Elicitation of Emotional Responses to Flying Robots with Facial Expressions

Viviane Herdel[1,2]
herdel@post.bgu.ac.il
[1]Magic Lab, Industrial Engineering & Management
Ben Gurion University of the Negev
Be'er Sheva, Israel

Anastasia Kuzminykh[1,3]
anastasia.kuzminykh@utoronto.ca
[3]Faculty of Information
University of Toronto
Toronto, Canada

Andrea Hildebrandt[2]
andrea.hildebrandt@uol.de
[2]Department of Psychology
Carl von Ossietzky Universität Oldenburg
Oldenburg, Germany

Jessica R. Cauchard[1]
jcauchard@acm.org
[1]Magic Lab, Industrial Engineering & Management
Ben Gurion University of the Negev
Be'er Sheva, Israel

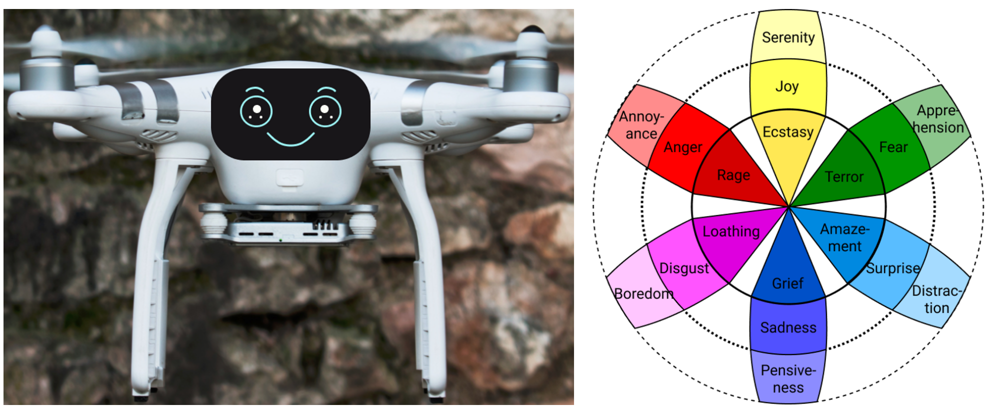

Figure 1: "The drone looks like it is in love." Example of a participant's reasoning when deciding on the drone's emotional state based on its facial expression (left). Wheel of six emotions derived from Plutchik's theory of emotion [27] (right).

ABSTRACT

Drones are rapidly populating human spaces, yet little is known about how these flying robots are perceived and understood by humans. Recent works suggested that their acceptance is predicated upon their sociability. This position paper describes how human emotions can be elicited by flying robots with facial expressions. We leveraged design practices from ground robotics and created a set of rendered robotic faces that convey basic emotions. We evaluated individuals' response to these emotional facial expressions on drones in two empirical studies (N = 98, N = 98). Our results demonstrate that participants accurately recognize five drone emotional expressions, were emotionally affected by the drone and showed empathy towards it. Note that this position paper is a subset of the full paper [14] that is published at CHI 2021.

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MEEC '21, May 09, 2021, Yokohama, Japan

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1 INTRODUCTION

Over the last few years, small-size drones have become increasingly popular, being used in a wide range of applications from photo and videography to deliveries and search and rescue [34]. Recently, researchers have highlighted novel opportunities created by *social drones* that operate in human spaces and can support people in their daily lives, such as when exercising [25], and as a personal companion [16]. Yet, designing a social drone [3] is not trivial, and we are only at the beginning of understanding which factors influence people's perception of drones [36]. However, the literature on interacting with ground robots is rich and teaches us that social robots can communicate with people using emotions and expressive behaviors designed around features such as: facial expression, posture, and voice [5]. Unfortunately, findings from ground robotics cannot be directly translated into drones [36]. For instance, prior work showed that robots with eyes and no mouth are perceived as unfriendly [15], while drones with equivalent facial features are perceived as likable and warm [29].

We address this gap in the literature by designing facial expressions to convey emotional states on a social drone. Our focus on facial expressions is motivated by their significance as a non-verbal communication channel in human-robot [15] and in human-human communication [26], as they trigger the tendency to read emotions and interpret intentions and personality traits [33]. Thus, the use of facial expressions in social drones might have a potential to, not only communicate the drone's state, but also to elicit particular reactions and behaviors from a user.

Note that this is a position paper for the MEEC'21 workshop and only contains a subset of the CHI 2021 full paper [14].

2 RELATED WORK

We present the state of the art on emotional robotics for both ground and aerial robots, and discuss the use of facial expressions in conveying emotions.

2.1 Affective Robotics

The enriching effects of integrating convincing emotions into non-human agents has been extensively researched in the robotics domain [7, 31]. Eyssel et al. [12] showed that users tend to perceive the interaction with an emotional robot as more pleasant, feel closer to it, and ascribe human attributes to it, such as intentionality. Attribution of intentions, in turn, can foster feelings of social connection, empathy, and prosociality [18]. Indeed, we know from the research on human-human communication that displaying emotions has crucial communicative and social functions [20], such as forming guidelines for future behavior [2]. Research showed that affective robots similarly induce people to make sense of their intentions to guide human behaviors [12, 28]. The communicative and social functions of displaying emotions motivates the interest in the exploration of its application to the design of social drones [3, 9]. In particular, it was recently argued that, in human spaces, drones need to present social features [3]. The researchers name the intuitive comprehension of drones' intentions – to what degree people are able to interpret intentions that the drone is trying to convey via the interaction – as one of the major human-centered concerns in the design of social drones. One major challenge is then to investigate how to appropriately embed the display of emotions into the interaction design of social drones, including *how to display* emotions and *what emotions* are reasonable to display.

2.2 Conveying Emotion in Aerial Robotics

In both human-human and human-robot communication, the display of emotions occurs though external, i.e., visible and audible, behavioral manifestations. Such manifestations can take diverse forms [20], such as verbal and non-verbal elements of language, gesture, posture, and gaze. Correspondingly, in robotics, researchers have explored diverse ways to convey emotions. For instance, there is a large body of work on affective perceptions of robots' body movements, sound and color, and diverse combinations of these elements [13, 21]. In drone design, the communication of emotions has been predominantly explored through flight path [9, 30]. Sharma et al. [30] proposed expressive flights and showed that people can differentiate between drone states along the valence and arousal dimensions. Cauchard et al. [9] later defined an emotional model space for drones and showed that humans can accurately associate a drone's movements and behavior to an emotional state corresponding to a personality model. Additional efforts have been conducted towards establishing design recommendations for social drones, suggesting the suitability of faces [16]. Although these works did not investigate emotional expression per se, they open the space to the use of facial features on drones.

2.3 Facial Expressions and Emotions

In human-human communication, information conveyed through one's face plays a fundamental role in interactions [10], leading to the human's strong ability to use the facial information to infer emotional states, personality traits, and intentions [26]. Facial features are also a key factor in creating affective robots, and it was shown that robots without a face are perceived as less sociable and amiable compared to robots with a face [8]. This is in line with findings from drone literature showing that the presence of facial features influence the perception of drones as more likable, trustworthy, and intelligent [29, 36] compared to drones without facial features. While a first attempt has been made at designing drone facial features (eyes) to enhance non-verbal communication with humans [35], the question of the recognition and interpretation of emotions displayed by drones remains open. This further highlights the challenge of identifying what emotions are relevant and appropriate to display in HDI.

For the purpose of this work, we focused on the six basic emotions [10]: *Joy, Sadness, Anger, Fear, Surprise,* and *Disgust*, along three levels of intensity: Low, Medium, and High. Building upon prior work, this paper explores the possibility to effectively convey drone's emotions through facial expressions. In the following section, we discuss our approach to the development of facial expressions and describe our design choices to display basic emotions on drones.

3 DESIGNING EMOTIONS FOR DRONES THROUGH FACIAL FEATURES

While affective robotics offers several developed sets of faces with emotion expressions (e.g., [1, 6]), the emotion recognition rates between these existing faces are inconsistent [32]. Additionally, there is an open question of whether these sets of faces are appropriate for drones. These considerations motivated our decision to develop a novel set of drone faces that would allow us to explore the perception of emotional facial expressions on drones for six basic emotions each with three intensity levels. In this section, we describe the corresponding design process

3.1 Constructing the Face

Our design used a cartoon-like 2D format since such faces led to higher emotion recognition compared to photo-realistic faces in prior work [17], and to minimize the risk of falling into the uncanny valley [22], which can trigger undesired emotional reaction [24]. The chosen cartoon-like format allowed us to minimize the number of included facial features, which contribute to reducing the cognitive efforts needed for a person to process the resulting facial expressions [17]. Our next step was to identify the minimal set of features required to convey the chosen set of emotions. We used the well-established Facial Action Coding System (FACS) [11], which documents single muscle units required to create universally recognizable basic emotions (Table 1). This provided us with the necessary systematical approach needed for creating emotional facial expressions for drones. Furthermore, we chose to include pupils, as rendered robot faces without pupils are perceived negatively [15]. Our final resulting set included: eyes, eyebrows, pupils, and mouth.

Table 1: Colored cells represent Action Units (AU) from the Facial Action Coding System (FACS) [11] required to create specific basic emotions.

AU	FACS Name	Joy	Sadness	Fear	Anger	Surprise	Disgust
1	Inner brow raiser		■			■	
2	Outer brow raiser			■		■	
4	Brow lowerer		■	□	■		
5	Upper lid raiser			□	□	□	
6	Cheek raiser	□					
7	Lid tightener			■	■		
9	Nose wrinkler						□
12	Lip corner puller	■					
15	Lip corner depressor		■				■
16	Lower lip depressor						■
20	Lip stretcher			■			
23	Lip tightener				■		
26	Jaw drop			■		■	

Notes. AU corresponding to dark colored cells were used to design the drone faces, while AU corresponding to light colored cells were not manipulated.

3.2 Designing Emotions on the Face

For each of the basic emotions, we designed representations with three levels of intensity by intensifying the corresponding Action Units. We put special attention in the design of each feature to represent the emotions by extensively surveying robot faces in the literature and on the market. The resulting core set of rendered faces (Figure 2) includes 18 images of cartoon-like facial expressions (6 basic emotions × 3 intensity levels). We additionally designed a neutral face.

4 METHODOLOGY

To explore the recognition, interpretation, and reactions to the emotional facial expressions on drones, we conducted two empirical studies, both employing a mixed-methods approach. Study I explored the perception of emotional facial expressions of different intensities presented statically (image-based). Study II was conducted four months after Study I and addressed the perception of animated emotional facial expressions on drones presented dynamically (video-based). We investigated both static and dynamic stimuli, as prior work had discussed [15] and proved [6, 29] that these stimuli can elicit different responses in humans. In this section, we describe the participants, stimuli, tasks, and data analysis.

4.1 Participants

Participants were recruited using the Amazon mechanical Turk platform. The recruitment selection was based on HIT rate (≥ 97) and approved number of HITs (≥ 100) with all participants located in the US. The resulting samples included N_1 = 98 (Study I) and N_2 = 98 (Study II). The surveys took in average respectively 30 and 25 minutes to complete.

4.2 Stimuli

Image and video stimuli are commonly used in perception studies in the robotics literature [15, 36]. We presented the developed set of faces (Figure 2) on a screen display embedded on the DJI Phantom 3 body[1]. In Study I, we presented 18 stimuli images (6 emotions × 3 intensities) each displaying one of the developed facial expressions on the drone's body (e.g., Figure 1 left). In Study II, the drone was presented in 16.6 seconds video clips. The drone was shown approaching in a straight line for 10 seconds. While the drone moved, its face displayed a neutral expression. Once stopped, its face changed from neutral to low, medium, and high intensity of emotion (in 600 ms). In total, Study II included five video stimuli: *Joy*, *Sadness*, *Fear*, *Anger*, and *Surprise*. *Disgust* was omitted based on low accuracy results from Study I.

4.3 Tasks Description

This section describes the main tasks of Study I and II.

4.3.1 Study I △. Participants first chose an emotion label to best describe the expression on the drone's face. The set of emotion labels was provided using a modified version of Plutchik's wheel of emotions [27]. Our wheel shows the six basic emotion categories [10] with labels describing high (inner circle), medium (middle circle), and low intensities (outer circle) of emotions corresponding to the 18 stimuli images. With respect to their best-choice answer, participants were then asked to justify their choice (free-form answer).

4.3.2 Study II □. Task 1 aimed to assess the participants' emotional response towards the drone and Task 2 measured how well dynamic facial expressions of emotions could be recognized, and how they would be interpreted by participants. In Task 1, participants were first presented with a video stimulus, and then asked to rate how they felt towards the drone using the Self-Assessment Manikin (SAM) [4], a 9-point Likert scale using sketches of a manikin to measure emotions along three dimensions: Valence (from negative to positive emotions), Arousal (from low to high intensity), and Dominance (from submissive to in control). In Task 2, participants were asked to watch the same video again and to select the emotion category that best matches the drone's facial expression on the original Plutchik's wheel of eight emotions [27]. As per Study I, participants then had to justify their best-choice answer (free-form answer).

4.4 Data Analysis

4.4.1 Qualitative Analysis. The qualitative data was analyzed using a thematic analysis for all free-form answers. This exploratory method strives to identify patterns of themes (categories) that depend on the related data (as in [19, 37]). Quotes were separated into elements respective to the categories. For each element that applied to a specific category, we incremented the occurrences by 1 in the respective category (e.g. empathy; negative or positive participants' response to drone's facial expressions). The within-subject study design of both studies led to paired samples, as all participants evaluated all stimuli. Thus, we used a linear mixed-effects model which is appropriate for paired data with the advantage that a Poisson link

[1] https://www.dji.com/phantom3-4k

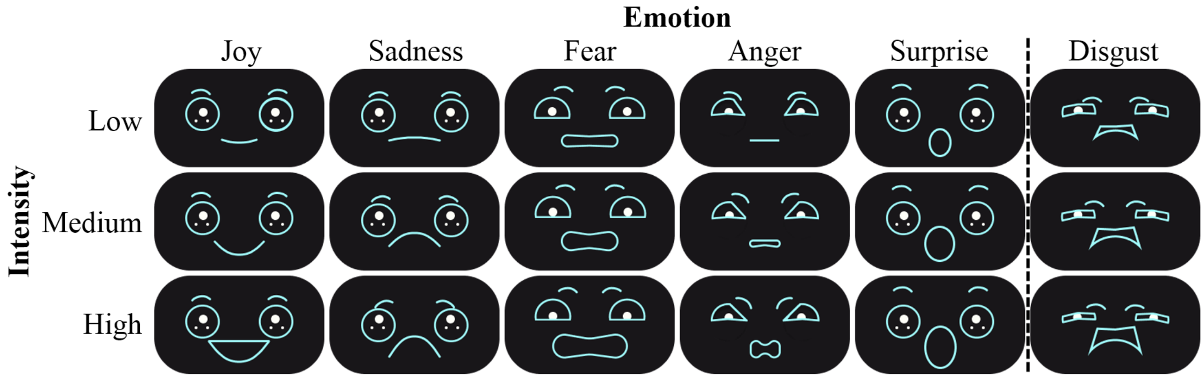

Figure 2: Set of rendered faces representing six basic emotions in three different intensity levels ©Viviane Herdel. The faces use four core facial features: eyes, eyebrows, pupils, and mouth based upon FACS (Table 1). All emotion categories performed well, only *Disgust* did not perform as well as the other emotion categories.

function can be used. This was here necessary for count dependent variables.

4.4.2 Quantitative Analysis. For Study I, we calculated the proportion of how often images belonging to an emotion category were associated with that category (e.g., images: serenity, joy, and ecstasy; participant's choice: serenity or joy or ecstasy). To test whether the participants' best-choice answers were significantly above random choice, we used a binomial test and Benjamini-Hochberg procedure to control false discovery rates (FDR). We used the same statistical procedure to analyze emotion classification accuracy in Study II. To analyze the SAM data in Study II, we applied a difference score path model (DSM) [23] for each of the three scales: Valence, Arousal, and Dominance. The aim was to quantify differences in participants' emotional responses after seeing a video of a drone with one of the five emotions (emotional condition) as compared with a drone displaying a neutral expression (baseline).

5 RESULTS

We report the results of Study I △ and Study II □ (see [14] for more detailed results). All statistical tests discussed as *demonstrating statistically significant results* have a p-value $< .05$.

5.1 Emotion Recognition △ □

Table 2 shows two confusion matrices illustrating the absolute frequencies of emotion category selections and the proportions of correct selections for each study. It shows, for example, that for static stimuli, *Joy* images (i.e., serenity, joy, and ecstasy for low, medium, and high intensities) were correctly recognized 95% of the time. In both studies, *Joy*, *Surprise*, *Sadness*, and *Anger* stimuli △ □ were recognized with high accuracy (above 70% and up to 99%). Interestingly, for *Joy*, *Fear*, and *Surprise*, the recognition accuracy was higher for static △ than for dynamic □ stimuli, while the opposite was true for *Sadness* and *Anger*. While *Fear* was recognized above average accuracy (62%) in static stimuli △, its recognition rate dropped for dynamic stimuli □, where we observed significant confusions with *Sadness* and *Disgust*. We further found that *Disgust* did not perform as well as the other emotion categories, with only 29% accuracy in static stimuli △. The confusion matrix shows that participants selected *Sadness* significantly more often than *Disgust*. As such, *Disgust* was removed from further analysis and was not used as emotion category in Study II.

Table 2: Confusion matrices illustrating correct emotion recognition rates for static and dynamic stimuli.

Static Stimuli

	Joy	Sadness	Fear	Anger	Surprise	Disgust
Joy	95			0	5	
Sadness		83	9	0	2	5
Fear	1	13	62	9	5	11
Anger	4	3	2	71	1	19
Surprise	0	0	7		92	
Disgust		51	4	15		29

Dynamic Stimuli

	Joy	Sadness	Fear	Anger	Surprise	Disgust	Trust	Anticipation
Joy	81				13		4	2
Sadness		99						1
Fear		24	43	10		22		
Anger		3	7	78		12		
Surprise	2	1	5	1	87			4

Notes. Values are rounded to the nearest integer with entries < 0.5 rounded to 0. p-values resulting from a binomial test were adjusted using Benjamini-Hochberg (BH) correction. Proportions correct with p-value $< .05$ are highlighted in green (correct choice). Grey indicates confusion frequencies above random choice. Rows correspond to emotion category of the stimuli and columns to the best-choice emotion. **Top.** In Study I, the emotion category is an aggregate across low, medium, and high intensity labels within the same emotion category. **Bottom.** In Study II, stimuli and labels directly correspond to the applied emotion categories.

5.2 Affect on Participants' Emotional State □

In Study II, participants were surveyed on their emotional reaction to the drone's video stimuli. We here describe the results of the SAM questionnaire and how participants described being affected by the drone in the free-form answers.

5.2.1 Emotional Assessment (SAM) □. The results of the SAM questionnaire expand across three dimensions. Baseline scores (assessed on a 9-point scale) averaged across all participants as follows: Valence 5.55 (SD = 1.26), Arousal 3.67 (SD = 1.81), and Dominance 5.29 (SD = 2.05). We estimated the average difference scores between the baseline and each emotional stimulus category by using DSM (see Section 4.4.2) to measure the affect change elicited for each emotion. Figure 3 illustrates the overall differences in each SAM dimension for each emotion compared to the baseline. Results can be summarized as follows:

- **Valence** was affected according to the emotion, such that it was significantly higher when individuals were exposed to a positive emotion: *Joy*; significantly lower in case of negative emotions: *Sadness, Fear*, and *Anger*; and did not appear to change significantly as compared to the baseline with a neutral emotion, such as *Surprise*.
- **Arousal** was significantly higher for all emotions displayed on the drone.
- **Dominance** was significantly increased for *Joy* and *Surprise*; and significantly decreased for *Fear* as compared to the neutral baseline.

5.2.2 Participants Emotional Response □. We found that participants discussed how the drone affected them emotionally in the free-form answer *"It's depressing and I would want to avoid it."*. The emotions *Joy* and *Surprise* significantly triggered participants to mention positive responses, while *Fear* and *Anger* significantly triggered negative emotion mentioning (see Figure 4). Interestingly, *Sadness* did not appear to lead to significant differences. However, we found much discussion around empathy when participants were exposed to expressions of *Sadness*.

5.2.3 Empathy and Prosocial Behavior □. Some emotions evoked empathy, such as *Sadness* which led to significantly higher empathy towards the drone compared to all other emotions (b = 1.299 - b = 3.5), gathering 64% of all empathy quotes. *Fear* and *Joy* also triggered empathy, with 17% and 12% of empathy quotes respectively. We found that empathy was linked to participants' motivation to prosocially interact with the drone. For example, when the drone displayed a sad facial expression, more than a third of participants suggested prosocial interactions (e.g., *"I feel protective towards it, like I want to assist it to fix the problem"*).

6 DISCUSSION

Here, we further discuss and highlight aspects of particular interest to the MEEC '21 workshop.

Ambiguity in Emotion Recognition. Our results show high to near perfect recognition rates for four emotions: *Joy* (best in static), *Sadness* (best in dynamic), *Anger*, and *Surprise*. However, *Disgust* showed poor recognition rates in static and was not further investigated in dynamic stimuli. Finally, while *Fear* could be well recognized in static stimuli, its recognition rate dropped by 19% in dynamic stimuli. We found that *Disgust* was more often associated with expressions of *Sadness*; and *Fear* was occasionally associated with *Disgust* or *Sadness* (in dynamic stimuli). We suggest two main factors that could have contributed to this ambiguity. The first one is the **perceived legitimacy** of the emotion in human-drone interaction, where the participants may not have envisioned this emotion as applicable to a drone. For example, participants made

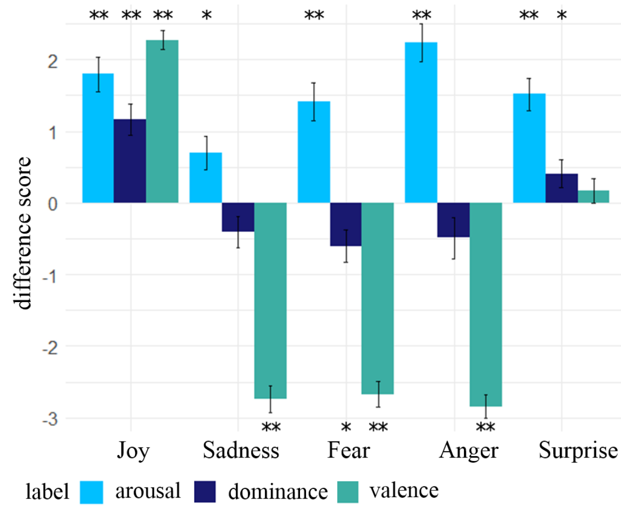

Figure 3: Results of the SAM questionnaire showing the participants' overall emotional assessment of the drone for each emotion across: Arousal, Dominance, and Valence. The bars represent standard error of mean. Positive values indicate values greater than the corresponding baseline, and negative values indicate values smaller than the corresponding baseline. * indicates p-values <.01 and ** p-values <.001.

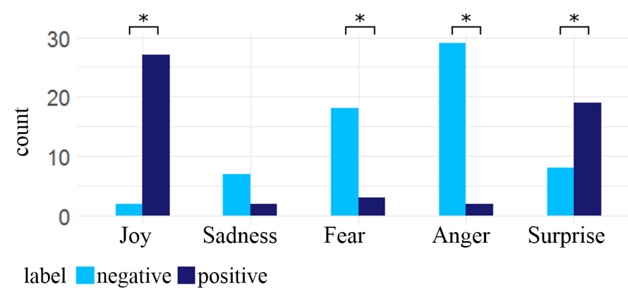

Figure 4: Compared absolute frequencies of participants reporting on being negatively or positively affected by the drone for each emotion. * indicates p-values <.01.

comments such as "I think it looks a little weird, seeing a drone with a scared expression", "It would have to be a fake fear as robot's do not feel emotion". Another potential contributing factor is the **design of the facial expressions**. Our choice of facial features did not include a nose into the drone's face, while it is included for *Disgust* in FACS [11] (see Table 1). Similarly, the recognition of *Disgust* as *Sadness* may result from the squeezed eye design that one participant referred to as if the drone had "been crying for a while". This suggests that future face designs should reconsider the shape of the eyes and potentially add a nose in the facial expression of *Disgust*.

Taking it Personal. The narratives revealed that participants expressed different emotional reactions to the drone's emotions; such as treating the drone's behavior as a reaction to their own actions or presence, or even experiencing empathetic emotions similar to the ones of the drone. The perception of the drone's state as an emotionally charged feedback to participants' actions suggests that some interpersonal mechanisms in human-human communication persist for HDI. These effects can become a powerful mechanism to shape human-drone interactions, where for example, the drone's expressions of emotions can serve to trigger behavior change, mediate human-human relationships, and be used in the development of **novel emotional support systems** [2, 9].

7 CONCLUSION

This work described some of the results from our exploration in the emotional perception of facial expression on drones. We designed a set of rendered robotic faces using a minimal number of facial features to represent basic emotions. In two user studies, we showed that people can recognize five basic emotions: *Joy, Sadness, Fear, Anger, and Surprise* on drones. Moreover, participants were further affected by the drone and displayed different responses, including empathy, depending on the valence of the drone's emotion.

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