Effects of position on just noticeable differences

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Abstract

Just noticeable differences *(JND)* measure how much something must be changed in order for an individual to notice a difference [1]. This experiment explores how the position of an object might affect a subject's ability to perceive differences. Instead of having subjects point out differences, this study asked users to look at an image and adjust a similar secondary image until they appear identical to the user. Using this method, we can produce a quantifiable result based on the difference between the two images.

Introduction

JND are an important metric in sensation and perception and are often seen in measuring subtle differences in day to day life, like reading and viewing images. JND can be an important factor in computer science and human-computer interaction systems where understanding how the user operates the system is crucial to the product. It can also be used in marketing campaigns to maximize the number of positive features perceived and minimizing the negative features.

Because cortical magnification allocates more cognitive resources to stimuli near or on the fovea, [2] I hypothesize that objects that are centered in the visual field are given greater attention than objects near the peripheral of the visual field, causing subjects to have a higher accuracy in noticing differences.

Methods

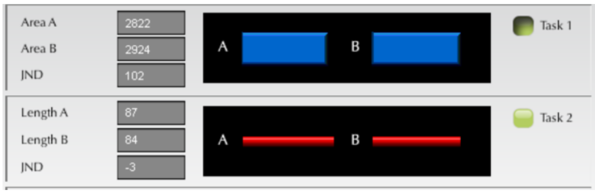
A total of ten test subjects were used in this study. The experiment was done through a Virtual Lab program. Participants were asked to sit at a laptop and then interact with the experiment program. The user typically sat approximately a foot or more away from the laptop, although this distance was not strictly enforced. The program displayed a total of three tasks to measure JND. Each task had a set of two images, the image to the right could be adjusted by the user and the first image to left was what the user had to compare to. The first task measured length similarity, the second area, and the third color saturation. Once done adjusting an image, the user was then instructed to press a "Result" button to record the data. Screen-captures of the results were then saved once the user finished.

In order to investigate the effects of position, the first five users performed the experiment with the program window centered, while the latter five users had the window moved to the top left corner before they started. The left upper corner was chosen as most users a statistically right eye dominant [3]. The intent of this was to reduce the amount of stimuli the user could perceive.

[1] USD Internet Sensation & Perception Laboratory, *http://apps.usd.edu/coglab/WebersLaw.html*

[2] Perception Chapter 4 Final Final Updated, *Dr. Jackie Berry*

[3] Eyedness, Chaurasia B.D., Mathur B.B.L., *https://www.karger.com/Article/Abstract/144681*



(a) Tasks 1 and 2

(b) Task 3 and control slider

Figure 1: Virtual Lab interface

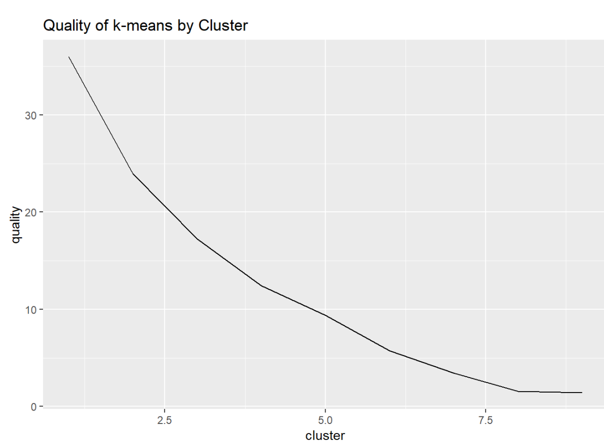
Results

The hypothesis asked if the position of an object has an effect on perceiving JND. In order to see if the data collected resulted in any noticeable trends to support this claim, we first determined if there were any distinct clusters of participants. If the entire dataset performed homogeneously, then the independent variable we were testing would have no effect on the data. In order to find distinct subgroups, the data was first normalized *(see appendix)* and then a K-means algorithm was used to find clusters. Since there were only 10 subjects, cluster sizes 1 to 9 was tested to find which cluster size would show a trend, *fig. 2.a* shows this relation graphed.

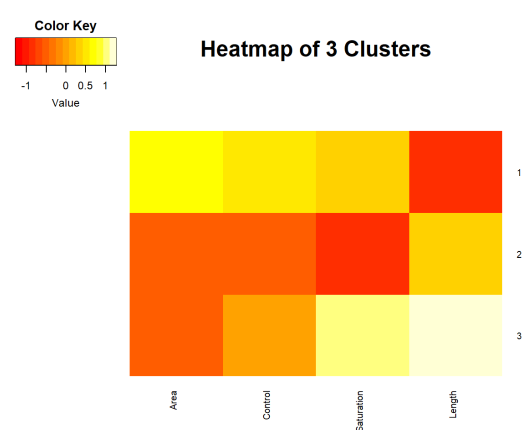
This algorithm takes advantage of partitioning the data into clusters by comparing the averages of combinations of data points together [4].

Examining the quality of the clusters, there is a distinct kink at $k = 2$ and a less noticeable kink at $k = 3$. This implies that there is a high level of variance between the subgroups we found at these cluster sizes. This also supports our original hypothesis as we had a control group and a variable group and so it is expected that our data should contain at least 2 distinct clusters. Due to the small sample size of participants, both clusters were explored to get a better understanding of the data.

At $k = 3$ we saw distinct clusters of size 4,4, and 2. This is the number of participants assigned to each cluster.



(a) K-means by Cluster



(b) Heat map

Figure 2: K-means analysis

[4]R K-Means clustering *https://stat.ethz.ch/R-manual/R-devel/library/stats/html/kmeans.html*

fig 2.b shows a heatmap comparing each group towards their performance of each task. Since the total number of participants were split into 3 clusters, each cluster contained some members from the control and variable groups. All three tasks measured the amount of difference between two images, therefore, a value close to 0 (orange) in the heat map indicates high performance whereas a very light or dark color indicates a larger difference and worse performance. Although the groups were partitioned by their performance there was little to no correlation between performance and which group the participant was in.
Cluster size 3 might indicate some other property between our participants but did not display any trend we were interested in, this is confirmed by box plots of each cluster, which showed no correlation between performance and group.

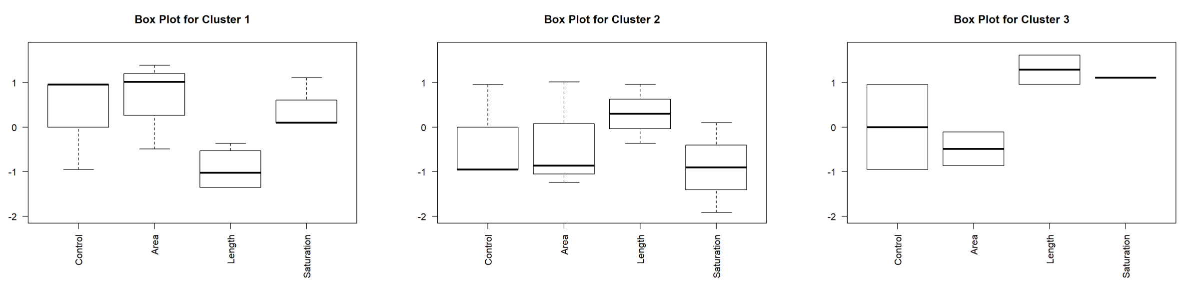
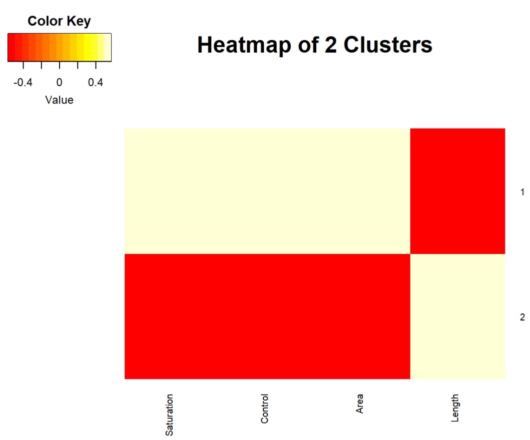


Figure 3: Box plot comparison

Examining cluster size 2 ($k = 2$) looked much more promising. Now the clusters were distinctly organized by which group its members belonged to which implies a correlation between group and performance exists.



This new heat map shows a clear distinction between groups. Cluster one is composed mainly of members from the control group ($4/5 \in control$). Cluster two is mainly variable ($4/5 \in variable$). Interestingly enough the two members who were in the minority of both clusters also composed cluster 3 when $k = 3$. This could imply that those two participants were outliers and might not have completed the experiment properly. Regardless, there is a clear distinction and we can infer some results from this set of data.
From figure 4, members in the control group scored almost opposite results to the variable group. This dataset implies that position effects JND on length differently than area and saturation.

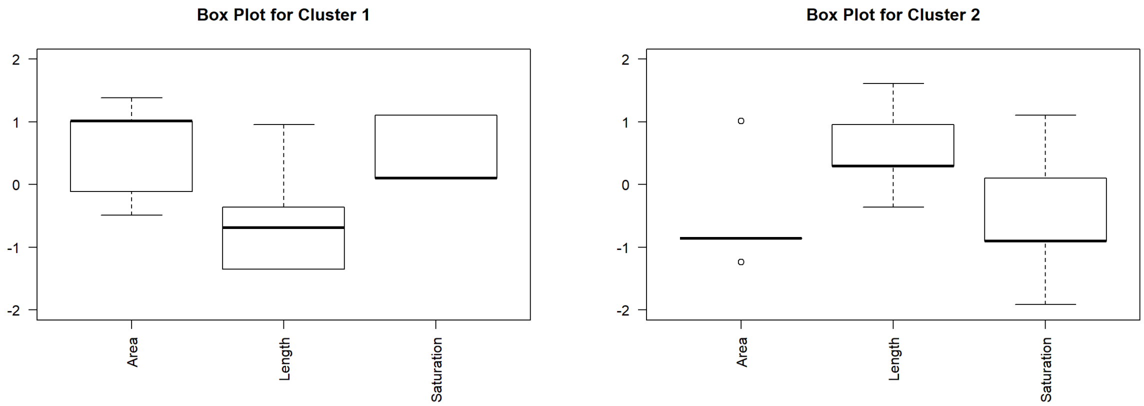


Figure 4: Box plot comparison for $k = 2$ *Note: Control has been removed since the amount of variance was far lower, 10% for each cluster*

The box plot for when $k = 2$ shows that cluster 2, the variable group performed typically better across all three tasks. However, due to the small sample size, there is a large margin of error. Due to this, the only statistically significant improvement is the task measuring area. There is not enough confidence between the other two tasks to assign any noticeable outcome to the position of the experiment window.

Discussion

Overall, the data shows that there exists some noticeable change in determining JND by changing the position of the object of interest. However, the extent of this change is hard to determine and appears to only affect specific properties over an object instead. Specifically, participants were able to notice differences in area more effectively than any other task. Since the stimuli were coming primarily from the left side to the left eye, perhaps the right hemisphere of the brain was activated more, which specializes in geometric patterns and spatial reasoning [5]. The control group was a little better at determining length, but not by a large amount. Since the stimuli, in this case, were centered, both eyes would receive information which would reduce the parallax effect caused by relying only on one eye. However, certain participants could have had an overly dominant eye which would reduce their ability to see differences in length as well, regardless of the position of the object.

The small sample size was a critical factor in limiting the effectiveness of this study because any discrepancy in performing the experiment could have dramatically shifted the results. It was also noted that some participants could have been outliers, because of the small sample size it was not feasible to remove them from the dataset without affecting the overall results too much.

Other factors such as the environment in which the experiment was taking place could have affected the results. For example, people moving and talking in the background was most likely a distraction that may have altered the participant's focus.

Finally, I believe these results do not support my original hypothesis but do support the idea that positioning objects in a certain way can force the brain to notice changes differently.

[5]Michael Gazzaniga - Cognitive Neuroscience. The Biology of the Mind - Hemispheric Specialization

Appendix

This page contains the raw data collected and operations performed on it.

Raw Data Collected:

Participant	Control*	Area	Length	Saturation
CC	1	102	-3	0
CK	1	-102	0	-8
DB	1	-34	2	4
JW	1	68	-2	0
KM	1	-68	-5	4
MM	-1	68	0	-4
MR	-1	-136	2	-4
RT	-1	-102	4	4
SJ	-1	68	-5	0
XH	-1	-102	-2	0

**Control is either set to a positive or negative number to differentiate which Participant is in which group*

Normalized data: *(R matrix scale operation)* [6]

Participant	Control	Area	Length	Saturation
CC	0.9486833	1.3864173	-0.6919318	0.1005602
CK	0.9486833	-0.1124122	0.9555249	1.1061625
DB	0.9486833	1.0117099	-0.3624405	0.1005602
JW	0.9486833	-0.4871196	-1.3509144	1.1061625
KM	-0.9486833	1.0117099	-1.3509144	0.1005602
MM	0.9486833	-0.861827	0.2965422	-1.9106443
MR	-0.9486833	1.011710	0.2965422	-0.9050421
RT	-0.9486833	-1.236534	0.9555249	-0.9050421
SJ	-0.9486833	-0.861827	1.6145075	1.1061625
XH	-0.9486833	-0.861827	-0.3624405	0.1005602

Special thanks to Thomas S. - Senior big data analyst & Submitty engineer for helping with data visualization and R programming.

[6] R scaling and centering matrices *https://stat.ethz.ch/R-manual/R-devel/library/base/html/scale.html*