Spatial Error in Virtual Reality

Data Vis Project Fall 2019

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Contents

1. PROCESS BOOK

1.1 Project info:

- **Class Website:** `https://matthewberger.github.io/teaching/vis/fall2019/project`
- **Github for Project:** `https://github.com/criselsuarez/Data_Vis_Project_2019`
- **Raw Data:** `https://vanderbilt.app.box.com/folder/90883476978`

1.2 Overview and Motivation

Virtual reality (VR) is a common conduit for examining how humans perceive and reason about space, because it provides a controlled, 3D environment for study. A subset of this area of research has evaluated how people reason about 3D space by looking at spatial orientation (or reorientation) where orientation is evaluated through a variety of a blindfolded pointing tasks.[1,2] In the current work, we want to create visualization to showcase how humans are behaving during these experiments so that we may better understand how humans make errors in spatial memory tasks.

1.3 Related Work

Prior VR studies that evaluate spatial memory through orientation only evaluate angular error on a single axis. Worse yet, error is typically displayed in a simple bar graph or line chart over aggregate data. As such, the underlying user behavior is unclear without an in-depth analysis of a given paper's statistics.

Moreover, target objects in these studies are typically placed at similar heights. For example, Williams et al.[1] evaluated target objects placed on the ground. And even when slope is encoded, orientation is evaluated from an allocentric–as opposed to an egocentric–perspective.[3] It is unknown how individuals encode height from an egocentric perspective in spatial memory tasks.

Furthermore, throughout all of the class assignments, we visualized bar graphs, scatter plots, line graphs, and heatmaps but we never touched on d3 polar graphs. We challenged ourselves to learn how to implement d3 polar graphs and considered the graphical perceptions of radius, angle and area.

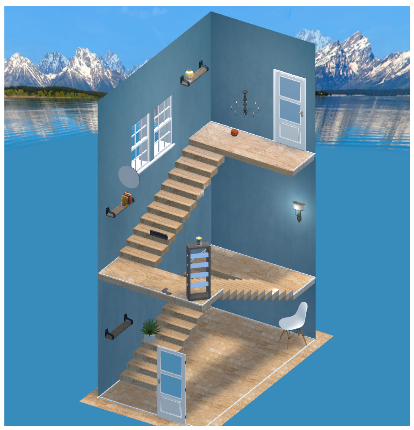

Figure 1. Virtual stairwell with target objects at variable heights

Figure 2. A participant explores the virtual environment

1.4 Questions

The main questions we asked were:

- How accurate are people at finding target objects in space?
- Where and how are they making errors? Was there bias towards a certain direction?
- What visualization is the most intuitive to visualize spatial error?

Other questions we tried to answer through the course of the project were: how accurate individual participants at finding target objects and where were individual participants making errors? However, we focused on individual objects angular error rather than the individual participant error.

1.5 Data

Preliminary data was collected from eight participants. All participants were tested in two environmental conditions: one in which nine target objects were placed near eye-height and one in which nine target objects were placed at varying heights (Figure 1). For the current experiment, we focused on evaluating the environment with varying heights since it provided the most novel condition of interest. The stairwells shared the same dimensions and features, excluding target objects. The order in which the two environments were displayed was counterbalanced across subjects. An image of a participant exploring the virtual environment can be seen in Figure 2.

An HTC Vive Pro (Figure 3) head-mounted display with a wireless adaptor was used to render the virtual environment and to track a user's position in space. For each condition, participants were allowed to freely

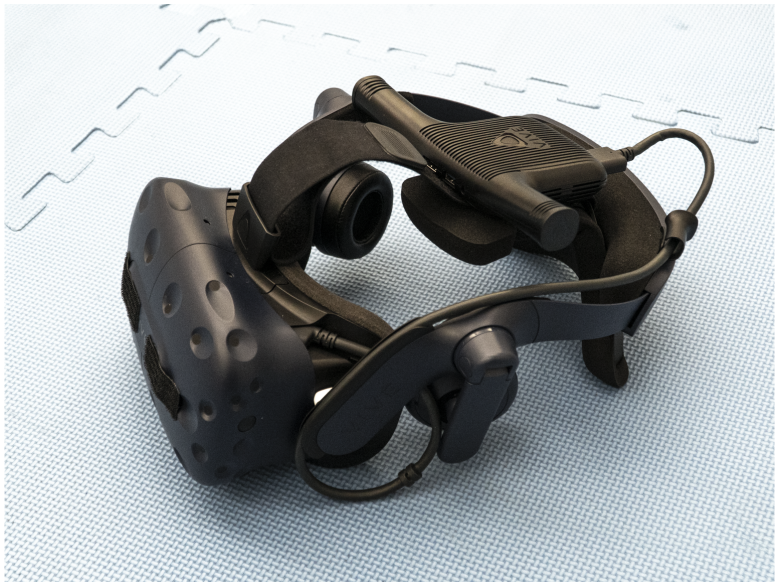

Figure 3. An image of the HTC Vive Pro with the wireless adapter)

explore the environment and they were told which objects in the stairwell were relevant for the experiment. After three minutes, participants were asked to stand at a predetermined vantage point on the stairwell from which all items were visible. The experimenter read aloud the testing protocol and removed visual feedback from the participant when they were ready to continue. During the experiment, the only visual feedback the participant received was a circle beneath their feet and a target placed at the center of the stairwell for resetting orientation between trials. Otherwise, the participant could only see a dark blue/gray hue. The two reset points were necessary to prevent drifting position and orientation during the experiment.

All participants conducted 27 total trials per condition. For each trial, participants were asked to turn to face a target object. And then they were asked to turn to face a target object. There were nine target objects total and participants were asked to turn to face each target three times.

For each trial, data was recorded at the start of the turn (when the participant faced the reset point) and data was recorded at the end of a turn (when the participant faced the target object). At these start and end points, information was extracted from the participant's gaze. Specifically, we recorded the user's direction vector and orientation. From these values a measure of angular error was recorded for the x and y axes. The time elapsed during a trial was also recorded.

1.5.1 Data Processing

For exploratory analysis of raw data, we included information from all 27 trials and we plotted pose using a polar coordinate system to accurately encode angle. However, performance on spatial orientation tasks is highly variable for a given subject. Therefore, for a more accurate representation of human performance we only observed median errors, which resulted in 9 trials per condition for each participant. Much of the data processing and cleaning was performed during collection (e.g,, angular error calculations) by one of our coauthors. The raw text data files we converted into CSV format for analysis, and recording errors were removed manually.

1.6 Implementation

In our final visualization (Figure 4) we implemented multiple scatter plots, polar graphs, and box plots. Each plot provided a unique view for observing turning errors collected from the spatial memory experiment, where turning error was recorded for each of the nine target objects across all participants. For each target, the signed turning angle error was recorded. A turning error of 0 corresponded to a completely accurate turn to the given target's position in the virtual room. If the turning error to a target object was negative in the 'Left/Right' plots, then the participant turned too far to the left of a target's actual position. If the turning error to a target

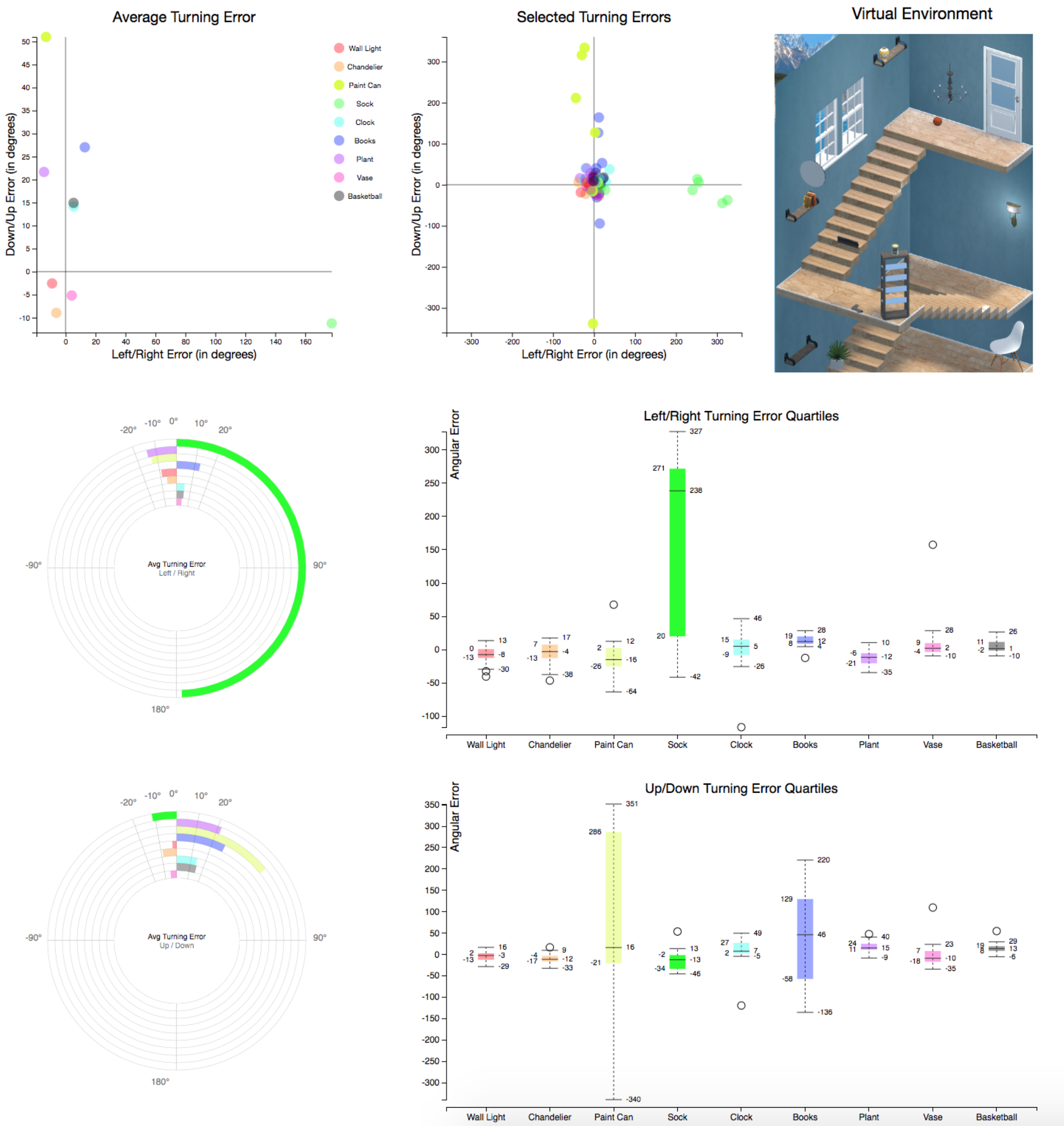

Figure 4. Final implemented visualization. Top Row: 1. Average Turning Error with hovering implementation to show Euclidean distances. 2. Selected Turning Errors, when clicking a selected object in Average Turning Error plot, that select object will populate the Selected Turning Errors with that objects turning error for all participants. 3. The Virtual Environment. Middle Row: 1. Left/Right Polar Coordinate Plot. 2. Left/Right Turning Error Quartiles. Bottom Row: 1. Up/Down Polar Coordinate Plot. 2. Up/Down Turning Error Quartiles.

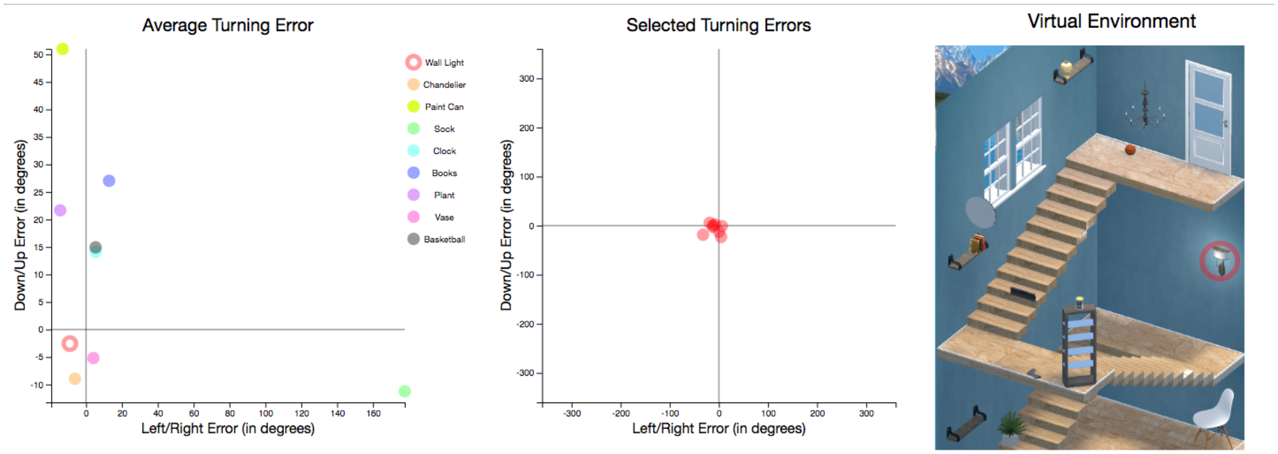

Figure 5. Subsection of final visualization to showcase interaction. If a user clicks on the Average Turning Error scatter plot labels or points, the Selected Turning Errors plot will update with all the error values of each participant. Additionally, a circle will appear where the object is in the Virtual Environment.

was negative in the Up/Down turning plots, then the participant turned to face down beyond the target object's actual position. An image of the virtual reality environment that was responsive to target item selections was also included among the more traditional plots.

For the Average Turning Error scatter-plot, the user could click elements on the legend and on the graph itself to make selective raw data appear on the adjacent Selected Turning Error scatter-plot. Furthermore, the corresponding target objects in the actual environment were highlighted with a transparent circle within the Virtual Environment image. For example, Figure 5 displays what the collection of interactive plots looks like when only the Wall Light target object is selected. Additionally, we included feedback for the scatter plot points to better inform viewers about individual points and to improve accuracy when reading our scatter plot. Specifically, we chose to show the pose of each point upon a mouse hover action as well as the euclidean distance from origin ($0°, 0°$).

In the polar coordinates plots we visualized the average turning angle for each object. We created two polar coordinates: one for the average Left/Right Turning Errors and one for Up/Down Turning Errors. For consistency, each object was depicted using the same unique color as used through the rest of the visualizations. The arcs that represented angular error were also placed at different radii to help distinguish marks. In each polar plot we visualized the angle by looking at the area mark for each angle to determine what objects had the greatest angular area error. The end result is a diverging radial bar chart.

In the box plots we implemented the five number summaries for each object in the study. We calculated the interquartile range (IQR), median, minimum, maximum and outliers. With the box plot we can see the variance and have a clear depiction of easy-to-understand quantities. Moreover, we implemented both Left/Right Turning Error Quartiles and Up/Down Turning Error Quartiles for each object. Once again, each objects is depicted in the same unique color throughout the visualizations.

Each type of visualization in the current demonstration comes with its own trade-offs. For example, the box plots visualize useful summaries but ultimately they cannot capture the fine details or even the distribution of the data set. In contrast, the Selected Turning Errors plot allows us to see each individual error that contributes to the mean value reported in the other plots. However, it is less useful for rapid analysis and takeaways for the observer. We believe that presenting these various visualization methods together will allow the viewer to explore and understand the data in a way that fits their needs.

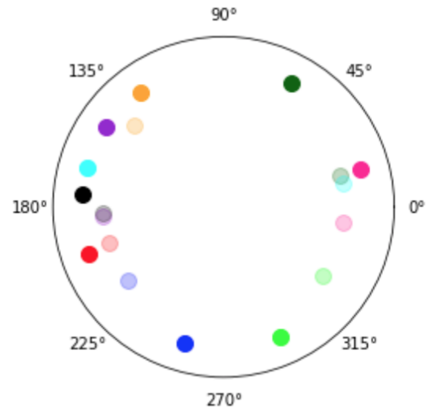

Figure 6. In this visualization the darker circles with higher opacity encode the true position of the targeted objects, while the lighter circles are the median position of three trails where the participant pointed. One of the issues we encounter with this visualization is the amount of clutter displaying 18 circles that were close to one another.

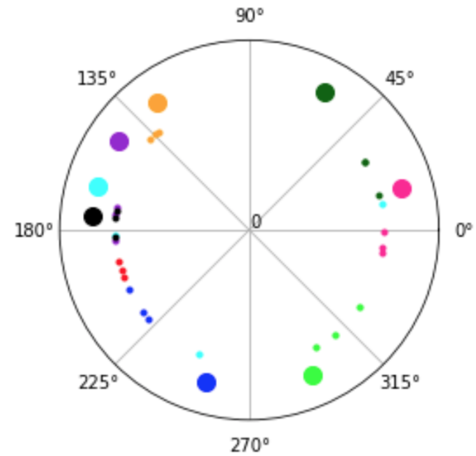

Figure 7. In this visualization we wanted to show all the 3 trails per object. We encoded bigger circles and longer radius to be the true position of the objects, while the smaller circles and radius were the participants' three different trails. One of the issues we encounter with this visualization is the amount of clutter displaying 27 circles that were close to one another and overlapping.

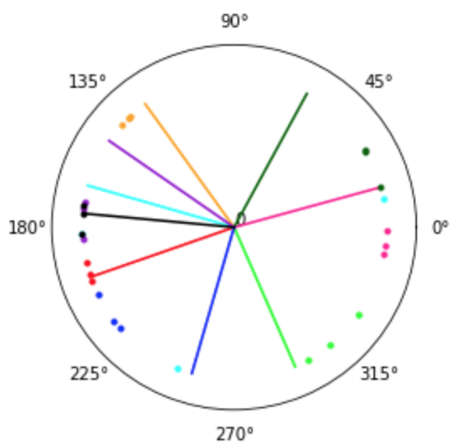

Figure 8. In this visualization the lines represent the true position of the targeted objects, while the circles are the position of three trails where the participant pointed. One of the issues we encounter with this visualization is the amount of clutter displaying 27 circles that were close to one another. Moreover, the lines displayed were somewhat distracting and seemed to inadvertently encode area.

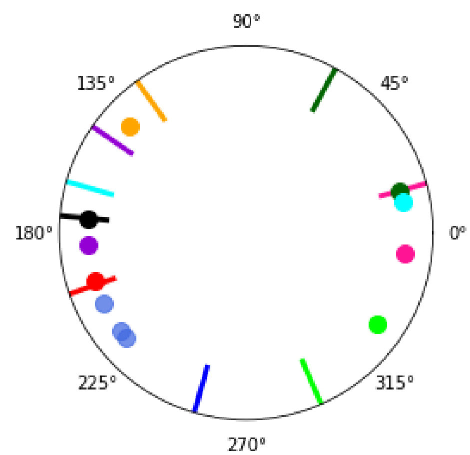

Figure 9. In this visualization the lines represent the true position of the targeted objects, while the circles are the position of median trail where the participant pointed. One of the ways we manged clutter was to only show the median position for each participant and then click on the object's position (circle) to see the three trails (example the three dark blue circles).

1.7 Exploratory Data Analysis

We first analyzed the performance of an individual during the experiment. Each different target object was encoded in a different color. One of the biggest challenges we encountered was clutter since many points would overlap across different trails, even for just one participant. This is due largely to the fact that target objects were placed in a circle around an individual who stood at the far end of a rectangular stairwell. This was done for the sake of creating a realistic environment. However, as a result, many target objects were placed close

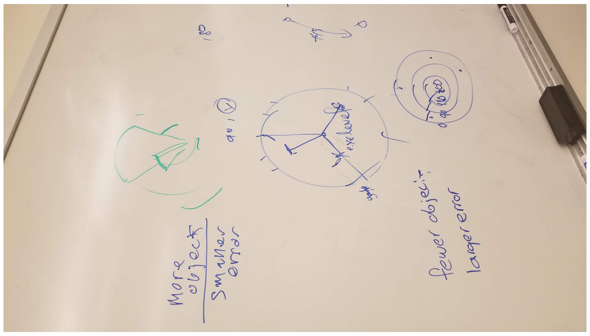

Figure 10. Several drafts for encoding angle and radius in polar plots. Here are a few examples in which we experimented cutting out overlapping areas of the circle, encoding error or time through radius, and the use of concentric rings to stagger data.

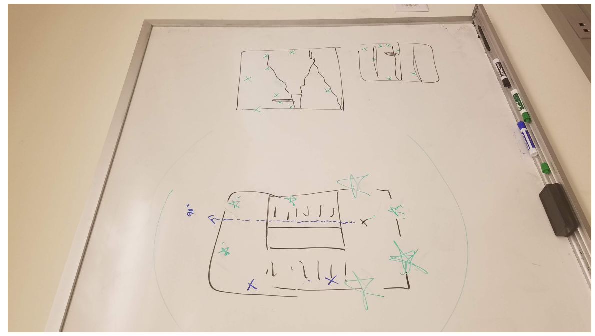

Figure 11. Early idea which involved superimposing glyphs on top of a depiction of the actual environment. Unfortunately, since both horizontal and vertical extents needed to be encoded, there was too much occlusion for this technique to be a viable option.

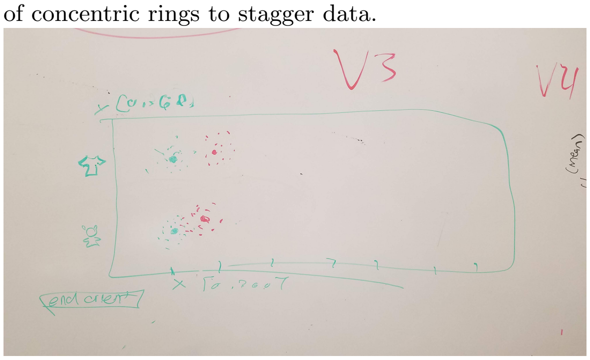

Figure 12. Initial scatter plot idea. Discarded early on due to a large number of overlapping points. However, we returned to this idea later on since the scatter plots were legible.

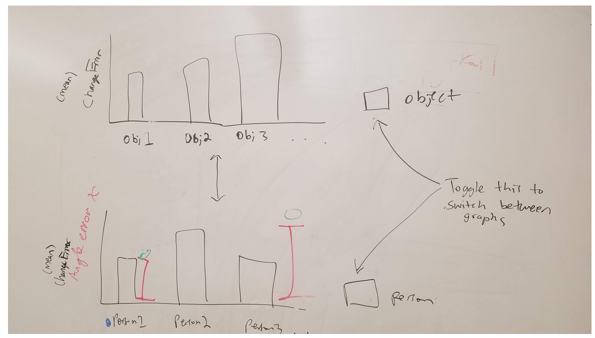

Figure 13. Initial bar plot idea. Discarded for lacking innovation and being inappropriate for depicting angles.

to each other. Figures 6-9 demonstrate several early versions of our polar graph that were created in Python. We used these preliminary polar coordinate plots to explore the data of a single participant and to see what challenges we would face when visualizing the data. The visual clutter problem was revealed due to these and several other early drafts.

Another issue with the data was that participants could momentarily forget where a target object was during the experiment or they could accidentally record an unintended angle during the experiment. If only a single measure of angular error were recorded, then our results would have suffered from a large number of experimental errors. To mitigate this issue, participants were asked to turn to face each target object three times and only the median turning angles for the x and y axis were recorded for visualization. These values were the most representative of the participants' spatial memory and they were also used to calculate the mean in all plots that reported averages across target objects.

We wanted to see where the participants were pointing to see overall patterns of where they were making mistakes, and we realized early on that this would be best accomplished by looking at the angular error (turning error) for each trial. This would allow for better comparisons of people's performance between target objects since they would have a common point of reference at 0 degrees of turning error.

1.8 Design Evolution

1.8.1 Early Visualizations

Throughout working on this project, one problem that we constantly faced was the cluttering of data. Even in some of our earliest drafts, Figures 10-13, spatial clutter gave rise to design headaches. As a result, the strategies we employed for data visualization continually shifted in an attempt to resolve this issue. However, throughout

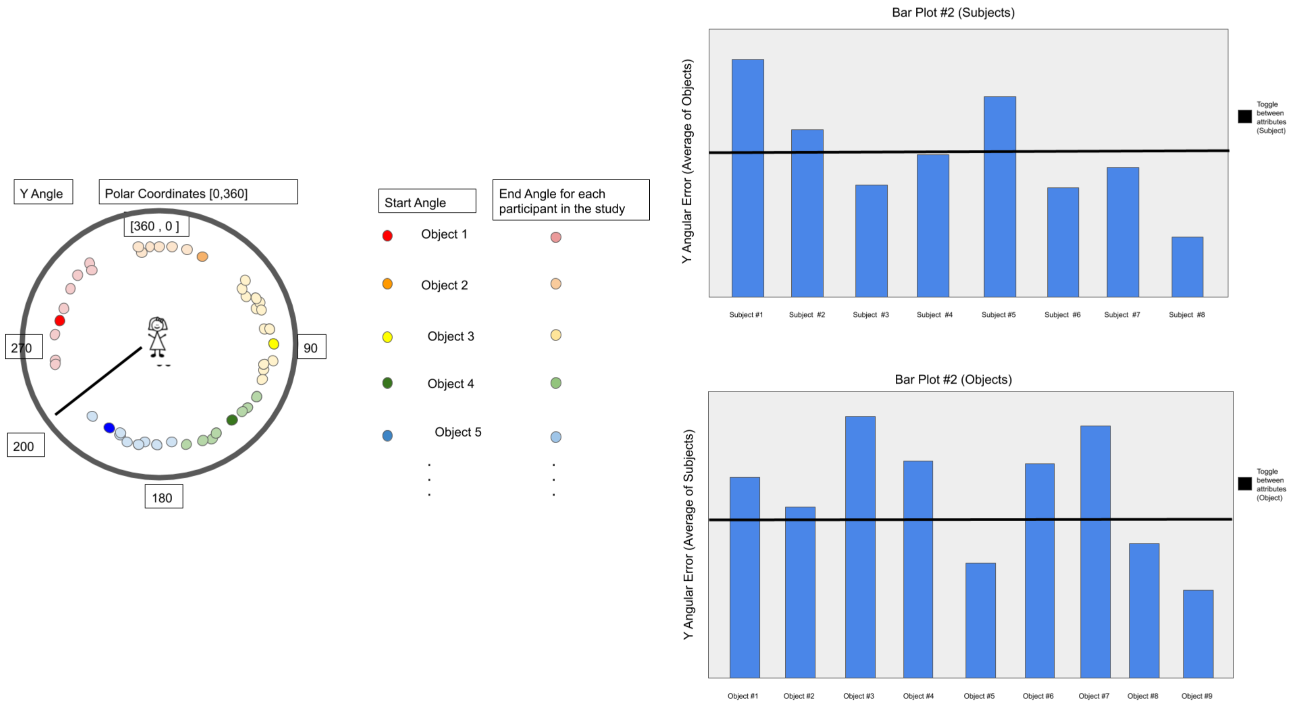

Figure 14. Left: Proposed visualization for each individual participant. Right: proposed visualization for the different angular error objects and individual participants.

the project, our core questions have remained. In the end, to resolve clutter, we primarily focused on plotting the average error (e.g., Figure 4's Average Turning Error scatter plot and polar graph). However, in doing so, we lost the nuance of the individual data points that we had originally hoped to capture in our visualization. Therefore, to visualize the variance and distribution of the error for each object we used the Selected Turning Error plot and Box Plots. And we added interactions along with a second scatter plot to reveal the values of individual measures that contributed to the averages.

In the ideation phase, we created numerous rough sketches for showcasing raw angle information for each object and angular error for each object and each person. Figure 10-13 showcases a collection of four hand drawn designs. The top left image (Figure 10) employs unique strategies for displaying angular information using a polar coordinate system. The bottom left image (Figure 12) attempts to transform this information into euclidean space to enhance legibility. The bottom right image displays and early attempt in which we wrestled with how to display error data in a meaningful way with interactions. Interestingly, the strategy displayed in Figure 11 was abandoned until the final version of our visualization. We realized that the space was too crowded for embedded visual encoding to be useful. However, we found a compromise much later in which we could use an image of the room at a responsive point of reference to inform other visualization indirectly,

An early challenge that we faced was deciding on which data attributes to focus our visualization on. However, we decided on this decision was made quickly. Turning error was identified as the most informative attribute (in comparison to raw angle measures, raw vectors, elapsed time, participant age, etc.). Displaying the raw end angles proved to be all the more troublesome since we needed to include an additional glyph to encode the actual position of each target for comparison (Figure 18). This only contributed to visual clutter and was less informative than just encoding turning error, which inherently captured the relationship between the user's performance and the ground truth. In particular, preliminary analysis showed that there was little variance between participants for many other fields, and we were primarily interested in understanding how individuals were representing their spatial memory of target objects.

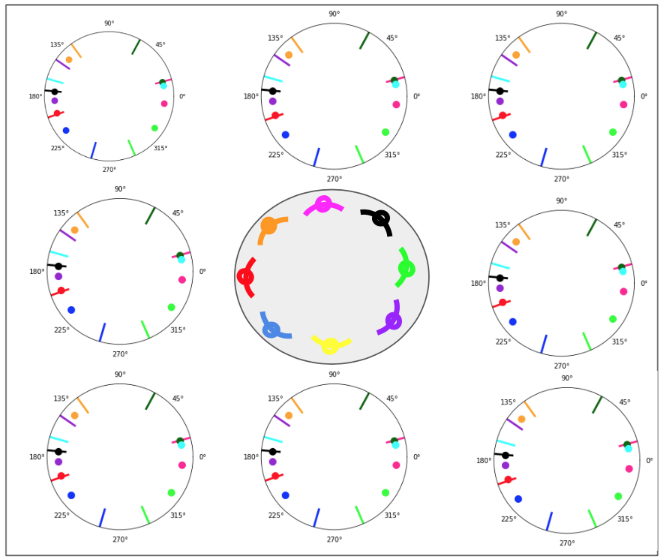

Figure 15. Proposed visualization for individual and aggregate angular data. The 8 smaller circles around the visualization represented each individual participant's trails for all 9 objects. The polar coordinate visualization in the middle represented the aggregate data for each object's angular data over all participants. In the center plot the lines across each point (individual objects) represented the angular error of each object.

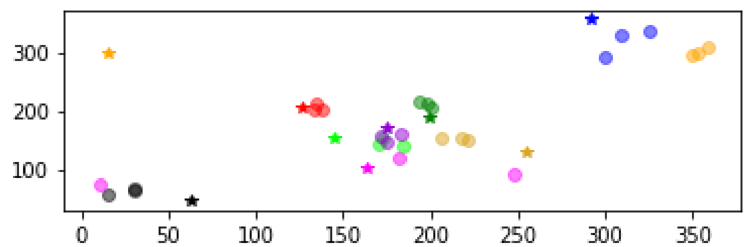

Figure 16. In this visualization instead of plotting the objects' angle in polar coordinates, we used a Cartesian plot. Here the stars are encoding the objects' true position and circles the participants' trails. However, this lead to clutter since we are plotting 36 points.

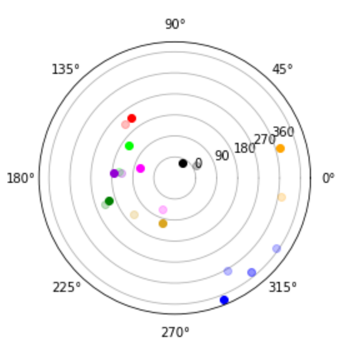

Figure 17. In this visualization we aimed to encoded both the x and y angle positions of the different objects. The x angle is encoded by the θ angle in the polar coordinate plot, and the y angle is encoded with the radius. Although the visualization seemed to reduce clutter, the interpretation of where the object in space was located was bewildering.

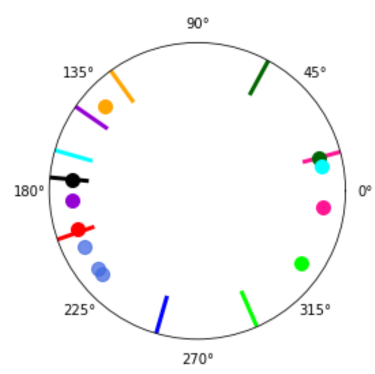

Figure 18. In this visualization the lines represent the true position of the targeted objects, while the circles are the position of median trail where the participant pointed. One of the ways we manged clutter was to only show the median position for each participant and then click on the object's position (circle) to see the three trails (example the three dark blue circles).

1.8.2 Intermediate Visualizations

In multiple instances, we discussed looking at visualizing individual participant's performances. One polished prototype of this type of visualization can be seen in Figure 14. Ultimately, the idea was discarded as we were more interested in how the target objects, which were placed at various vertical and lateral extents, affected performance. In the same mode of thought, we considered looking at polar coordinates through small multiples plots to gain better insight into how we may represent both aggregate and individual data simultaneously with polar coordinates. However, the resulting prototypes (See Figure 15) were visually confusing as well as cluttered. In fact, even with a plot based on Cartesian coordinates 14 proved confusing when all targets were depicted at a single time. Later on, we alleviated this issue to an extent by introducing interactions into our final visualization.

Polar coordinates presented a special challenge throughout development due to the aforementioned clutter issue and they presented an especially hard challenge from a design perspective–perhaps due to them being an unfamiliar form of visualization for the common viewer. Without even considering the clutter issue, which has been sufficiently expounded upon, we found polar coordinates difficult to design in a way that would not perplex readers. For example, a encoding both the x and y angles simultaneously proved more confusing than helpful for viewers (Figure 17). In addition, we found that the radius of the circle tended to distort our perception of area, depending on its length! This made it particularly difficult to design visualizations that maintained perceptual fidelity through polar coordinates, which was our main goal to preserve in these plots since were were displaying angles along 360°. In polar coordinates we had to be careful with our graphical perception of glyphs, radius, angle, and area. The vast majority of both our early and intermediate drafts were poor visualization. The limited amount of space provided by the polar plot in combination with the distortion of the perception of area relative to the centroid of the plot, and the number of unique variables we wanted to encode within a limited space proved to be tremendously limiting. Finally, during the final stages of the visualization design process, we settled on using area and compressing the radius along the edge of the plot to mitigate some of these issues (See Figure 4).

1.9 Analysis

From our different visualizations we can clearly see that two objects (the sock and paint can) result in an abnormally large amount of spatial angular error. Both our Average Turning Error scatter plot and our Average Turning Error polar plot demonstrate the direction and magnitude of this error well. In these plots, we can also deduce details about participant error. For example, participants generally turned too far to the right when they were asked to turn to face the sock. In the Left/Right Average Turning Error polar plot we can see how the area contribution of the sock is biggest compared to all other objects. In the box plot the sock has the largest interquartile range, meaning that there is a lot of variance in our sock data. This can be confirmed by looking at the different trails in the Selected Turning Error plot.

Similarly, for the paint can, the average participant was turning further up than the actual position of the paint can in the VR environment. Additionally, in the Selected Turning Error we can see how several participants were turning further to up than true position of the paint can. In the Down/Up Average Turning Error polar plot we can see how the area contribution of the paint can is biggest compared to all other objects. In the Down/Up box plot the paint can has the largest interquartile range, meaning that there is a lot of variance in our paint can data. Again, this can be confirmed by looking at the different trails in the Selected Turning Error plot and observing the distribution of points.

From the Average Turning Error scatter-plot, we learned that people had the most trouble spatially perceiving the sock and paint can accurately, as they had the highest margin of error for the left/right and up/down turning respectively. This may be largely due to the location of the sock and the paint can as they were both located in a particular spot: off the right shoulder of the subject.

In practice, identifying these outliers proved to be beneficial for the research study linked to our dataset since we were able to inform the primary investigator about the strange user behavior. Better yet, within our visualization, we can pinpoint the specific values that may be distorting our aggregate values. For example, we can hover over the sock position in the scatter plot and read the Euclidean distance of 178 form the origin ($0°, 0°$). This feature may be beneficial once more data is collected. Unfortunately, while the visualization is able to inform us about how users behave, they have brought us no closer to understanding the underlying reasons behind user responses. It is unclear, therefore, why participants were so terrible at locating the sock and paint can target objects. However, we suspect that if a participant had to move further from the start point, it lead to more angular error since there is a precedent for this response in spatial memory literature.

Our final visualization allows the viewer to analyze different representations of turning error to enhance their understanding of how people perform in a spatial memory task. In this task, the visualization performs fairly well. In the future we may consider visualizing how each participant performed and see if there are any trends or patterns for individual participants. If time had allowed, for our current visualization we would like to add more interactions to explore and compare data. One of the interactions we planned to implement was clicking on a specific object in the polar coordinate plots and moving that object to its spatial position. Moreover, we would have liked to had a filtering interaction for the box plots, only showing the object selected to make fast queries.

1.10 Peer Assessment

1.10.1 Haley's

We were fortunate in that all members proactively contributed to the project. Even when we repeatedly encountered frustrating design hurdles, everyone maintained a respectful, positive attitude and contributed to group meetings. In addition, the skill sets of all three team members complimented each other nicely. For example, Crisel's prior experience with Python allowed her to quickly produce prototypes for the team to test ideas sketched from meetings. Nick's speed with JavaScript programming allowed for rapid versioning in D3. And Haley's prior experience with web development and her intimate knowledge of the dataset contributed to refinement. However, all members were also more than willing to contribute to areas outside of their original comfort zones at any given time. As a result, the final visualizations could not have been realized without every team member. If there are flaws with our visualization, then they are at least not due to a lack of effort! It has been a pleasure to work together.

- **Preparation:** All team members came to meetings prepared to work on the design project.
- **Contribution:** All team members contributed productively to the team discussion and work.
- **Respect:** All team members encouraged others to contribute their ideas.
- **Flexibility:** All team members were flexible when disagreements occurred.

1.10.2 Crisel's

We were all prepared during our team meetings with new ideas, visualization, and plots. We all showed up and never missed a meeting. Everyone contributed to the team discussion, presentations and visualization. Everyone encouraged each other to contribute. In our final visualization, everyone worked together: Nick worked on the scatterplot, Haley on the polar plots, putting all the visualizations together, and Crisel in the boxplots. I do not think we had major disagreements. Most of our disagreements where about the visualization if we should make a line with higher opacity or if a visualization was too cluttered. As a team, we effectively communicated and worked together in the visualization and progress book. We were all very flexible with everyone busy schedule. I very much enjoyed working with Haley and Nick on the project.

1.10.3 Nick's

As a team, rarely did we ever not have all members show up for meetings. During the meetings, everyone was adequately prepared to share his/her ideas and no one member "dominated" in the discussions. For the visualization design and implementation, we all contributed separately but equally. I worked on the 2 scatter plots and incorporating interaction features whereas Haley worked on learning and implementing the polar graphs. Crisel was responsible for implementing the box plot visualizations. Often times, members of the team had different ideas but we settled them all through logical discussions and compromising. New ideas were always encouraged in our discussions. Due to everyone's busy schedule, there was no one perfect time for everyone to meetup but nevertheless we still met up on a consistent basis. Overall, it was a pleasure working with this group.

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[2] Kelly, J. W., McNamara, T. P., Bodenheimer, B., Carr, T. H., and Rieser, J. J., "The shape of human navigation: How environmental geometry is used in maintenance of spatial orientation," *Cognition* **109**(2), 281 – 286 (2008).

[3] Kelly, J., "Head for the hills: The influence of environmental slant on spatial memory organization," *Psychonomic Bulletin & Review* **18**, 774–780 (2011). 10.3758/s13423-011-0100-2.

2. APPENDIX

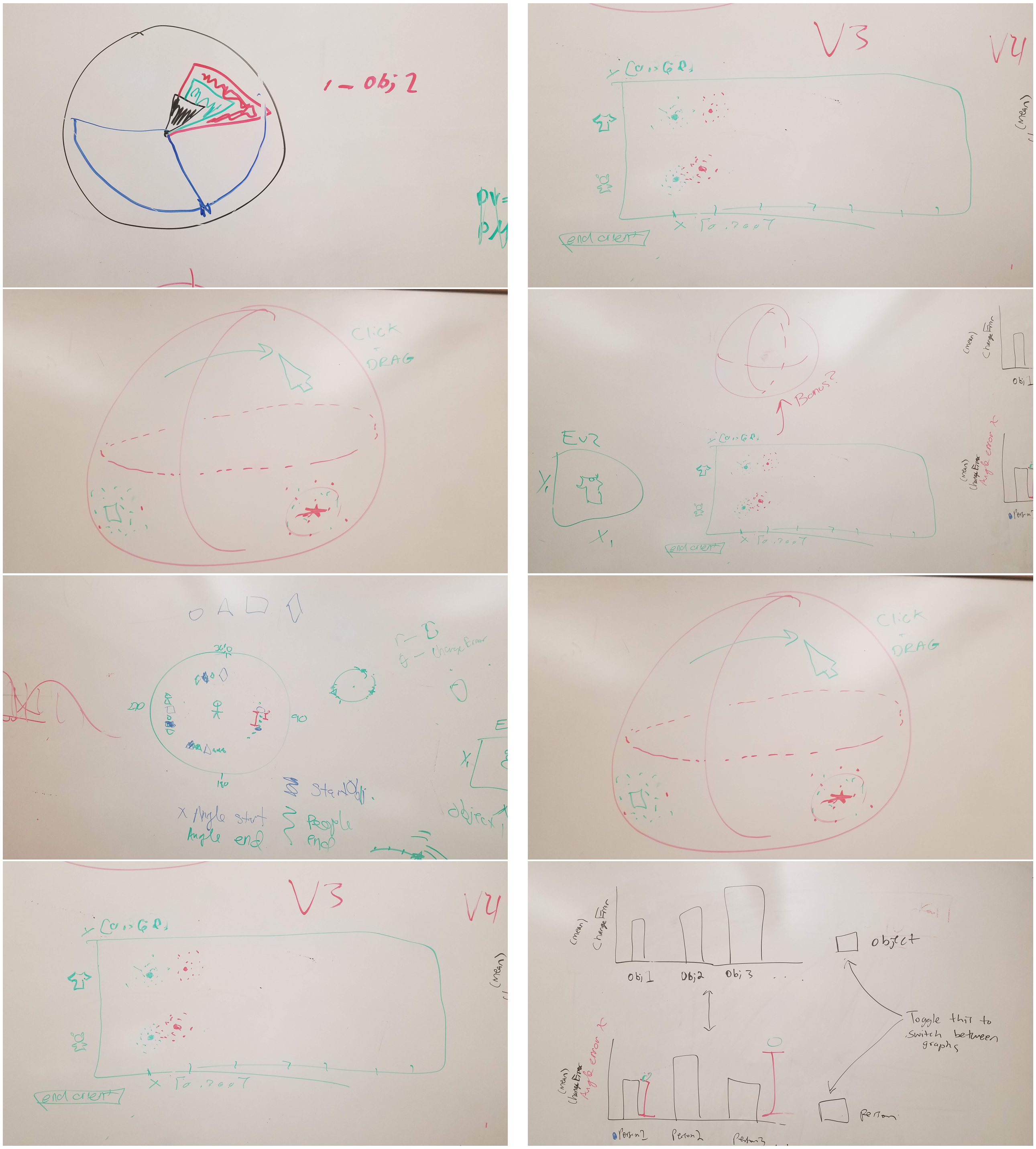

Figure 19. Additional early visualization drafts

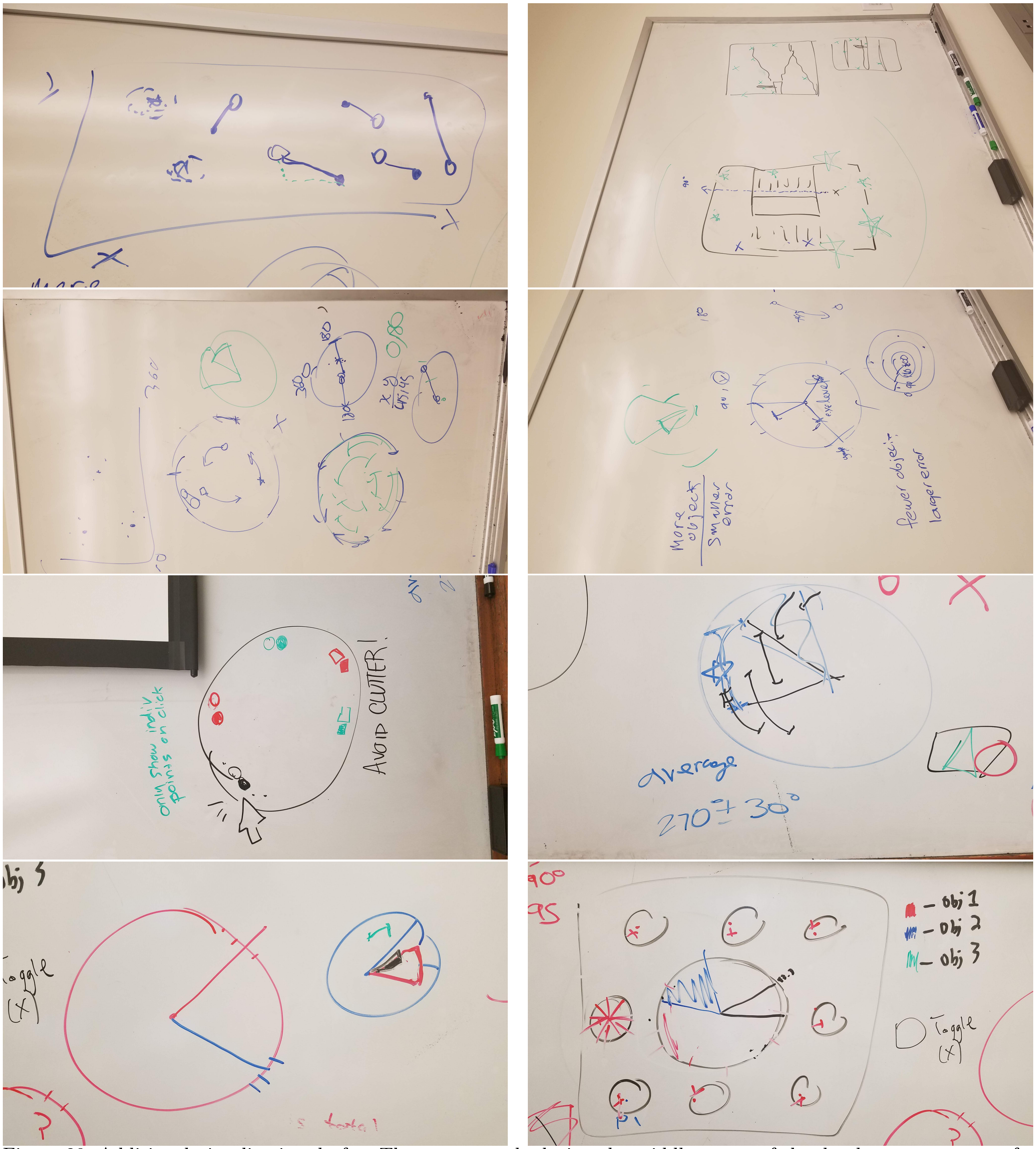

Figure 20. Additional visualization drafts. These were made during the middle stages of the development process after scrapping many of the original designs

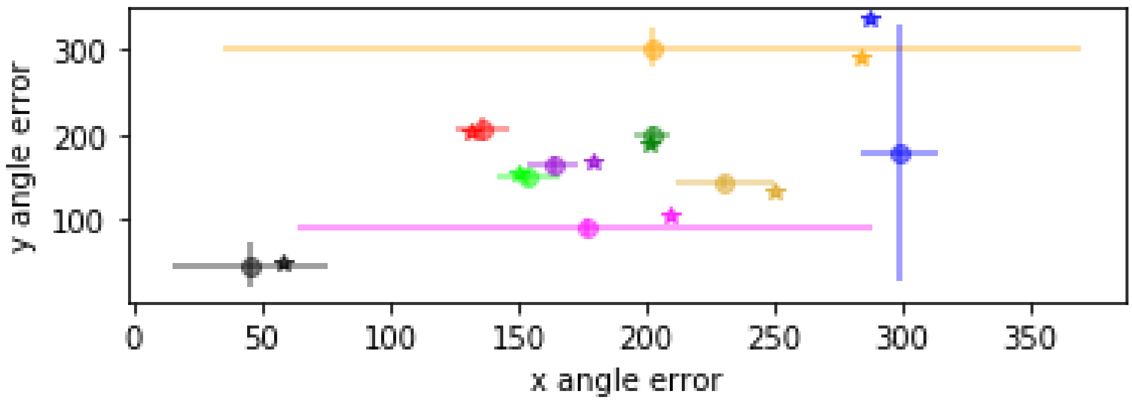

Figure 21. After rejecting polar coordinates alone to be sufficient for our visualization goals, we began rapidly prototyping visualizations on a Cartesion coordinate system.

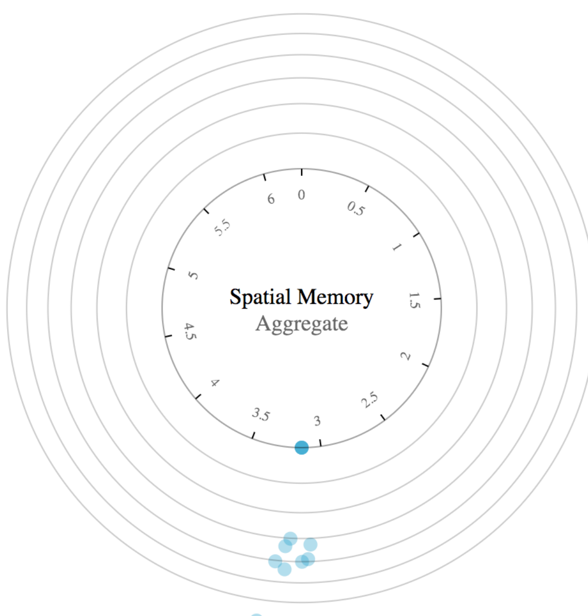

Figure 22. An initial plot within D3 to test polar coordinates