An Analysis of Visual Subitization Across Different Modes of Peripheral Vision

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Abstract

Subitizing, the ability of people to unconsciously and accurately count sufficiently small quantities of objects, is heavily tied to both visual perception and a somewhat fundamental understanding of mathematics. Peripheral vision, despite its wide range, has relatively poor visual acuity relative to central vision, which is primarily used when one focuses on an object. By using a custom testing interface (which flashed an image for a specific duration of time) and logging the result, it was possible to see the effect that peripheral vision, and by extension its reduced perception, had on the ability of one to subitize. The results indicated that there was a statistically significant difference for the accuracies between central vision and peripheral vision, but such a difference was not found between near peripheral vision and far peripheral vision.

Keywords
Subitization, counting, perception, peripheral vision, numbers.

1. Introduction
Subitization allows humans to visually deduce the quantity of a group or category of objects given that the number is less than 5 (Campbell, 1976). When one uses this process of subitizing, they can instantaneously recognize the numerosity of objects with almost absolute certainty (Kaufman, 1949). In this study, I investigated the connection between visual perception and subitization by testing the effect of different forms of vision on one's ability to precisely subitize a small group of objects.

Peripheral vision allows people to see objects that are outside the focus of the eye. Although central vision within the focus requires most of our mental resources, such as memory and attention, and allows us to see things with sharp detail, peripheral vision enables us to view objects around the entire visual field. However, peripheral vision has relatively poor acuity relative to foveal vision (Strasburger, 2011). Testing one's ability to subitize the number of objects presented to the peripheral vision compared to central vision will thus unveil whether visual resolution has a significant effect on subitization ability. While previous research has studied the perceptual aspects of subitization, this study will give some insight into the ability of humans to parse and count while simulating visual hindrance.

1.1 Objectives
I collected and analyzed data to evaluate the ability of people to accurately subitize the number of objects in a drawing along different angles of vision and the time in which an image was presented. I intend to find the accuracy of subitizing across different modes of peripheral vision and effects of the presentation duration on participants' performance.

2. Literature Review
Researchers concur on the idea that people are able to subitize instantly up to numbers less than five. A study by Campbell (1976) flashed afterimages, rather than displaying images, to force participants to subitize over direct counting, and the results indicated an almost instantaneous response for quantities less than or equal to four. Unless given the opportunity to linearly count, Cordes (2001) found that the variability of a person's response grows proportionally to the number displayed, indicating that the perception of numbers persists for larger numbers. Despite

the differences in accuracy between subitization and counting, however, Piazza (2002) demonstrated that similar neural pathways are used in both processes, albeit with different amounts of activations.

Although counting objects mostly involves visual activity, Riggs (2010) used a set of congenitally blind participants (who would have had minimal exposure to vision) and found no difference in subitizing ability between them and the visually sound. This appeared to indicate that subitizing had less of a link with vision and more with perception.

Previous studies have also shown that there exist differences for the ability of humans to perceive configurations of shapes with different arragements, particularly in the domain of peripheral vision. The results of Yildirim (2020) indicate that participants, when tested under peripheral vision, were progressively less capable of differentiating between figures spaced less than 0.25 times the eccentricity tested, along with irregular patterns producing better accuracy. The ability to differentiate between different item types also exists between subitizing and normal counting, as Trick (2008) demonstrated that a heterogeneous set of items was counted faster when participants used counting and slower when subitizing compared to a homogeneous set of items (with the same color and shape). These differences were also explored by Goldfarb (2013), who demonstrated that, unless non-counted objects had a specific pattern attributed to them, increasing their prevalence decreased subitizing performance.

3. Methods

Each participant was tested for five iterations for each of all possible combinations of the two dimensions tested - flash time (250ms, 500ms, 750ms, 1000ms) and type of vision (0 degrees, 30 degrees, 60 degrees). The 0 degrees of eccentricity was included as a control condition to test the effect that using peripheral vision would have on the participant. For testing, the ability to count numbers between 1 and 9 was tested so that the participant would have reduced certainty as to what number would be flashed.

I collected data with computer programs, as described in Section 4 in greater detail. A simple user interface consisting of forms was used to prompt the participant for the number of objects they saw. The experimenter could also change the two varying parameters: the time that an image is flashed and the angle at which the participant is tested. The five different parameters of the data point (the name of the participant, the flash time, the type of vision, the number of objects flashed, the participant's response) would then be dumped into a log, which could then be parsed by a python script. Matplotlib was also used in the script to generate graphical results.

I relied on standard deviation of a response from the correct number of objects to evaluate the spread of the responses. In order to evaluate mean differences across different treatment conditions, I used a two-sample t-test and a one-way ANOVA test, both implemented in scipy.

4. Data Collection

Due to restrictions of COVID-19, five people were able to take part in the study. While the sample is small, each participant has been tested on multiple occasions leading to a high-dimensional dataset of over 300 data points.
The study took place in a secure setting with a demarcated 11x17 piece of paper, a portable computer, and an object used as a point of focus.

The paper was taped close to the edge of the table where the participant would sit so that accurate markings could be done. A point was marked on the edge of the paper from where the participant's eyes would roughly be, and 5 lines representing deviations of 0, 30, and 60 degrees left and right of the participant's central vision were marked stemming from that point. On each of those five lines, a point was marked which was exactly 20cm from the point of concurrency of the lines. These five points were marked so that the monitor of the 13' Macbook Pro would be consistently 40cm away from the participants and so that the angle of vision tested would be consistent.

On the line where the participant's central vision is expected to be (The center line at 0 degrees of deviation), a narrow object was placed to ensure that the participant would not easily deviate from their vision (see Figure 1).

The laptop used was loaded with a set of PHP scripts located at https://github.com/junikimm717/OMSB9-Final-Project/tree/main/website to allow for interactive usage and automatic logging during the experiment. When testing, the script flashes a randomly chosen pre-loaded image (with javascript) for a quantity of time specified by its HTTP

GET parameters. The experimenter then queries the participant for the number of objects they saw and the data is logged when the experimenter submits the form.

The images consisted of identical and disjoint black circles whose diameters were ¼ to 1/5th the width of the canvas. The color contrast and size ratios were used to eliminate the vision of the participant confounding with the data of the experiment.

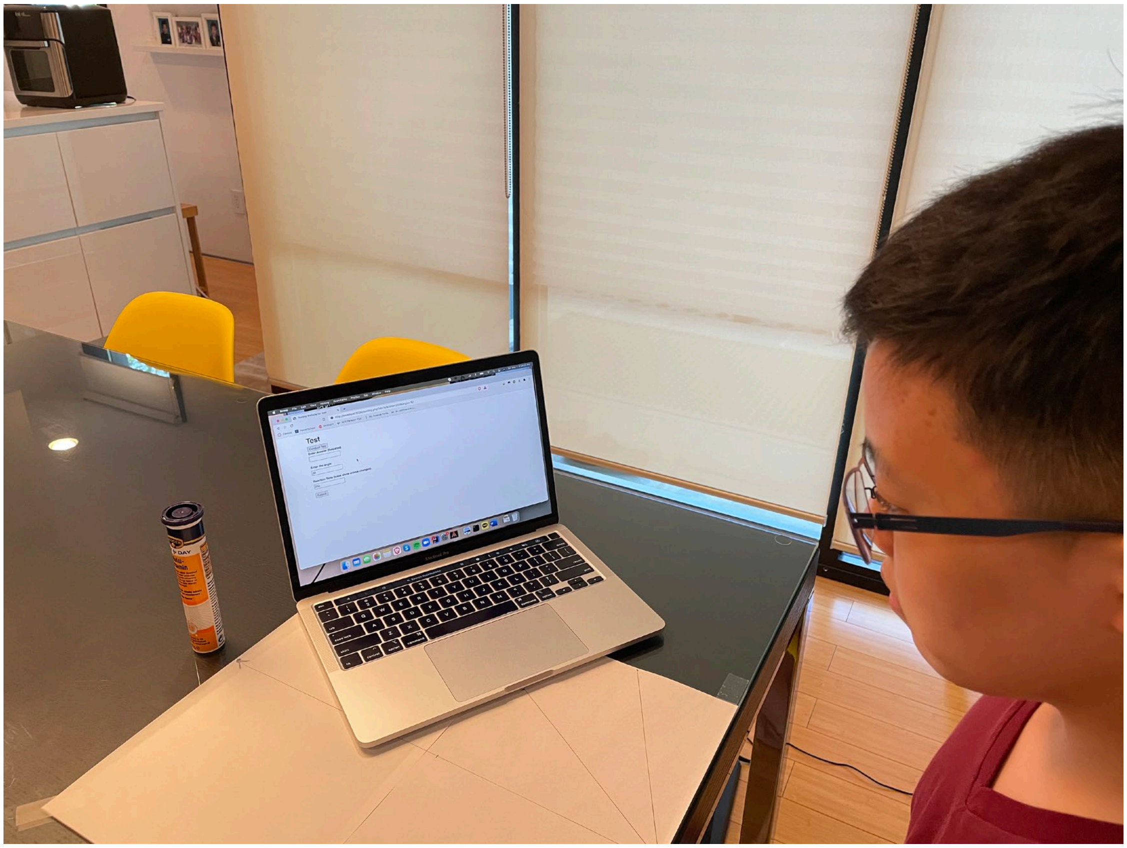

Figure 1: How the data collection process should appear

5. Results

5.1 Numerical Results[1]

The one-way ANOVA test resulted in a test statistic of 47.5 with a p-value of less than 0.001, which indicates that there is a statistically significant difference between the results across different angles.
To test whether the near peripheral vision yielded a statistically significantly better precision, I used a two-sample t-test. The results indicated a test statistic of -1.707 with a p-value = 0.121. This suggests that there this no statistically significant difference between precision when participants viewed the pictures from 30 degrees (near peripheral vision) versus 60 degrees (far peripheral vision).

[1] The logs generated by the script can be found at the following link: https://github.com/junikimm717/OMSB9-Final-Project/blob/main/data/data.txt Each row has four distinct columns: the time flashed (marked after "time:"), the id of the participant (marked after "id:"), the response the participant gave (marked after "answer:"), the actual number of items flashed (marked after "correct:"), and the angle of vision at which the participant was tested (marked after "angle:").

5.2 Graphical Results

Figure 2 shows the frequency of each amount of deviation, calculated as the absolute difference between the number of dots displayed and the participant's response, across all data points tested that had each form of eccentricity. The blue dots display frequency results for 0 degrees of eccentricity, the green for 30 degrees, and red for 60 degrees. The distribution of errors for central vision was highly positively skewed relative to the other distributions, suggesting that central vision yields significantly more accuracy than peripheral vision when subitizing.

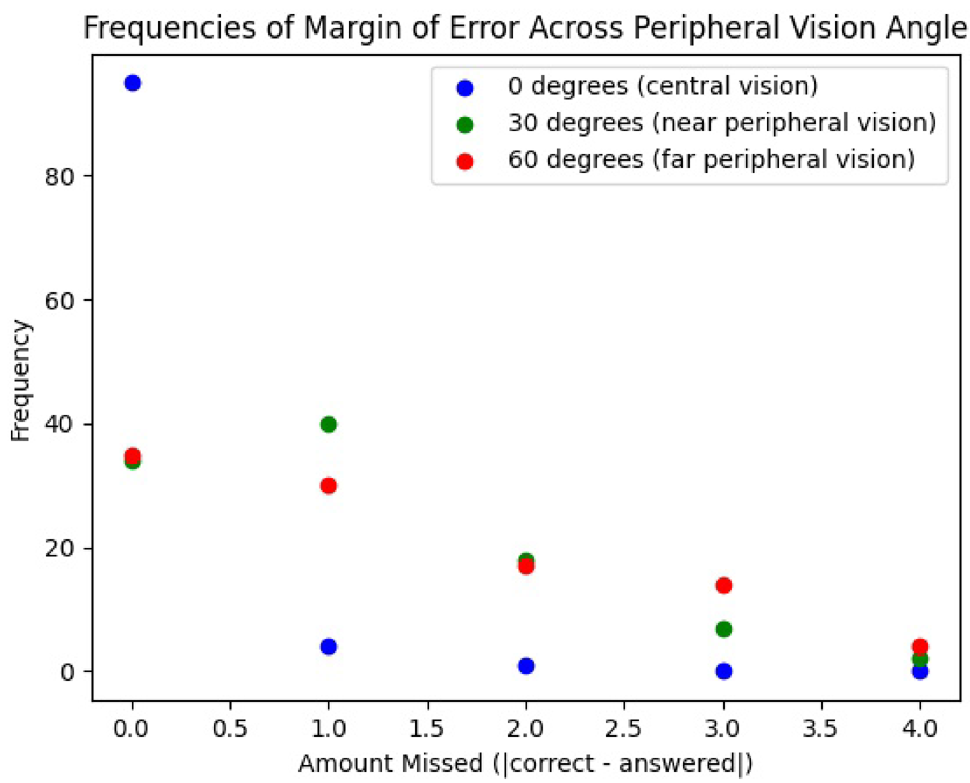

Figure 2: Frequency of deviations by vision type

5.3 Proposed Improvements

Given the limitations of the data, specifically a small number of subjects, I have not been able to perform all analyses to fully address my research question on the effects of the visual angle and stimulus duration on participants' subitizing performance.

Given COVID-19 restrictions, I was unable to get a larger set of peripheral vision angles to check, which might have allowed me to do a correlation analysis and thus gain better insights. Future researchers should also be able to obtain more volunteers than I have been able to.

There were also constraints from the programs that I used to run the tests. As I used browser javascript to flash the images, there were rendering issues within the browser once I set the flash time to below 150ms. It is possible that using a faster GUI program written in a faster environment would have allowed me to examine the correlations between flash time and subitization ability more precisely.

6. Conclusions

Based on the data collected and statistically analyzed in this study, I have been able to illustrate that the mean precision is different among tests from different angles of vision ($F = 47.5$, $p < .001$.). However, I have been unable to detect such a difference exists between near and far peripheral vision (same as for previous sentence—need ot report the actual values!). Despite the relatively large amount of data points tested, the p-values for statistical significance should be considered as an upper bound due to the small amount of people tested. The convenience sample could have also caused further confounding of the variables.

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Biography

Juni Kim is a rising sophomore at Stanford Online High School. He primarily conducts statistical analysis and data science by collecting data from UNIX-like operating systems and by creating programs to obtain data from people.