Emotion Encoding in Human-Drone Interaction

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***Abstract*—Drones are becoming more popular and may soon be ubiquitous. As they enter our everyday environments, it becomes critical to ensure their usability through natural Human-Drone Interaction (HDI). Previous work in Human-Robot Interaction (HRI) shows that adding an emotional component is part of the key to success in robots' acceptability. We believe the adoption of personal drones would also benefit from adding an emotional component. This work defines a range of personality traits and emotional attributes that can be encoded in drones through their flight paths. We present a user study (N=20) and show how well three defined emotional states can be recognized. We draw conclusions on interaction techniques with drones and feedback strategies that use the drone's flight path and speed.**

Keywords—Drone; UAV; affective computing.

I. Introduction

Until recently, personal drones were generally thought of as radio-controlled technologies for hobbyists and professionals to take pictures or videos. With recent improvements, drones are becoming increasingly autonomous, able to fly a path or follow a person without the constant guidance of a "pilot". We expect drones will soon be able to support users in tasks such as sports coaching, tour guiding, shopping, and even in search and rescue missions. As drones become increasingly prevalent, and to facilitate their acceptance in the everyday environment, it is critical to create natural HDI.

Emotions have been shown to have a vital role in human interaction and support processes such as perception, decision-making, empathy, memory, as well as in social interactions [1]. Prior work shows that adding this affective dimension can aid in intelligent interaction and decision making [1], as well as gain social acceptance for robots in domestic environments [2].

Typically, emotions have been added to robots using facial features or by modifying the gait based on context. Drones are in essence flying robots. Yet, they present different physical characteristics, especially by being non-anthropomorphic or when flying further away from users than robots would typically move. These differences precludes drone designers from using facial features or gait to represent emotional states.

We envision that adding an emotional state to the drone will help reflect its reactions to the user's commands. For instance, the drone could look scared when instructed to fly further than the controller's range. It could look confused when not understanding a command or tired when its battery is low. We imagine that the drone's perceived emotional state will be relevant to users and help them to modify their behavior in a natural manner. Moreover, encoding data into the flight path will better support multiple users' interactions, as only one person can have the remote but all can look at the flight path.

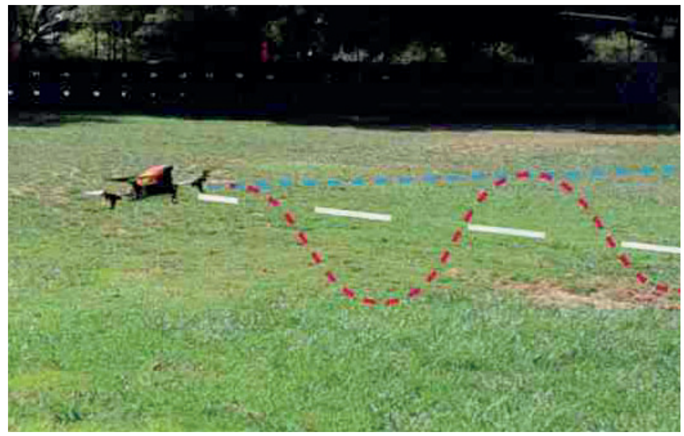

Fig. 1. Example of three different flight paths to reflect different emotional states of the drone (Each personality profile is represented by a color: *Adventurer Hero*: Red, *Anti-Social*: Blue, *Exhausted*: White).

This paper explores the use of the drones' movements and flight path to encode emotions (Fig. 1). We explore the drones' emotional model space and define three emotional states that can best be represented using only the movement of the drone. We tested those models in a study (N=20) and show that drone movements can indeed portray emotions that can be recognized at 60% using a single keyword and at 85% using multiple keywords in a realistic outdoor setting. This paper shows that emotions can be encoded in a drone's flight path, opening up options for feedback in HDI.

II. Related Work

This section discusses the related work on HDI, the effect of appearance, and the role of affective computing in HRI.

A. Human-Drone Interaction (HDI)

FlyingBuddy [3] envisions several scenarios where the drone could extend human abilities, by for example, flying to see things beyond the person's field of view, reporting accidents from above, or even supporting people when shopping. Schneegass et al. [4] propose using drone-based

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flying displays as personal companions (e.g., during sports), as a way to actively support people in emergency situations (e.g., search and rescue), or as a tour guide.

To enable such scenarios, we need to provide suitable collocated interactions, which can be mediated (i.e., using a remote or a phone [5]) or direct (i.e., using voice or gestural control [6, 7]). While there is a variety of possible inputs, there are few feedback techniques (outputs) for HDI. Prior work looked at adding LEDs around a quadcopter to communicate direction [8]. Other work modified the drone's flight path, using techniques such as arcing, to communicate directional intent [9]. Results show that users felt safer interacting when the flight path was communicating intent.

Recently, the Daedalus [10] drone was augmented with head movement, eye color, and the propeller noise to show various emotional states, while Sharma et al. [11] modified a drone's flight path following the Laban Effort System [12] to communicate affect. In this latter work, the drone performs pre-defined movements with four different criteria: Space, Weight, Time and Flow. Participants could differentiate different states along valence and arousal for all criteria but Flow. This work shows promises that people can discriminate different characteristics of the drone's flight path.

We go beyond this prior work and establish an Emotional Model Space for drones and test it in real-world conditions with the drone flying outdoors.

B. Appearance in Human-Robot Interaction (HRI)

Mavridis [13] discusses verbal and non-verbal human-robot collaboration and establishes a list of necessary features (desiderata) towards fluid HRI. This list includes affective interaction and non-verbal communication. Most prior work on affective HRI assumes that the robot is anthropomorphic in shape [2, 14], and uses gait, body posture, and even facial expressions to convey emotional responses.

Yet, prior research shows that non-anthropomorphic robots can still be perceived as emotional [15], by for example, using the robot's movements as in Hoffman and Ju's design process [16]. Both the Ranger robotic toy box [17], with limited facial features, and the mechanical Ottoman [18], with no facial features could communicate emotion and intention using only horizontal and vertical movement. In a similar fashion, Saerbeck and Bartneck [19] use acceleration and curvature to study perceived affect of a mobile robot. Picard [1] explains that computers and robots can demonstrate emotional expressions through facial displays and noises (i.e., Star Wars' R2D2), and movements (i.e., Disney's Aladdin's magic carpet). Similarly, Novikova and Watts [20] show that emotion can be conveyed through the Approach, Energy, Time, and Intensity of non-humanoid robots' movements.

These results are encouraging that affect can be perceived on drones, despite being non-anthropomorphic in nature, and without the need for added facial features, which would not be seen at all times during the interaction with a drone.

C. Models of Emotions in HRI

The space of emotions that can be recognized in HRI is not set in stone. Ekman [21] shows that six facial expressions for six emotions can be universally recognized: *Anger*, *Disgust*, *Fear*, *Happy*, *Sad*, and *Surprise*. Other prior research evaluates facial expressions for the following mental states: *Boredom*, *Confusion*, *Happiness*, *Interest*, and *Surprise* [22] or *Anger*, *Fear*, *Happiness*, *Sadness*, and *Surprise* [23].

So as to not view emotions as categories (e.g., sad, happy, etc.), other researchers think about the dimension of emotions as a span between arousal and valence. Russell's circumplex model of affect [24] positions emotions as a combination of valence (positive or negative) and intensity (also called arousal). Other models add a third component, the dominance, to distinguish between emotions with the same level of valence and intensity [25]. For instance, Kismet's [2] emotions are mapped around three values: Arousal, Valence, and Stance.

Given the difference in form factor and limitations in expressivity of drones, we could not directly apply any existing model to our work and decided to first define an emotional model space for drones.

III. Definition of Emotional Model Space for drones

The emotional model space for drones needs to be defined based on emotions that can be both recognized by users and performed by the drone. To identify which emotions could be performed, we collected a list of emotions from the literature and ran a design workshop to 1) map those emotions to personality models and 2) identify the physical characteristics that would best map the models to drone movement.

A. Emotions vs Personality

The perceived personality of a robot can effect how willing users are to interact with it and establish a relationship with it. Fong et. al [26] argue that one way to characterize personality is using emotions to portray stereotype personalities. While personality can only be evaluated over time, emotional state is immediate. Here, we start from an emotional state, identify the matching personality type to best design the drone's movements to represent this personality, and go back to the corresponding emotional state for the evaluation stage.

B. Emotions and Personality Traits

To choose the most suitable range of emotions, we first looked at characteristics in people and animals, as prior work shows that users tend to interact with drones as if interacting with people and pets [27]. We referred to the storytelling folklore literature that anthropomorphize characters using specific personality traits. We specifically use Walt Disney's version of the Grimms' Snow White tale, where the seven dwarfs represent key personalities that are well known across cultures. Similar personalities are found in Peyo's smurfs, which are also well known across cultures. The chosen emotional states are: *Brave*, *Dopey*, *Grumpy*, *Happy*, *Sad*, *Scared*, *Shy*, and *Sleepy*. We chose to leave aside aggressive traits, such as Anger, that could be dangerous if implemented on a drone given today's form factors (e.g., quadcopters using four propellers that are not fully enclosed). We also removed *Disgust*, as it did not seem to make much sense for HDI.

C. Definition of Stereotypes of Personality

We ran a half-day design workshop with five members of the design team. Four had experience designing interactions with drones and one had design experience with robots and industrial design. Three were skilled visual designers. During the workshop, the eight chosen emotional states were matched onto stereotypes of personality models that were designed to help develop interactive object behavior [28]. The stereotypes of personality use five traits represented by two opposite poles: *Openess to Experience*, *Conscientiousness*, *Agreeableness*, *Extraversion*, and *Neuroticism* (Fig. 3). Each trait has several attributes. For example, "Extraversion" is represented by the tendency to be sociable, fun-loving, and affectionate versus retiring, somber, and reserved.

The idea was that using the stereotypes of personality models would make it easier to define the drone's movements. The chosen stereotypes of personality are derived from [28], shown in Fig. 3 and detailed in TABLE I. below. The chosen characteristics in TABLE I. were established during the workshop, mapping the personality to some of the drone's expected behaviors. Note that the results for Dopey and Sleepy were collapsed into a single model.

TABLE I. CHARACTERISTICS OF STEREOTYPES OF PERSONALITY AND MATCHING EMOTIONS

Personality (Emotional State)	Characteristics
The Big Boss (Brave)	• Confident and Disciplined • Looks directly at a person • Never goes backwards; instead, turns around and moves forward • Directly executes commands, although it may take charge and do the task its own way • Moves quickly and smoothly
The Goofy Comedian (Dopey / Sleepy)	• Delayed reaction time to commands (Misunderstands / Slow to react) • Moves sloppily / Wobbles (rotating) • Uneven rhythm / Slow (starts and stops as it gets distracted or needs to rest) • Gets distracted, bumps into things, unpredictable
The Detached Philosopher (Grumpy)	• Reserved, uncooperative, impulsive • Have to repeat commands (begrudging) • Keeps its distance • Drags along
The Lovable Romantic (Happy)	• Trusting, affectionate, comfortable close to the user • Disciplined but imaginative (follows commands its own way, may not take the most direct path) • Moves and reacts quickly • Constant speed but unpredictable path
The Peaceful Artist (Sad)	• Self-pitying, keeps its distance • Non-responsive (slow, dragging) • Gentle and small movements • Flies low to the ground
The Sneaky Spy (Scared)	• Anxious, insecure, suspicious, reserved • Nervous, looks around for danger (jerky movements and stops to look around) • Scared when called • Keeps its distance, stays low
The Model Student (Shy)	• Anxious, insecure • Gradually builds trust (starts slow with some delay, that changes over time) • Takes coaxing for commands

D. *Definition of Movements*

Once the stereotypes of personality were chosen, each workshop participant was given one to two, together with a representation of the *Interaction Vocabulary* [29]. This vocabulary follows the concept of "aesthetics of interaction" and allows the creation of interaction profiles for tangible interactive objects using physical interaction attributes. The interaction can be slow or fast, stepwise or fluent, etc. Each participant was asked to develop a drone interaction profile (Fig. 2) according to their assigned stereotype(s) of personality (Fig. 3) and using the provided *Interaction Vocabulary*. Each profile was then discussed, so that new ideas could emerge and the model could be enriched and validated by the group.

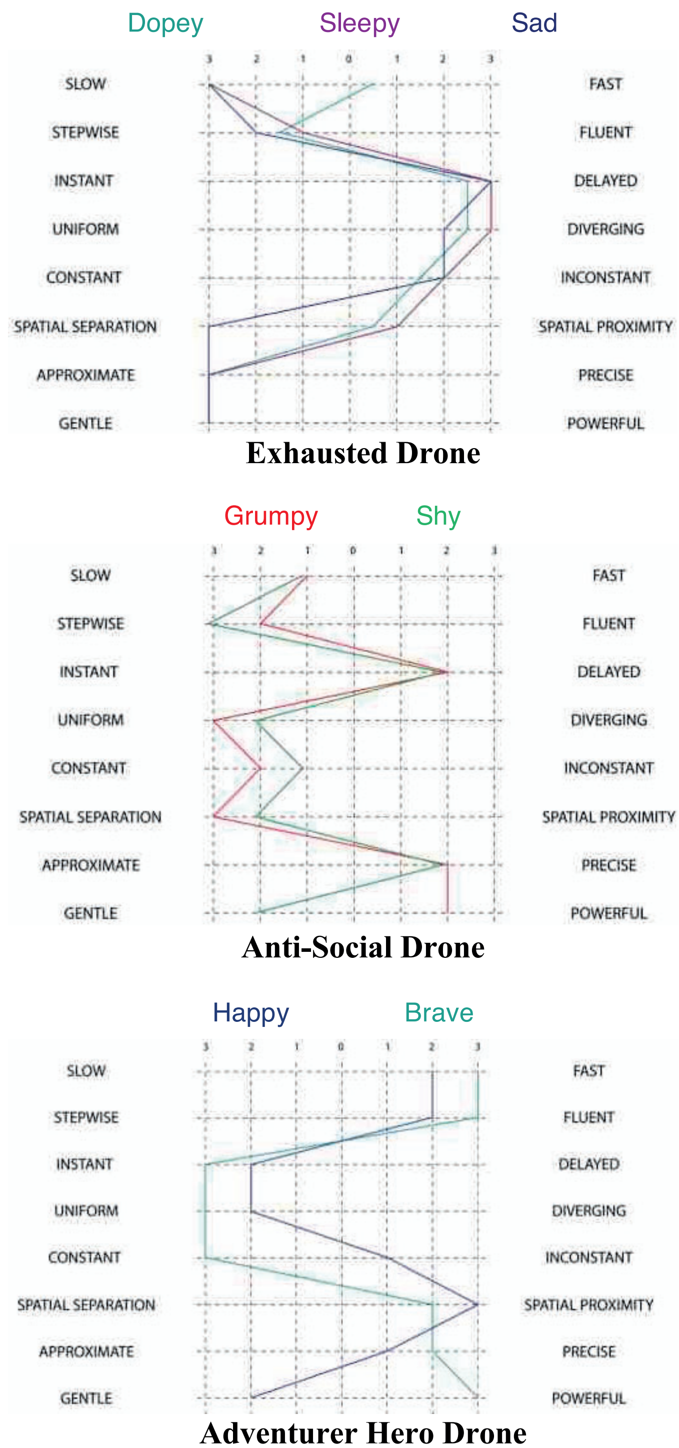

Fig. 2. Interaction profiles for each stereotype of personality.

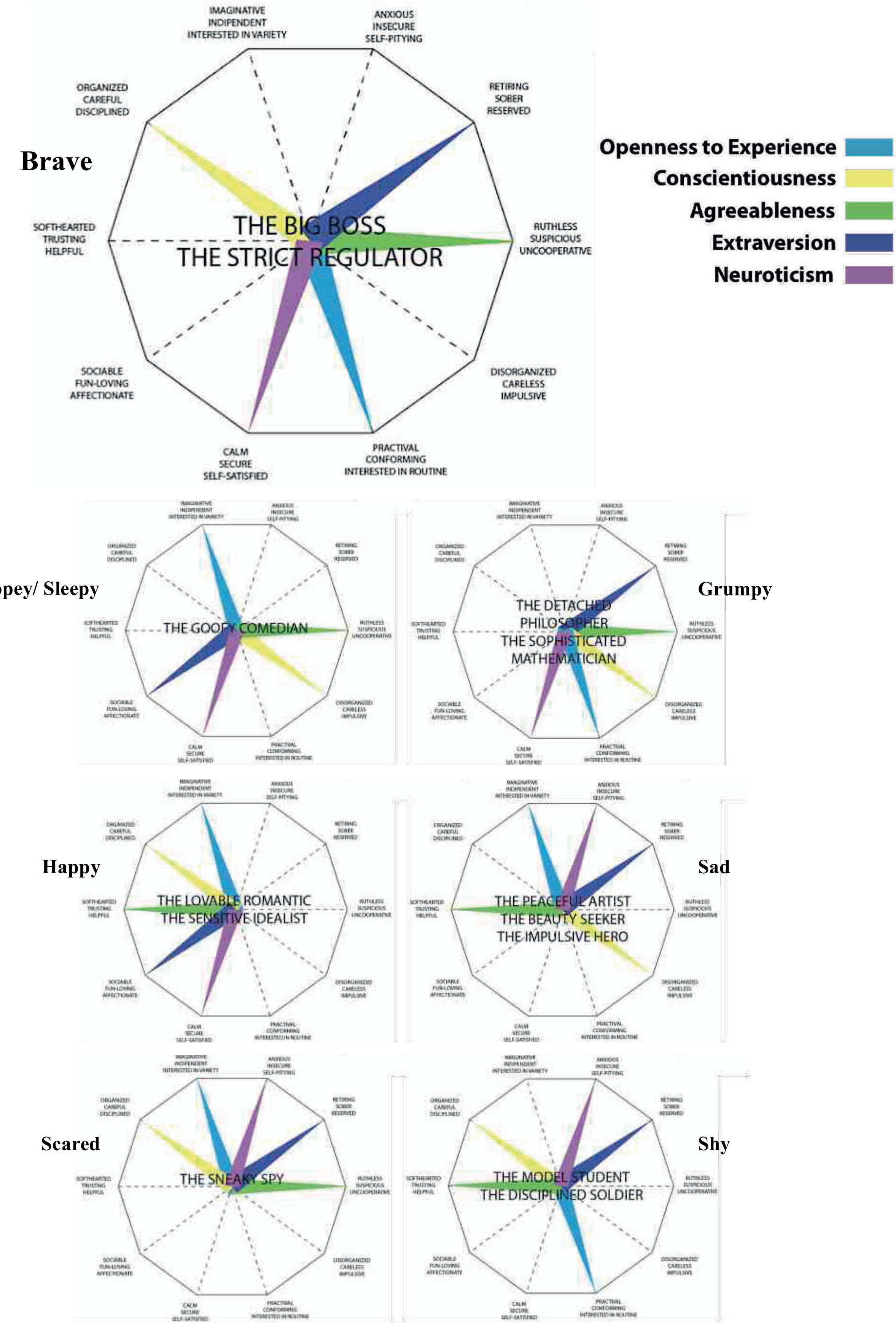

Fig. 3. Wheels of Personality stereotypes matching the eight emotional states defined for drones.

E. *Redefinition of Personality and Emotional Spaces*

We observed in Fig. 2 that some of the interaction profiles were nearly identical and chose to merge these. In particular, Dopey, Sleepy, and Sad, together become the *Exhausted* Drone. Grumpy and Shy were merged as the *Anti-Social* Drone, and Happy and Brave joined together as the *Adventurer Hero* Drone. We now have four different stereotypes of personality models that constitute the Emotional Model Space for drones:

- The Exhausted Drone
- The Anti-Social Drone
- The Adventurer Hero Drone
- The Sneaky Spy Drone

Since the Sneaky Spy Drone does not cover any emotional state other than *Scared*, it was not implemented in this first study. The interaction profiles allow an implementation of the drone's movements to fit with the stereotype of personality.

IV. Implementing Personality Models Onto the Drone

This section describes the implementation of the stereotypes of personality models onto the drone.

A. *Control Parameters*

The next step in our workshop was to associate physical properties of the drone to the Interaction Vocabulary (and therefore to the stereotypes of personality models). The parameters that can be modified are: the drone's position and direction compared to the user, speed, rotation angles (roll, pitch, and yaw), and altitude (Fig. 4), as well as the drone's reaction time and compliance to commands.

Fig. 2 shows that for speed (Slow-Fast movement), the Adventurer Hero Drone is faster than the Anti-Social Drone, which is faster than the Exhausted Drone. We tested the different personality models with pilot participants to determine appropriate speeds and other parameters (see TABLE II.).

TABLE II. Control Parameters for the 3 Personality Models.

Personality Profile	Control Parameters			
	Speed (mph)	*Reaction Time (sec)*	*Altitude*	*Special Movements*
Adventurer Hero	7.7	Instant	High	Spins / Flips
Anti-Social	4.4	Delay (2s)	Middle	Starts and Stops
Exhausted	1.1	Delay (3s)	Low	Wobbles

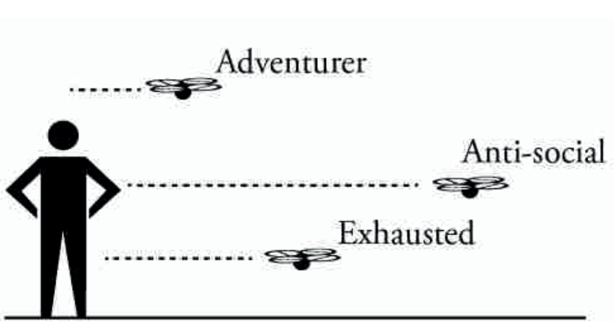

Fig. 4. Drone's altitude compared to the user for each personality model.

B. *Hardware and Infrastructure*

We used an AR Parrot 2.0 Drone equipped with a WiFi network and controlled via a personalized web interface hosted on the experimenter's laptop (Fig. 5).

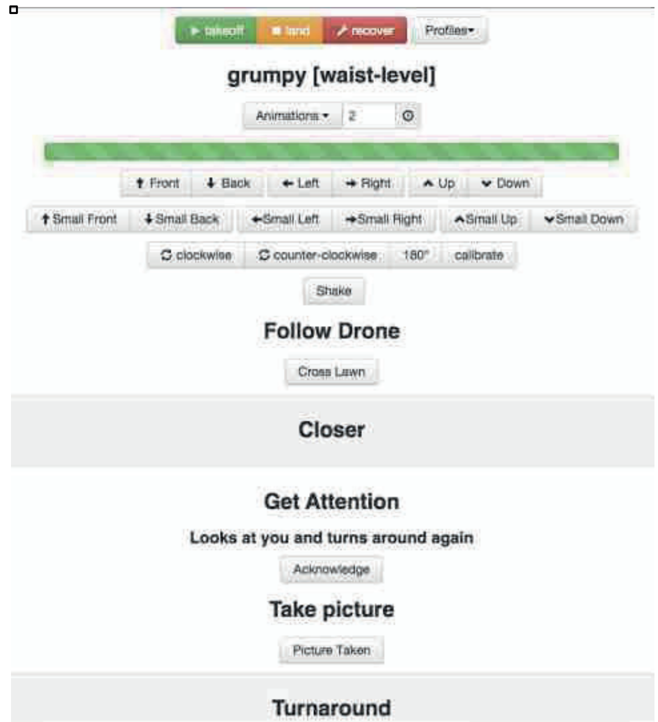

Fig. 5. Example of the web-based control interface.

The drone 2.0 API was used to send commands through Node.JS server using the Faye messaging system via the laptop. The web interface was based on an open source drone browser. By choosing the drone's stereotypes of personality model from a drop-down list, parameters such as the speed and some pre-defined paths could be set automatically.

Some of the movements were basic translations, such as up, down, left, and right, while some were pre-programmed paths. The paths included animation sequences with spins, tilts, and flips, as well as movements in the x, y, and z planes for given durations. For example, the "acknowledge" function, performed when the drone has finished a task, is a simple nod in the *Adventurer Hero*, while the *Anti-Social* drone first faces the user and then turns back around to look away. Some simple commands were sequenced to build longer pre-defined paths.

V. User Study

To validate whether the stereotypes of personality models can be properly recognized, we ran a user study with all three models. We test the participant's recognition of the corresponding emotional state rather than the stereotypes of personality, allowing for a shorter evaluation time which is more realistic given current drone battery life.

A. *Participants*

We ran a within-subjects user study with 20 volunteers from 18 to 39 years old (10 female / 10 male) across the three personality models. Most had seen a drone before, three had experience piloting one, and one participant owned a drone. Volunteers were shown five tasks per personality model. The models and task orders were randomized to avoid interaction and learning effects. The study took approximately 30 minutes per participant, who were compensated $20 for their time.

TABLE III. DRONE TASKS AND HOW THEY DIFFER BASED ON THE PERSONALITY MODELS.

Tasks		Differences between personality models
Navigation	Stop	• Loitering animation sequence • Distance and height compared to participant
	Precise Location	• How direct the path is • How quickly the drone reaches its target
General Motion	Stop (after flying)	• How quickly the drone obeys the command after hearing it
Relative to User	Get Attention	• How quickly the drone acknowledges the participant and where it "looks"
	Take a Selfie	• How the drone confirms that a picture was taken

A. Tasks and Procedure

The participant's role was to observe the drone's movements and reactions to a set of commands and interpret them as an emotional state. The participant stood by the experimenter and observed the drone's reaction to a set of five tasks per personality model (TABLE III.). The tasks were chosen from a larger set used in prior Human-Drone Interaction work [27]. The study was run outdoors on a large semi-secluded lawn space, fairly protected from wind gusts.

B. Measures

To explore how recognizable the drone's emotional states were to people, we created a questionnaire. As per previous studies, given the wide variations in language that people use to define emotions and the small number of subjects, we used a forced choice paradigm [2]. After seeing all five tasks for one personality model, the participant could choose the best emotional state that matched the drone's behavior from eight possible labels (i.e., *afraid*, *brave*, *dopey*, *grumpy*, *happy*, *sad*, *shy*, and *sleepy*) (primary keyword). In a follow-up question, they could circle any other labels that they thought could also apply (secondary keywords). On a 7-point Likert scale, the subjects were also asked to rate the intensity of the emotion and the certainty of their answer. They were also asked to write down any comments they had. This protocol corresponds to the ones found in prior HRI literature [2, 23].

VI. RESULTS

This section describes the results of the user study.

A. Forced Choice Questionnaire (Primary Keyword)

The subjects' responses to the questionnaire are summarized in TABLE IV. We see that the *Adventurer Hero* model is well identified, with 90% of the participants correctly identifying one of the corresponding emotional states (happy or brave). The *Exhausted* and *Anti-Social* models are not identified as well, with 45% accuracy only. We see that the level of confidence of the participants matches the accuracy with 6.3/7 confidence in the *Adventurer Hero* model compared to 5.4 and 4.7 in the *Exhausted* and *Anti-Social* models, respectively. The same results were found with the intensity of the emotion decreasing from 6/7 (*Adventurer Hero*), to 5.2 (*Exhausted*), and to 4.6 (*Anti-Social*).

TABLE IV. SUMMARY OF THE FORCED CHOICE QUESTIONNAIRE RESULTS (IN PERCENTAGE OF TOTAL ANSWERS)

Emotion	Personality Models		
	Exhausted *(Dopey, Sad, Sleepy)*	**Anti-Social *(Grumpy, Shy)***	**Adventurer *(Happy, Brave)***
Dopey	**25**	10	10
Sad		5	
Sleepy	**20**	15	
Grumpy	30	**25**	
Shy	5	**20**	
Happy	10	10	**70**
Brave			**20**
Afraid	10	10	

The average recognition rate of the personality models based on the associated emotional states for the drone is 60%. This is comparable with early work in HRI using coarse facial features [23], which showed 55% recognition amongst adult participants in a similar setting. This result is however not as good as Kismet's emotional expressions that can be recognized at 77.6% using videos of Kismet moving [2].

B. Secondary Keywords

When using both the primary and secondary, we find a large increase in the recognition rate, with the *Adventurer Hero* model being recognized by 100% of the participants, the *Exhausted* Drone recognized by 80% of the participants and the *Anti-Social* drone by 75% of the participants (TABLE V.). This is extremely promising that all three personality models can be recognized by people who have little to no previous experience with this type of technology.

TABLE V. AVERAGE RECOGNITION RATES OF PERSONALITY MODELS USING BOTH PRIMARY AND SECONDARY KEYWORDS.

Condition	Exhausted *(Dopey, Sad, Sleepy)*	Anti-Social *(Grumpy, Shy)*	Adventurer *(Happy, Brave)*
Primary keyword	45	45	**90**
Primary + Secondary keyword	**80**	**75**	**100**

C. Qualitative Data

We find that when participants chose a specific primary keyword for the emotional state, they typically understood what the drone was doing but did not always correctly interpret its corresponding emotional state. Adding a second keyword helped make their choices more accurate.

For example, P19 understood that the *Anti-Social* drone was showing "delayed responses" and even "incomplete responses", but interpreted it as being Dopey (primary keyword) and Grumpy (secondary keyword). Similarly P18 found that the *Adventurer Hero* Drone "obeyed all commands but often with a slight delay and/or with additional flair, like whatever it felt like doing". They also found it "pretty cute, especially when it did flips". The delay mentioned was minimal and only due to the WiFi and not to any implemented delay. Still, the subject perceived the drone as being "Dopey" (primary) and Brave and Happy (secondary).

We find that participants could properly perceive changes in the drone's behavior, whether they were due to the flight path itself, its reaction time, compliance to command, or speed. This is extremely promising as this is the first proof that drones' movements themselves can be perceived as portraying an emotional state. The following sections give examples of the participants' comments when selecting keywords.

- Exhausted Drone

P1	*"It kind of wobbled in the air and dropped – tired"*
P3	*"Sharp movements but not always very coordinated, seems incompliant but bold"*
P4	*"It usually messed up the first time or was extremely wobbly when flying"*
P7	*"Could also be a drunk drone, seemed to like to rest a lot by landing"*
P8	*"Shakey and stayed low"*
P16	*"Slow to respond, disobedient, could be because it's mad or stupid"*
P18	*"Since commands didn't really require multiple promptings, I figured it was faithful and obedient, so when it kept dropping and acting drunk, I immediately assumed sleepy"*

- Anti-Social Drone

P1	*"There was a part where the drone spun around, which was maybe angry or just refusing to do something."*
P4	*"More "obedient""*
P5	*"The drone was resistant to commands so it made me feel as though the drone was displaying aggression to the driver"*
P9	*"The drone didn't seem to "get it". Just kind of moped around"*
P11	*"stops after some meters and goes on...not frontal facing"*
P16	*"Quick to move away, slow to come back"*
P18	*"At first I was thinking sad/low energy because it took multiple commands every time and it kept flying so low and dropping. But at the end, when it was disobeying by not stopping, I figured it was capable but reluctant"*

- Adventurer Hero Drone

P1	*"Faster responses = brave/happy"*
P2	*"mostly thought it was happy because it twirled a lot"*
P3	*"The drone danced and did flips, usual indicators of happiness. It was fun and exciting to watch."*
P4	*"More distinct actions - flipping, responsiveness"*
P5	*"It flew a lot with its nose down so it seemed to me to signal bravery"*
P7	*"Extra movements made it look like the drone couldn't contain its excitement"*
P8	*"Moving quickly and all around, doing flips ("fun" things)"*
P9	*"It seemed really excited!"*
P13	*"Seemed very excited"*
P16	*"responded to command quickly, moved quickly, extraneous flips give the happy impression"*
P19	*"Excess movement/ornamentation, comparable to an excited dog"*

VII. Discussion

This section discusses some of our findings as well as the limitations of this study.

A. *Encoding Personalities and Emotional States*

This study shows that there is a space for social drones. The emotional model space that we have defined is non-exhaustive, but it is a good starting point in developing the area of emotional computing with drones. We show that the drone's movements, such as its speed, altitude, and orientation, as well as its reactivity, can encode personalities and associated emotional states for collocated HDI. We believe that this can extend the possibilities in using the drone's movement as feedback to users' commands.

B. *Drone as Pet*

Several times during the study, participants compared the drone to a pet. In the *Adventurer Hero* model, P1 mentioned that the drone looks "like a dog chasing its tail", P7 said that the drone "seemed more like a pet than anything else", and P19 noted that the drone was "comparable to an excited dog". In the *Anti-Social* model, P3 "believed that [the drone] was listening to its owner the way a happy pet would". These remarks fit with prior work on interacting with intelligent objects [18] and is also consistant with prior findings on interacting with drones [27].

C. *Limitations*

The study was run outdoors, in realistic non-controlled conditions. We experienced a certain amount of wind during the study. P14, for instance, mentions that they are "not sure if the wind affected movement pattern that would influence emotional impression". Despite these external factors, participants were able to recognize the drone's flight paths, its reactions, and its speed. The personality models were recognized at 60% on average across all conditions for single keywords and at 85% when also using secondary keywords. This shows the robustness of the models and the possibility to work with social drones outdoors.

VIII. Future Work

We imagine drones as having their own personalities as pets do. Drones would become more interesting objects to interact with and the stereotype of personality model could bring more realism to the interaction, facilitating their acceptability in personal spaces. We could also envision other behaviors of the drone, beyond personality traits, such as a drone that would mimic one's emotional state. Drones could also support users in behavior change, e.g., by looking sad when the user hasn't exercised for too long or happy when going for a run, bringing awareness of how well the person is doing. Future work will also include refining the models to better match the drone's behavior with the personality models.

IX. Conclusions

We presented the first exploration into drones' personality models and how to encode emotions into their flight path. We believe that drones are a viable platform to become accepted sociable entities. We showed that people can precisely identify the behavior of the drone by observing its physical movement and its response to commands. Participants managed to accurately associate this behavior to an emotional state corresponding to a personality model. In the future, this might be used to inform users of the drone's intentions and convey meaningful feedback that would be hard to convey otherwise.

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