

# Drone & Wo: Cultural Influences on Human-Drone Interaction Techniques

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## ABSTRACT

As drones become ubiquitous, it is important to understand how cultural differences impact human-drone interaction. A previous elicitation study performed in the United States illustrated how users would intuitively interact with drones. We replicated this study in China to gain insight into how these user-defined interactions vary across the two cultures. We found that as per the US study, Chinese participants chose to interact primarily using gesture. However, Chinese participants used multi-modal interactions more than their US counterparts. Agreement for many proposed interactions was high within each culture. Across cultures, there were notable differences despite similarities in interaction modality preferences. For instance, culturally-specific gestures emerged in China, such as a T-shape gesture for stopping the drone. Participants from both cultures anthropomorphized the drone, and welcomed it into their personal space. We describe the implications of these findings on designing culturally-aware and intuitive human-drone interaction.

## ACM Classification Keywords

H.5.2. Information Interfaces and Presentation: User Interfaces; User-centered design.

## Author Keywords

Drone; UAV; quadcopter; human-drone interaction; gesture; elicitation study; cross-cultural design

## INTRODUCTION

As small-sized drones are becoming increasingly part of our environment, it is important to understand how people want to interact with them. A previous study that was run in the US elicited interaction techniques for a number of tasks that would be likely requested of a collocated drone [2]. The authors describe a number of commonly proposed gestures in their study and give design insights. However, are these insights culturally specific? The Human-Robot Interaction (HRI) literature

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CHI 2017, May 06–May 11, 2017, Denver, CO, USA

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ACM 978-1-4503-4655-9/17/05...\$15.00

DOI: <http://dx.doi.org/10.1145/3025453.3025755>

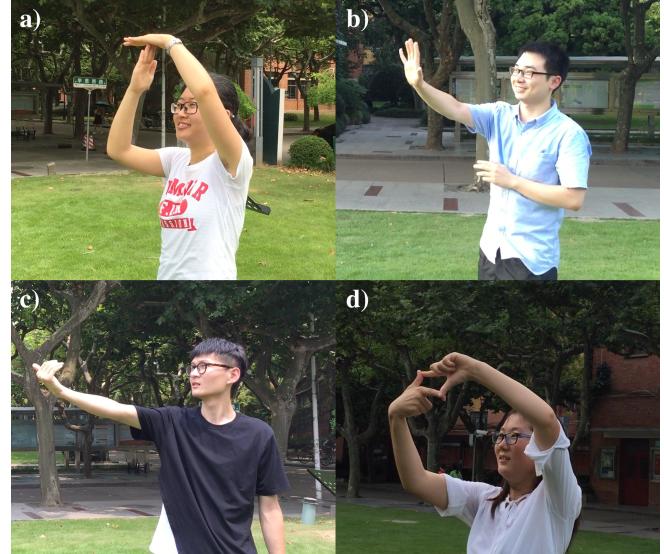


Figure 1. Participants interacting with the drone during the user study.  
a) T-shape gesture for stop; b) Palm out stop gesture; c) Beckon;  
d) Frame gesture for taking photos.

details the cross-cultural variation in attitudes towards robots. We know the US and China are culturally different, as China is a more high-context, collectivist culture [10]. Thus, the Chinese tend to communicate in a more implicit manner and are less likely to welcome newcomers to their in-group. How does this affect how Chinese people interact with personal drones? To explore the answer to this question, we replicated the Cauchard et al. [2] US study in China with 16 participants and compared our findings.

We observed that the Chinese participants' most preferred interaction modality was also gesture (e.g., Figure 1). However, they were more likely to add sound, resulting in a higher percentage of multi-modal interactions. In these interaction proposals, we also noticed more implicit communication, which matches the high-context nature of China's culture. For instance, two participants expected the drone to follow them by default. We noted that participants in China anthropomorphized the drone, as was found in the US study; they were able to accept the drone and allowed it into their personal space [8]. US participants were more likely to interact with it as a pet, while Chinese participants expressed more appreciation for the drone's obedience. In this paper, we demonstrate the importance of cultural awareness in the context of designing interaction for drones.

## RELATED WORK

Cultural differences can manifest in many different ways when interacting with technology. Hofstede [10] provides measures for defining these cultural differences, such as individualism. Researchers have also cataloged common gestures, noting similarities and differences across cultures [1, 15].

In relation to robots, cultural differences in communication styles have been shown to influence the willingness of a person to listen to its recommendations [27], the assumptions made about them [19], the perceived trustworthiness [5, 12], as well as the desired proximity to a person [11, 22]. In addition to studying how humans speak with robots [13, 25] and how this differs by culture [5], researchers have also studied how humans cooperate with robot assistants [7] and their tendencies to anthropomorphize robots [6].

In comparison, there is currently little understanding of how cultural differences impact human-drone interaction. Researchers are trying to understand how people would intuitively interact with a personal drone [2, 20], presenting designs for communicating a drone's navigational intention to facilitate collaboration with humans [23, 24], and using drones to aid humans in everyday activities like jogging [16].

## USER STUDY

We replicated the approach of Cauchard et al.'s interaction elicitation study [2]. In this Wizard of Oz study, the drone's autonomous behavior was simulated by an experimenter.

### Method

Participants are presented with 18 tasks (Figure 2) of varying complexity. Tasks are presented on individual cards (placed face-down, in random order) as a start and end state of the drone (ex. flying around, following you). On an instructions sheet, participants are told to flip one card at a time, read the card, and complete the task at their own pace. They interact through methods of their own choice with no guidance on interaction style (*Part 1*). Participants are then given a sheet with some suggested interaction methods, and asked to redo 4 *representative tasks* (marked in Figure 2 with asterisks). Short interviews followed each task in which participants explained their interactions, and a qualitative interview concluded each study. For more details, please refer to [2].

All experiment materials were translated into Chinese and back-translated to ensure standardization. We used the same drone model, a DJI Phantom 2, and found a similar outdoor location on a Shanghai university campus. Due to the density of people in China, we were unable to find a fully secluded space. We added a question to the post-study interview to confirm that passersby did not affect their interactions. We also added questions to gauge cultural measures of the participants.

### Participants

We recruited 16 participants (7 m), 18 to 26 y.o. ( $\mu = 22$ ) from local universities in Shanghai. Their backgrounds were in math (7), engineering (2), industrial design (2), philosophy (2), education (1), tourism (1), and one incoming college student. They were compensated 100RMB (~\$15). All participants

Tasks Performed	US			China		
	Gesture	Sound	Both	Gesture	Sound	Both
All	<b>86%</b>	<b>38%</b>	<b>26%</b>	<b>86%</b>	<b>58%</b>	<b>45%</b>
Representative tasks (Part 1)	88%	37%	28%	80%	56%	38%
Representative tasks (Part 2)	70%	57%	33%	84%	59%	48%

Table 1. Percentage of use of common interaction modalities. Within each culture, interactions using both modalities are counted in all three columns (rows that sum up to greater than 100%).

answered at least half of the cultural measures questions in ways that are predicted for East Asians [14, 18].

## RESULTS

The data collected included videos, post-task and post-study interviews, as well as qualitative feedback. Two authors coded all participant videos, working together on the first three videos to establish a consistent coding scheme. Inconsistencies in coding were resolved by watching the video together.

### Interaction Modalities

Table 1 quantifies the most common modalities (gesture, sound, or both) that were used during different parts of the study (entire study, representative tasks in Part 1 and Part 2) by participants from the two countries (US, China).

To analyze our data, we used the G-test [21], a more modern version of the Pearson Chi-Square test, better-suited to handling small counts. We found a significant difference in US and Chinese participants in terms of the proportion of the modalities ( $G = 30.3$ ,  $df = 2$ ,  $p < .0001$ ). During all parts of the study, Chinese participants tended to combine sound with gesture more than the US participants ( $G = 17.8$ ,  $df = 1$ ,  $p < .0001$ ). US participants seemed to switch from primarily using gestures (Part 1, representative tasks in Part 1) to using sound more (Part 2), while Chinese participants increased use of multi-modal inputs during Part 2 (and thus all modalities).

### Agreement

Figure 2 shows the agreement scores for each referent (within the cultures), calculated using Eq 1 where  $P$  is the set of proposed interactions and  $P_i$  is the subset of identical interactions for that referent. Comparisons of agreement between participant pools is accounted for through two normalization factors [2, 26].

$$A = \frac{|P|}{|P|-1} \sum_{P_i \subseteq P} \left( \frac{|P_i|}{|P|} \right)^2 - \frac{1}{|P|-1} \quad (1)$$

We count each interaction that a user performs for a single task individually. This results in some over-counting, in particular with more complex tasks such as "Take a picture of a tree" where participants decompose the task into several parts: indicating a subject for the photo and taking the photo. It is evident that within cultures, agreement scores tended to be relatively high; almost half of all the agreement scores are over 0.5 and both means are over 0.5 (China:  $m = 0.51$ ,  $SD = 0.21$ ; US:  $m = 0.53$ ,  $SD = 0.27$ ). Across cultures, very few of these highly agreed upon interactions match.

Category	Task name	Gesture		Sound		
		China	US	China	US	
Navigation	Within body frame	Fly closer	0.74	0.78	0.34	0.63
		Fly higher (to user's height)*	0.66	0.20	0.41	0.70
		Fly lower (from user's height)	0.69	0.38	0.41	0.67
		Fly sideways (small delta)	0.37	0.36	0.41	0.34
		Stop by me	0.26	0.86	0.40	0.71
	Outside body frame	Fly further away (far)	0.49	0.33	0.30	0.45
		Fly sideways (large delta)	0.59	0.27	0.50	1.00
		Fly to a precise location*	0.38	0.42	0.34	0.30
		Fly higher	0.75	0.26	0.49	0.67
		Fly lower	1.03	0.19	0.33	0.65
Action	General motion	Stop motion (when flying)	0.29	1.00	0.38	0.79
		Land	0.86	0.24	0.35	1.17
		Take off	0.71	0.28	0.37	0.27
	Relative to user	Follow*	0.61	0.54	0.70	0.39
		Stop following	0.25	0.48	0.39	0.24
		Get attention	0.68	0.22	0.42	0.70
	Photo	Take a 'selfie'*	0.39	0.33	0.30	0.60
		Take a picture of a tree	0.84	0.93	1.03	0.86

**Figure 2. Agreement of task interactions per culture.** Agreed upon interactions across cultures are highlighted in dark gray. Cultural disagreement, one culture high and one low, is highlighted in light gray. Representative tasks are marked with asterisks. US data from [2].

## DISCUSSION & DESIGN IMPLICATIONS

Our observations lead us to some suggestions for designing suitable human-drone interaction across both cultures.

### Modality Preferences

Chinese participants were more inclined to use multi-modal interaction than US participants, adding sound to gestural interactions. They expressed that speaking is more natural in Chinese culture than gesture: “We Chinese people use less movement... I would likely prefer to use speech” [P1]. Agreement was lower for US participants in gesture and for Chinese participants in sound. P11 noted that there are often more options in Chinese than in English for tasks such as “stop.”

We suggest designing support for multi-modal interaction—allowing use of slight variation in gestures, and extra contextual words. The addition of speech support can further simplify interaction, especially for complex tasks.

### Multi-Modal Interaction Correlation

When Chinese participants used multi-modal interaction, the sound would often (75%) align in meaning with the gestural interaction (i.e., palm out, “stop”). For the other 25% of multi-modal interactions, the sound augmented the gesture used to convey the task. P8 used a pointing up gesture to mean, “this is related to me”; adding the sound “stop” signaled “stop near me” and “high” meant to “fly up to my height.” This contextual form of communication is characteristic of China’s high-context culture [9] and is described in Wang et al.’s exploration of robots with implicit versus explicit communication styles [27]. A few participants (2) even assumed that the drone should be able to automatically follow the person.

### Cultural Agreement

For some of the tasks the agreement was high across cultures.

**Beckon:** For both the “Fly closer” and “Follow” tasks, the beckoning gesture, with palms facing up and fingers waving towards self, were highly agreed upon. Participants from both studies commonly described this gesture as something they used in daily life to communicate with other people or pets.

**Picture:** Like participants in the US, many Chinese participants were unsure of how to complete the “Take a picture of a tree” task, finding it relatively complex. However, there was still high agreement both within and across the two cultures. Participants from both cultures frequently spoke the word “picture.” We also noticed a similar sequencing of gestures: pointing at a target, and then making a framing gesture.

**Sideways:** Another task with high agreement across cultures was “Fly sideways (large delta)”—participants asked the drone to “go left/right.” This implies that voice navigation is consistent in both cultures, though accompanying gestures vary.

### Cultural Disagreement

We detail a few tasks where agreement is particularly high in one culture, but low in the other.

**Stop:** “Stop motion (when flying)” had 100% agreement in gesture amongst US participants, with everyone holding their palm out as in Figure 1b. In China, agreement was low, with participants split between this gesture and a “T-shape” gesture (Figure 1a), a common East Asian gesture for stop [15]. It is crucial for this task to be intuitive so as to ensure safe flying.

**Height:** Two navigational tasks, “Fly higher” and “Fly lower,” showed higher gestural agreement in China than in the US. Participants in China consistently preferred a repeated wave gesture, whereas Cauchard et al. described more variation [2].

### Cultural Gestures

We observed a number of gestures documented in Matsumoto et al.’s categorization of gestures by culture [15]. While the OK gesture, waving, and pointing are all defined as US gestures, they were used by the Chinese participants as well. The OK gesture (thumb touching index finger, others slightly spread) was used by 3 Chinese participants repeatedly to signal to the drone that a task was completed. Participants from both cultures pointed their index fingers to convey a location, and waved to the drone to greet it. Overall, this suggests reasonable comfort using the same gestures across both cultures.

### Designing to Lower Uncertainty

Also reflected in the US study, we observed that Chinese participants expressed some uncertainty with the clarity of their gestures (9): “This method isn’t too good because it is similar to close” [P15]. In designing gestural interactions, it is important to avoid ambiguity. The addition of voice could also aid in clarifying intention.

### Feedback

Like in the US study, Chinese participants asked for feedback (9) for complex tasks such as taking a picture or going to a precise location. For these tasks, participants had some similar

suggestions to the US participants, such as flashing a light when a photo is being taken (3), or having an auxiliary screen (3). Participants also expressed that they would like to be able to have a conversation with the drone (2), or have some means of knowing when the drone understands a command (4).

### **Interaction Metaphors**

Like their US counterparts, many Chinese participants compared the drone to a person (14) and/or a pet (5).

**Person:** Both Chinese and US participants were likely to compare the interactions with the drone to those with people. Some physically anthropomorphized the drone (4): “I can see your eyes” (referring to the drone’s battery indicators) [P1], “it almost seems like it’s blinking at me” [P15]. P15 suggested it “breathe” by slightly moving up and down when idle, and “wake up” when approached by slowing turning on its lights.

Participants also expressed an emotional relationship with the drone. Some mentioned feeling more natural interacting with the drone during Part 2 because they were more “familiar” with it (4), thus trusting it to interpret more ambiguous commands (4). Participants respected the drone’s emotions (3), asking the drone to “go to whatever place you like” [P1] or to fly higher “if you want to... you might be unhappy like this” [P13].

P13 thought of the drone as a person, “because what else could I think of it as?” This supports the claim of Epley et al. that people with less alternate knowledge are more likely to anthropomorphize [4]. To build on this, drones could interact in ways that exhibit emotion [3].

**Pet:** Chinese participants were less likely than US ones to think of the drone as a pet ( $G = 4.5, df = 1, p < .05$ ). Nonetheless, participants who noted this metaphor fully embodied it in their interactions. P4 explained that “If I had a pet dog, I would just look at it... and the dog would follow,” expecting the drone to imitate. P14 ran alongside the drone like when walking a dog.

### **Proxemics**

Table 2 shows the proximity to the drone that participants in each culture were comfortable with [8]. Participants in China allowed the drone to be extremely close, preferably at eye-level, as was noticed in the US study. In fact, many participants immediately began walking up to within arms length of the drone from the first task. We expected Chinese participants to be less likely to anthropomorphize and accept the drone as an in-group member due to the collectivist nature of China’s culture, but this did not seem to be true.

### **Body Movements**

All but 2 participants used body movement for communicating tasks to the drone (all walked for “Follow”/“Stop following”).

	US	China
Intimate Space (1.5ft)	37%	50%
Personal Space (4ft)	47%	38%
Social Space (10ft)	16%	6%
Public Space (>10ft)	0%	6%

**Table 2. Percentage of participants allowing drone within these spaces.**  
Note: terms and distances defined with respect to Western cultures.

To take a photo, 9 participants walked towards the target. When lowering the drone, 7 participants leaned down or even squatted to mimic their request of the drone. P14 described this tendency to squat as a need to “demonstrate” the task to the drone as if training a pet. P14’s extensive body gestures also led to the thought that the proposed interactions “might be hard for someone with disabilities to interact this way.” This may have led to the fact that Chinese participants overall felt interacting with the drone was more physically demanding (Wilcoxon-Mann-Whitney Test [17]:  $Z = 2.4, p < .05$ ).

### **Relational Behaviors**

We observed several relational behaviors in China [13]. Some participants would say “hello” (3) or wave (2) to “give the drone a heads-up” [P15]. Participants talked about being “polite” to the drone (3). Some felt uncomfortable “controlling” the drone (preferring to communicate or teach) because it felt impolite (2) and “too straightforward” [P1]. Many also fondly called the drone “obedient” (5), potentially reflecting China’s higher power distance index [10].

Participants complimented the drone (6), either to encourage it—such as “Wow, you really are pretty!” or “I believe that you can do it” [P13]—or simply to congratulate it after completing a task: “Great job” (2), “Great! Come on down!” [P11], giving a thumbs up [P1] or applauding [P15].

### **Scenario**

Given our findings, here is how our insights might apply to a specific scenario. Imagine a user wants to take a selfie. She beckons the drone, while saying “Come closer, a little to my left, almost there...” It flies closer at her eye-level. She stops it with a T-shape gesture, 1m in front of her. She makes the frame gesture and the drone’s lights start blinking to indicate a countdown and capture. She gives the drone a thumbs up, saying, “Great job!”

### **CONCLUSIONS**

As new technology is integrated into our home and work environment, cultural differences can play a major role in determining whether it is socially accepted. We replicated a Wizard of Oz user-defined interaction elicitation study [2] to understand the potential cultural effects on human-drone interaction. We discovered that there are significant similarities and cultural differences between US and China that should inform the design of intuitive human-drone interaction. In both cultures, participants draw on interaction metaphors from interacting with friends or pets to communicate with the drone. A key difference was that Chinese participants instinctively use multi-modal interaction more than US participants. We contribute a set of design implications that consider intuitive interaction styles across two different cultures, and hope to realize some of them in a semi-autonomous drone assistant.

### **ACKNOWLEDGMENTS**

We would like to thank Jacob Wobbrock and Charles Ashton for their help with the statistical analysis. This work was supported by a Microsoft Graduate Women’s Scholarship and a Magic Grant from the Brown Institute for Media Innovation.

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