INVESTIGATION OF VISUAL SEARCH TASK WITH CONSTANT DIMENSION AND VARYING VALUES

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1 ABSTRACT

The search time was recorded while each subject identified a target of single value among distractors of varying number of values. Three tasks were designed: purple in varying shades of purple, green in varying shades of purple, and upwards arrow in varying orientations of arrow. The search time of 9 subjects were examined in the task. This task was designed to investigate whether the feature integration theory of attention could be refuted.

The search time did not differ significantly despite increasing the number of values in the distractors. This resulted in a nonmonotic function relating search time and the number of values in the distractors. This relation was observed for all three tasks.

The nonomonotic function means that I fail to refute the claim from the feature integration theory that to idenify a target of single value, parallel search is possible. This study's and Treisman and Gelade's findings converge to reveal that FITA could be the mechanism by which the brain perceives objects. It is also worth noting that the average search time varied for the three different tasks. This could imply that the brain has a mechanism for delaying the registration of each value of the object before integrating them in the attentive phase.

2 INTRODUCTION

When we observe a rubik's cube, we can see the various colors, orientations, and shapes of the object as a coherent unit without much effort. There does not appear to be a need to parse each part of the object before perceiving the object. Based on this intuition, the Gestalt psychologists asserted that we first register the entire object as a whole, and only analzye the parts later if necessary [1]. The Feature-Integration Theory of Attention (FITA), in contrast, claims that values are registered early, automatically and in parallel across the visual field. Objects that contain values from multiple dimensions are identified separately and only at a later stage with focused attention[1] (Figure 1). Note that dimension is defined as the "complete range of variation which is separately analzyed by some functionally independent perceptual subsystem". Color, orientation, and direction of movement are examples of dimensions. A value is defined as a "particular value of a dimension". [1] Red and vertical are values of color and orientation respectively [1].

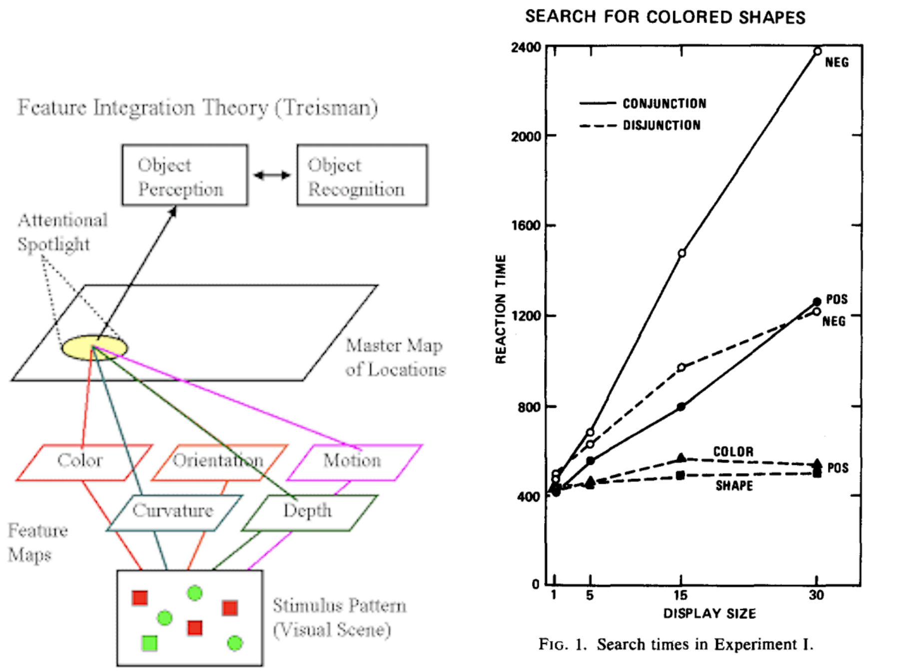
Treisman and Gelade conducted multiple experiments that converge to FITA. One aspect of FITA of interest in this paper is that **simple values can be detected in parallel given no attention limits**. The authors demonstrated this with a visual search task, varying the number of distractors in display. When a single value was sufficient to identify the target, the relationship between the search time and the number of distractors was nonmonotonic. In other words, participants displayed parallel search time (ST). (Figure 1) [1]

The ability to process information in parallel exists in computers, known as parallel computing. Computers have processors known as CPU and GPU, with the latter able to process instructions concurrently. We are unaware of processes like GPU in the brain consciously, and complete tasks serially like a CPU. There is also no known structure or mechanism that resembles the capacity of a GPU. Though we may lack the tools to study such mechanisms at this time, skeptism regarding the ability to process information in parallel remains.

1 Note that value is also referred to as feature

This paper addresses this skepticism by testing whether parallel processing is possible when identifying a single value among distractors of varying number of values. Note that instead of varying the number of distractors, this study varies the number of values among the distractors. For instance, when looking for a purple circle, there is a fixed number of distrators with varying numbers of colors, such as red and blue. According to FITA, regardless of the number of values among the distractors, as long as the target is distinguishable from the distractors, parallel processing should be possible.

The findings of this study can have implications on the mechanisms by which the brain processes information in a visual search task. There could also be implications on the validity of FITA.



(a) Graphical representation of the Feature Integration Theory of Attention[2]

(b) Treisman and Gelade reveal parallel search time for identifying simle feature

Figure 1: The Feature Integration Theory of Attention

3 METHODS

I created a visual search task (VST) for targets specificed by a single value. The following three tasks were tested (Figure 2)

1. Task 1: Purple in varying shades of purple
2. Task 2: Green in varying complementary colors
3. Task 3: Upwards arrow in varying orientations of arrow

3.1 Stimulus Design

Stimulus displays were programmed using Pschopy package in Python [3].25 circles of identical size and varying colors or orientations were presented. In each trial, the target may not be present. I randomized when the target is absent in the task. If the target was present, only one target was present. The location of the target and the varying color or orientation of distractors were also randomized. The random library was used to implement the randomness.

Each task had one to six varying values among the distractors. For task 1, the target had the color (162, 0, 255). The distractors had colors (183, 56, 255), (203, 112, 255), 223, 168, 255), (126, 0, 199), (91, 0, 143), (55, 0, 87), For task 2, the target had the color (162, 0, 255). The distractors had colors (255, 0, 0), (255, 255, 0), (255, 255, 0), (0, 255, 255), (0, 0, 255), (0, 0, 0). For task 3, the target had angle $0°$. The distractors had angles $45°, 90°, 135°, 180°, 270°, 315°$. (Figure 2)

3.2 Procedure

Each trial was presented through a 13in laptop screen. At the beginning of each task, subjects were given a practice round of five trials. Participants were instructed to take both accuracy and speed into account when searching for the target. After the practice, the participants pressed a button to start the task. Subjects were instructed to press "m" if they detected the target and "z" otherwise. Participants were shown the target for 1.5 seconds before each trial. During the trial, if the participant does not press any button after 10 seconds, the task moves onto the next trial. The search time (ST) was mesured using the clock class of PsychoPy, triggered by the pressing of "k" or "m". Each subject was tested for all three tasks in the following order: tasks 1, 2, 3. Accuracy of the visual search task was also measured in the program.

3.3 Subject

Nine subjects, eight male and one female, participated in the study. They were all undergraduate students from Duke University. None of the participants had participated in this study previously. Consent was obtained from each subject.

3.4 Data Analysis

The data was analyzed using MATLAB's standard library and the Statistics and Machine Learning Toolbox. I assumed that subjects with accuracy less than 70% were guessing, and thus excluded their data from analysis. To find the function relating search time to the number of values in the distractors, I averaged the ST from all qualified subjects for each number of values. Only the data when the target was present was considered. A linear regression model was used. An ANOVA test was also used to test for statistical significance.

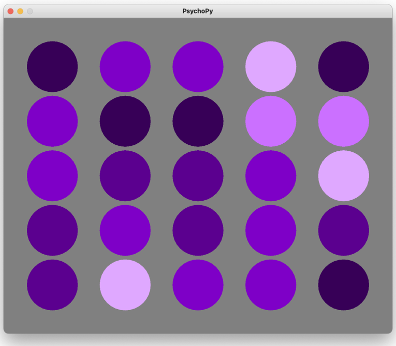
3.5 VST Program

The code is open source and can be found on GitHub.

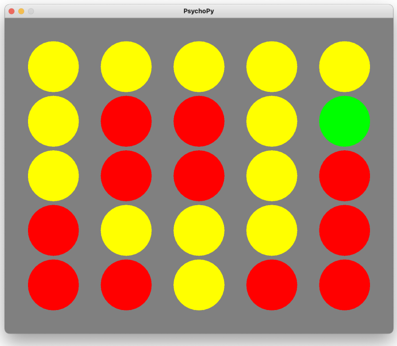
4 RESULTS

4.1 Linear Regression Model

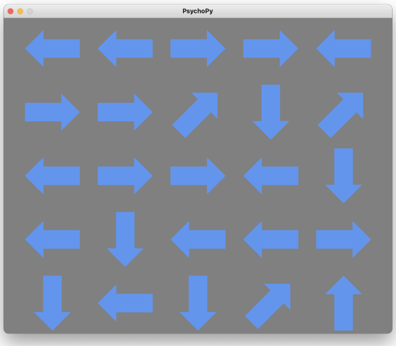
A linear regression model was used to approximate a function that relates varying number of values in the distractors and ST. For each task, the *slope* represents the average amount of ST increased when one additional value is added to the distractors. The p-value represents the significance of the linear model's representation of the data. The R^2 value represents what proportion of the data can be explained by the graph. This data is presented in a table (Table 1). The slope, p-value, and R^2 of the linear model after removing the dataset for which there is one value among the



(a) Task 1



(b) Task 2



(c) Task 3

Figure 2: An instance of a trial for each visual search task

distractors is also presented. The modified data has significant implications for the ANOVA test.

Table 1: Linear Model of Function Relating Number of Values and ST

Task	Slope	p-value	R^2
1	0.051111	0.054141	0.646
2	0.030596	0.010126	0.84
3	0.13955	0.014124	0.812
3^2	0.082912	0.0052637	0.947

4.2 ANOVA test

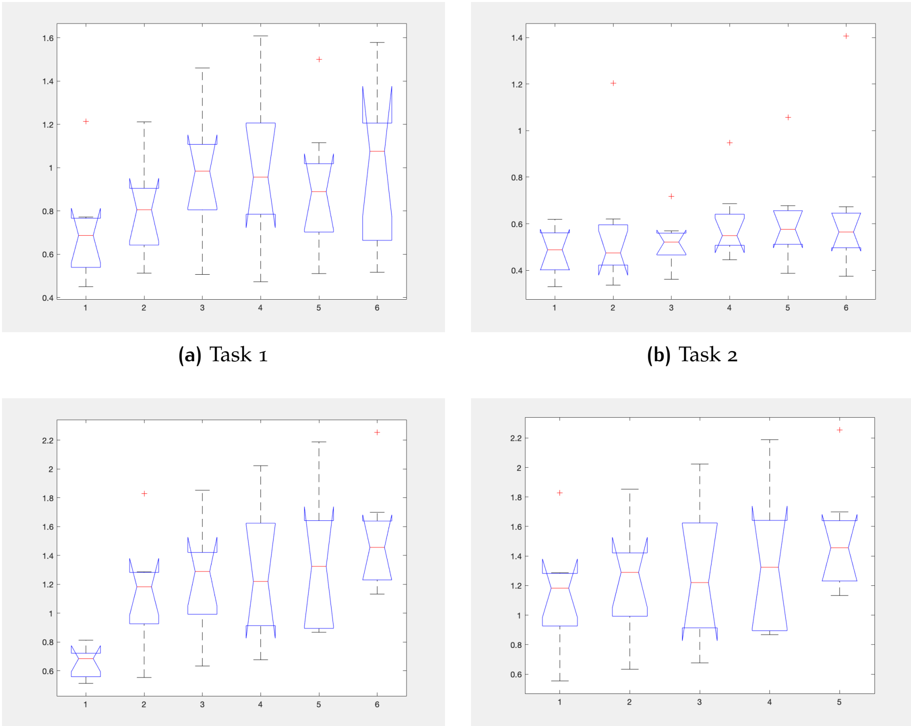
An ANOVA test was conducted to measure the significance of the relationship between ST and the number of values in the distractors (Table 2). It is worth noting the substantial increase in p-value for task 3 when the dataset for which there is one value among the distractors is removed. The results from the ANOVA test can also be visualized graphically (Figure 3).

4.3 Search Time Averages

The average search time was calculated for each task for all subjects. The ST for when the target was present and not present were calculated separately (Table 3).

Table 2: ANOVA Test

Task	p-value
1	0.2894
2	0.6185
3	0.0017
3[3]	0.4994



(a) Task 1

(b) Task 2

(c) Task 3

(d) Task 3

Figure 3: Graphical visualization of the ANOVA test for each task.

5 DISCUSSION

5.1 Parallel ST for Tasks 1 and 2

The R^2 values for all tasks were high, with the minimum being 0.646. Then the linear model is a fair representation of the data. The slopes of the linear model was smallest for task 2, followed by task 1 and task 3. It is important to note that the slope for task 2 and task 1 are close to 0, meaning that there is minimal increase in ST with the increase in the number of values in the distractors. To test the significance of tasks 1 and 2, ANOVA tests were conducted. The p-values for both tasks were less than 0.05. Then the null hypothesis cannot be rejected. In other words, there is no significant difference in the ST for the varying number of values

Table 3: Average Search Time when Target is Present and Not Present

Task	Avg ST with Target	Avg ST without Target
1	0.8963	1.3732
2	0.5720	0.7743
3	1.1946	2.5026

in the distractors. Then increassing the number of the values in the distractors does not affect the search time for tasks 1 and 2.

This is contradictory to our intuition. All subjects reported that they felt task 2 became more challenging as the number of values increased. In fact, some people found it hard to distinguish the varying shades of purple. Even then, their ST remained consistent with the increase in the number of values.This may hint that there is a computational process in search for a target that occurs subconsciously. This would conform to FITA, which states that immediacy and directness of an impression may not necessarily reflect the informational processing stage of the nervous system [1].

5.2 ST for Task 3

The slope for task 3 is substantially greater than that of tasks 1 and 2. The p-value of the ANOVA test is significant, meaning that we can reject the null hypothesis. In other words, for at least between two different number of values in the distractors, the search time was significantly differnet. Then we can definitely say the search time is not parallel, which would refute FITA.

However, if we remove the group when there is one value among the distractors, the p-value of the ANOVA test becomes not significant. Then, similarly to tasks 2 and 3, we fail to reject the null hypothesis that there is a significant difference in ST among the varying number of values in the distrators. We can also note that the slope for task 3 decreases substantially once the dataset is removed, becoming closer to 0. This hints, again, at parallel ST. Then we can claim that eventually for all three tasks, the function between the varying number of values in the distractors and ST is nonmonotonic. Note that the removal of the data is justfied because in real life, there are rarely instances when only one value exists other than the target.

5.3 Implications for FITA

The data conforms to the possibility that the brain is conducting parallel search in the visual search task. However, there remains a logical possibility that the brain is conducting serial search in the three tasks. Even though we are unaware consciously, the brain may be going through each object serially at a subconscious level until the target is found. As the number of distractors is fixed, the fast serial search would also record a flat function between ST and the varying number of values in the distractors. Treisman and Gelade, however, have refuted this possibility by comparing ST and varying number of distractors (Figure 1) [1]. The findings from this study and Treisman and Gelade's study converge to reveal that FITA could be the mechanism by which the brain perceives objects. Experiments that changes both the number of values in the distractors and the number of distractors should be explored in future studies. Parallel ST in this proposed experiment would further solidify FITA as the means by which the brain interprets objects.

One interesting finding to note is that the average ST for each task differs significantly. This raises the question of how the brain combines multiple dimensions after identifying multiple values, such as the color red and orientation at 47°. It appears that the brain will register the color first, then will have to wait for the orientation to be registered before becoming aware of what the object is. Note that we are unlikely to be consciously aware of this delay as the delay lasts only miliseconds. But to the brain, because action potentials occur in miliseconds, such delays would have significance. Therefore, it would be interesting to study how the brain implements such timing differences at a cellular level.

5.4 Limitations

The visual search task may fail to measure naturalistic behavior of identifying objects in life. For instance, when an individual identifies an apple, they are not actively trying to look for a target; they see the apple effortlessly. In fact, in this experiment, some subjects strategized to more efficiently find the target. The artificial nature of the experiment leaves questions as to whether FITA can be translated to settings outside experiments.

Moreover, it is challenging to know whether the individual is guessing answers in the visual search task. Asking the participants to not guess may not have been sufficient. I addressed this by filtering out data with accuracy less than 70%, but this number is arbitrary and does not neccessarily indicate that people with accuracy greater are not guessing. An experiment to determine the exact threshold at which people are not guessing would improve the reliability of this study.

The distance from the screen when partaking in the visual search task is also worth considering. Some subjects reported that the task became easier if they were looking at the screen from further distances. Though each subject were likely looking at the screen from similar distances, strictly controlling the distance could improve the reliability of the findings.

6 CONLUSION

I was skeptical that the brain could conduct searches in parallel time when one value was sufficient to identify the target. Therefore, this paper attempted to refute FITA by mesuring the function between varying the number of values in the distractors and the ST. The findings, however, fail to refute FITA and adds further support that we can search in parallel time. This is a fascinating outcome, especially given how challenging it has been for computer scientists to improve upon search time algorithms. Given an unorderd list of items, the fastest search time for a computer is $\mathcal{O}(n)$. This means that ST increases linearly with the increase in the number of objects. However, the brain appears to be able to search in $\mathcal{O}(1)$. Understanding the algorithm by which the brain uses neurons to search for objects at this rate would have massive implications not only for neuroscience but also computer science. Therefore, FITA should continue to be explored at multiple levels of neuroscience.

REFERENCES

[1] Treisman Anne M. and Gelade Garry. A feature-integration theory of attention. *Cognitive Psychology*, 12:97–136, 1980.

[2] Hniedziejko Christine. Feature integration theory. http://www.perceptionsense.com/2011/07/feature-integration-theory.html.

[3] Pierce J. W. et al. Psychopy2: experiments in behavior made easy. *Behavior Research Methods*, 50:195–203, 2019.