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Investigation of Communicative Flight Paths for small Unmanned Aerial Systems*

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Abstract— **This project seeks to generate small Unmanned Aerial System (sUAS) flight paths that are broadly understood by the general population and can communicate states about both the sUAS and its understanding of the world. Previous work in sUAS flight paths has sought to communicate intent, destination, or emotion of the system without focusing on concrete states (e.g., low battery, landing, etc.). This work leverages biologically-based flight paths and experimental methodologies from human-human and human-humanoid robot interactions to assess the understanding of avian flight paths to communicate sUAS states to novice users. If successful, this work should inform: the human-robot interaction community about the perception of flight paths, sUAS manufacturers on how their systems could communicate with both operators and bystanders, and end users on ways to communicate with others when flying systems in public spaces. General design implications and future directions of work are suggested to build on the results here, which suggest that novice users gravitate towards labels they understand (draw attention and landing) while avoiding more technical labels (lost sensor).**

Fig. 1. Concept imagery depicting UAV operators at a prescribed fire, where bystanders work around the fire and may need state information.

I. INTRODUCTION

Small unmanned aerial systems (sUAS) have sophisticated control stations and a rich variety of interfaces to communicate with their operators. Yet, as these vehicles become part of applications involving stakeholders that are not the operators, they will increasingly need to establish broader communication channels in order to be accepted in public spaces and to create safer interactions.

Consider for example existing public-facing applications, such as Amazon Prime Air [1] or the Alphabet's burrito delivery [2]. For such applications, the sUAS might be required to communicate not just with their control base, but also with the customers expecting a delivery, and bystanders that may not be fully aware of the intent of the vehicle. These other stakeholders may not have experience dealing with the sUAS but they will ultimately render their judgment about the application in part based on how the vehicle communicates with them. In other more specialized application contexts, like that of sUAS supporting fire management activities [3] as depicted in Fig. 1, communicating dangerous situations to fire personnel and accidental observers is critical. Alternately, these gestures could be used in agricultural applications of UAS, such as those in orchards [4] where most workers are unlikely to be trained on technologies unrelated to their tasks, but should be alerted to off-nominal operations.

Our approach to communicating to such stakeholders is through sUAS gestures, more specifically flight motions that convey the sUAS state. This communication medium is appealing in that it requires no additional equipment (such as speakers or lights) and can be easily incorporated into existing systems. If well designed, these motions are also robust to communication challenges such as partial occlusion, viewing angle, or ambient lighting (as in [5]).

One of the challenges of using sUAS gestures is identifying those that can be consistently interpreted by stakeholders that may not have been trained in the technology. In this work we start investigating this challenge by asking: *Do novice users show broad agreement on the meaning of sUAS gestures?* We investigate this question using Amazon's Mechanical Turk (mTurk) platform to gain access to 64 general users for a video-based study of sUAS communications.

Leveraging methods from human gesture understanding, this paper contributes the first study of general communications by sUAS. It is distinct from previous work on sUAS gestural communication in that we are attempting to communicate relevant action information from simple sUAS gestures to novice users, instead of attempting to mirror users' emotions or communicate about only direction of flight. The results indicate that novice participants are able to properly label gestures associated with landing or drawing attention, with less agreement for other gestures. We also found that, contrary to the findings of previous work, user attitudes towards robots did not seem to affect their ability to recognize the meaning of a gesture.

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II. RELATED WORK

The human ability to infer intentionality from random motion has been well established, beginning with Heider's work on apparent behavior in 1944 [6], which was later extended to understand perception of biological motions from humans and animals [7], [8]. Through studies such as these, we can begin to understand the intentionality that is applied to observed motion and the components that make this intentionality more broadly understood. In this section, relevant work on human and robot gestural communications will be presented.

A. Human Gestural Communications

Human gestural communications have been studied for their communicative ability in order to understand how they are perceived and what they can be used to communicate. Krauss, Morrel-Samuels, and Colasante [9] conducted a set of studies to understand how co-speech hand gestures are understood and found that while hand gestures convey some information, they do not communicate as well as speech. Prati and Pietrantoni [10] investigated the use of hand gestures when verbal communication would be difficult to understand differences in communicative ability of different gesture types. Their participants watched videos of firefighters performing ten gestures and labeled them using free response. In both studies, these gestures had meanings that were similar to gestures participants had previously seen.

B. Robot Gestural Communications

Gestural communications in robots can be split into ground robot gestural communications and sUAS gestural communications. While gestures have been examined in humanoid robots, this has been limited to social gestures and collaborative gestures. The current state of the art with sUAS has been to communicate high-level state information or to use gestures for control of a vehicle.

1) Ground Robot Gestural Communications: Social gestures have been investigated in HRI in much the same way that was described above for communicative hand gestures. Salem et al. [11] investigated the ability for co-speech gestures to enhance humanoid robot communications. Huang and Mutlu [12] evaluated the use of gestures to improve recall in humanoid robot interactions. Ng, Luo, and Okita [13] developed a gesture model to produce gestures from text input and tested the modification of parameters to convey excitement or expressiveness. Riek et al. [14] tested cooperative social gestures on a humanoid robot to understand the impact of speed and viewing angle, and found that negative attitudes towards robots correlated with a decreased ability to understand the gestures in the study. Overall, these works have assessed understanding of gestures, but they are focused on leveraging the existing understanding of participants from interacting with other people in order to improve humanoid robot communications.

Of more interest to this work are the collaborative gestures that have been developed primarily for industrial applications as in [15], [16], but one limitation of the work in this area is the assumed presence of a visible goal as reported in [17]. Dragan and Srinivasa [15] tested the integration of an observer into motion planning for an industrial robot. Gleeson et al. [16] observed gestural communications between humans, derived terms and gestures for use by the robot, and implemented them on a robot to observe their communicative ability. Both of these studies indicated that gestures were more effective when they conveyed context and goal, which is a challenge for the sUAS gestures to overcome.

2) sUAS Gestural Communications: Communications with sUAS can be split into communication from the sUAS and communication to the sUAS.

a) Communication from sUAS: Communicative flight paths have been investigated for ability to communicate affective state [18], [19], intended destination [20], and intended direction of flight [5]. These flight paths would enhance interaction with sUAS in collocated environments, but do not communicate actions or states that might be necessary in uses with more bystanders or broader application.

Sharma et al. [18] investigated the ability to communicate affect via flight path with collocated users and found that to increase valence or arousal communication, space should be used more indirectly and the motions should be faster. Cauchard et al. [19] explored personality models for the sUAS to increase interest in interaction and possibly allow them to mirror the personality of their users in the future. Findings from both studies were operationalized by keeping these parameters as constant as possible across flight paths.

Szafir, Mutlu, and Fong [20] used both mTurk and in-person interactions to explore the perception of animation principles applied to sUAS flight paths to increase the communication of intent. Szafir, Mutlu, and Fong [5] next assessed the ability of a light ring to communicate the direction of sUAS flight through in-person testing where the participants would predict the end state of the vehicle. This work considered: viewing angles, movement in multiple dimensions, occlusion, and ambient lighting. While very informative to the field at large, this work is better applied to close interactions in more controlled environments so we primarily focused on possible problems in communication.

b) Communication to sUAS: Gestural communication to sUAS for commanded control has been investigated [21], [22], [23], but this work is not directly relevant to the work described here.

III. DEFINING sUAS COMMUNICATIVE FLIGHT PATHS

This paper presents an initial study to address the question: *Do novice users show broad agreement on the meaning of sUAS gestures?* From a methodology perspective we start exploring this question by following established protocols used to investigate human gestures [9], which seek to understand the level of agreement by exposing participants to a limited gesture set and then requesting those participants to apply a label from a limited set. From the sUAS gesture perspective, we start by adopting flight paths used in nature, which are robust to viewing angle or occlusion, oscillatory in nature to allow looping, and adapted from biological inspiration to explore any templates that might exist. Given the formative stage of the work, we limit the impact of environmental factors (through being performed in an indoor space), constrain the labels (to understand agreement rather than generation), and do not introduce a visible goal state (to assess understanding rather than inference). Further description of the motions and labels are described in Section IV and the methodology details appear in Section V.

IV. sUAS Flight Path Design

The initial paths created from this work were developed from flight patterns used by birds in order to leverage the advantages inherent in biologically inspired behaviors, as described in [24], [25]. This section will describe the avaiable labels, flight path selection, programming environment, and video creation for the experiments described later in this work.

A. Possible Flight Path Labels

The current labels were chosen based on likelihood that they would be encountered in flights and generally would require redirection or intervention from the operator, or awareness from bystanders. It was also anticipated that these states would be understood by novice users due to the widespread use of hobbyist systems or observations of other aircraft (e.g., Landing, Low Battery, Draw Attention), commonality with other taskable systems (e.g., Missed Goal, Change Position), and potential similarities to states encountered in smart phone technology (e.g., Lost Sensor, Lost Signal). Another consideration was to choose states that were domain independent rather than focusing on possible applications of the technology (e.g., not Deploying Sensors nor Taking Pictures).

B. Flight Path Selection

The avian flight paths we selected were originally identified by Davis [7] as oscillatory motions (those with a steady periodic motion and which could be created from sinusoid functions). More details on their inclusion/exclusion criteria can be found in the original work, but these motions were of interest to this work because they are biologically inspired, can be created in a replicable way, offer the ability to scale and loop as needed, and can generally be perceived in the presence of occlusion or multiple viewing angles. The requirement for biologically inspired behaviors also takes into consideration the requirements for deployment of these motions, such as the need to be observable against a natural background, able to contend with energy constraints, and understandable by other animals (or in this case humans). The eight cyclic motions used by birds and identified in [7] are: Circle, Figure-8, Left-Right, Loop, Spiral, Swoop, Undulate, and Up-Down

When designing the labels for this study, we considered states that may impact and may need to be communicated to bystanders. The states we chose were: lost signal, lost sensor, draw attention, landing, missed goal, change position, and low battery. We then performed an initial assignment of those labels to the motions to later gauge whether participants would confirm these assignments or realize alternative ones. The initial assignments with a brief description of the thought behind these assignments follows:

- Circle: lost signal, in which the movement could help the sUAS regain signal
- Figure-8: lost sensor, which looks like the motion used to recalibrate your phone's magnetometer
- Left-Right: missed goal, which looks like shaking head
- Loop: draw attention, which might be reminiscent of a ferris wheel
- Spiral: landing, which could be used in indicating a position of landing
- Swoop: draw attention, since this is eye catching
- Undulate: change position, since this motion could be performed while starting in the direction
- Up-Down: change position, which looks like nodding to acknowledge the command

C. Flight Path Programming

To perform each gesture, the Ascending Technologies Firefly hexcopter (weighing less than 1.6 kg and 60.5x66.5 cm) would take-off, hover at the starting point of the gesture, perform the flight path representing the gesture for 30 seconds, and then land.

To create the flight paths, the sUAS autonomously flew along pre-programmed paths. A Vicon motion capture system tracked reflective markers attached to the sUAS and measured its position and orientation to a high degree of accuracy (submillimeter error and 200Hz). The sUAS performed each gesture by following a target position that was continuously moved through a three dimensional space, using a PID pose controller to have the sUAS chase the target. The target's x, y, and z coordinates were coded as mathematical functions of time, as described next, thus yielding a parametric path for the gesture. Each gesture was programmed to move the sUAS at approximately 1 meter per second.

1) Flight Path Parameters: Table I shows the equations used to generate the eight paths. The x, y, and z positions are evaluated based on a specified range of time, t, starting at zero. In addition, the table shows the typical displacements observed during the sUAS flights for each motion.

2) Flight Path Visualizations: Fig. 2 shows a visualization of some of the flight paths reproduced from logged pose data. The red path shows the actual sUAS path, each square is 1 meter wide, and the gesture primarily took place over the center of the grid. Some gestures (e.g., swoop) are shown from an off-angle so that the path can be better viewed.

D. Flight Path Video Creation

Each flight was filmed by a video camera, and the video was later trimmed to include only the gesture and to ensure that all gesture videos were the same length and size. The camera's view was orthogonal to the gestures' width and height displacements, and its height centered the gestures within its view. Each video was uploaded to Youtube.com

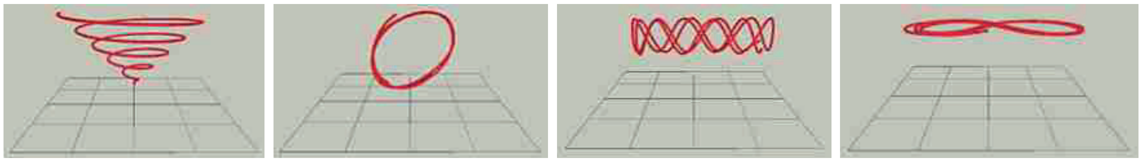

Fig. 2. Visualizations of the Spiral, Loop, Undulate, and Figure-8 paths from the flight log. Each square is 1m wide.

TABLE I
MOTIONS' EQUATIONS AND TYPICAL DISPLACEMENTS OBSERVED.

Motion	Equations	Displacement (m)
Circle	for $0 \leq t \leq 30$: $x = 2.5cos(t)$ $y = 2.5sin(t)$ $z = 1.5$	$x : 2.5m$ $y : 2.5m$ $z : 0.0m$
Figure-8	for $0 \leq t < 2PI$: $x = 0.75 - 0.75cos(t)$ $y = 0.75sin(t)$ $z = 1.5$ for $2PI \leq t \leq 4PI$: $x = -0.75 + 0.75cos(t)$ $y = 0.75sin(t)$ $z = 1.5$	$x : 4.0m$ $y : 2.0m$ $z : 0.0m$
Left-Right	for $0 \leq t \leq 30$: $x = 1.5sin(1.5t)$ $y = 0$ $z = 1.5$	$x : 2.5m$ $y : 0.0m$ $z : 0.0m$
Loop	for $0 \leq t \leq 30$: $x = 0.75sin(0.75t)$ $y = 0$ $z = 1.25$ $+0.9 \times 0.75cos(0.75t)$ $+0.4 \times 0.75sin(0.75t)$	$x : 2.0m$ $y : 0.0m$ $z : 1.5m$
Spiral	for $0 \leq t \leq 30$: $x = cos(t) \times (30 - t)/20$ $y = sin(t) \times (30 - t)/20$ $z = 2 - t/20$	$x : 2.0m$ $y : 2.0m$ $z : 1.5m$
Swoop	for $0 \leq t < 2.4$: $x = 0.5t$ $y = 0$ $z = 0.5 + ((t - 1.2)^2)$ for $2.4 \leq t \leq 4.8$: $x = 1.2 - 0.5t$ $y = 0$ $z = 0.5 + ((t - 1.2)^2)$	$x : 1.5m$ $y : 0.0m$ $z : 1.5m$
Undulate	for $0 \leq t \leq 6$: $x = -1.5 + t/2$ $y = 0$ $z = 1.5 + 0.5sin(3.14 * t)$ for $6 \leq t \leq 12$: $x = 1.5 - t/2$ $y = 0$ $z = 1.5 + 0.5sin(3.14 * t)$	$x : 3.0m$ $y : 0.0m$ $z : 0.8m$
Up-Down	for $0 \leq t \leq 15$: $x = 0$ $y = 0$ $z = 1.25 + 0.4sin(4t)$	$x : 0.0m$ $y : 0.0m$ $z : 0.5m$

with dimensions of 854 by 480 pixels and sound was included in each video. Original videos can be found at https://unl.box.com/v/ICRA-duncan-videos and a summary of representative videos is included in the media attachment to this paper.

V. FORCED CHOICE LABELING STUDY

This study investigates the ability of novice users to discern possible intent of gestures. We employ the n-alternative forced-choice technique, which has been used in psychology [26], [27], [28], human-robot interactions [29], [30], and human gesture recognition in [9], [10]. More specifically, we conduct two studies. The first one employs a two-alternative forced-choice (2AFC) model to test the recognition of a gesture from two labels (one chosen by us and one distractor). The second one, a seven-alternative forced-choice (7AFC), is meant to test the recognition of a gesture among seven labels, to assess broad agreement.

A. Approach

As in [9], it was expected that for the 2AFC condition users would be able to select the preferred label (chosen by the experimenters) more often than chance. One major difference in this work than in the work on co-speech gestures by [9], [10], [12], [11], [13] is that the gestures tested here do not have an inherent meaning within speech; instead we are assessing whether they map to concepts assumed to be already understood by the users.

We also wanted to take this experiment a step further to see if there was convergence from participants on label assignment by testing all labels and all gestures in the 7AFC task. Here, it was expected that gestures with high recognition in the 2AFC task would also show high convergence in the 7AFC condition.

B. Participants

Participants were a convenience group recruited from mTurk and paid \$2.00 dollars for their participation in the experiment. All participants were required to have a 95% task approval rate with a minimum of 10000 tasks and with a Master rating. To prevent participants from working in more than one posting (condition) of this study, the experimenter assigned an ID to all workers who completed a task, which prevented them from accepting another.

In the 2AFC, thirty-two participants (22 male, 10 female) with an age range of 26-49 (mean=34.75, standard deviation=6.97) were involved in this study. Sixteen participants reported prior robot experience with seven participants reporting robot ownership. Thirteen participants reported prior piloting experience with remote controlled or manned aircraft. Twenty-one participants had completed a bachelor's degree or higher, four completed some college, three had an associate's degree, and four completed high school.

The 7AFC had thirty-two participants (21 male, 11 female) with an age range of 21-61 (mean=33.88, standard deviation=9.06). Seven participants reported prior robot experience with four reporting robot ownership. Thirteen participants reported prior experience piloting a remote controlled or manned aircraft. Fifteen participants completed a bachelor's degree or higher, eleven had some college, two had an associate's degree, and four completed high school.

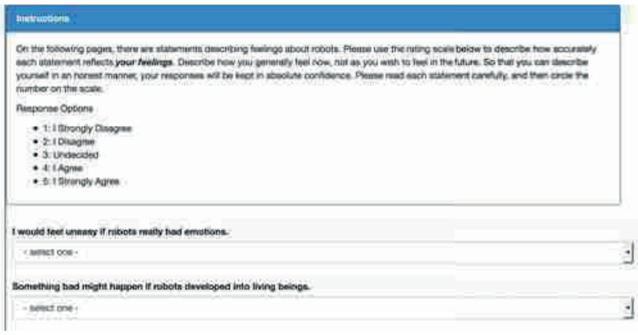

Fig. 3. Participant view of the mTurk task.

One important note about the robot experience questions is that they were phrased to solicit interactions in a broad context. Robot experience was assessed by: asking whether participants had "ever interacted with a robot", the frequency of interaction, and the type of robot (consumer, including Roomba or a pool cleaning robot; industrial, including telepresence or other workplace robots; educational, including Lego Mindstorms or those in a museum; or entertainment, including Parrot AR.drone, DJI Phantom, or Sony Aibo). These prompts also serve to remind people about times when they may have interacted with a robot, so might be overly sensitive to individual interactions. Within the participants that had robot interactions, 6 of 23 had only interacted with a robot once.

C. Experimental Procedure

Participants were required to click a button labeled "I Accept" to consent to participate in the study, otherwise they had to decline and return the task. After accepting, they were given a short demographics survey, positive and negative affect assessment, and negative attitudes towards robots scale to answer. Upon completion of the questions on mTurk, the participants were redirected to a Google Form (while being instructed to keep the task open for a completion phrase to be provided at the end of the Google Form). This allowed the task time to be tracked and all information for task approval to remain within mTurk, while also enabling filtering of repeated workers and a fixed ordering of both the videos and post-experiment questionnaires. While not very streamlined, this guaranteed ordering was important for the counterbalanced conditions in order to prevent the participants from reordering on the single page design required by mTurk (participant view is shown in Fig. 3).

The Google Form began by requiring the mTurk ID to prevent repeated access by the same workers. Next, participants were required to perform a manipulation check to ensure that their computer displayed video and they could follow directions (enter the word displayed in a video similar to those they would watch for the task). Following this, they were shown a set of four videos (counterbalanced in four presentation orders with eight participants each for each experiment). For each video they were shown an embedded video with a label that read "Please use this video to answer the next question." The task was shown below with the title of the video and a subtitle reading "Watch the above video and select the word that best describes what the robot is trying to communicate." and below this was a set of either two words or seven words depending upon the participant condition (a sample 2AFC participant view is shown in Fig. 4). After completing these four videos, another manipulation check was performed before the participant continued to another four videos to label (with each participant seeing all eight videos). Finally, a post-experiment questionnaire was administered to assess: positive and negative affect, whether they thought the robot was looking at them, whether they were scared of the robot and if they would approach it outdoors, comments about the robot, comments about the experiment, and general comments.

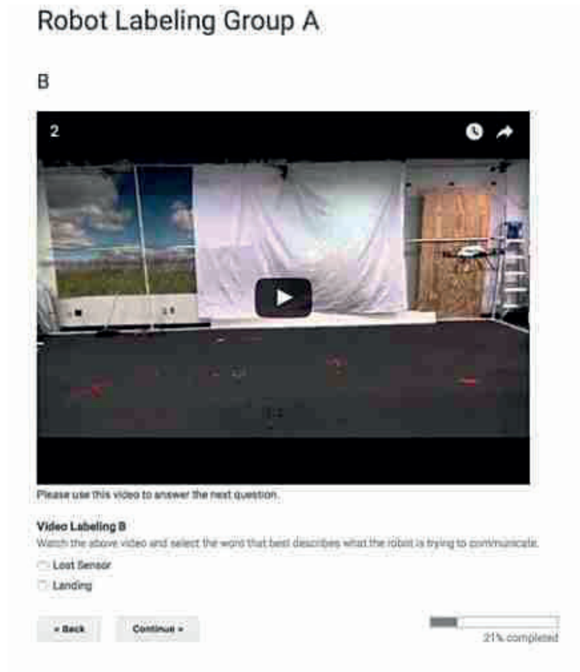

Fig. 4. Participant view of a Google Form question.

Participants completed the entire task in an average of 24.63 minutes (SD=12.18) in the 2AFC task and 26.15 minutes (SD=12.29) in the 7AFC task.

D. Experimental Materials

The same videos were used for all of the experiments, with the only difference in materials being the choices provided in the forced-choice tasks, shown in Table II.

E. Analysis and Results

The results in these studies were judged using a binomial test for 2AFC (compared to 50%) and a Chi-square test (compared to an even distribution) with $p < 0.01$; the resultant necessary agreement was 75% agreement in 2AFC and 34.4% agreement in 7AFC. In the 2AFC, subjects labeled gestures with a chosen label compared with a distractor chosen from a set of seven labels (draw attention, lost sensor, landing, change position, lost signal, low battery, and missed goal). Those labeled with high agreement are: Figure-8 (Lost

TABLE II
AVAILABLE LABELS FOR EACH CONDITION.

	2AFC		7AFC
Motion	Label	Distractor	Label
Circle	Lost Signal	Draw Attention	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery
Figure-8	Lost Sensor	Landing	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery
Left-Right	Missed Goal	Lost Sensor	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery
Loop	Draw Attention	Low Battery	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery
Spiral	Landing	Missed Goal	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery
Swoop	Draw Attention	Low Battery	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery
Undulate	Change Position	Low Battery	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery
Up-Down	Change Position	Lost Signal	Lost Signal, Change Position, Landing, Missed Goal, Draw Attention, Lost Sensor, Low Battery

TABLE III
RESULTS FROM A PRELIMINARY TEST WITH 64 PARTICIPANTS (32 IN EACH CONDITION), WITH ONLY P <0.01 SHOWN.

	2AFC		7AFC	
Motion	Percent Chosen	Label	Percent Chosen	Label
Circle			40.6%	Draw Attention
Figure-8	84.38%	Lost Sensor	40.6%	Change Position
Left-Right				
Loop			34.4%	Landing
Spiral	87.5%	Landing	59.4%	Landing
Swoop	75%	Draw Attention		
Undulate			34.4%	Draw Attention
Up-Down				

Sensor, 84.38%), Spiral (Landing, 87.5%), and Swoop (Draw Attention, 75%). To further explore these results, a 7AFC test was run with all labels available for each motion. These results suggest that 5 motions (3 unique from the first set) could be discriminated at a p <0.01, these are: Circle (Draw Attention, 40.6%), Figure-8 (Change Position, 40.6%), Loop (Landing, 34.4%), Spiral (Landing, 59.4%), and Undulate (Draw Attention, 34.4%). These results are also shown in Table III.

VI. DISCUSSION

We now discuss the results found in the studies presented above before remarking upon the manipulation considerations, limitations, research and design implications, and future work related to these studies.

A. Use of Avian Flight Paths to Convey sUAS State Information

The primary finding in this work was that sUAS flight paths can be used to communicate information about the sUAS and its understanding of the world to diverse participants. Participants broadly agreed that a Spiral could be used to indicate landing and participants in the 7AFC also suggested that Undulate could be used to draw attention, and we believe these gestures could likely be used by developers now to indicate these states in public facing interactions. It was also interesting that there was significant agreement in 2AFC for the use of Figure-8 for lost sensor and Swoop for draw attention, but that Figure-8 was more recognized for change position in the 7AFC. This suggests that users may understand in the presence of suggestion but might be less likely to apply these labels without prompting.

The states proposed in this work were based on a developer's understanding of states that would be helpful to communicate and which might align with participants' prior experiences in the world. Also of interest is that the assumptions about the participants' likely mental models were largely unconfirmed in the 2AFC study, but the 7AFC study should provide insight into the ability for participants to engage with labels for future studies. When less constrained in their choices, the participants largely agreed about gestures to draw attention and to land, which might be due to the ability of novice users to better understand these states. Participants without experience in working with sUAS may not understand the impact and standard responses to states such as lost signal or lost sensor. This was thought to be a benefit when designing the study, but may have led to a reluctance to use these labels or a less principled application of their use. Draw attention and landing were both used at least 20% of the time, while the others were used 15% or less of the time and lost sensor was only used in 10% of responses across both conditions. A recommendation would be to follow these studies up with an open-ended study, but this would be largely dependent upon the instructions given to the participants and the ability to create meaningful categories from the unconstrained data. On the other hand, it would provide a richer data set from which to generalize states to communicate.

B. Impact of Negative Attitudes towards Robots

Riek et. al [14] found that people with negative attitudes towards robots, as assessed by the Negative Attitudes towards Robots (NARS) scale [31] had more difficulty in recognizing robot gestures when interacting with a humanoid robot. We also examined our data to assess whether this finding was supported with sUAS and the results are presented in Table IV. There were 17 participants with positive attitudes towards robots (8 in 7AFC and 9 in 2AFC with means below 2) and

TABLE IV

RESULTS FROM A PRELIMINARY TEST WITH 64 PARTICIPANTS (32 IN EACH CONDITION) COMPARING BROAD AGREEMENT OF PARTICIPANTS WITH NEGATIVE ATTITUDES TOWARDS ROBOTS VERSUS THOSE WITH POSITIVE ATTITUDES TOWARDS ROBOTS.

	2FAC			**7FAC**		
Motion	Positive Attitude	Negative Attitude	Label	Positive Attitude	Negative Attitude	Label
Circle	77.8%	50%	Draw Attention		50%	Draw Attention
Figure 8	77.8%	100%	Lost Sensor	50% Draw Attention	50% Change Position	
Left-Right	66.7%	100%	Lost Sensor	50%		Missed Goal
Loop	77.8%	50%	Draw Attention			
Spiral	88.9%	83.3%	Landing	50%	66.7%	Landing
Swoop	88.9 %	66.7%	Draw Attention	50%	50%	Low Battery
Undulate	55.6%	50%	Change Position			
Up-Down	66.7%	50%	Change Position		50%	Lost Signal

12 participants with negative attitudes towards robots (6 in each 2AFC and 7AFC with means above 3).

This data does not seem to support the Riek finding, which could be due to multiple factors such as the lack of a clear meaning for prejudice against robots to interfere with, lack of mapping from humainoid or ground robots to aerial vehicles, and too small samples for those with extreme opinions about robots. Note when viewing the table that 50% was the expected agreement in the 2AFC, which was shown 4 times in the negative attitudes conditions, but the two highest agreements also appeared in the negative attitude conditions. Across all attitudes and conditions, the recognition of spiral relating to landing was shown.

C. Manipulation Considerations

To confirm that users were able to play the videos and follow directions, each task had two test tasks, which said "Watch the video above and type the word shown." Each of these videos displayed words on the screen and participants were required to type those words into a text box to have their tasks approved. These test tasks were displayed at the beginning of the task and again halfway through the labeling task.

One manipulation that we did not assess, but should be considered in future work, is whether the users have sound enabled on their computer. This task did not require sound to be enabled, but also did not remove the sound from the videos, which may have resulted in different sensory interactions from different participants. Some participants mentioned the sound in their post-experiment feedback on the robot, for example:

- P14, 2AFC: "It's very loud. I can see how the noise can become grating soon enough."
- P11, 7AFC: "Never realized just how loud they are."
- P15, 7AFC: "It is an excessively loud robot. "

D. Limitations

At this formative stage, we attempted to control several factors to gain an understanding of communicative ability with limited complexity. The work is replicable and also a valuable starting point that has been successfully used in human-human communication studies [10], [9]. The design choices we made, however, limit the generalization of our findings, and we intend to relax them in the next studies. Among those are moving from indoor flights to outdoor flights and from video to live flights, adding goal states, and enriching both the response set and the whole context.

From a population perspective, since the participants were recruited from mTurk, they did have more diversity in age and education than we would generally see on a college campus, but they were overwhelmingly American which could limit the application of these results in other cultures, as suggested by [32].

One final limitation of note is the idea that the gestures could interfere with other tasks being undertaken by the sUAS. While this is a possible drawback from the visual communication, it is anticipated that the states proposed for communication would necessitate the pausing of a task. For example, if a sUAS is taking pictures or videos of a farm and finds something important then the sensed information would potentially override the value of the other mission. The states presented here are targeted for generality, but some such as attract attention, may less valuable to communicate in hobby domains and essential in applied domains.

E. Research and Design Implications

A major implication of this work is to suggest investigations into how naive users understand sUAS problem states when compared to users with experience in piloting these vehicles. The communication of more technical states will be predicated upon a user base that can understand them, which may result in recommendations for team training prior to implementing use. This training will be unlikely with general novice users, but may be resolved through a more participatory design process or through communication of the states they do understand. For example, it may be less important that bystanders understand the "lost sensor" signal if it is followed by a spiral landing, which they can generally understand and predict the final state.

Another path for exploration is the idea of a "guessability" study as conducted by [33], [16], [23] to have a small set of participants design gestures and then test them with a larger pool in order to see if there are understood methods for conveying these ideas. An interesting aspect of these tests is that the users may converge on any number of parameters, such as height change indicating attention drawing and combine these ideas into a richer gesture set than the one that we applied here. This approach has limitations which were considered to make it an inappropriate starting point (such as the limitation to the culture that created the gestures as seen in [10]) while the labeling study here was deemed to be a sanity check to understand whether opinions could converge on given flight paths. With the information here, it is expected that a "guessability study" would be a valid method for refinement, allowing a comparison against the baseline described here and is recommended for additional study.

Additionally, it is recommended that the Negative Attitudes towards Robots scale [31] be investigated for applicability to sUAS research. This recommendation is based on the inconclusive support for Riek's [14] humanoid findings to the sUAS gestures.

VII. CONCLUSIONS

This paper presents an initial study on the ability for novice users to understand communicative flight paths from an sUAS to increase safety in future interactions in public spaces. Results indicate a strong understanding across users for a spiraling path to communicate "landing", but users primarily gravitated towards well understood states (draw attention and landing) while avoiding more technical states (lost sensor). Recommendations for future work include: outdoor tests, visible goal state, open-ended responses, and user generated flight paths. An initial finding questions whether the findings from humanoid robots that negative attitudes towards robots decrease understanding of gestures also applies to sUAS, and leaves a more broad question on whether a version of NARS should be revised to apply specifically to sUAS.

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