Investigation of Unmanned Aerial Vehicle Gesture Perceptibility and Impact of Viewpoint Variance*

Paul Fletcher, Angeline Luther, Brittany Duncan, and Carrick Detweiler[1]

Abstract— **Unmanned Aerial Vehicle (UAV) flight paths have been shown to communicate meaning to human observers, similar to human gestural communication. This paper presents the results of a UAV gesture perception study designed to assess how observer viewpoint perspective may impact how humans perceive the shape of UAV gestural motion. Robot gesture designers have demonstrated that robots can indeed communicate meaning through gesture; however, many of these results are limited to an idealized range of viewer perspectives and do not consider how the perception of a robot gesture may suffer from obfuscation or self-occlusion from some viewpoints. This paper presents the results of three online user-studies that examine participants' ability to accurately perceive the intended shape of two-dimensional UAV gestures from varying viewer perspectives. We used a logistic regression model to characterize participant gesture classification accuracy, demonstrating that viewer perspective does impact how participants perceive the shape of UAV gestures. Our results yielded a viewpoint angle threshold from beyond which participants were able to assess the intended shape of a gesture's motion with 90% accuracy. We also introduce a perceptibility score to capture user confidence, time to decision, and accuracy in labeling and to understand how differences in flight paths impact perception across viewpoints. These findings will enable UAV gesture systems that, with a high degree of confidence, ensure gesture motions can be accurately perceived by human observers.**

I. Introduction

Research in human-robot interaction suggests that robots can use gestures to communicate with human observers [1]–[6]. Gestural communication may be beneficial in contexts where other communication devices (such as light or sound) either fail or are limited by environmental noise. Enabling gestural communication in Unmanned Aerial Vehicles (UAVs) is a unique challenge. Unlike many other robotic systems, UAVs do not possess anthropomorphic qualities such as robotic arms that can mimic a human arm when performing gestures [7]. Also, due to their aerial motion, UAV gestures can be seen from a wide range of angles and positions. Thus, gestural communication requires an understanding of how gestures may be perceived by varying observer perspectives. Understanding the impact of viewing angle is particularly important in domains where gestures may be viewed by multiple people at different locations and viewing angles, such as search and rescue [8], [9]. While previous work suggests that UAV gestures can be used to communicate with observers [3], [4], application of these results may be limited by particular viewing perspectives.

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[1]All authors are affiliated with the NIMBUS Lab in the Department of Computer Science and Engineering, University of Nebraska, Lincoln, NE, 68588, USA {pfletcher, aluther, bduncan, carrick} @cse.unl.edu

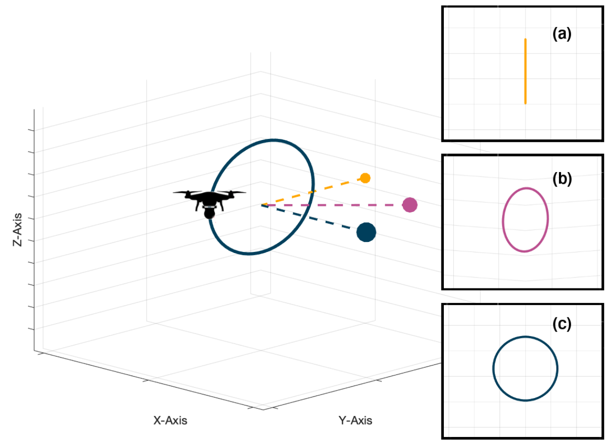

Fig. 1: Changes in the perception of a two-dimensional shape (circle) from varying viewpoint perspectives.

We chose to examine how observers perceive gestural motion in two-dimensions from varying viewpoint perspectives. Fig. 1 demonstrates how the flight path of a circular gesture be perceived from varying viewpoint perspectives. While the intended shape of the gesture's motion is clear from one perspective (viewpoint (c)), the shape becomes distorted from other perspectives (viewpoint (b)), and can even resemble a vertical line (viewpoint (a)) when all of the motion in the y-axis is occluded from view. We explore how observers perceive gestural motion as the viewpoint rotates along the z-axis, either obscuring or revealing more motion along the y-axis. In doing so, we seek to answer the following questions:

1) How does viewpoint rotation affect an observer's ability to perceive the intended shape of a gesture?
2) Does a historical mode of viewpoint rotation impact an observer's motion classification accuracy?
3) Does a viewpoint threshold exist, beyond which observers can accurately classify the shape of a gesture?
4) How do gesture shapes differ with respect to participant classification accuracy and confidence?

Our work contributes evidence for a viewpoint threshold from which two dimensional gestures can be accurately perceived by observers. This will enable UAV gesture designers to develop systems that ensure a human observer can perceive the intended shape of a UAV gesture's motion. We focus on trajectory animations and leave studies with real UAVs for future work. We start by discussing the challenge presented by human gesture perception and viewpoint variance. We then outline the results from three online user-studies designed to explore viewpoint variance, the impact of viewing history, and the relative independence of perception.

II. Related Work

Researchers have studied how robotic gestures can communicate meaning to human observers [1], [2], [4], [5]. Salem et al. [1] conducted an experiment to explore how gestures influenced human-robot dynamics during a collaborative task. The results suggested that participants preferred robot communication with gestures, however the findings are limited to humanoid robots. Szafir et al. [3] examined the potential for UAVs to communicate via gestures. Participants evaluated flight paths with and without gestures, with results indicating that users preferred working with the manipulated flight paths. In [4], Duncan et al. evaluated a series of UAV gestures trajectories that were chosen in part for their ability to be perceived in the presence of occlusion and from multiple angles. Participants were shown videos of each gesture and asked to label them based on a series of concrete UAV states (i.e. lost sensor, landing, etc.), demonstrating significant agreement on the meaning of two of the gestures. The results of these studies show that robot gestures can convey meaning and positively impact interaction with human observers.

As humans move around a 3D object, their perception of the object's shape will remain unchanged due to a concept called shape constancy [10]–[12]. Gestures are described as meaningful due to distinguishable shape features [13], [14]. In [15], variance in viewpoint perspective was shown to impact how musicians understood gestures from orchestra conductors. Researchers have studied viewpoint variation in scene interpretation [16], point-light character motion [17], and object memory recognition in film [18], demonstrating that perspective of the observer impacts how they perceive visual information. In the case of robotics, viewpoint variation presents a unique challenge to gestural communication.

El-Shawa [19] conducted a study with a robotic arm capable of performing gestures and asked participants to choose an optimal viewing angle and position to observe the gesture. Researchers noted that gestures existing solely on the sagittal plane resulted in higher variance in preferred viewing angle possibly due to the gesture occluding most of the motion along a single axis. Sheikholeslami [7] examined the capacity for a robotic hand to communicate instructions to a human observer during a collaborative car door assembly task. The researchers suggest that certain gestures were misinterpreted due to the viewing angle, likely making it difficult for participants to differentiate between gestures.

Nikolaidis et al. [20] explored how observer viewpoint variation impacts robot gesture motion legibility. In [6], Dragan outlines a formalism that distinguishes between legibility and predictability of robot gesture, where legibility is specifically characterized as motion that is intent-expressive. In [20], researchers developed a model to generate legible gesture trajectories across variance in viewpoint perspective. To evaluate participant perception of motion, Nikolaidis et al. developed a legibility scoring system, which we have adapted in our work and will be discussed in subsequent sections.

The results of these studies demonstrate that viewer perspective can indeed affect perceived meaning from visual communicative mechanisms. In particular, gestural motion may function to obfuscate meaning or even self-occlude from different viewing angles.

III. Approach

We seek to quantify a range of viewpoints from which humans can accurately and confidently perceive the intended shape of motion for a UAV gesture. We designed three studies to examine participants' ideal viewpoint rotation range, whether perception is derived from viewpoint rotation, how absence of viewpoint rotation affects perception, and how motion in the z-axis impacts perception across viewpoints.

Hypotheses

H1: Participant response accuracy will improve as gesture viewpoint rotates away from the most occluded angle.
H2: A historical model of viewpoint rotation will yield higher response accuracy than random viewpoint rotation change.
H3: At some viewpoint perspective (v), gestures will be perceivable with an accuracy probability of 0.9.
H4: The proportion of total motion in the z-axis for a planar gesture will correlate positively to perceptibility.

Gesture Set: While UAV gesture designers have certainly explored a variety of gesture flight trajectories [3], [4], including three-dimensional gestures, we are specifically interested in exploring perceptibility of two dimensional gestures. Two-dimensional gestures are characterized by motion in a single plane. These types of gestures may be especially useful for designers because they are simple and the full shape of their motion is visible from an ideal angle. Fig. 2 (top) depicts the two-dimensional trajectories for the gestures tested in this study. At an ideal viewpoint, all of the gesture's motion may be visible; however, from some viewpoints, the shape of motion may be unintelligible to human observers due to occlusion, prompting the current study. Fig. 2 (bottom) demonstrates the visible motion for a two-dimensional gesture from most to least occluded. From the most difficult viewpoint a two-dimensional gesture may look like a simple line. We identified our set of gestures based on prior work in UAV gestural communication [4], which demonstrated that some of these gestures effectively communicated meaning to untrained observers. While our work is focused on perception of shape in motion rather than meaning, we chose to build off of prior work that demonstrated perception of meaning.

Survey Design: To determine a range of viewpoints from which observers are able to understand the shape of a UAV gesture, we designed three user-studies in which participants viewed an animated gesture trajectory and chose an appropriate response based on a set of images representing each gesture motion shape. Animations were generated in MATLAB and consisted of a single red dot moving along a gesture trajectory. To ensure consistency between gestures, the range of motion for all trajectories were aligned along the z-axis and bounded within a range on the y-axis. For

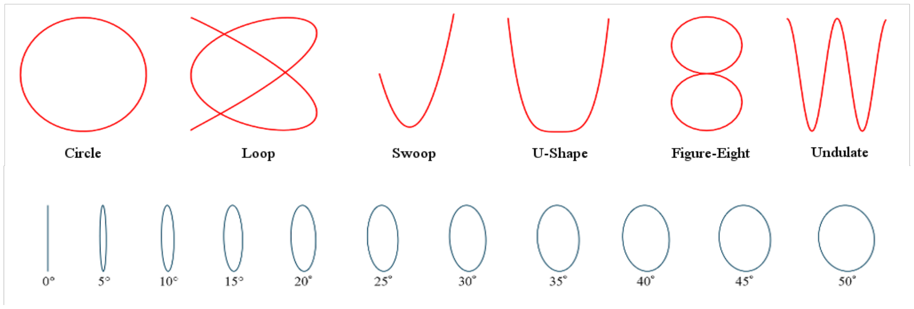

Fig. 2: Gesture set tested in this study (top) and sample progression of viewpoints from most to least occluded (bottom).

each gesture, there was no motion along the x-axis and we chose to maintain a viewpoint elevation that is level with the height of the observer. Doing so allowed us to reduce the viewpoint space and characterize how perceptibility changes with respect to self occlusion and viewpoint variance.

It is unlikely that a UAV will maintain an altitude level with the height of an observer, however, we suggest that gesture systems replicate a similar viewport with respect to elevation and observer line of sight (through axis motion transformation). In this way, the results of this work can be used to consider self-occlusion and perceptibility from varying UAV elevations respective to observer viewpoint. We designed each survey using Qualtrics and recruited participants via Amazon's Mechanical Turk (mTurk). As mTurk participants are motivated to complete surveys quickly, we integrated an attention test to ensure they were watching the full gesture.

1) User Study I. Preferred Viewpoint Angle: In our first user-study, our goal was to assess how much a participant needed to rotate the viewpoint to be able to accurately identify the shape of the gesture's motion. Each gesture was first shown to participants from the viewpoint where all of the motion in the y axis is occluded, as in Fig. 2 (bottom left). Participants were then given two options, to rotate the angle of the viewpoint or to choose the shape of the gesture's motion. If participants chose to rotate the viewpoint, they would then be shown a video of the same motion trajectory rotated five degrees along the z-axis. As participants continued to rotate the viewpoint, the shape of the gesture's motion became clearer. Participants were able to rotate the viewpoint ninety degrees in total, displaying the gesture in a full non-occluded state, as in Fig. 2 (bottom right). Participants were shown animations representing six gestures, with three of the gestures randomly repeating once, totalling nine classification tasks. Gestures were presented in random order. Participants had the option to choose the shape of the gesture's motion and were presented with eight images of shapes to choose from as shown in Fig. 2. Of the eight images, six represented the shape of trajectories being tested in the user-study, while two were distractors.

2) User Study II. Perception and Viewpoint Rotation: Our second user-study resembled our first user-study, however, we adjusted the initial viewpoint perspective by twenty degrees from the most occluded angle. Participants were initially shown a perspective of the gesture that demonstrated more motion in the y-axis, making the shape of the gesture clearer. The purpose of this user-study was to understand if participants needed to see some degree of viewpoint rotation in order to understand the shape of the motion and build a historical model of the motion. Similar to the first user-study, participants were able to rotate the viewpoint perspective as much as they wanted and, when confident, were asked to choose the shape of motion from eight static images.

3) User Study III. Absence of Viewpoint Rotation: In our third user-study, we removed the participants' ability to rotate the viewpoint perspective. For each animation, participants were asked to choose the intended shape of motion from a series of eight static images and rate their confidence in their decision on a four point scale. All animations were presented in a random order. The purpose of this user-study was to assess gesture classification accuracy and confidence from different viewpoints without the ability to rotate the viewer perspective. Based on the results of the initial user-study, we chose to limit the range of viewpoints from zero to forty degrees away from the least ideal perspective in five degree increments.

Gesture Perceptibility Assessment: In [20], viewpoint perspective is considered when determining the legibility of a robot's motion. To evaluate the efficacy of different motion trajectories, Srinivasa et al. used a legibility score metric by calculating a weighted sum of three participant response variables (goal prediction accuracy, explanation of prediction, and confidence). Borrowing from this method, we generated a *perceptibility score* (P_g), given by Eq. (1), that calculates a weighted sum of three participant response variables for each k response. Inaccurate responses $A(k) = 0$ receive a perceptibility score of zero, accurate responses receive $A(k) = 1$. Confidence is characterized by participant self-report on a four-point scale $C(k)$. The number of times a participant chose to view a gesture motion from a single viewpoint, $V(k)$, is used to measure difficulty in quickly determining the shape of motion. A logistic regression analysis of accuracy and degree of rotation provided values for weights $W(k)$ that correspond to viewpoint rotation angles, thus assigning more weight to accurate responses at low degrees of viewpoint rotation.

$$P_g = \sum_{k=1}^{n} \left[W(k)A(k) \left(\frac{C(k)}{4} + \frac{1}{V(k)} \right) \right] \tag{1}$$

To examine how qualities of gesture motion compare to perceptibility, we calculate the proportion of motion in each z-axis for each gesture. This calculation is given by Eq. (2) and (3) where M_z represents the total motion in the z-axis given by a summation of the absolute value of difference between p_z^i (the z component at position i) and the subsequent position p_z^{i+1}. The proportion of motion in the z-axis Pm_z is given by Eq. (3) where M_y is computed in the same way as M_z.

$$M_z = \sum_{i=1}^{n-1} |p_z^i - p_z^{i+1}| \tag{2}$$

$$Pm_z = \frac{M_z}{M_z + M_y} \tag{3}$$

Participants: Our study was conducted online using Qualtrics and participants were a convenience group recruited from Amazon's Mechanical Turk and were paid \$4.00 dollars for participating. All participants were required to have a Master rating. To deter participants from participating in more than one user-study, we assigned an identifier to each participant who completed a study. We included an attention test in our survey to ensure that participants were fully watching each animation. Participants who did not pass the attention test were not included in our results. Overall, our data reflects fifteen participants in user-study I, twelve participants in user-study II, and fifty-four participants in user-study III.

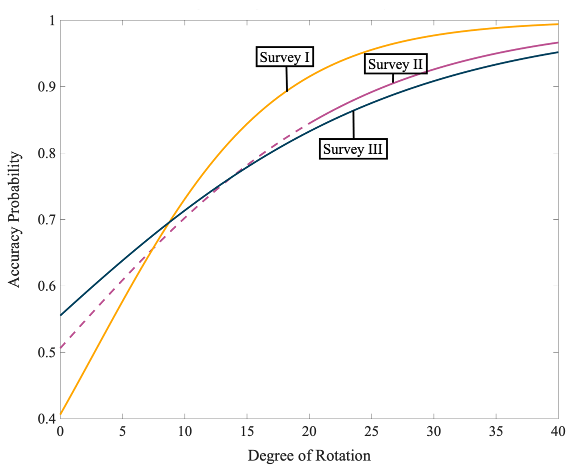

Fig. 3: Logistic regression probability curves for each user-study (dashed line for predictions in absence of data).

IV. RESULTS

We conducted a logistic regression on the results of each of our user-studies to characterize the relationship between the continuous independent variable (degree of viewpoint rotation) and binary dependent variable (accuracy). The analysis yielded a predictive curve indicating the probability of accuracy at particular viewpoints. Associated p-values for each of the regression analyses were well below 0.05, suggesting that there is a relationship between degree of rotation and response accuracy. Figure 3 shows the resulting probability curves from each logistic regression analysis.

Accuracy Probability and Viewpoint Rotation: In user-study I, participants were asked to rotate the viewpoint angle until they felt confident enough to assess the shape of the gesture's motion. Fig. 4 shows the distribution of gesture angle responses and associated mean accuracy values at each viewpoint angle. Response accuracy generally increases as the viewpoint rotation angle increases. The logistic regression analysis predicts 90% response accuracy at twenty degrees of viewpoint rotation. Thirty percent of participants chose to assess the gesture motion shape without rotating the viewpoint perspective, resulting in forty percent response accuracy. We conducted a one-tailed hypothesis test to evaluate the probability that participants were guessing at zero-degrees of viewpoint rotation. Comparing the proportion of accurate responses from the sample (0.4) against the probability of accurately guessing (0.125) yielded a z-score of 3.22 and p-value of 0.0006, suggesting that some participants were able to accurately evaluate the gesture motion-shape without guessing.

In user-study II, participants were shown gesture motion beginning at a viewpoint angle twenty degrees away from the angle of highest occlusion and were asked to rotate the viewpoint until they were confident enough to assess the shape of the gesture's motion. Fig. 4 represents the distribution of viewpoint angles chosen along with associated mean accuracy values. The highest distribution of participants chose not to rotate the viewpoint angle. However, mean accuracy accuracy increased to eighty percent as participants started off from a viewpoint that showed more of the gesture motion in the y-axis. In contrast to user-study I, the probability curve in Fig. 3 suggests that a 90% motion assessment accuracy can be achieved at twenty-seven degrees of viewpoint rotation.

User-study III differs from the other studies as the distribution of viewpoint rotation values was uniform across all participants. Every participant saw each gesture from the same number of viewpoints. However, gesture viewpoints were presented in a random order. Fig. 3 shows the accuracy probability curve yielded from the logistic regression analysis. When participants viewed gesture motion at zero degrees of viewpoint rotation, they were able to accurately characterize the motion with fifty-five percent accuracy. The regression analysis also suggests that participants are able to assess the gesture-motion shape with 90% accuracy at twenty-nine degrees of viewpoint rotation. We also fit logistic regression curves to accuracy responses for individual gestures. While the majority of gestures converged to 90% accuracy at similar viewpoints, the 'Circle' gesture proved to be a statistical outlier across the majority of viewpoint perspectives, demonstrating low overall response accuracy.

Perceptibility Scores by Gesture: We calculated perceptibility scores given by Eq. (1) to quantify how individual gesture motions related to the capacity for participants to accurately and confidently assess the shape of a gesture's motion. Figure 5 outlines resultant perceptibility scores for each gesture tested in this study. The 'Swoop' and 'Undulate' motions generated the highest scores, with 0.7825 and 0.7312 respectively while the 'Circle' yielded the lowest score at

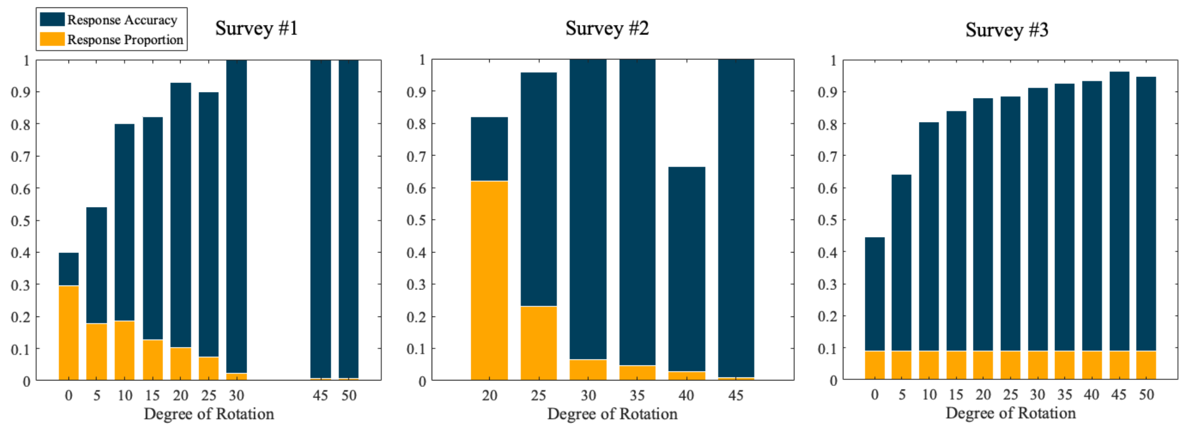

Fig. 4: Distribution of responses at each viewpoint rotation angle with associated response accuracy proportion.

0.363. ‘Loop’, ‘U-Shape’, and ‘Figure-Eight’ resulted in middle range scores at 0.5023, 0.6055, and 0.6616.

V. Discussion

H1: *Participant response accuracy will improve as gesture viewpoint rotates away from the most occluded angle*.

The distribution of responses in user-study I and II resulted in a high distribution of chosen viewpoint angles at or close to the initial viewpoint. The results in user-study I demonstrate that a large proportion of participants felt confident in their assessment of the shape of motion a viewpoint angle where much of the motion was not visible. However, this degree of confidence conflicts with response accuracy. While a smaller distribution of participants chose to rotate the viewpoint beyond ten degrees, the probability of an accurate response increased significantly. However in both user-study I and II, because participants chose at which angle to assess the motion, the distribution of responses per viewpoint angle was not uniform as will be discussed further in limitations. In user-study III, the distribution of responses per viewpoint is uniform as all participants were shown each viewpoint perspective in random order. Fig. 4 demonstrates that as the viewpoint angle increases, response accuracy increases. The results of our logistic regression analysis from user-study I and II support this relationship, both yielding positive regression coefficients (0.14 and 0.07) and p-values less than 0.01, thus providing support for Hypothesis 1. While the logistic regression from user-study II yielded a positive regression coefficient (0.08), the results were not statistically significant with a p-value of 0.28. We believe this may be due to the high distribution of responses at the initial viewpoint angle in user-study II.

H2: *A historical model of viewpoint rotation will yield higher accuracy than random viewpoint rotation change*.

User-study I presented participants first with the gesture viewpoint where the motion in the y-axis was fully occluded. In user-study II, we chose to present participants with an initial viewpoint angle at twenty-degrees away from the most occluded viewpoint in order to assess if the probability values would remain the same in the absence of a historical model of motion from subsequent viewpoint rotation. Similarly, user-study III presented animations from random non-sequential viewpoints, similarly exhibiting an absence of historical model development. We chose to compare the accuracy values from user-study I with those from user-study II and III at twenty degrees of rotation to determine if a historical model of the gesture’s motion improved response accuracy. Fig. 3 represents each of the logistic regression probability curves associated with each user-study. User-study I demonstrates a steeper progression of accuracy probabilities, resulting in an accuracy probability of 0.92 at twenty degrees of rotation. User-study II and III exhibit similarly lower accuracy probabilities at twenty degrees of rotation, 0.84 and 0.83 respectively. To evaluate these relationships, we conducted two one-tailed hypothesis tests comparing the proportion of accurate responses from user-study I against those from user-study II and III, however, the results were not statistically significant in either case with p-values of 0.1469 and 0.2776 respectively. We believe this is due to low number of participant responses at twenty degrees of rotation from user-study I. Overall, these results do not provide support for Hypothesis 2. Future work will examine this relationship further by conducting a forced rotation survey from zero to twenty degrees of rotation to increase the distribution of responses that reflect a historical model of rotation.

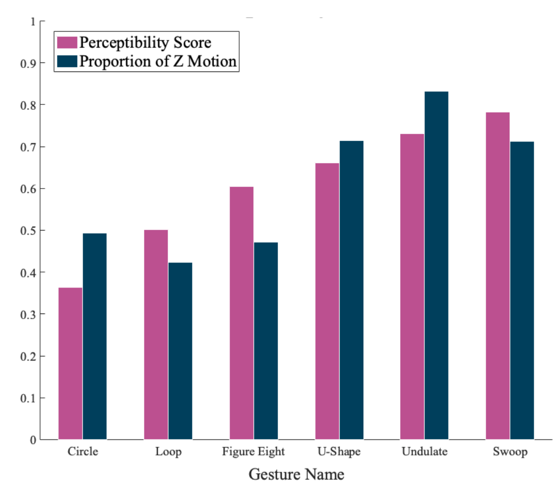

Fig. 5: Perceptibility scores by gesture.

H3: *At some viewpoint perspective (v), gestures will be perceivable with an accuracy probability of 0.9.*
We chose to characterize an accuracy threshold where participants are able to assess the gesture's motion with at least 90% accuracy. Fig. 3 shows the logistic regression probability curve from each user-study. Predicted 90% percent accuracy values range from viewpoints at nineteen degrees in user-study I to thirty degrees in user study III. The results of user-study II predicted 90% accuracy at thirty degrees of rotation. These results suggest that a 90% accuracy viewpoint range exists between nineteen and thirty degrees of rotation. However, these models include the 'Circle' gesture, which proved to be a statistical outlier, demonstrating poor response accuracy across most viewpoint perspectives. This may be due to a lack of identifiable motion characteristics in the z-axis, which will be discussed further in the next section. To characterize a 90% accuracy viewpoint threshold, we conducted a one proportion z-test on response accuracy values from user-study III for all gestures except 'Circle.' The results suggest that, beginning at twenty degrees of viewpoint rotation, observers will be able to classify the shape of a gesture with at least 90% accuracy. These results are statistically significant with a z-score of 2.97 and p-value of 0.0015, providing support for Hypothesis 3. Future research will be done to determine if this viewpoint threshold generalizes to new gestures, as well as to examine what qualities of motion contributed to poor accuracy response for the 'Circle' gesture.

H4: *The proportion of total motion in the z-axis for a planar gesture will correlate positively to perceptibility.*
Using Eq. (1), we calculated perceptibility scores for each of the gestures tested in this study. Our results indicate that the 'Circle' was the most difficult for participants to accurately and confidently classify, while the 'Undulate' and 'Swoop' gestures yielded the highest perceptibility scores. It is important to note that in this study when participants are shown a gesture motion from the most occluded viewpoint angle, all of the viewable gesture's motion occurs in the z-axis. Thus, gestures that exhibit identifiable motion characteristics in the z-axis may be easier to identify. To characterize each gesture's motion, we determined the proportion of total motion that occurred in the z-axis. We then conducted a Pearson correlation analysis to examine the relationship between perceptibility, as defined in Eq. (1), and z-axis motion (Eq. (2) & (3)). The results suggest that there exists a strong positive correlation between the proportion of motion in the z-axis and perceptibility, with a correlation coefficient R-value of 0.7736 and a p-value less than 0.10, providing support for Hypothesis 4. Figure 5 shows the perceptibility scores and associated z-axis motion proportion values. These results suggest that a relationship between the proportion of motion in each axis and perceptibility, however, it is important to note that our work focused on occlusion of y-axis motion. 'Loop' and 'Undulate' demonstrate high perceptibility when the y-axis motion is occluded, but this may not be the case if the z-axis motion is occluded. Ideally, a gesture will be robust to occlusion of motion in both axes. The 'Figure Eight' gesture demonstrates a relatively high degree of perceptibility in contrast the proportion of motion in the z-axis. The motion qualities of the 'Figure Eight' gesture may yield better perceptibilty in the case of occlusion in either axis. In the case of the 'Circle' gesture, the proportion of z-axis motion is higher than 'Loop' and 'Figure Eight,' however, it yields a lower perceptibility score. In this way, the qualities of the 'Circle' gesture's motion trajectory may be difficult to distinguish.

VI. Limitations

While our results indicate that participants are able to perceive the shape of motion from our MATLAB animations, our work has yet to confirm the results of this study in field setting with real UAVs. However, by characterizing a range of perceptible viewpoints, our work contributes a foundation from which future field studies can focus. In addition, our work considers how a set of gestures is perceivable with respect to occlusion in the y-axis. To understand how robust to viewpoint variance these gestures are, future work will need to characterize how their motion is perceived in the context of z-axis occlusion as well as depth perception. To understand how participants also perceive these changing viewpoints from different depths would have resulted in a number of animations that may have been burdensome for participants. We suggest that future work calculate the motion displacement along the y-axis and associate displacement values with known accuracy and confidence values to make predictions of perceptibility with varying depth ranges.

VII. Conclusion

To ensure that observers can accurately perceive the intended shape of a UAV gesture's motion, gesture systems must consider the viewpoint perspective of the observer. In contexts where a UAV must communicate with multiple observers, a path planning algorithm could leverage viewpoint angle perceptibility scores to determine a position that optimally displays a gesture within the combined observation space. Systems must account for the perspective of the viewer to ensure communicative function. In this work, we reviewed the results of three user-studies conducted to characterize the relationship between viewpoint perspective and assessment of gesture motion-shape. We identified a viewpoint threshold range of 19-30 degrees from the most occluded viewpoint, within which participants were able to classify the shape of a gesture's motion with 90% accuracy. We also discussed a scoring method for evaluating gesture perceptibility for individual motion trajectories. The results of this work demonstrate that UAV gesture systems must consider the viewpoint perspective of an observer to ensure that they can accurately perceive the intended shape of the gesture's motion. However, the results may be limited to the gesture set explored in this study. Future work will seek to determine if the threshold discussed in this work will generalize to new gestures.

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