dr. Mario Fific, and two anonymous reviewers for their insightful ideas and suggestions on earlier versions of this paper. I also would like to thank Dr. Daniel Little for sharing his GRT-LBA code with me and for his generous help with the logical rule-based models. Finally, I would also like to thank Roslana Noredizki and Ran Neuman for helping with data collection.

Appendix Multidimensional-scaling experiment

In this [appendix](#), I describe the results of the similarity-scaling for the color stimuli used in the Experiment.

Method

Participants

Eighteen volunteers from Ariel University participated in the experiment. These observers had not participated in the SFT experiment. They received course credit for their participation.

Stimuli

The stimuli were the nine color patterns from the experiment reported. The color patches were presented in pairs on the computer screen. All possible pairs (81) were presented in a block. There were 10 blocks that amounted to 810 trials per participant. On each trial, participants rated the similarity of the pair of color patches on a scale from 1 (*very dissimilar*) to 8 (*very similar*). The order of presentation of pairs and the left-right placement of each color patch stimuli was randomized by the computer within each block.

Results

I analyzed the mean similarity judgments for the pairs of color patches using the Euclidian and Manhattan (city-block) models from the cmdscale function in R. The goodness of fit for the Euclidian model was slightly better (0.76) than that of the city-block model (0.72). The scaling solutions are displayed in Fig. 10. It is apparent from the visual display that the solution roughly mimicked the general structure of the 3×3 experimental design. Stimuli 1–4 (the target category) preserved the physical interrelation of the experimental structure. They were perceived as equally distant from each other and are placed in their right location. Stimuli 5–9 (the contrast category) mimicked the factorial structure to a lesser degree, mainly due to the dislocation of Stimulus 7.

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