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Are Drones Ready for Takeoff?

Reflecting on Challenges and Opportunities in Human-Drone Interfaces

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ABSTRACT

Recent technical advances introduced drones into the consumer market. Thus, past research explored drones as levitating objects that provide in-situ interaction and assistance. While specific use cases and feedback scenarios have been researched extensively, technical and social constraints prevent drones from proliferating into daily life. In this work, we present past research in the area of human-drone interaction we conducted. We present technical boundaries and user-based considerations that arose during our research. We discuss our lessons learned and conclude how to deal with current challenges in the area of human-drone interaction.

KEYWORDS

Human-Drone Interaction; Human-Drone Interface; Tangibles; Object Tracking; In-Situ Interaction

INTRODUCTION

Drones have proliferated into the research domain and consumer market with various selection of use cases. The application of drones ranges from professional and personal aerial videography, delivery services, surveillance, and simple radio-controlled toys. Past research explored how unique properties of drones, such as their fast movement in three-dimensional space without any suspension, can be used to provide flexible just-in-time interfaces. While the use cases are many-fold, the deployment of drones is not always trivial and involves many obstacles and trade-offs which need to be considered. For instance, the use of autonomous drones requires reliable self-localisation mechanisms in the

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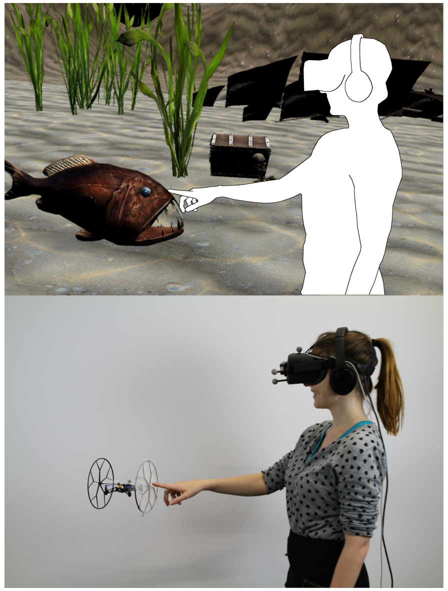

Figure 1: VRHapticDrones is providing haptic feedback for VR by aligning a touchable surface to an virtual object.

interaction space. However, this limits the use of drones to the dedicated tracking space. Further considerations include drone control, user safety, and a suitable interaction design space.

In this work, we first provide an overview of human-drone interaction research we conducted. Followed by the lessons learned throughout the implementation and evaluation of the research prototypes. By presenting our insights, we believe that future human-drone interaction practitioners and researchers benefit from our insights on how to design, model, and conduct research in this area.

BACKGROUND

In the following, we summarise past human-drone research projects we conducted. We give a short project description categorised our work into interaction modalities, haptic feedback, and navigation. Further, we highlight the challenges we encountered during the development, implementation, and evaluation.

Interaction Modalities

We investigated suitable interaction modalities between users and drones. This includes interaction via (a) direct contact and (b) remote controls [6]. We researched how drones can be used as levitating interaction elements that augment the environment of the user. We presented participants with three different interaction modalities for drones. This included two different input modalities (i.e., touch and push to provide input) and one output modality (i.e., drone drags user to a certain position). While users preferred input via touch, output via drag was not well perceived by the participants. Due to the low efficiency of drone motors, output via drones was barely perceived.

Instead of controlling drones with direct body contact, we investigated the efficiency of different remote controllers to steer drones [9]. In a user study, we compared how efficient users interacted with drones using a keyboard and smartphone controls as well as using a pointing remote control. We found that the remote control was preferred by the participants to control a drone. However, participants took more time to complete their task since a customised PID controller [1] regulated the velocity of the drone. Thus, an optimised or adaptive PID controller that is set accordingly to the users' individual skills or environment can resolve this issue.

Haptic Feedback

VRHapticDrones and Tactile Drones [5, 7] utilises drones to provide haptic feedback in Virtual Reality (VR). VRHapticDrones are equipped with a touchable surface, that the drone automatically aligns with the surface of a virtual object. VR users can reach out to touch a virtual object while feeling the touchable surface as the drone serves as a haptic proxy (see Figure 1). Tactile Drones uses an

Figure 2: A pedestrian receives navigational instructions by a projector attached to a drone.

attached actuator to nudge the users and therefore simulate feedback for bumblebees, arrows, and other objects hitting the user, while the user is visually and acoustically immersed in VR.

Navigation

Providing navigation through drones has been researched in various contexts [4, 8, 10]. For example, navigation through visual projections by a mobile levitating projector was proposed recently (see Figure 2). The projections were controlled by a microcontroller unit. The user study revealed that the users were compelled by projected in-situ navigation. While GPS was used to track the drone, it does only provide a low level of accuracy, as current outdoor tracking systems do not provide the same positioning accuracy compared to sophisticated indoor tracking.

Auditory and haptic properties of drones have been used to support people with visual impairments. Thereby, the ability to process visual elements is significantly affected. By providing auditory cues, visually impaired people were able to follow the sound that is emitted by a drone [2] (see Figure 3). Follow up studies showed that this approach is socially accepted among visually impaired people [3].

In loud environments, haptic impulses of drones can be used to support navigation for visually impaired. By mounting a leash on a drone, visually impaired people were able to follow a route similar when using a blind mans dog [2]. However, the study took place in a Wizard-of-Oz setting and that does not use automatic drone positioning to provide an autonomous user experience.

LESSONS LEARNED

While drones offer a wide variety of application scenarios their usage can be quite challenging and many aspects have to be considered depending on what they are used for. There is a wide availability of consumer drones from various manufacturers that can be used right out of the box. While they are easy to use, they often do not offer properties needed for a human-drone interaction project. In the following, we provide the lessons we learned throughout our research.

Physical Limitations

While the size of drones is constantly decreasing, characteristics such as noise production, short flight times, and low payload capacities are still limiting factors. For human-drone interaction that needs a certain amount of payload, small off-the-shelf drones are usually not suited. Therefore, they have to be modified and mounted with additional hardware. This is limited to a certain weight and again impacts the battery run time, increases noise production, and impacts the flying abilities and maneuverability of the drone.

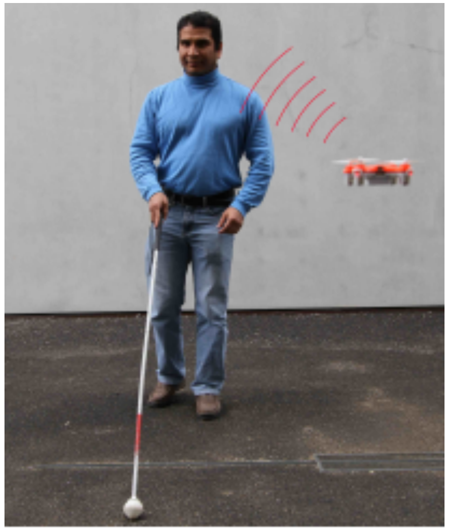

Figure 3: The sound of a drone is capable of guiding visually impaired.

The power potential of the motors limits the payload and can negatively impact the quality of force feedback. This can affect that a user cannot feel the drone dragging their hand [6] or that the level of resistance the drone can provide is not enough to stop the pushing of the users' hand [5].

Safety

When working in human-drone interaction, the safety of the user is an important factor. Regular consumer drones are not secured in a way that there is no danger of harming users during an interaction. Providing protection for users reduces the hesitation from interacting with the drone. For instance, users that wear an HMD and cannot observe the drone visually may get distracted and cannot perceive a potential danger. Therefore, off-the-shelf drones often have to be modified with security cages. However, this may increase the payload and impact the maneuverability by blocking the propeller airflow. To prevent collisions of the user with the drone, no-fly zones are recommended. Manoeuvres, such as fast acceleration towards the user, have to be limited and the position of the needs to be detected (e.g., position of VR HMD). All of this demands the implementation of a framework that enables more than the use of basic functions, such as positioning of a drone.

Drone Tracking

For indoor tracking, we used a dedicated tracking system and facilitated reflective markers on the drone. This restricts the use of automated drones and limits the use of autonomous drones to a tracking space that is often constrained to a single room. During VRHapticDrones [5] and Tactile Drones [7] we experience issues with the tracking and controlling as the drones internal camera stabilisation system cannot be turned off. The simulations application of the internal stabilisation and the external tracking system sometimes led to positioning issues while hovering, as both systems tried to correct the positioning of the drone. This again is caused by the fact that the used drones are consumer products that are not meant to be automated. Several studies employed a Wizard-of-Oz approach as outdoor tracking systems were not accurate enough [8]. Furthermore, inside-out-tracking were not sophisticated enough for indoor applications which were not restricted to a single room [3].

Data Connection

Bluetooth and WiFi pose the major connection modality for drones. This vastly expands the variety of remote controllers for drones. While this also allows the use of computers as a controlling unit for automated steering, it also inflicts issues and creates overheads

Development Framework

Controlling and automating drones is complex since many factors have to be considered. Among these are the adjustment of the Proportional–Integral–Derivative (PID) controller [11]. A PID controller communicates the next movements between drones and computing units. Depending on the use case and environmental factors, adjusting the PID controller poses a major overhead.

While there are libraries [12], they only work with proprietary drone models and do not allow full control over the firmware of the drone. Further, we experienced Bluetooth connection issues, where several attempts were needed to connect to a drone. Connectivity is even more complicated if more than one drone is used. When connected, sending commands to the drone sometimes led to delayed movements or commands that were not executed at all. Therefore, connectivity and controls that are handled via Bluetooth, by our experience often lead to various issues and make the system less responsive.

In general, frameworks need to be developed from scratch, are not standardised, and are highly heterogeneous. This is a challenging obstacle for interested developers and users. Furthermore, this makes it difficult to reproduce research since similar programming parameter needs to be used.

CONCLUSION

In this work, we summarise our work regarding human-drone interaction. We describe the challenges we encountered throughout the implementation and evaluation of human-drone interfaces. These issues are partly responsible that drone implementations need to be adjusted for specific use cases and thus extensively increase the effort of research projects. This is often due to the large overhead which is generated by implementing drone projects from scratch. We provide lessons learned regarding the aspects *Physical Limitations*, *Safety*, *Tracking Drones*, *Data Connection*, and the *Development Framework*. We expect that the human-drone community benefits from our insights and experiences usher the creation of a standardised drone framework to enable rapid prototyping of human-drone interfaces.

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Designing human-drone interactions with the Paparazzi UAV System

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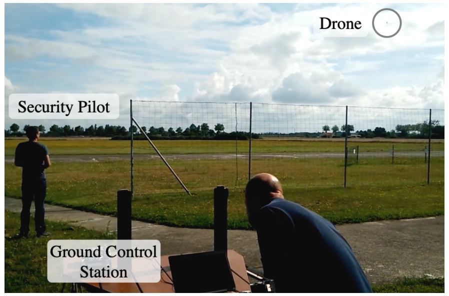

Figure 1: Flying drones outdoor with Paparazzi.

ABSTRACT

This paper presents the *Paparazzi* Unmanned Aircraft Vehicles (UAV) system and its use for designing novel interaction techniques for human-drone interactions. *Paparazzi* is a complete system of open source hardware and software for UAVs, including both the airborne autopilot as well as complete ground station mission planning and monitoring software utilizing a bi-directional data link for telemetry and control. We describe three examples of interactive systems built with *Paparazzi* to illustrate its capabilities to create new interactive UAV systems: augmented-reality glasses for safety pilots, adaptable interactions for pilots with disabilities and embedded interactions.

KEYWORDS

Human-Drone Interaction, Unmanned Aerial Vehicles, Paparazzi System

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Figure 2: Paparazzi System overview [10].

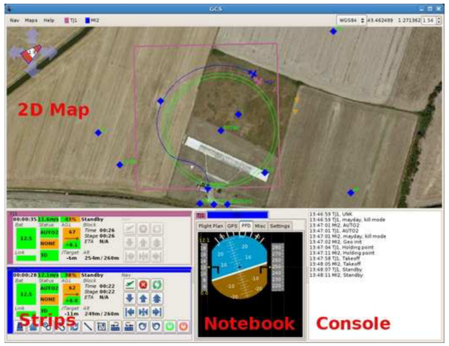

Figure 3: Ground Control Station Graphical User Interface [10].

INTRODUCTION

Human Drone Interaction (HDI) is gaining more and more interest due to the increasing number of affordable systems and research efforts in the field [2, 3, 5, 8]. However, designing and prototyping HDI remains challenging due to the distributed nature of such systems using both hardware and software platforms. As emphasized by Funk [8], building and prototyping interaction in this context requires: *controlling the drone, knowing where the drone is, and providing communication between the drone and other systems*. Unfortunately, existing technologies are often commercial products that offer little support for developers to tweak the systems or to adapt them to their needs.

In this paper, we first present the *Paparazzi* Unmanned Aircraft Vehicles (UAV) system [1, 10] and its architecture. We then describe three cases studies of new interactive systems built with *Paparazzi* which highlight its ability to support the prototyping of various HDI systems. Our case studies cover information visualization with Augmented Reality glasses, new control methods to support users with impairments and face tracking drones. Finally, we discuss the possibilities offered by *Paparazzi* to support HDI designers and possible improvements.

PAPARAZZI

Paparazzi [1, 10] is a complete system of open source hardware and software for UAV, including both the airborne autopilot as well as a ground station mission planning and monitoring software utilizing a bi-directional data link for telemetry and control.

Figure 2 details its global architecture which includes: 1) an airborne segment with the aircraft and its micro-controller, actuators and sensors to control the flight; 2) a ground segment to prepare flight plans, operate and monitor the drones during the mission but also to analyze the flights upon completion; 3) a communication segment that defines the various protocols that can be used between ground and airborne segments. Figure 1 illustrates a typical *Paparazzi* use case in which a drone performs an autonomous flight that is supervised by an operator near the ground station and a security pilot who keeps track of the drone's position at any point of the flight.

The airborne segment runs on the drone's autopilot board and features several modes: a manual mode, an assisted mode and a navigation mode. The manual mode allows the drone to be piloted using a controller. The assisted mode provides various automation routines to stabilize the drone or to limit its height or speed. The navigation mode interprets high level instructions that are described in flight plans. The flight plans can include various primitives such as waypoints, predefined navigation patterns (lines, circles) or conditional events. The flight plan is organized in blocks that are short sequences of elementary instructions performing tasks such as "make a circle around a waypoint" or "land here". The airborne segment can accept messages from the ground segment but also from embedded hardware or software via its API.

Figure 4: View from the security pilot with "Where is My Drone". 1) Gauges indicating the power and battery level, the air speed and the ground speed. 2) 3D model displaying the drone attitude 3) Drone's altitude and climb gradient. 4) The localization ring that helps finding the drone.

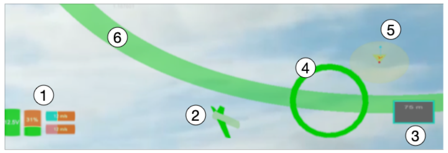

Figure 5: View from the security pilot with "Where is My Drone" second prototype. 1) to 4) as in Figure 4, 5) Radar view with the drone and pilot positions, 6) Line representing the current flight path.

The ground segment is made of several agents connected via the Ivy software bus [4]. This enables developers to use one or many of the existing agents such as the message monitoring agent or to develop new ones that can be integrated in the *Paparazzi* ecosystem. Two of our use-cases rely on this high level messaging system to process flight data and send commands to the drones. The ground control station provides a Graphical User Interface (Figure 3) to setup the flight plans and to operate them, i.e. to navigate in the collection of blocks and to adjust the flight parameters.

Paparazzi is versatile as it can accommodate rotor-craft UAVs as well as fixed wings UAVs, and can be used outdoors as well as indoors thanks to a positioning system. In our case studies, we used an Optitrack system [12] capturing markers fixed to any air-frame in a flight hall.

CASE STUDIES

Here, we describe three case studies illustrating new interactions with drones. For each use case we describe the interactions and how we leveraged the possibilities offered by the *Paparazzi* system to prototype them.

Where is my drone?: head-up display for safety pilots

Safety pilots must monitor the drone during the flight to ensure the safety of people and equipment. They have a dedicated remote control for each drone that allows them to manually control the drone if necessary. During observations of safety pilots at ENAC we found that they had trouble watching the drone with bad weather conditions or when there are several similar drones flying together. They also must constantly communicate with the operator near the ground control station to monitor critical information such as the battery level or the drone's expected flight plan. Figure 1 gives an example of such context.

Where is my drone? (Figures 4 and 5) is an Augmented Reality (AR) application that supports safety pilots in keeping the drone in sight and monitoring it in order to be able to regain control quickly if needed. It is a head-up display working on AR glasses. A localization ring centered on the drone's position facilitates its localization (see 4 in Figure 4). When the drone is not in the visible area, the ring stays on the border of the image, with its radius increasing proportionally to the angle between the drone and the pilot orientation, as with the Halo3D technique [13]. The application also features a radar view displaying the drone's position relatively to the pilot (see 5 in Figure 5). To help the pilot assess the status of the flight, several gauges display flight parameters such as battery level, throttle or altitude (see 1 in Figure 4). A 3D model of the drone is also displayed and rotated using the drone's attitude to help pilots better understand climbing and descending phases (see 2 in Figure 4).

Another feature that emerged from a workshop with pilots is the ability to visualize the programmed flight plan of the drone and to validate its current distance with respect to the flight plan. Figure 5.6 illustrates our first prototype implementation of this feature in which the current circular trajectory

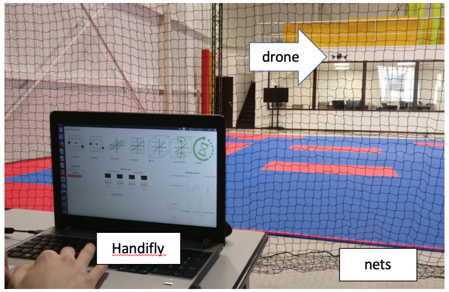

Figure 6: HandiFly in the flight arena [9].

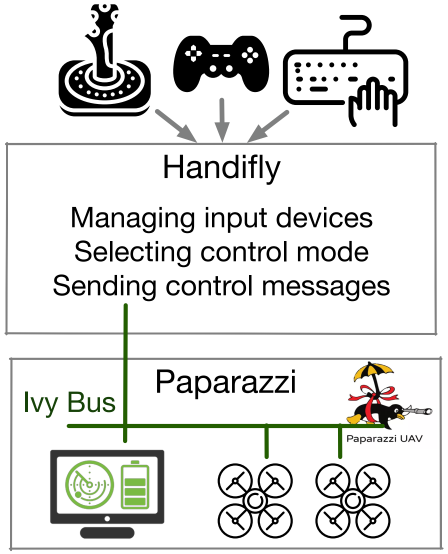

Figure 7: HandiFly Architecture [9].

is represented. The trajectory's color is updated according to distance between the drone and the expected trajectory. When reaching critical distance thresholds, it is colored in yellow (>5 meters) or red (> 10 meters) to alert the pilot. Representing the flight plan is important for situation awareness when using dynamic flight plans that can be modified by the operator. In the previous setup this required verbal communication between the pilot and the operator at the ground station and possibly led to confusions due to unexpected changes.

Where is my drone? is implemented in Unity and runs on EPSON Moverio Glasses [7]. It can be used with any type of UAV working with *Paparazzi*. The application listens to messages from the Ground Control Station via the Ivy bus. Position, speed and battery levels are included in messages that are parsed and displayed on the application. Positional information can be obtained from the glasses' sensors (compass and GPS when outside) or from the Optitrack agent if used in the flight arena. The latter requires to add markers on the glasses and to stream positional data via Ivy messages.

HandiFly: an adapted and adaptable application

HandiFly is an application to support pilots with disabilities who are flying drones as a leisure activity [9]. HandiFly features several adaptations to leverage diverse physical and cognitive abilities of the pilots, on the hardware, software and automation level. On the hardware level, we experimented using different physical controllers to match the users' motor skills, such as game controllers, keyboards or a DIY controller using makey makey [6]. On the software level, we provided a Graphical User Interface that allows to easily configure HandiFly depending on each user's needs, e.g. regarding the fine tuning of controls and the choice of physical controller. On the automation level, we implemented 6 piloting modes with different levels of assistance from fully automatic to manual control. This allows to simplify flying by restricting possible motions (e.g. limitation to a 2D plane, or turning off the yaw), and by (partially) automating the flight.

For this project, we used a Parrot ARDrone 2 modified to use *Paparazzi*'s autopilot (Figure 1) in our flight arena with Optitrack system. As explained above, HandiFly integrates with the existing *Paparazzi* ecosystem by exchanging messages on the Ivy bus [4] as illustrated in Figure 7. Thus it is possible to retrieve the drone's current position and data such as the battery level and to send control instructions to operate the drone.

In a pilot study, three users with motor and cognitive impairments were able to use HandiFly more successfully than their prior system and expressed enjoyment (Figure 8).

Look at me: face and marker based orientation

Look at me is an example application in which a drone stays at the same position and altitude but automatically orients itself towards a marker or a face as illustrated in Figure 9.

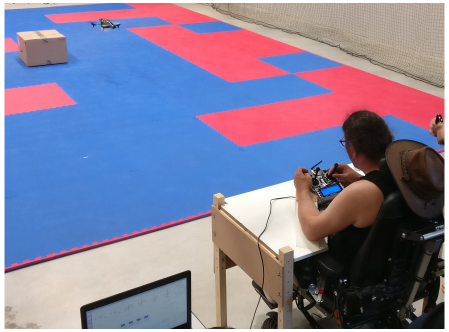

Figure 8: P4 trying landing the drone on a box [9].

Figure 9: Drone automatically orienting itself towards a marker.

We added a JeVois camera [11] which features computer vision tools processing on the drone. We implemented specific C code to get the data from the camera and call the autopilot API via the serial port to control the drone's orientation. This use-case is an example of enhancing drones' capabilities with additional sensors or computing modules that are directly embedded in the air-frame. Thus the system becomes autonomous and does not require the ground segment.

CONCLUSION AND DISCUSSION

We presented the *Paparazzi* UAV system and its use for designing three use cases. *Where is my drone?* provides data visualization for both autopilot modes with flight plan representations in addition to battery level or the drone's attitude. *HandiFly* builds upon the assisted mode to adapt the flying controls to various disabilities. *Look at me* embeds an extra sensor and its processing unit to create an autonomous system that does not require the ground segment.

The use-cases demonstrate how the system supports the necessary building blocks identified by Funk [8]: control, locate and communicate with the drone. *Paparazzi* also provides open-ended access to the autopilot (manual, assisted or navigation) via its API, both at hardware level via a serial port and at software level via network communication.

Designers and developers of HDI can use the existing software modules and the Ivy bus to build and integrate new visualization or control agents using any programming language. *Paparazzi* can be used for both outdoor and indoor applications, with fixed wings or rotor-crafts air-frames from several manufacturers. This makes it an extensible platform for creating new HDI.

While *Paparazzi* provides a wide number of tools and utilities, the online documentation still needs to be improved to make it easier for novice users to learn how to use it. However the active community of users can provide useful support thought the wiki, a forum and a gitter. Including safety oriented interactions to prevent damaging the material while prototyping interactions would be very valuable. In our use cases, we added safety settings such as setting a maximum speed. We also created emergency interactions such as "land here" or "stop engines" to avoid problems during tests phases. Such functionalities could be integrated in *Paparazzi* and exposed to designers and developers.

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DisplayDrone as Police Deployment Tool for Ubiquitously Available Public Displays and Digital Signage

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ABSTRACT

With the increasing payload and commercial proliferation of drones, creating ubiquitously available public displays becomes reality. While previous research suggested using flying public displays for emergency scenarios and crowd control, in this paper, we explore practical application possibilities of a flying media display – called DisplayDrone – in a police context and law enforcement. While a display is positioned in a visible location in 3D space, police officers can dynamically change the displayed text using a tablet-based control application. The work indicates that flying media displays have a large potential as a police deployment tool, but they are still subject to further investigations and technical developments.

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KEYWORDS

Human-Drone Interaction; Public Displays; police deployment tools; drones; DisplayDrone

Figure 1: Police officers are using DisplayDrone to deploy a temporarily available "danger" sign that notifies passers-by about an upcoming hazard. The text on the display means "Stop! Danger!"

INTRODUCTION AND BACKGROUND

Drones and their future uses are currently subject of much controversy. On the one hand, drones are still an emerging technology [4] that are not fully explored, understood, and accepted [2] by the vast population yet. On the other hand, they offer a high innovation potential, both in terms of technology development and application area and therefore can facilitate the creation of flying user interfaces [6].While traditionally, user interfaces have to either be user-carried or mounted in the environment, with this step forward in drone technology, whole computer systems can fly to any 3D position and create new possibilities for Human-Drone Interaction.

Communicating information from drones to users is one of the key challenges in Human-Drone Interaction. Using the visual channel, most works were attaching flying displays, fog displays, or projectors to the drone to convey information to the user. For example, Schneegaß et al. [13] and Scheible et al. [12] attached displays to drones to provide ubiquitously available information displays. Another approach is to mount a projector onto the drone and provide information rather in-situ than just on a display. Scheible and Funk [11] suggested a projector and a canvas that is mounted to a drone for displaying information. In contrast, Brock et al. [3] and Knierim et al. [8] use a projector that displays information in front of the user on the floor. Research also suggested to mount projected fog displays [14], which add a see-through aspect to the projection or adding spherical LED displays to the drones [15]. Other works encode information in the bare presence of the drone. While Avila et al. [1] convey sound from the drone for navigation purposes, Cauchard et al. [5], Kim et al. [7], and Müller and Muirhead [10] are positioning the drone in a distance to the user and conveying information by just moving the drone.

This project adds to the field of display drones that can display information mobile, flexible and ad hoc in space as a flying media display (fMD). Through this, texts, images, videos or interactive content can be placed in real time where groups of people are temporarily present or in motion. We see potential applications among others by the police as well as authorities and organizations with security tasks. The focus of this work is on the exploration of flying media displays as information dissemination and guidance systems for the police (see Figure. 1).

Figure 2: Flying outdoor prototype of our DisplayDrone

Outdoor Prototype. It is intended for outdoor use, e.g. in the city on squares or streets, on event areas or in nature. For this purpose, a concept was developed based on our own preliminary work (displaydrone, In-situ displaydrone). As a flying device we used the standard aircraft DJI Matrice 600 Pro drone and mounted an HP 27es" 27-inc-LCD-Display" with a 1.920 x 1.080 Pixel resolution on it. The display has a weight of 3.5 kg and its brightness is 250 cd/m2. It is connected via an HDMI cable to an Asus Tinkerboard PC, which is mounted on the drone and functions as a media server. The total weight of the entire system is 14,5 kg. The flight time is approx. 20 minutes.

SYSTEM: DISPLAYDRONE

Figure 3: Outdoor usage of our prototype DisplayDrone by police officers.

Since airborne media displays can be brought very quickly and precisely into the area of operations, they have a high potential for an effective and security-promoting accompaniment in situations of operations. Using Flying media displays to warn, evacuate and steer affected people is seen as an essential step in the further management of such situations. Figure 3 shows a fictitious scenario, how the ad hoc commissioning of a flying media display could look in a danger scenario for the rescue of a group of people.

We built two prototypes of flying media displays (for outdoor usage - Figure 2, and indoor usage Figure 4) in order to gain initial insights into the suitability and effectiveness of flying media displays and to explore and demonstrate the added value of such displays.

Figure 4: Indoor prototype of our DisplayDrone

Indoor Prototype. Its use is intended for scenarios in the indoor space, such as sports halls, event halls or stages. In order to explore the use of a DisplayDrone indoors, a custom made prototype was implemented with a double-sided display, which makes it possible to make display contents visible on the front as well as on the back of the flying media display, so that groups of people on opposite sides can read the contents simultaneously. The total weight of the prototype is 4.6 kg. The flight time is approx. 10 minutes. Built-in pressure sensors make it possible to keep the flight altitude stable indoors. The device must be controlled manually by a pilot. To protect the environment, a propeller protection device was installed around the rotors.

DroneCast software. We have built the DroneCast software [8] that is used to upload media content to the DisplayDrone. For example, if the DisplayDrone is to be used during a police evacuation of a large event site to display temporary collection points to which people are to move. Depending on the situation, context, and task of the use of the display, the content must be able to be adapted dynamically and ad hoc. With the DroneCast software it is possible to switch content such as pictures, animations, videos, or scrolling text to the display of the DisplayDrone. Figure 5 shows the system-components diagram and outlines the components’ interactions.

Police applications

The possible areas of application in which flying media displays are a useful communication and information instrument touch almost all police operations. This applies to a large number of tactical individual measures as well as to special operational situations. The tactical individual measures in which the media display can be sensibly used include, for example, barricade of the area, reconnaissance, tracing, public relations work, evacuation, tactical communication, traffic measures, warnings, clearing emergency and rescue routes as well as guidance of groups of people on the move. Other situations include unorganized gatherings such as flash mobs, but especially large events with a high risk potential such as meetings, public viewing, open-air concerts or public festivals, Christmas markets or city festivals. Furthermore, a flying media display would be useful in the event of major damage events such as train accidents, traffic accidents or weather catastrophes in order to support the rescue of human lives.

DISCUSSION

In order for flying media displays to be used sensibly in emergency situations, their display contents must meet certain requirements. Since the displays have to inform people in panic, they should provide simple and clear information in conjunction with strong optical and acoustic signals, such as blue light and siren. The contents of the display must take into account the heterogeneity of those affected, e.g. children, the elderly, other nationalities, etc. Multilingual advertisements and announcements are therefore indispensable. The correct positioning of the display is also important so that the target group can perceive and see the flying media display accordingly. This means that the pilot must hold the display at a suitable height and distance from the group of people so that the text size and images appear large enough and the information is clearly recognizable.

Large potential. We see a large potential for fMDs as a police tool, as they can be airborne, brought very quickly and precisely into the area of operations. They therefore have a good chance of becoming an effective and safety-enhancing tool to support operations, especially as an information and control instrument. Since the display contents can be loaded in real time and dynamically populated with

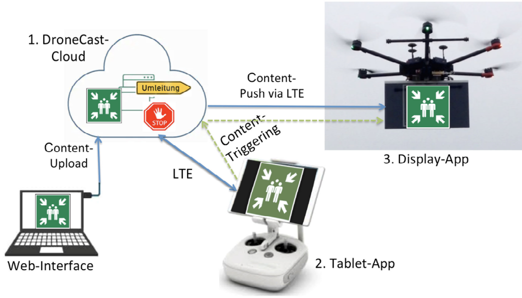

Figure 5: Components that are integrated in our DisplayDrone system

Figure 6: A police officer uses the tablet computer to dynamically control the content of DisplayDrone.

messages to match the context, there is a very wide range of applications. However, there are a number of important factors that still need to be resolved or investigated:

Effectiveness of fMDs. The effectiveness of fMDs should be examined more closely, i.e. on the one hand whether fMDs prove themselves in the reality of the operation in the manner intended by the police, and on the other hand whether the information and instructions for action disseminated via fMDs are actually recognized, understood and implemented by the population concerned. What things play a role here? How, for example, do the positioning of the display (including height, distance, speed) affect the target group so that they can perceive and see the fMD well?

Weather resistance and wind. Furthermore a high wind and weather resistance of the fMDs is necessary. Our Outdoor DisplayDrone prototype flew very stable in the tests. Future fMDs should always be usable even in humid weather and not be susceptible to stronger winds. The size of the display and the exposed area to the wind can become a problem. Therefore a high air permeability of future display types and materials plays an important role.

Light conditions. The LCD display of our Outdoor-DisplayDrone prototype had a brightness of 250 cd/m(2). This meant that the ticker could still be read easily by the naked eye at 100 meters in daylight and slightly cloudy weather. In sunny weather, however, this would have been more difficult or even impossible. In order for fMDs to find their way into everyday police operations in the future, the brightness of the displays must increase drastically.

Our next steps of our ongoing research with the prototypes we have built, will include user tests together with the police in realistic contexts.

CONCLUSION

In summary, our explorations so far have shown that the operational suitability of fMDs as a police tool is subject to further investigations and further technical developments. On the basis of the current state of knowledge and the results achieved to date on fMDs, the German police team, which we have been working with in our workshops, believes that after proven efficacy and technical improvements, fMDs will in future be integrated into police operations as an everyday tool.

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Drones for Remote Collaboration in Wilderness Search and Rescue

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ABSTRACT

Wilderness search and rescue (SAR) is an activity that could potentially be well supported by drones, both as search tools and as devices to help with collaboration between remote helpers and workers on the ground. However, even with this potential, there are still usability challenges that need to be addressed. In our work, we are exploring potential use cases for drones to support wilderness SAR, as well as design solutions for wilderness-SAR drone systems. We discuss these explorations in this position paper, as well as some of our ideas and plans moving forward.

KEYWORDS

Drones, search and rescue, remote collaboration, outdoors, emergency situations

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INTRODUCTION

Search and rescue (SAR) has long been seen as an activity that can be well-supported by drones. Wilderness SAR in particular, which involves searching and scanning large swaths of unpopulated wilderness for a lost person (e.g., a hiker, skier, or mushroom picker) [7], could benefit from the use of drones, as they can provide searchers with a unique overhead perspective and allow them to cover more territory in a shorter amount of time. Drones can also get to hard-to-reach places (e.g., steep mountain tops, deep valleys) and inspect them from both afar and up close.

While this is the case, a number of usability challenges in state-of-the-art drones still act as barriers in their use in most real wilderness-SAR incidents. For example, most drones have to be manually flown by a co-located user, or the user has to define a specified flight path for the drone in advance. Manual piloting is mentally demanding and physically cumbersome to SAR workers, given that they have to use both of their hands to control the drone, and they have to direct all of their attention to it. When a SAR worker pilots a drone in this way, they cannot perform other tasks with their hands, and it becomes more difficult to pay attention to other things. Pre-defining flight paths alleviates these issues, though it takes in-the-moment control of the drone away from the SAR workers, and it makes it less easy for them to change the course of the drone based on new information. Additionally, pre-defined paths often do not take into account the locations of obstacles, other SAR workers, or important details in the field (such as clues and footprints). There are other control strategies between full control and full autonomy to consider that could be beneficial to SAR. We will discuss these later.

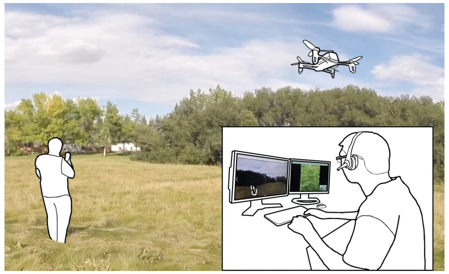

Figure 1: A drone enabling remote collaboration between an outdoor user and a remote (indoor) user. Such a system could be used to support remote collaboration in wilderness SAR. From [6].

In our work, we are exploring various use cases in which drones could support wilderness SAR. From these, we are coming up with a set of recommendations for the design of drone interfaces to support wilderness SAR, as well as implications for both local and remote users. Currently, there are two main purposes in which we see drones being used for wilderness SAR: (1) to allow a single user (remote or local) to search and inspect an area; and (2) to allow a remote user to collaborate with a local user, usually to provide guidance, give instructions, or work together on some task. In this position paper, we discuss examples and ideas from both of these.

DRONES FOR SEARCH AND INSPECTION

Drones provide users with a unique perspective of an environment, allowing them to inspect the space from angle that would otherwise be unachievable [6]. This can be beneficial for SAR, as it can allow searchers to see the environment in a brand new way, either spotting things they may not have seen before (even spotting the lost person) or seeing familiar things at a new angle, thus helping with navigation and spatial problem solving.

With this new perspective though comes challenges. For example, if the drone is high up, depending on the fidelity of the camera it could capture a lot of information. While this is certainly beneficial, it could easily be too much information for a human to comprehend and make good use of. Similarly, since humans are not used to inspecting visual information from up in the air (since we are ground creatures after all), matching this information to what we see on the ground and planning in accordance to it can sometimes be tricky. In a previous study we ran [6], we found that while users collaborating on outdoor activities using a drone (as the remote user's view into the activity space; see Figure 1) find the information visible in the drone view to be useful, they often have a hard time matching the visual information to the frame of reference of the collaborator on the ground (similar to what has been found in [11, 15]). To illustrate a simple example, a remote collaborator viewing through a drone might say "move up" or "move down," but these directions would need to be translated to the frame of reference of the collaborator on the ground (e.g., *up* might be *forward* for the collaborator on the ground). It gets even more complicated when the remote collaborator needs to give directions in relation to landmarks she can see through the drone view, but she is not sure whether or not her partner on the ground can see them from his point of view.

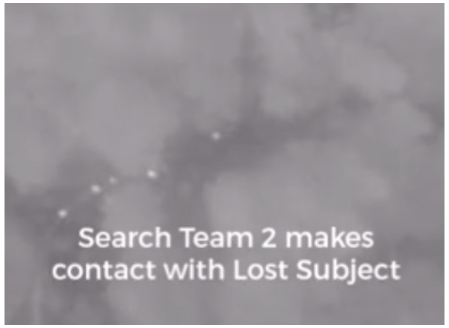

Figure 2: Heat cameras on drones could help SAR workers easily spot lost people in areas dense with trees and vegetation. From Kamloops Search and Rescue [2].

Beyond simple RGB cameras, drones can also fly with other types of cameras and sensors. Infrared (thermal) cameras can be particularly beneficial for wilderness SAR, as searchers can spot people with them easily due to the fact that human bodies produce enough heat to stand out easily on thermal images (see Figure 2). A wilderness-SAR group we are working with has been trialing the use of thermal cameras on drones during training activities. In addition, drones with thermal cameras have been successful at spotting lost subjects in at least one real SAR incident [1]. With this potential though, there are still some challenges. These include (but are not limited to) tree density in some wilderness areas blocking the view of victims, challenging weather conditions such as strong winds, difficulty getting up close while avoiding collisions with trees and other obstacles, avoiding disturbing wildlife, the importance of not distracting SAR workers on the ground, and local drone laws and regulations (e.g., not being allowed to fly a drone out of one's line of sight). In terms of laws and regulations, this is largely dependent on the jurisdiction of operation, and drone laws could potentially become more relaxed (at least for SAR and other emergency-response agencies) as drones themselves become more socially acceptable. Challenges such as obstacle avoidance, weather conditions, and distraction-free flight will likely be addressed through improvements of the technology. For example, newer drones will likely be built to emit minimal noise and fly more stably in difficult weather. In addition, artificial intelligence (AI) and machine perception (e.g., computer vision) could allow drones to more-effectively avoid obstacles, allowing the user to focus more on inspecting the images coming from the drone.

Aside from inspecting live video images from up in the air, drones could also be used to capture imagery of the search area for viewing at a later time. A sequence of images of multiple spots could be taken, of which a SAR manager at a command centre could search and scan through. Furthermore, these images could be stitched together, forming either a 2D overhead representation of the search area (similar to satellite imagery) or a 3D reconstruction of the search area (e.g., similar to [3]).

Beyond assisting users with inspecting wilderness environments, developments in AI and machine perception will likely allow drones to carry out much of the work of searching the space by themselves. Future drones may be able to fly around the wilderness environment autonomously and pick out the missing subject(s) by themselves; or at least help SAR workers narrow down their search from a vast area to one or a few smaller spots.

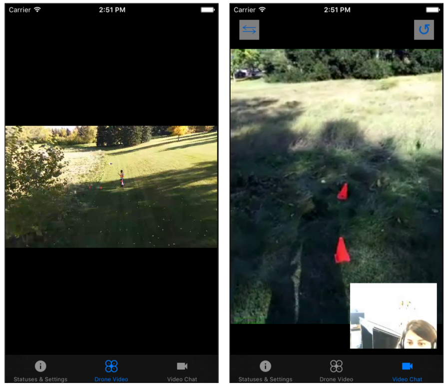

Figure 3: A video-conferencing system utilizing a drone, enabling remote collaboration between a local user on the ground and a remote user providing assistance. From [6].

DRONES FOR COLLABORATION BETWEEN REMOTE AND CO-LOCATED USERS

Drones can also be used to accompany a SAR worker in the field as they communicate with and receive assistance (e.g., navigational instructions) from a remote worker at command. We have explored similar scenarios in previous work [6]. We see a lot of potential for these types of designs in wilderness-SAR scenarios—specifically, designs that allow drones to act as collaboration tools, serving both remote users and users in the field. But when they are used in this way, they should be designed to account for both sets of users, and human-drone interfaces should allow for interactions (e.g., inputs and outputs, communication and feedback) with both remote and co-located users.

In previous work, we designed a drone-video-conferencing interface in which the drone follows the local (outdoor) user (Figure 1) and the remote (indoor) user views through the drone's camera feed (Figure 3). With this system, we gave the remote user slight control of the drone by allowing them to adjust the camera pan/tilt/zoom and define how high up and how far back it flies from the local user. With this system, we studied scenarios between two collaborators, in which one collaborator is in the outdoor environment where the task is taking place and the other is in a remote indoor location such as an office. We ran a study in which participants worked on activities that involve searching, inspecting, and organizing objects around large spaces. These activities require the remote collaborator to give navigational instructions, understand the spatial layout of the environment, and provide search guidance to the outdoor collaborator based on the perspective they have. We found that while the interface allows workers to collaborate on such tasks with greater ease than with a typical mobile-video-conferencing setup (e.g., a FaceTime-like interface), remote collaborators sometimes had difficulty rephrasing navigational directions in the frame of reference of their local counterparts. In addition, when there was a lot in view, the remote collaborators had trouble understanding and contextualizing all of the visual information they could see. On the local side, users were sometimes concerned for their own safety with the drone nearby, and also for the safety of the drone itself. In addition, given that the drone followed the local user, local users often felt a sense of responsibility for the drone, making sure to walk around such that the drone does not fly to unsafe spots. While this study did not specifically look into wilderness-SAR scenarios, we outline below some wilderness-SAR scenarios in which drones could be used in a similar way as tools to support collaboration between remote and local users.

(1) Guidance and Navigation: A remote user could use a drone to help a SAR worker on the ground navigate to where they need to go. Previous work has studied the use of drones for providing navigational cues, through positional cues [13, 14] and projections on the ground [4, 9]. Even if the local user has a reliable map and compass, knows where they are, and where they are going, in unpredictable wilderness environments it can sometimes be a challenge to figure out exactly how to navigate to where one needs to go. A remote user flying a drone can inspect the scene from up above to determine where obstacles are and what is the shortest or most feasible path for the local workers to traverse. Once this inspection is done, the drone can then use its physical form and embodiment to communicate the necessary navigational instructions to the field workers.

(2) Collaborative Search and Inspection: Similar to our previous work [6], drones in wilderness SAR can be used for collaborative search and inspection. A SAR worker on the ground could inspect an area of wilderness while a remote worker viewing through a drone inspects the same area from a different perspective—one that is unreachable to the worker on the ground—and offers advice to the ground worker based on what they see through the drone.

(3) Physically Handling Materials: Finally, a drone can be used to physically move or handle materials in the wilderness environment. Depending on the weight and size of the objects that need to be moved and the power of the drone, a drone could help SAR workers move materials to hard-to-reach places. For example, if workers need to move one end of a rope to the top of a cliff or the bottom of a steep valley, they could have the drone fly that end of the rope to where it needs to go.

DESIGN CONSIDERATIONS

While drones certainly have potential to serve wilderness-SAR workers, some considerations need to be taken into account.

First, it is important that the workers on the ground do not become too distracted by the drone. SAR workers need to remain focused on listening for the subject, watching for hazards, and using their hands to handle equipment (such as ropes, pulleys, and bags) and climb through difficult terrain. Thus, it is important that any awareness of the drone, whether it is through hearing or seeing it, provides a utilitarian purpose for the SAR workers on the ground. For the most part, it is ideal for the drone to be either unnoticeable to field workers (while they are providing some use to a remote user) or to have the sight and sound of the drone provide some use to them—for example, using the embodiment of the drone to guide the workers, or having the presence of the drone assure the workers that they are being looked after by command.

Second, the level of control given to users should take into account the user's goals, abilities, and any other responsibilities they have. If the user has other responsibilities to attend to beyond operating the drone (e.g., the user is a field worker paying attention to immediate surroundings, or a manager with other responsibilities in the command centre), it may be beneficial to give the user more indirect control of the drone, so that she can affect what the drone does, but without being too mentally invested in the act of operating it. The Human-Robot-Interaction concept of *shared control* [5, 8, 10, 12], both between the user and the drone [8, 12] as well as between two or more human operators [5, 10] would be worth exploring in SAR. Automation is preferable wherever possible, while still allowing higher levels of control to be passed on to the necessary user during critical moments (e.g., where the lost person may have been spotted, or the drone is in danger). In addition, the ability to pass total or partial control to another user may be beneficial in situations where, for example, a field team no longer needs the drone and wants to pass it on to another team that needs it.

Finally, we also see the benefit of coupling drones with other technologies and interfaces (rather than just using them on their own) to leverage their benefit. As a simple example for remote workers in a command centre, an interface that contextualizes the visual information in the drone's camera feed with information that the SAR agency already has about the search might be useful. Displaying annotations and overlays on the drone video feed showing the locations of SAR workers, clues found in the field, and other important information would help the viewer put what is in view into context, rather than just seeing a set of trees, mountains, and rivers, without meaning. As an example for local workers on the ground, an augmented-reality (AR) interface that displays an overlay over a drone in the sky, showing the worker who is controlling the drone, what the drone is doing, and where it is flying to might provide some use to them.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

For future work, we plan to work closely with wilderness-SAR workers in western Canada to iteratively design, through a participatory-design process, remote-collaboration systems for wilderness SAR utilizing drones. We also plan to evaluate the more-refined iterations of our prototypes through two stages: (1) field trails, in which pairs of participants use the prototypes to complete search and inspection tasks designed to mimic wilderness-SAR scenarios (to the extent which they are safe), and (2) long-term deployments with SAR teams for training activities and mock searches. Our work will lead to a further understanding of how drones can be used to assist wilderness-SAR volunteers, as well as potentially an early understanding of how they can better support other emergency responders.

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Drones for Search and Rescue

Figure 1: A traditional search and rescue scenario in a secluded area, without any connection to the outside world.

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ABSTRACT

Natural disasters are increasingly common as climate change becomes more severe. Search and rescue operations become more and more important to societies worldwide. Rescue services are often engaged in missions in rural areas, treating the injured or searching for missing persons. Often, time is an essential factor for a positive outcome of search and rescue missions. Due to their capacity for flexible deployment, drones have a great potential to be deployed in search and rescue scenarios and thus reduce the rescue time. In this work, we discuss how drones can effectively assist rescue crews in their mission to save human life.

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CCS CONCEPTS

• **Human-centered computing** → **Interaction techniques**; **Collaborative and social computing systems and tools**; **Ubiquitous and mobile computing**; Human computer interaction (HCI).

KEYWORDS

Drone, unmanned aerial vehicles, UAV, quadcopter, human-computer interaction

INTRODUCTION

In search and rescue scenarios, time is often the most critical factor as lifes are at risk. Often the time factor is combined with uncertainty as the exact location of the person concerned is not known. Thus, search and rescue services are required to search a vast area within a very short period of time. Emergency services have already started to deploy unmanned aerial vehicle (UAV) in an attempt to search a larger area in a shorter time span (c.f. freewaydrone[1]). Time and the vast space are the most common critical factors in these missions, but natural disasters often cause constraints which cannot be overcome by humans. Avalanches, floods, and wildfire are among the most common natural disasters which make search and rescue missions extremely hard for humans. Moreover, contamination (e.g. nuclear disaster, and biohazards) may occur in the same area [8].

In these search and rescue scenarios, UAVs have a number of advantages over humans. Firstly, UAVs can be sent to any location without the operator knowing the exact conditions in the target area. This reduces the possibility of rescuer injury or death. Moreover, using the latest tracking and communication techniques, UAVs can scan a large area in a short time span. Here RGB, infrared, and thermal cameras combined with state-of-the-art machine learning (ML) can be used for identifying and tracking humans.

However, a number of factors are still hindering the effective deployment of UAVs for rescue operations. While swarm intelligence can be used to control and operate a large number of UAVs at the same time, the general control concept is still unclear. Today, most of the time one UAV is operated by one pilot which makes scalability insufficient as intensive labor is required. Multimodal interaction coupled with ML can support pilots in operating one or multiple UAVs at the same time [3]. Moreover, the to be rescued person could control UAVs and thereby for instance send in formations to the search and rescue troops.

In this work, we first map the possible deployment scenarios for UAV in search and rescue. Then, we outline challenges and opportunities from a human-computer interaction (HCI) perspective but also beyond this scope.

Figure 2: Drone overfly of a remote path in a forest. Credit: https://www.instagram.com/bongokaiser/

[1]https://youtu.be/6t-hYnWPiFk

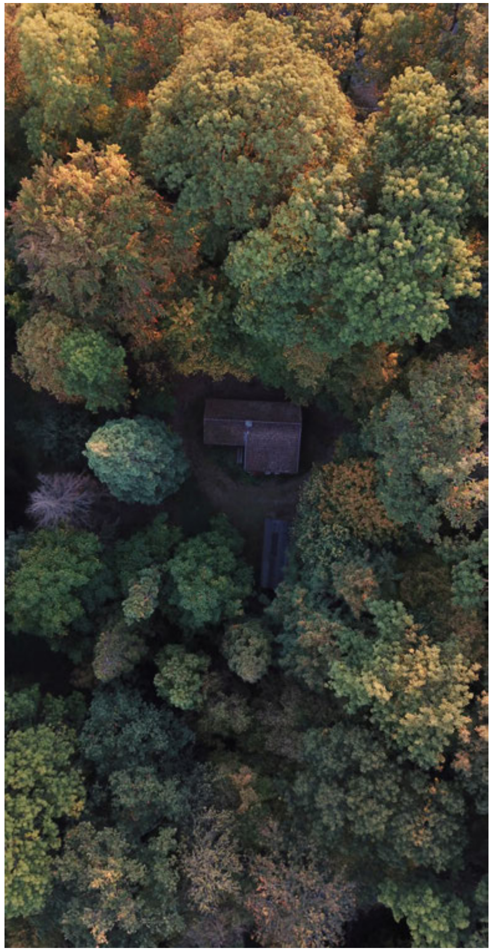

Figure 3: UAV overfly of a remote house in a forest. Credit: https://www.instagram.com/bongokaiser/

SEARCH AND RESCUE SCENARIOS

For the design space of search and rescue we identified four axes: 1) Outdoor - Indoor; 2) Urgency; 3) Remote action; 4) Subjects. In the following, we will explain the four axis and describe their interplay.

Outdoor - Indoor

UAVs have extensive abilities to overview large and remote areas, see Figures 2, 3 and 5. They can transmit image and sensor data from remote locations faster than conventional means and without the risk of injury to the person monitoring the situation, see Figure 4. In all kinds of natural disasters, UAVs can help emergency forces understand the situation and identify injured persons or persons requiring support. This is particularly relevant when the area is hard to access or accessing it would endanger the rescuers. Such tasks include avalanche rescue, wildfires, floods or contamination (e.g. nuclear disaster). In these situations, UAVs can transmit not only visual information, but also other sensor data such as temperature, air quality or radioactivity. Further, UAVs can provide a communication connection to inaccessible people or even deliver urgently needed tools.

Even without natural disasters, people require remote assistance. When people involved in outdoor sports, such as running [11] or hiking, health conditions can change quickly and finding the injured or proving remote assistance can be required [7]. Furthermore, people can get lost while performing outdoor sports and have to be brought back home. This can be supported by UAVs. This is also the case when children get lost while playing outside or pets elope. In amusement parks or during large events, people lose their companions or their children. Here, UAVs coupled with computer vision can help find the required people in crowds.

This challenge of relocating other people is not only relevant for outdoor scenarios but also for fairs, shopping malls, and even in smaller houses UAVs could be used in case of a fire. Firefighters can use UAVs to analyze the situation in a house without entering the building. Here, missing people could be located before sending in firefighters. Additionally, through thermal imaging [1] and air quality sensors collected information would help firefighter to act faster and safer.

Urgency

Rescuing and locating people is not always time critical. For instance, finding one's friends in an amusement park might increase the happiness of people, but is not urgent. On the other hand, the more common scenarios for search and rescue missions are time critical. Such as in natural disasters, fire, or critical health conditions have a high urgency. Here UAVs offer the means to capture first impressions even before the troops are ready to work and provide them with the necessary information when they arrive. This can improve coordination and limit the risks associated with rescue.

Figure 4: Search and rescue at a beach with communication by gestures.

Remote Action

In many cases, it is advantages to obtain an overview of a situation remotely to be able to react to emergencies quickly, see Figure 5. Also, transmitting the geo-position of a lost or insured person speeds up the rescue process significantly. In the next step, it might be required to communicate with a person remotely, see Figure 4. When a quick rescue is not possible, tools, medicine or nutrition could be delivered by an UAV even before emergency responders arrive. In the worst case, the person could also be transported by an UAV.

Subject

The search and rescue of humans are definitively the main target. However, as already indicated, not only humans might be rescued by UAVs, but also pets. UAVs can assist in emergencies in farming where the farmer can search and monitor animals remotely and securely.

OPPORTUNITIES

Traditional UAV deployments often suffer from risks like e.g. polluted airspace [14], privacy concerns and a negative effects of the UAV sound [4]. However, we argue that while theses challenges exist, they are, in search and rescue scenarios not as important.

Common challenges in UAV control are navigating, with Global Positioning System (GPS) often not providing enough precision. However, recent advantages in optimization problems a swarm search strategy [5] would help operating multiple UAVs this will improve current drawbacks as easy pathfinding and easy navigation using UAVs is still an open research challenge.Another common challenge is the limited communication range. Here, WLAN [9] or 4G [13] (and future 5G networks) can be explored to extend the range. We envision that UAVs could either deploy repeater on the fly, act as repeater themselves, or even fly back to transmit information.

Finally, beyond technical challenges which currently exits, we identify a number of challenges within our design space which should be addressed by HCI research.

Control and UAV ownership

In not safety critical search scenarios, like searching for friends during sport events, UAVs could be provided by organizer of the event. Thereby the number of UAVs in the airspace could be controlled and reduced. However, when possible users would need access to the UAV control. Here, bring-your-own-device [2] as UAV controllers need to be explored. While direct control of a UAV is one challenge, even getting direct live video footage and other information from a UAV to the observer is challenging itself [11]. Thus, it remains a challenge to HCI to understand the design requirement for UAV sharing interfaces.

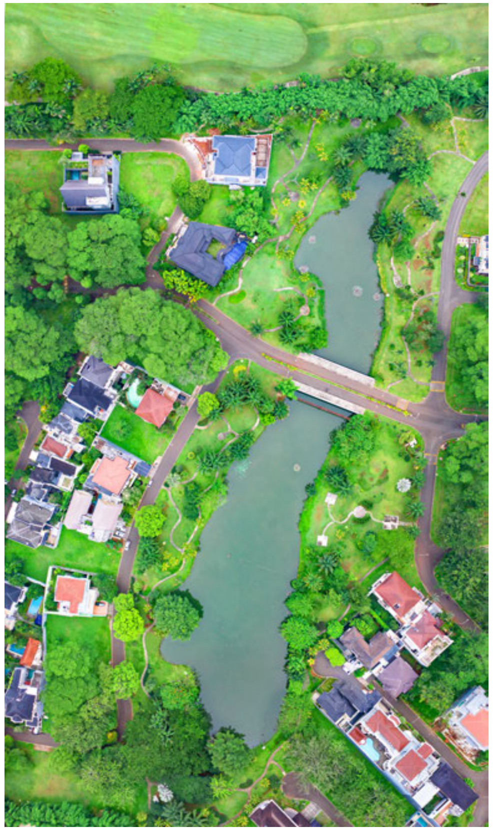

Figure 5: Drone flyby of an village to get an overview.

Today, UAV pilots control one UAV at most. Sometimes, even multiple operators are needed to perform flight maneuvers. In safety-critical search scenarios, the demand for operators needs to be minimized to ensure effcient operations. Thus, new interfaces for the control of one UAV or UAV swarms are necessary.

Here, we see opportunities to transfer solutions from common HCI interface control system to help the direct UAV operator. For example, easy drag-and-drop WYSIWYG implementations will help also novice users to operate UAVs. On the other hand, gesture control will help personnel in the field to redirect UAVs to support them in-situ with new upcoming challenges.

Privacy

UAVs will collect large amounts of personal data in search scenarios. Thereby, the UAV will not only collect data about the missing person or object, but also from all other persons within the field of view of the UAV. Furthermore, in most cases, the missing person will have no chance to agree or disagree to the data collection. HCI research should identify possibilities to minimize the affect on privacy. Furthermore, HCI faces the challenge of being transparent, explainable UAV interfaces that ensure the society's privacy.

Data Analysis, Observation, and Decision-Making

UAVs can provide large amounts of data at a high speed. Particularly, when the UAV is equipped with more sensors than a regular RGB-camera (e.g. thermal cameras) this data will be multidimensional. In urgent situations, rescuers will analyze large live stream data sets (e.g. object tracking [10], and face recognition [12]) from multiple UAVs at the same time. Here, HCI research needs to develop new techniques for monitoring and observation tasks. These techniques will include attention management, interactive data visualizations and interaction with multidisplay environments [6].

Range, and Goods Delivery

Today, UAVs are very limited in payload capacity and flying distance. However, we argue that solving the path planning and controlling issue solves these limitations, as the UAVs will then fly multiple times. Therefore, the UAV can autonomously deliver multiple smaller packages and get a new battery.

FUTURE WORK

UAVs offer extensive opportunities in search and rescue scenarios. We outlined a number of scenarios where we envision UAVs being deployed to help emergency services in their tasks. Nevertheless, making UAVs successful for search and rescue tasks requires research in multiple domains, such as battery technology or sensor fusion. However, we see that the biggest development gap is in interacting, operating, and controlling a large number of UAVs, but also even controlling single UAVs.

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Drones with eyes: expressive Human-Drone Interaction

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ABSTRACT

Drones are showing potential for many applications in which the interaction with humans are needed. In this paper, we demonstrate how affective computing can be applied to achieve a more natural Human-Drone Interaction. We proposed a learning approach for automatic and context-dependant coupling of emotion recognition and expression in a human-drone interaction. The drone performs facial emotion estimation to autonomously produce emotional expression through minimalistic animated eyes, using small displays. Additional testing is needed to further refine the interactions and establish how emotional interactions evolve in longer term interactions.

KEYWORDS

Human-Drone Interaction; Learning-driven behaviors; Affective Computing; Social Robotics; UAV

INTRODUCTION

Robots will increasingly become part of our lives, both in professional and social contexts. In the future, robots are expected to replace around 47 percent of total US employment by automating jobs [7], and drones will take a fair share in this process. Among all robots, drones are not a typical choice for a social partner since their applications are mostly outdoor, for example in transport and parcel delivery [8], search and rescue [2], the film industry and 3D mapping contexts [1]. We explore the potential for indoor applications of drones, in sports [17], warehouses, greenhouses, and eventually at homes. In this class of applications, the social abilities of a drone will be of higher importance for better communication and eventually for establishing long-term relations with the inhabitants of the indoor environments.

Emotion and intention are highly relevant in human-robot interactions [10]. Applying an affective dimension in human-robot interaction could reduce frustration during interaction [17], and increase robot acceptance in domestic environments [4]. One major challenge of affective interaction is to create a meaningful expression of emotion and intention in a drone with an embodiment that is hardly anthropomorphic or zoomorphic [4]. Eyes expressivity [3], and the whole body movement [4] were shown to be a very promising cue. In this study, we develop expressive drone eyes that are controlled by the emotional expression which the drone perceives from the facial expression of the interacting human. We base our assumption on the outcomes from the research on how to build longitudinal emotional interactions between people and drones on the data-driven model of emotional interactions between humans [9][11]. These results are based upon observations of 520 days long intermittent interactions between the same individuals.

RELATED WORK

Latest developments in research have already made significant steps in developing technologies that have positively affected social comfort [15] and working efficiency [14]. In attempts to recognize human emotions accurately, previous work by A. George [8] utilizes a minimal number of geometrical feature points. In this referred study, a dataset of input from a series of position numbers is reduced to only two features: eyes and eyebrows of the human face. Using only these features, an 87.4% recognition rate of facial emotions was achieved. Other related research investigates emotions in Human-Robot Interaction (HRI) [4][5][12].

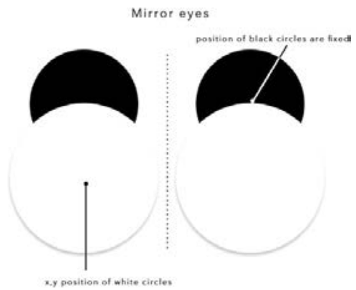

Figure 1: The expressive eyes are defined by varying two parameters of overlapping circles. This way the autonomous expression is easily achievable.

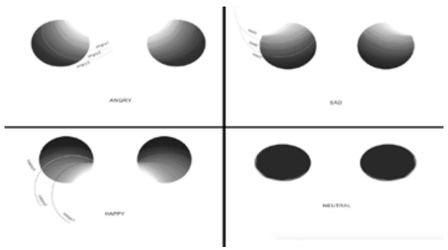

Figure 2: Visualization results of different emotional states and intensities.

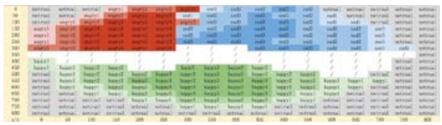

Figure 3: Emotion lookup table to find the best positions of the drone eyes.

Emotion or intention based interaction with drones included controlling a drone using face orientation and hand direction [12], and arm movement and body posture [18][13]. In another study, Szafir, Mutlu, and Fong [16] explored the design of a visual signaling mechanism to express a drone's intention via a ring of LED lights surrounding the drone.

We intend to explore how drones should react to the emotion of a specific person. For this purpose, the drone needs to recognize the person's emotion and change its expression automatically by controlling the openness and the direction of the drone eyes. The research and the design featured in this paper is focused on the non-verbal communication between a human and a drone, shown only through the shape of the eyes.

DESIGN OF THE DRONE BEHAVIOR AND THE HUMAN-DRONE INTERACTION

Used technologies and usability testing overview

For emotion expression of the drone, simplified eyes were designed, as shown in Figure 1 and Figure 2. The eyes consist of a static black circle on a white background. A white circle with a fixed radius and a variable position is then projected on top of it, leaving a moon shaped black form. The white circle is mirrored on the opposite black eye, thus requiring only two variables to generate the both eyes (see Figure 1). Depending on the location of the white circle, the black circles will represent eyes with different emotional expressions. For this study, we limit the expressions to four basic emotions, namely happiness, sadness, anger, and a neutral state. The visualization of these four emotional expressions is shown in Figure 2.

Two pilot usability tests took place. The first test aimed to find out which eye shapes fit the different emotions. An application based on human emotional perception was made in Processing language for the testing. The application randomly generated eyes that exhibited the specified four emotions and different levels of expression of these emotions. We tested with several fellow students and the results were exported to a table, providing us with a lookup table for each of the required facial expressions (see Figure 3), which we later used to train the learning algorithm. The blank ones were not associated with any of the emotions and were not used for training or as a valid expressions.

The second test needed to establish the connection between the expressed emotions by a person and the response of the drone, i.e. the affective interaction. Although the concept is created for a drone, a prototype for testing has been developed on a computer screen. For this test, the human will be in front of a laptop equipped with a webcam. The persons's face is analysed in order to determine its facial expression. The computer screen shows the corresponding eyes of the drone and is placed on a comfortable distance in front of the person.

Intelligent behavior and embodiment

Current human-computer interaction (HCI) designs generally involve traditional interface devices such as the keyboard and mouse and are constructed to emphasize the transmission of explicit

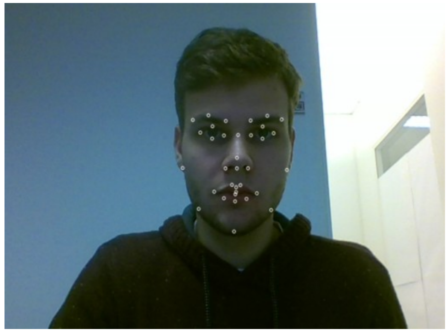

Figure 4: Facial emotion tracking by Affectiva SDK.

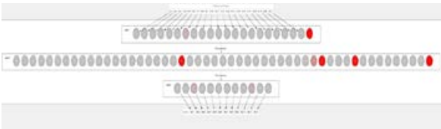

Figure 5: The used neural architecture in Neuroph studio.

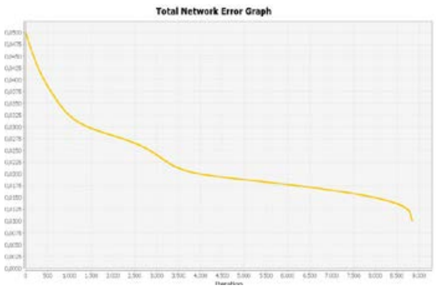

Figure 6: Graph displaying the decline of the learning error.

messages while ignoring implicit information about the user, such as changes in the affective state [12].

On the level of physiology, the sympathetic nervous system prepares the body for action and indicates the change of emotional state: increased blood pressure and heart rate, respiration increases, and pupil dilation. On a behavioral level, emotions are expressed using body posture, facial expressions approach/avoidance, and different accelerations of movement [4]. Plenty of methods to detect human emotion using audio or visual cues have been developed. In public spaces, audio information is too difficult to process due to the noise. In public areas, few people use body gesture to express emotion. Therefore for our context, the facial expression is the most straightforward and easiest method of emotional expression to detect.

Design of Neural-based controller for human-drone emotional interaction

We used the Affectiva SDK for facial emotion detection and analysis of the expression obtained from the camera. The 21 expressions output (e.g., brow raise, cheek raise, jaw drop, etc.) are used as the inputs for a neural network, training the network to link it to certain emotional expressions (see Figure 4).

Training data. Training data was collected from 5 persons by tracking 21 different points in their face using Affectiva's SDK. The participants were asked to express four emotions: happiness, sadness, anger and a neutral expression on three intensity levels from low to high, providing 12 known outputs. Since the neutral emotion does not have different intensity levels, we asked participants to vary their neutral expression slightly.

Neural network. Using Neuroph Studio, a multilayer perceptron network is set up with 21 inputs, a hidden layer with 50 nodes and 12 outputs (see Figure 5). The network was trained in the Neuroph Studio using supervised learning to train the data. The learning parameters are set to have a 0.01 max error and a learning rate of 0.2. The network was trained until the error rate decreased to 0.01 as can be seen in Figure 6. The network is exported to a *.nnet file which is imported into Processing to create an online interactive prototype.

Relationship building

To develop a realistic interaction between a human and a drone, the drone should be able to recognize individual human faces and react based on their previous mutual experiences. As shown in [12], people seem to have emotional memory – previous encounters influence their current emotion. A simplified version of such a relationship was implemented in the current system, utilizing previous facial expressions from the user to determine the state of their relationship. Happy or angry gazes from the user either positively or negatively affect this state.

Although the process of building a relationship is overly simplified in this initial phase of testing, the people will notice that the drone will not just mimic them. In the current experiment, the participant will see the relationship level on the screen as a numerical value, in order to make the person more aware of the context of the drone behavior. This level is a number where low means the relationship is mostly negative and high means that it is positive. When the relationship is good, the drone will react more happy and compassionate, whereas in a bad relationship the drone will have a more angry expression. Furthermore, the participant will eventually notice that positive facial expressions will make the relationship value go up, and see it decline when looking angry.

Table 1: Comparison of the emotion estimation of our network and Affectiva, a validated software for emotion estimation.

Emotion	Our network	Affectiva
Happy 1	Happy 2	Joy: 90-100%
Happy 2	Happy 2	Joy: 100%
Happy 3	Happy 3	Joy: 100%
Sad 1	Sad 1	Neutral
Sad 2	Sad 2	Sad: 0-2%
Sad 3	Sad 1	Sad: 20-40%
Angry 1	Neutral	Anger: 10-20%
Angry 2	Angry 2	Anger: 20-30%
Angry 3	Angry 2	Anger: 35-40%
Neutral	Neutral	Neutral

TESTING AND ANALYSIS

As previously mentioned, the Affectiva SDK was used to gather live data. This SDK features emotion detection as well based on its deep learning algorithm. The Affectiva emotion detection was needed for developing our system to compare the emotion estimation made by Affectiva with the results from our learning algorithm. We needed to implement own learning algorithm, so the pattern classification can be embedded in a flying drone with limited computational capacity.

For an illustration, different facial expressions were analyzed by the two systems, providing both with three different emotion levels for happy, angry, sad and neutral and comparing the results. The output from Affectiva is measured in percentages. The test subject had not been included in the training set for either of the two systems.

The presented neural network showed to be quite accurate in detecting the expressed emotion. However, the intensity of the recognized emotion was sometimes classified in the neighboring class – a bit angry as neutral, etc. (see Table 1).

DISCUSSION

We designed a system for emotional interaction of a social drone aiming to build longitudinal empatic relationships. The drone uses a neural learning for emotion recognition and heuristics for relationship building to produce an emotional expression using the drone eyes. This work is in a preliminary phase – a lot of additional work is needed to determine the proper data-driven model for relationship building in design through research approach. The prototype is working and ready for implementation on the BlueJay drone, which is a research platform for domestic and indoor drones that takes place at the Eindhoven University of Technology.

Currently, the tests are performed with a screen version of the eyes, rather than using eyes on an actual drone. The emotion recognition system utilizes a stationary setup as well. After implementation on the drone itself, some real-life constraints may arise.

The learning algorithm can recognize three intensities of four different emotions. The number of emotions could be expanded to create more complex interactions between drones and humans. It should be mentioned that although the data from the test subject had not been used to train the neural network, the training and testing took place in a similar setup as the training data gathering. While happiness is rather easy to express, the facial expressions for sadness and anger may not fully resemble natural facial expressions during those emotions, as the training set for these emotions was created while acting.

The relationship level is currently rapidly changing from positive to negative. For demonstration purposes, these values are close together and change based on the emotion displayed from the user. The current prototype proposes a very simple application of relationship building between human and drone. Gazing angrily at the drone will negatively impact the relationship between human and drone and produce an unfriendly facial expression from the drone in return. Changing the facial expression of the human to a friendlier one will not directly result in a friendly response, although it will improve the relationship. Looking angrily at the drone in a positive relationship will produce a sad expression from the drone and negatively impact the relationship. Since human relationships are far more complex, future studies could find correlations based on emotions and relationships. The ongoing research on this subject such as in [10][12] should be used to improve this interaction.

A large training set is needed for better generalization of the algorithm. Currently, we are unaware of how well our algorithm recognizes people from different ages and ethnicities, although within the training set already a diversity of male & female, and Asian & Caucasian participants are present.

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Exploring Cognitive Load of *Single* and *Mixed* Mental Models Gesture Sets for UAV Navigation

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ABSTRACT

We compare four gesture sets for controlling a UAV in terms of cognitive load, intuitiveness, easiness, learnability, and memorability, by means of users' subjective feedback. Additionally, we evaluate the level of cognitive load associated with each gesture set under study using dual-task performance measures (errors and response time) and time perception. Our participants used all four gesture sets under study in a Wizard of Oz based simulated environment. Results confirm our hypothesis that *mixed mental model* gesture sets perform worse than *single mental model* gesture sets in terms of all the considered attributes. However, we did *not* find a significant difference in cognitive load between the three classes of mental models identified in our previous work.

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KEYWORDS

Mental model; gesture vocabulary; user study; UAV; navigation; cognitive load; time perception; Wizard of Oz; interaction vocabulary; memorability; learnability; intuitiveness; coherence

INTRODUCTION

As sensing devices for HCI such as Kinect [9][22] and Leap Controller [12][23][26] have become affordable, a higher interest in the design of more natural and intuitive HCI has arisen, especially in Human-UAV Interaction [5][7][16][17][18][19][20][21]. We interact with machines using a wide spectrum of natural input modalities: gestures, speech, facial expressions, and gaze direction.

One of the key questions addressed in recent interaction studies is the *design of interaction vocabularies*. A typical way to design a vocabulary for controlling a device is to conduct an elicitation study to collect user suggestions and then to follow the majority principle, taking into account the most frequently suggested items to define the final interaction vocabulary. However, we consider this method insufficient to approach an "optimum" interaction vocabulary.

While several authors suggest to achieve interaction intuitiveness using different metaphors that evoke certain mental models of the system to interact with [4][5][14][15], Peshkova et al. have previously advocated the importance to **restrict commands** (vocabulary items) **to those associated with a *single* mental model** when aiming at intuitive interaction [18][20] and have grouped collected examples of such models into three classes – *instrumented*, *imitative*, and *intelligent*. The imitative class suggests that a device can imitate its operator's movements. In the instrumented class, an operator interacts via an imaginary link, e.g., an invisible joystick. In the intelligent class, a UAV is associated with an intelligent living being that can understand and follow more abstract commands.

The key difference between the three classes is the expectations they raise and the need for initial instruction. According to the authors' hypothesis, the intelligent class has the lowest cognitive load because a user controls a system akin to everyday interactions, and thus no additional advice is necessary. For the other classes, a user needs a hint defining the interaction characteristics (e.g., "your hand represents a UAV") – and must remember them, so the cognitive load is slightly higher, while the instrumented class requires some knowledge about the imaginary link that is used to control a UAV. Thus, in the latter case, cognitive load should be the highest. In our study, we investigate this hypothesis. For this purpose, we selected one gesture set from each class of mental models among user-defined gesture sets from a previous exploratory study [20] and decided to use the following measures to test the hypothesis: *dual-task performance*, *participants' subjective evaluation*, and *time perception*.

The second hypothesis put forward by Peshkova et al. is that a single mental model interaction vocabulary is in overall "better" compared to a mixed mental models interaction vocabulary. Therefore, we evaluated the two types of interaction vocabularies in terms of their respective intuitiveness, easiness, memorability, and learnability. We assessed these attributes through questionnaires. To create a mixed mental model gesture set, we intentionally mixed gestures from different mental models.

***Single* mental model** vs. ***mixed* mental model gesture vocabularies**: If *all* gestures within a gesture set (vocabulary) are based on a *single* underlying mental model, we call the set a *single mental model vocabulary*, otherwise *a mixed mental model vocabulary*.

Time perception: A relatively new measure in HCI, but according to pilot studies, promising to represent a reliable indicator of cognitive load [2, 3, 8]: It is based on the observation that when a person focuses on a task and is actively engaged in it, the time seems to pass faster than usual, while when being occupied with something easy (and perhaps even a bit boring), the time seems to pass slower.

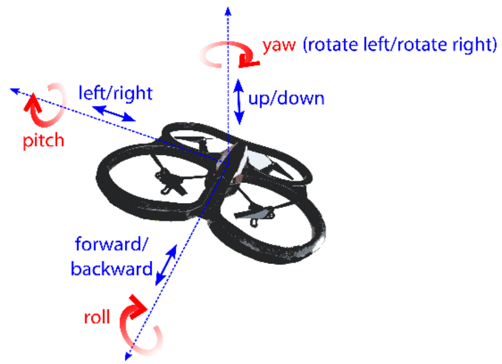

Figure 1. Moving directions, yaw, pitch, and roll axes

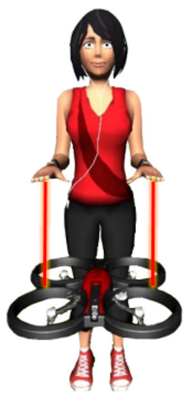

Figure 2. Neutral position for Puppeteer

GESTURE SETS

Peshkova et al. [19] investigated spontaneous gestures that non-experienced users invent to steer a UAV using basic commands (Figure 1). In a first user study, they interviewed novice users to gather their suggestions for relevant gestures for UAV navigation. In a second study, they observed spontaneous behavior of another group of novice users who were controlling the flight of a real UAV using their own gestures. As an outcome, the authors came up with a collection of gesture sets, some of which are employed in this study.

Later, Peshkova et al. [21] analyzed commonalities of the obtained gesture sets. As a result, three classes of mental models were identified: *imitative*, *instrumented*, and *intelligent* (see Introduction). For our study, we selected the *Full Body* mental model as a representative of the *imitative* class of mental models: A UAV imitates its operator's full-body movements – if you step forward, the UAV flies forward etc. The *instrumented* model class is represented by the *Puppeteer* mental model: The user carries an imagined vehicle right ahead of her/him, "linked" with the user's hands via two virtual strings, the real vehicle copies the actions of the imagined one (Figure 2). In the *intelligent* class, a user interacts with a UAV supposing that it is intelligent enough to interpret the user's "high-level" gestures. Following this idea, we asked our participants to invent their own "intelligent" gestures for basic navigation commands (in the following called *MyG*, short *for "My Gestures"*). The participants had complete freedom to use any relevant gestures under the condition that a human user controlling the UAV could interpret the invented gestures.

Figure 3 shows the three predefined gesture sets. The last row of Figure 3 presents the gestures from the *Mixed* gesture set. This set consists of gestures from diverse mental models: *Puppeteer* (*up* and *down*); *Full Body* (*forward* and *backward*); *Indication* (rotation commands); and *Airplane* (*left* and *right*: based on the "airplane" mental model). Thus, *Mixed* represents a mixed mental models gesture set as opposed to *Full Body* and *Puppeteer* which are associated with a single model each.

In our study, we investigated how the user's cognitive load depends on the employed gesture sets. We checked whether we could find a difference (1) between the three classes of mental models and (2) between *single mental model* gesture sets and *mixed mental models* gesture sets.

Based on the discussion provided earlier (see Introduction), we hypothesize that the lowest cognitive load is associated with intelligent mental models (*MyG*) and the highest with the instrumented mental models (*Puppeteer*). We expect gesture sets with gestures from *imitative* mental models (*Full Body*) to impose cognitive load higher than *intelligent* and lower than *instrumented* (H1). Our second hypothesis (H2) is that people experience higher cognitive load and lower intuitiveness, memorability, learnability, and easiness using *mixed mental models* gestures sets (*Mixed*) compared to *single mental model* gesture sets (*Full Body* and *Puppeteer*).

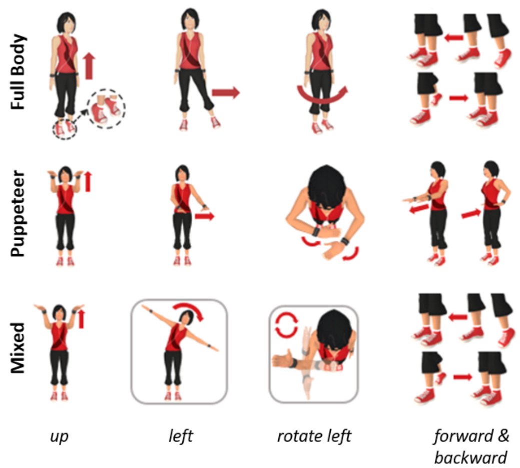

Figure 3. The three gesture sets investigated

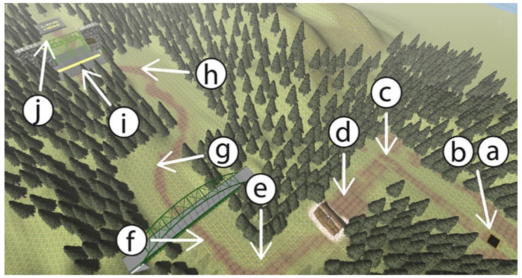

Figure 4 [20]**. Overview of Route 1**

USER STUDY

We simulated a UAV's flight using a 3D computer simulation that consists of four pre-defined flight routes of equal difficulty [20]. The 22 participants' (aged between 19 and 34 years; 6 female) task was to control the vehicle on these routes using different gesture sets. To fly along each route, the participants had to use the same ten navigation commands, but in changing order.

Figure 4 offers an outline of the first route. There are eight checkpoints between the start (a) the end point (j). Providing the appropriate commands, the user crosses all checkpoints and reaches the destination (j) where the vehicle is supposed to land.

In order to measure the participants' baseline time perception, we recorded the time the participants felt to constitute one minute.

After having watched a short video of one of the four routes, each participant performed the navigation task four times, first with set *MyG* and then once with each pre-defined gesture set (counterbalanced to prevent problems with sequence effects [11]): *Full Body*, *Puppeteer*, and *Mixed*.

We collected users' time perception and their subjective evaluation of cognitive load experienced when using different gesture sets. The participants also reflected their subjective evaluation of the used gesture sets in a questionnaire before proceeding with a new gesture set. They answered the questions in regard to cognitive load (7-point scale) and time perception (how long it took to finish the route in their opinion). During the entire experiment, the experimenter took notes about think aloud data. When the participants completed the tasks, we asked them to evaluate the four gesture sets in terms of their intuitiveness, easiness, and memorability. In the final questionnaire the participants also gave a description of the gestures and selected their favorite/least favorite gesture set(s). The participants were also asked to explain their choice.

Before starting the navigation task with each of the pre-defined sets, the experimenter showed all the gestures one by one (*Mixed*) and also explained the underlying idea of the single mental model gesture sets (*Full Body* and *Puppeteer*). Moreover, the participants received an instruction sheet that showed all gestures (see **Figure 3**). The participants could take as long as they required to study the gestures before proceeding to the task execution. As we observed, participants spent no time studying the instruction sheets and started steering the UAV right after the explanation (a couple of participants took a few seconds to review gestures from set *Mixed*). For the duration of the task, the participant could not look into the list of gestures.

During each navigation task, the experimenter asked participants five simple math questions ("3+2=?", "2x4=?", etc.), wrote down the participants' answers, recorded time delays (when the response time was more than 5 seconds) and wrong answers, and took notes about think-aloud data. These math questions represented the second task that our participants had to perform simultaneously with the main navigation task. The information regarding time delays and wrong answers is intended to reflect the participants' cognitive load.

A video recording explaining the study can be found on YouTube [29].

Gesture set	Min.	Med.	Mean	Max.	S.D.
MyG	-68.5	43.48	62.24	255.88	83.31
Full Body	-99.31	29.86	24.06	166.59	58.79
Puppeteer	-62.66	21.33	26.73	128.27	56.15
Mixed	-64.19	22.13	24.74	146.29	58.34

Table 1. Descriptive statistics of the error of time perception: Estimated Time – Actual Time

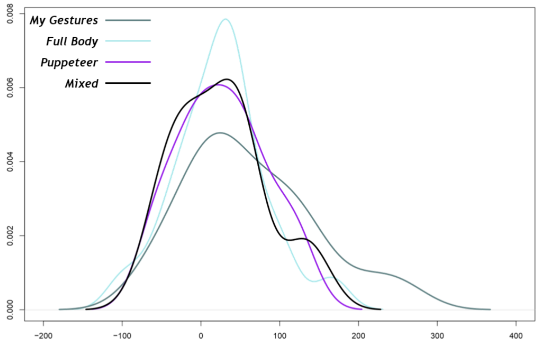

Figure 5. Densities of time deviations

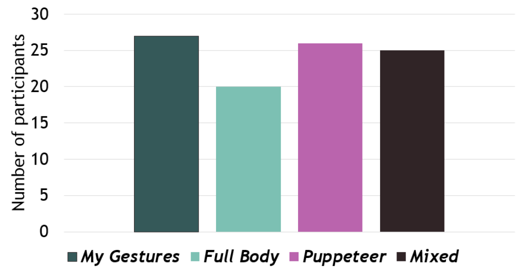

Figure 6. Delays and wrong answers

RESULTS

Cognitive load

To evaluate the level of cognitive load, we used time perception, dual-task performance, and participants' subjective evaluation [1][2][4][8][10][24][26][28]. We also assessed intuitiveness, easiness, memorability, and learnability of the considered gesture sets through questionnaires.

Time perception: After performing the navigation task with each gesture set, our participants guessed the time spent to complete the task. Block & Gellersen explored the influence of cognitive load on the perception of time [2]. It has been found that an increase of cognitive load leads to a decrease in time perception [1]. Hart [8] and Zakay & Shub [28] discovered that participants usually underestimated time intervals when the task load was higher [1]. The descriptive statistics for the error in time perception for each gesture set is presented in Table 1. From Figure 5 we can see that some participants notably overestimated the time spent with *MyG*. We conducted Friedman's test [13] and found that the main effect of gesture set tended to be significant: $\chi^2(3) = 7.25$, p = 0.06. Overall, we observed an overestimation of time (Table 1). The participants perceived the time spent with *MyG* longer than with other gesture sets. The number of participants who underestimated the time was: 5 (*MyG*), 7 (*Full Body*), 8 (*Puppeteer* and *Mixed*). That supports (though not significantly) our hypothesis that the cognitive load associated with *intelligent* gesture set (*MyG*) was the lowest, with *imitative* (*Full Body*) slightly higher, and the highest with *instrumented* (*Puppeteer*).

Dual-Task: We counted how many delays and wrong answers to math questions the participants made while steering the UAV. Figure 6 shows the obtained results. We did not find significant differences between the four gesture sets (Friedman's test: $\chi^2(3) = 1.46$, $p = 0.69$).

Subjective Evaluation: Figure 7 shows the results of the subjective evaluation of cognitive load experienced using 7-point scale (1 – very low, 7 – very high). The most frequent evaluation (mode) for *MyG* was 3, perhaps because of the fact that it was always the first set. *Full Body* and *Puppeteer* were most frequently evaluated as 1 and 2, respectively. The most frequent evaluation for the *Mixed* gesture set was 4, implying that this set was perceived the most complicated. However, the difference between the four sets was not significant (Friedman's test: $\chi^2(3) = 4.38$, $p = 0.22$).

Learnability

At the end of the experiment, we asked the participants to write down a description of each gesture set for the next participant who would not see the actual gestures, but control the flight using the written description. They should either describe each gesture individually *or* describe the idea behind each set if they consider it sufficient to complete the navigation task. As shown in Figure 8, 5 and 11 participants decided that it is enough to give a hint (the "main idea") to describe *Full Body* and *Puppeteer* set, respectively. The majority of participants gave a full description for *MyG*, perhaps because they had not enough time, or they did not recognize an idea behind their own gestures. As expected, all participants gave a full description for *Mixed*.

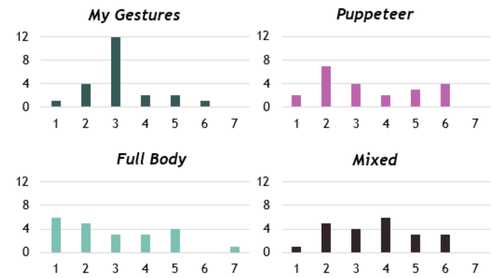

Figure 7. Subjective evaluation of cognitive load

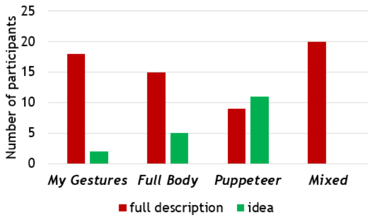

Figure 8. Description of gesture sets

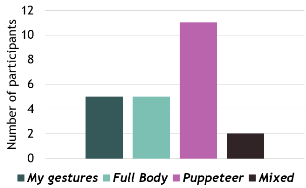

Figure 9. Favorite gesture set

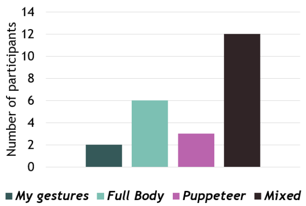

Figure 10. Least-liked gesture set

Priorities

After completion of all tasks, we asked the participants to choose their favorite and least-liked gesture sets (multiple answers allowed). Participants also ordered the four gesture sets based on their intuitiveness, easiness, and memorability. We analyzed the differences between the subjective evaluations with Friedman's test. A pairwise Wilcoxon test with Bonferroni correction was used for the post-hoc analysis. *Puppeteer* was favorite of most of the participants while *Mixed* was disliked most (Figure 9, Figure 10). 5 participants mentioned that they got the best impression from their own gestures and *Full Body*. 12 participants scored *Mixed* as least-liked. A significantly greater number of participants found the *single mental model* gesture sets (*Full Body* and *Puppeteer*) *more intuitive* compared to the *mixed mental models* gesture set (*Mixed*): $\chi^2(3) = 12.90$, $p = 0.005$; post-hoc for *Mixed* with *Full Body* and *Mixed* with *Puppeteer:* $p = 0.007$, $p = 0.058$, respectively. *Mixed* was evaluated significantly *more complicated* than the other gesture sets: $\chi^2(3) = 17.12$, $p = 0.0007$; post-hoc (*MyG*): $p = 0.008$; post-hoc (*Full Body*): $p = 0.0002$; post-hoc (*Puppeteer*): $p = 0.0042$. *Mixed* was also evaluated significantly *less memorable* than the other gesture sets: $\chi^2(3) = 17.08$, p 0.00068; post-hoc (*MyG*): $p = 0.02$; post-hoc (*Full Body*): $p = 0.001$; post-hoc (*Puppeteer*): $p = 0.003$.

DISCUSSION

We did not find significant differences between gesture sets in terms of cognitive load. However, we did observe some notable differences between the four gesture sets. Specifically, based on our time perception measures, we noticed that set *MyG* was associated with the lowest cognitive load indicator among the four sets under study. *MyG* represents the *intelligent* class of mental models: consisting of gestures borrowed from human-to-human interaction. Though the participants had complete freedom to suggest gestures, we did not find much variety among their behavior. Basically, their gestures could be described via a single sentence: "Use your hand to indicate the direction to fly or rotate." Thus, the participants tended to follow a single idea and their gestures actually adhere to a single mental model – which constitutes another interesting finding.

Overall, *Mixed* received the worst evaluation compared to the other three sets, thus supporting hypothesis H2 and previous research [20]. As a result, this set was selected by the majority of participants as the least-liked one. Considering that we intentionally selected gestures from different mental models for this gesture set, the obtained result is not really surprising, but it does stress the importance of adhering to a single mental model when designing a gesture-based vocabulary.

Though the obtained results do not formally support our first hypothesis (H1, cognitive load grows from *intelligent* over *imitative* to *instrumented* gesture sets: *MyG* < *Full Body* < *Puppeteer*), we did observe some tendency in favor of this hypothesis. Thus, it seems promising to us to further investigate cognitive load associated with different classes of mental models using more precise measures, such as pupil dilation, and to consider a couple of representatives from each class of mental models for a more comprehensive comparison. However, as shown by E et al., due to cultural differences, in any case, we cannot expect a single "one size fits all" solution [7].

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Exploring Drones to Assist Firefighters During Emergencies

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ABSTRACT

In the near future, emergency services within Canada will be supporting new technologies for 9-1-1 call centres and firefighters to learn about an emergency situation. One such technology is drones. To understand the benefits and challenges of using drones within emergency response, we conducted a study with citizens who have called 9-1-1 and firefighters who respond to a range of everyday emergencies. Our results show that drones have numerous benefits to both firefighters and 9-1-1 callers which include context awareness and social support for callers who receive feelings of assurance that help is on the way. Privacy was largely not an issue, though safety issues arose especially for complex uses of drones such as indoor flying. Our results point to opportunities for designing drone systems that help people to develop a sense of trust with emergency response drones, and mitigate privacy and safety concerns with more complex drone systems.

INTRODUCTION

Since the late 1960s, people in the USA and Canada have had to place a telephone call to the number 9-1-1 to share details about an emergency [11]. In the next few years, Canada will move towards Next Generation 9-1-1 (NG9-1-1) where callers and 9-1-1 services will increasingly use additional technologies [13]. One such technology is a drone which is a small-scale aircraft remotely controlled and provide video recording and/or streaming features. We have chosen to explore drones given

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KEYWORDS
Emergency calling; firefighters; drone; surveillance

Figure 1: Fire from top

Figure 2: House fire (close-up)

their likely ability to provide important contextual information about an emergency situation [4]. For example, if an emergency is called in to a 9-1-1 call centre, one could imagine a drone flying to the emergency (either automatically or controlled by an operator) and providing a birds-eye view of the situation and sharing it with 9-1-1 call takers and, subsequently, first responders. In our work, we have chosen to focus on *firefighters* as they handle and respond to a range of emergency situations, including car accidents and hazardous material situations, in addition to fire response.

To date, there has been limited research into how drone systems should be designed to best match firefighters' needs when responding to 9-1-1 emergency calls nor the benefits and challenges that might be raised by citizens about drone use during these situations. We explored this topic through an interview and scenario-based study of emergency situations with firefighters and people who have experience in calling 9-1-1 to report emergencies. We focused on 'everyday emergencies' such as automobile accidents, fires, and injuries that a citizen might call in to 9-1-1, as opposed to disaster response, crisis management, or search and rescue. Our goal was to answer several research questions. For firefighters, how might firefighters make use of drone footage in an emergency? And, how should drone systems be designed to aid firefighters during an emergency? For 9-1-1 callers, what benefits and challenges do they feel exist for drones that capture video of an emergency situation?

Our results show that drones could provide a number of benefits to 9-1-1 callers and firefighters, including knowledge of the context of an emergency, which could save valuable time. Drones can be thought of as 'non-human firefighters' which have the ability to reassure people that 'help is on the way' and provide additional perspectives to the firefighters to help them size-up an emergency scene. Privacy and surveillance were largely not an issue in our study for participants unless they were at fault for an incident or doing something illegal. Together, these results illustrate design opportunities for emergency response drones with an emphasis on designs supporting trust by the public; communication between dispatchers and those on scene; appropriate and useful camera work; and multiple drones and possibly indoor drone usage.

RELATED WORK

Information about an emergency is shared with firefighters in textual form through a computer aided dispatch system (CAD) when they are travelling to the scene with additional information being shared over radios [8]. Firefighters attend emergencies ranging from fires to hazardous material incidents to motor vehicle accidents [5]. Previous research looked into the needs of information sharing between firefighters and emergency control centres [7], mobile applications to enable text messaging between firefighters [1]. However, drones were not explored. Drones have the potential to be effective for emergency situations by providing a bird's eye view [4]. A study suggests that drones can be socially adapted and accepted [2]; however, a lack of regulatory frameworks calls for an investigation into how drones should be used [6]. People's privacy perception of drones was explored by Yang et al. [10] who found privacy concerns around inconspicuous data collection and inaccessible controllers of the drone. This work explored civil, government, and recreational drones

Figure 3: Apartment complex

Figure 4: HAZMAT from ground level

while our study aimed at understanding people's perception of drones in emergencies. Chang et al. explored privacy and security issues involving drones [3]. While they did not find any new concerns, they found out that the drone design itself can shape people's privacy and security concerns. Other work in this area explored how the registration of drone owners could reduce people's privacy concerns [12].

USER STUDY

We conducted an exploratory study with 9-1-1 callers and firefighters to understand how firefighters could make use of drone footage during everyday emergencies; how drone systems should be designed to aid firefighters during such emergencies; and what benefits and challenges everyday citizens feel exist for drones that capture video of an emergency situation. Our study was approved by our university research ethics board.

Participants

We recruited twenty participants in total through snowball sampling (word-of-mouth), social media (posts on Facebook), and contact directly with emergency response centres within our city. Participants were in two groups.

Everyday People: We interviewed twelve everyday people (six males, six females) who were experience with calling 9-1-1. Their age range was within 18 to the late 60s. They were experienced with calling 9-1-1 for diverse situations including gas leak, house fire, medical emergencies, police emergencies etc.

Firefighters: We recruited eight firefighters with the age range of 36 to 65. They had firefighting experience ranging from five to forty years. Three of them had extensive experience with using drones for emergencies.

Method

We conducted semi-structured interviews with each participant. Interviews were conducted in-person with local candidates living in Metro Vancouver, Canada. Other participants were interviewed through Skype. Interviews lasted between 25 and 75 minutes. Questions were different for everyday people and firefighter groups given their backgrounds and needs. We structured the interview in two phases.

Context: The first phase focused on the experience of both of the groups. We asked them to share details about the previous emergencies and asked how they would feel about drones capturing those situations; how they would want the drone to capture the scene; what they would not want captured etc.

Figure 5: HAZMAT from top

Figure 6: Accident (far-out)

Video Scenarios: The second phase of the study focused of understanding participant reactions to actual drone like footage of emergencies. We collected various footages of emergencies which were publicly available on YouTube (Fig. 1-7), clipped each footage to 30 seconds in length, and showed it to participants where we asked them to imagine themselves in the scene. The videos were categorized and purposely selected to be in four groups representing a range of emergency

situations: fire, hazardous material, vehicle accident, and injury in an apartment. These videos were a mixture of actual drone footages and smartphone footages. We started the interview by showing each participant a ten second video of a high-end commercial drone so they would understand what a drone was, if they were unfamiliar. Then, we showed them each of our video scenarios one-by-one and asked participants a series of questions about the video. Videos were shown in the order presented in Figures 1-7. Our questions sought to understand the benefits, challenges, and the usage of drones for emergencies.

Data Collection and Analysis

All interview data was transcribed and analyzed using thematic analysis to draw out main themes. The transcripts were read iteratively by one researcher to initially code the data to find similarities and differences across participants. Through frequent meeting with a second researcher, we explored the data for categories and central themes.

RESULTS

Benefits and Basic Usage

Our first responders pointed out how drones are already being used by some firefighters to get an overall view of the scene. Firefighters currently use drones for large scale structural fire emergencies or wildfires. A drone pilot controls the drone on the scene and shares the footage with them as per their request. They mentioned drones being inexpensive (compared to a helicopter) which provides high quality video stream. All participants talked about a number of benefits associated with using drones.

Participants thought drones would be most useful for fire incidents. They mentioned drones being able to locate nearest fire hydrants or provide a view from the top, for example. Firefighters thought drones could be useful to size-up the scene.

Firefighters thought drones could be particularly useful for situations involving hazardous materials with the ability to detect placards on vehicles. Drones were also seen to be useful in cases when it was dangerous for a human to come near a scene. Firefighters showed interest in having the drones equipped with different sensors to detect chemicals.

During vehicle accidents, participants thought drones could be useful to help regulate traffic and investigate the scene for evidence which might be helpful for post-investigation. For in-home medical emergencies, participants with children at home thought drones would be useful to assess the scene while two participants thought Google Maps would do the job well. Firefighters thought drones could help with traffic information, pointing out entry and parking areas in such scenarios.

Figure 7: Accident (close-up)

Design Needs and Challenges

Appearance and Location: Participants, both callers and firefighters, thought emergency service drones should have a prominent appearance which would make them feel more comfortable in the event of an emergency. Six callers and two firefighters suggested that a drone should be able to go inside buildings in case of emergencies. This would require the drone to be very small. Also, Firefighters suggested that drones could be equipped with different sensors such as gas or IR camera.

Locating the drones strategically around a vicinity is important because a drone should not take more than a minute to arrive to a scene during an emergency.

Capturing a Scene: Firefighters specifically wanted the drone to circle around a scene counter-clockwise starting from the address side of the building. They also mentioned capturing the scene from different height ranging from around 10metres to 200 metres. They also thought drones should be autonomous in part with manual controls since firefighters wanted to be able to request specific views.

Two-way Communication: We asked participants about the possibility of drones streaming or recording audio in addition to video. Callers felt that drones should not only have audio, but there should be two-way communication as well. Callers thought they would find it comforting if the firefighters would be able to provide instructions through the drones. That said, some participants thought two-way communication could distract firefighters from doing their work. Firefighters thought this could cause information overload and they would use it rarely. Still, they wanted the option to be available in case they ever had to use it.

Privacy and Safety: Two callers showed concerns related to privacy in terms of being captured by drone. These situations involved when the person is inside an apartment or a house or if the drone gets too close to the person. Other than that, all participants thought privacy was not important in the event of an emergency. Generally, firefighters did not have any privacy concerns but they pointed out unintentional data collection may cause privacy. For example, when looking for a victim, other people might be captured as well. They also showed genuine concerns in the event of seeing someone die on the drone footage when they cannot do anything to help that person.

Safety issues involved drone being stolen or getting hacked. Some participants thought drones could hit someone on duty or interfere with air traffic. Other concerns related to the possibility of firefighters neglecting their duties if drone does most of the work (for example, size-up a scene).

DISCUSSION AND CONCLUSION

Our study points to a range of design possibilities and challenges associated with drones and everyday emergency response. We explore these next.

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Drones as a Trusted Companion

Callers showed a great deal of trust in emergency drones. Drones can be thought of as companions in emergencies. Compared to literature around public video streaming [9], we see a high level of public acceptance of drones. Therefore, emergency service drones should be clearly recognizable. Callers also talked about drones in a way that somewhat personified them as emergency responders in and of themselves. That is, they saw drones as a tool that might allow them to talk with actual 9-1-1 dispatchers or even first responders where the drone would act as an embodiment for a person. Although there is a possibility of information overload on call takers or first responders because of two-way communication.

Capturing an Emergency

Capturing an emergency starts with the challenge of initially locating drones. Most participants valued drones placed in areas of authority that resonated with notions of help and existing emergency services, e.g., fire halls. Once arriving at the scene, we see further design requirements around the camera work needed to adequately capture the scene. Desirable views involved a mixture of close-up and far-out video, with various flying patterns to size-up the scene, gain broad contextual awareness, and monitor situations on the go. Also, a combination of autonomous vs. manual control could ensure the capturing of right information. Image processing software might mark important object around the scene such as fire hydrants or damaged vehicle.

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FOLDAWAY DroneSense, a controller for haptic information encoding for drone pilots

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ABSTRACT

Over the last decade, the number of drones has significantly increased. In parallel, researchers have started to investigate new human-drone interaction paradigms for a more natural and immersive piloting experience. The use of haptic feedback to establish a bidirectional interaction with a remote drone is a promising yet not fully exploited paradigm. In this article we introduce FOLDAWAY DroneSense, a portable controller with multi-directional force feedback for drone piloting. We also discuss four haptic interaction paradigms with the aim of boosting immersion and safety during teleoperation, and to simplify the training of first-time users.

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KEYWORDS
Human-machine interaction; Drones; Haptics

INTRODUCTION

The recent years have witnessed an exponentially increase in the use of drones. Miniaturization of electronic components and advances in perception algorithms enabled commercial and recreational applications like inspection, delivery and imaging [1]-[3].

As these applications are becoming ubiquitous, the number of naïve users that interact with drones has exponentially increased. With this respect, the quest for new human-machine interfaces to make the control of drones more natural and intuitive is becoming a significant research challenge. Indeed, despite the recent advances in sensing and autonomy, there are several scenarios where a direct control of the drone is still desirable or even needed. Notably, in aerial imaging and inspections, users often need to teleoperate drones to reach a point of interest or the best perspective. In these scenarios, users fly the drone using controllers, and receive a video feedback from onboard cameras. However, screens or googles are overfilled with data on drones' attitude, battery status, location of nearby obstacles (see Fig. 1). As a consequence, users get overwhelmed by a multitude of visual information and piloting becomes a challenge that requires a continuous cognitive effort and a long practice to be mastered.

In this paper, we introduce FOLDAWAY DroneSense a new controller equipped with force feedback for bidirectional interactions with drones. We discuss different user-interaction paradigms where haptic feedback can complement visual feedback to achieve a more immersive and safe flight control.

RELATED WORK

Control in human-drone interactions

The control strategies for drones can be broadly divided in two main categories: non-gestural and gestural. Non-gestural control usually relies on electroencephalography signals or gaze detection [4]-[6]. In gesture-based control the movements and poses of the pilot are translated into commands for the drone. The gestures can be tracked using external cameras [7], robotic platforms [8], exosuits [9], or hand-held controllers [10][11]. Every type of control approach and associated interface has specific advantages and disadvantages, a detailed discussion can be found in [8]. In this work, we use a hand-held controller as it is the most commonly used interface for commercial drones, and we discuss the integration of haptic feedback.

Figure 1. Visual interface of a DJI drone during the flight in close proximity to obstacles.

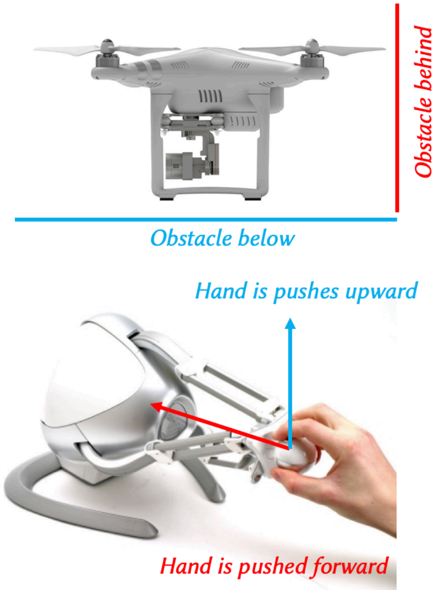

Figure 2. Example of use of kinesthetic haptic feedback to increase spatial awareness during the teleoperation of drones

Feedback in human-drone interactions

The teleoperation of drones relies in most cases on the visual feedback through screens or googles. The images captured by onboard cameras are streamed with low latency to the pilot. Using visual feedback, experienced pilots can perform high speed and aggressive maneuvers, for examples in drone racing. However, there are scenarios where relying only on visual feedback could hinder the user experience. In the examples in Fig. 1, while it is clear that the top icon warns the pilot about obstacles in front of the drone, the bottom icon could signal obstacles either behind or below the drone causing a misunderstanding. In addition, the considerable amount of information in the display can overwhelm the visual channel of the pilot.

Previous studies have shown that haptic feedback, namely convening information through the sense of touch, is an effective solution to complement vision and increase safety and efficiency during teleoperation [12]-[14]. For example, force feedback can help the pilot to better perceive the attitude, dynamics, and interactions of the drone with the local environment, for example for obstacle avoidance 0-[17]. As illustrated in Fig. 2 haptic interfaces can render directional forces and the pilot can intuitively understand the position of obstacles with respect to the drone.

However, the use of force feedback for drone piloting is currently hindered by the lack of portable and affordable haptic interfaces. On the one hand, the aforementioned studies have been performed with bulky and heavy haptic devices (e.g. Omega, Force Dimension), which are not suited for field operations where portability is a primary requirement. On the other hand, currently available controllers for drones are equipped at most with vibration feedback on the thumbsticks, which is suited to send alerts to the user (e.g. low battery level, or stall), but fails to convey more complete information about the status of the drone.

In this work we present a bimanual controller for drones with directional force feedback on the thumbsticks.

IMPLEMENTATION

FOLDAWAY DroneSense

FOLDAWAY DroneSense is a force feedback controller for drones. Each thumbstick integrates a miniaturized origami robot that can deliver kinesthetic feedback to the fingers of the user. Like a conventional controller, the thumbsticks can be pinched by the user and rotated in two directions (i.e., pitch and roll [21][19]) to send commands to the drone. In addition, the thumbsticks can actively generate rotations and forces that can be used to provide kinesthetic feedback to the fingers of the user.

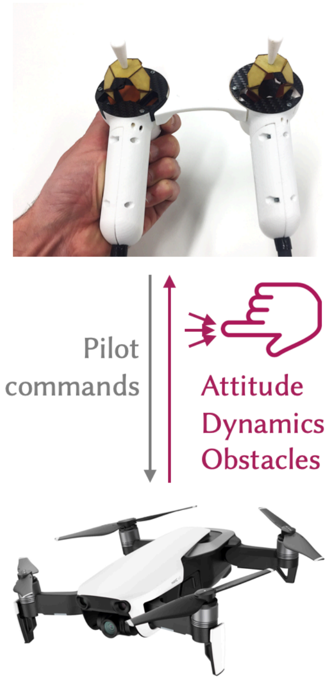

Figure 3. FOLDAWAY DroneSense is a controller with force feedback thumbsticks. It is conceived to establish a bidirectional interaction with drones.

By doing so, FOLDAWAY DroneSense allows to establish a bidirectional interaction with a drone. The pilot can use the thumbsticks to send commands, but also to receive haptic feedback that renders the status of the drone while flying (Fig. 3)

Haptic modes

We envisage four strategies to enrich the teleoperation of drones through haptic feedback:

- **Personalization mode**. Each pilot has different preferences for the stiffness of the thumbsticks. Nowadays pilots who want to adapt the mechanical response of controller have to physically replace a set of springs connected to the thumbsticks. With haptic thumbsticks, the stiffness profile can be regulated via software. Furthermore, it can self-adapt to different flight conditions and tasks. For example, during the transition from free flight to the inspection of an infrastructure, the thumbsticks can stiffen to maximize the accuracy of the input provided by the user.
- **Immersion mode.** Force feedback thumbsticks can provide real-time information about the dynamic behavior of the drone. For example, the thumbsticks can stiffen when the drone flies faster, or can move replicating the oscillations induced by turbulences.
- **Training mode.** Today training relies on visual or oral instructions form manuals or instructors. Actively moving thumbsticks can be used for haptic training while flying. The drone could enter a "tutorial mode" and autonomously perform standard flight maneuvers that are replicated by the thumbsticks to ease the learning process. Once the training is completed, haptic feedback can be used to further refine the skills of the user by correcting wrong inputs during flight.
- **Obstacle mode.** The thumbsticks can apply forces to alert the pilot about obstacles nearby the drone. Directional forces can help to increase the spatial awareness of the pilot and prevent collisions.

We are developing a flight simulator where we are implementing and testing the aforementioned haptic modes. Fig. 4A depicts a cluttered environment where we test the “obstacle mode”. The pilot can fly a drone with assisted obstacle avoidance. When the drone is heading toward an obstacle, it autonomously executes an avoidance maneuver which is reproduced by movements of the thumbsticks to increase spatial and situational awareness. In Fig. 4B we test the “training mode” with first-time users. In this experiment, we ask participants to fly a simulated quadcopter through the red targets. The controller provides a haptic guidance to correct the pilot when the drones deviates from the nominal path represented by the red line.

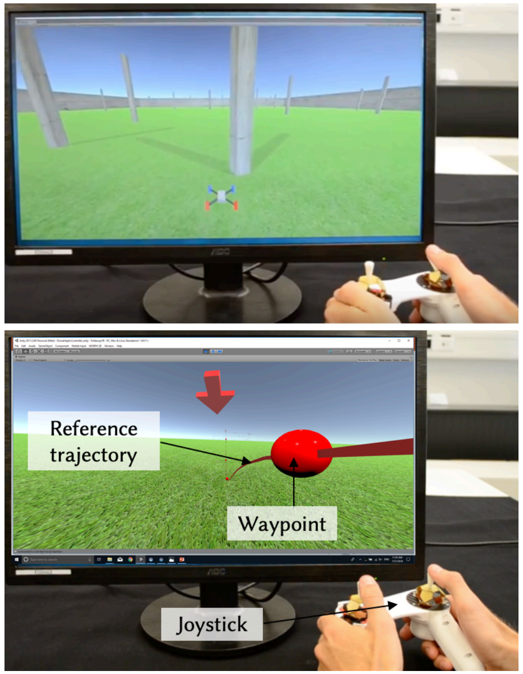

Figure 4. Different haptic modes tested in simulation. Top, obstacle mode. Bottom, training mode.

DISCUSSION

The increasing number of naïve users that approach drone piloting is calling for a new generation of natural and intuitive user interfaces [20]. In this context, multisensory feedback is fundamental to increase awareness about the status of the drone. Yet drone piloting rely almost entirely on visual feedback. The lack of portable and affordable force-feedback joysticks is hindering the use of haptic feedback in commercial applications. With the FOLDAWAY project, the authors are tackling the challenge of developing ultra-portable and low-cost haptic interfaces by investigating new design and manufacturing solutions based on origami micromachining 0. FOLDAWAY DroneSense is a prototype of drone controller that will be used to test and evaluate different haptic feedback paradigms for drone piloting. The goal is to develop a new generation of portable interfaces to create a bidirectional interaction between the pilot and the drone to increase intuitiveness and safety during teleoperation.

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Figure 1: Flying tethered drone with prolonged flight time

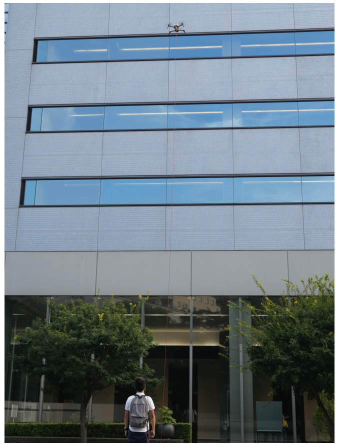

Figure 2: Extending User's Vision

Falconer: A Tethered Aerial Companion for Enhancing Personal Space

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ABSTRACT

With the growing popularity of drones, we start to see more wearable drone concepts. For the user to carry around a drone, it must be lightweight as well as have a small portable form factor. However, these constraints affect the battery capacity and therefore decrease the flight time of the vehicle. With *Aerial Tethered Companion*, a bigger battery is installed in the user's backpack allowing to extend significantly the flight time. Moreover, without an on-board battery, the quadcopter can carry more payload. Such system can be used in various scenarios for example in sports augmentation where the user would see itself through the drone's camera. Furthermore, *Aerial Tethered Companion* can be applied in telepresence where an external user would be able to see and navigate around the local user.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**.

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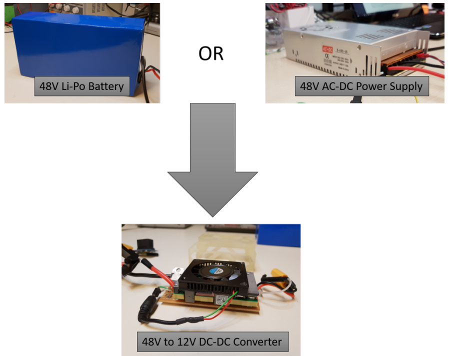

Figure 3: Power Unit of Tethered Drone

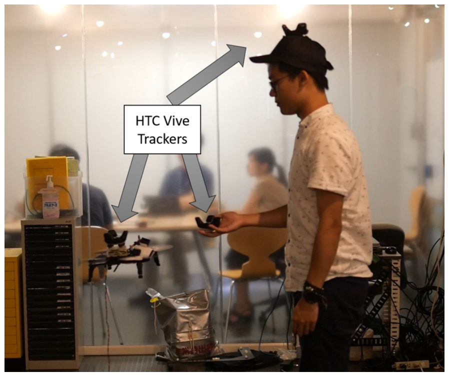

Figure 4: HTC Vive Motion Capture Setup

KEYWORDS

Quadcopter, Drone, UAV,Tethered Vehicle, Augmented Perception, Augmented Sports, Telepresence

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INTRODUCTION AND BACKGROUND

Drones are becoming more and more popular these days. Unfortunately, the flight time is limited by the batteries'capacity. Therefore, to extend the flight time, the operators must choose to either change and charge multiple batteries or carry a bigger capacity battery with the cost of decreasing the weight of the payload. To keep the aerial vehicle in the sky without interruption and maximize the payload, companies like *Elistair* and *Powerline* developed tethered solutions. The idea is to decouple the battery from the chassis to have a lighter vehicle but also to increase its flight time significantly compared to current products (around 21min with at DJI Mavic Pro).
Most of the applications are aimed towards professional usage such as filmography, surveillance or exploration. However, Falconer aims to apply the tethered drone technology for human enhancement. DroneNavigator [1] already utilizes tethered drones to guide visually impaired travelers but also to extend the battery life. Whereas Flying Head [7], Drone-Augmented Human Vision [4] and Multi-View Augmented Reality with a Drone [8] show how drones can augment human vision by exploring places where the user could not go or see. Additionally, with tele-operating capabilities, Falconer allows virtual users to explore new locations.

TETHERED DRONE

For a wearable drone, the main criteria are weight and size. The Parrot's Bebop 2 falls into this category as it is small and light enough to be carried around but also delivers enough power to fly outdoors to counter drifts. Additionally, with its GPS and ground-facing camera, the UAV (Unmanned Aerial Vehicle) can maintain its position accurately via Parrot's low-level software.

Power Unit

As designed for outdoor usage, the Bebop 2 can peak up to 480W at full throttle. In this scenario to avoid having a heavy cable disturbing the balance of the drone, we decreased the current by increasing the voltage in the power delivery cable. Therefore, the power system is composed of two elements: a 48V power source and a 48V to 12V DC-DC converter as shown in Figure 3. Since the drone is capable of pulling 10A at 48V, we chose to use 20 AWG wires allowing a maximum of 11A to flow through the cable safely according to the American wire gauge table. Furthermore, for our application we will

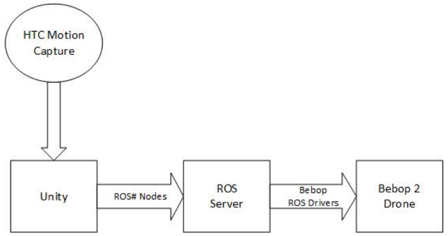

Figure 5: Manual Control System Architecture

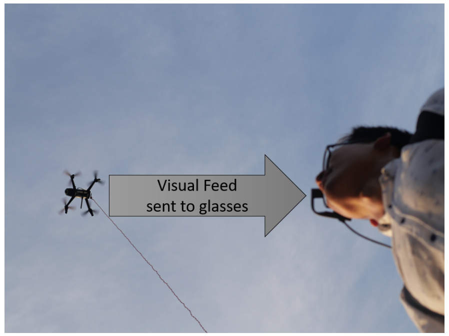

Figure 6: User's Vision Extended by Drone's Camera Through AR Glasses

[1]ROS Sharp by Siemens: https://github.com/siemens/ros-sharp

[2]bebop_autonomy - ROS Driver for Parrot Bebop Drone (quadcopter) 1.0 & 2.0: https://bebop-autonomy.readthedocs.io/en/latest/index.html

only be deploying 5m of cable, but the system can easily be scaled up to 16m (33.31mΩ/m). With the different proposed applications, the power source can vary from a wall outlet through a 48V AC-DC power supply or directly at 48V battery pack. With a capacity of 10Ah, we can expect around 1h15min of flight time if we assume a constant current draw of 8Ah.

Tracking

We used HTC Vive Trackers mounted on the drone, the user's head and hand to track each other's position. The head tracker is used for user 's location and orientation whereas the hand tackers detect gestures to control the drone. As the HTC Vive system needs IR transmitters called Lighthouses, tracking can only be done indoors at the current state.

CONTROLS

System

The main tools used are Unity and ROS. Unity takes care of all the controls using the tracking information gathered by the HTC Vive Trackers and sends it to a ROS server through nodes using Siemens' ROS# [1] Unity plugin. Finally, the server communicates to the Bebop 2 drone through *bebop_autonomy*'s [2] ROS driver.

Gesture Control

Human tend to interact with drones like the would with another individual or a pet[2]. A combination of both gesture and voice commands could add various type of control over the drone. However, voice recognition might be hard to detect in an outdoor environment, especially with the loudness of the current generation of drones. Therefore, a simple User Interface illustrates how the user can interact with the drone using only gestures. When the drone is grounded, the user flips its tracked hand, palm facing up, to takeoff the vehicle. The latter will make its way to the front of the operator by circling around him/her depending on where it is located. He/she can then move in any direction, the drone will follow by maintaining the same distance and orientation according to the user. To trigger gesture control, the operator raises its tracked hand above hip level and can then move the drone similarly to a joystick approach. By bringing the hand back below hip level, the UAV will remain in its the last known position relative to the user, even when the latter is moving. Finally, to land the drone, the operator keeps his/her hand with the palm pointing the sky but brings it behind his/her back.

Follow Me

Ideally, we would use solely the drone 's camera to track and follow the user. Flying Eyes [6] proposed a system using computer vision but distance estimation was inaccurate. By combining accurate GPS

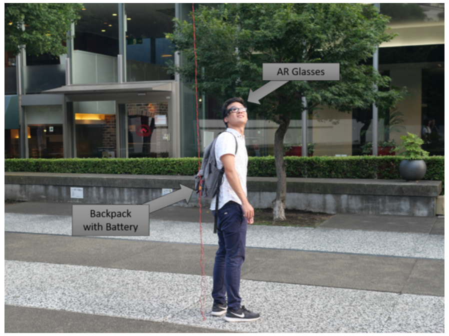

Figure 7: User equipped with AR glasses and battery backpack

Figure 8: Telepresence video conference with external user

coordinates from the two points of interest, we can increase the estimation but only on a 2D plane. Therefore we added a barometer alongside the GPS sensor to extract the altitude. Using a simple projection, we can find the respective distance between the drone and the user. However, the proposed solution is greatly limited by the accuracy of the sensors and did not output reliable data. However, DroneTrack [10] uses acoustic sounds to locate and track the user. Unfortunately, this solution is only ideal for close environments usage as there are too many noise disturbance in the outdoors.

APPLICATIONS

Perception Augmentation

Falconer is a personal companion that augments the user's abilities, more specifically in this scenario, its vision. Since the Parrot drone is equipped with an on-board camera, the live feed can be easily extracted. With an extra pair of eyes in the skies, the quadcopter provides information of the surrounding through a pair of augmented reality glasses to maximize the user's visibility. Figure 6 illustrates how the user can use Falconer to see the horizon from a higher point of view.

Sports Augmentation

The Flying Eyes [6] research showcases an innovative method of training for a sport where the user see itself in a third person view. Being able to see one 's self when practicing an activity helps highlight body motions and optimize each movement. In a similar fashion, dancers already apply the technique in front of a mirror. Furthermore, a third person view training appears to have no diminishing results compared to the normal perspective [3, 12]. On the contrary, a third person perspective does enhance one 's performance when the activity involves the need for surrounding knowledge. In rock climbing, the climber has a restricted view to what is above him/her. With an out-of-body view, Falconer can aid choosing the most optimized path. Therefore, through Falconer's eyes, an out-of-body experience helps athlete with various training as well as act as a tool to help athlete make better choices to improve performance.

Engaging Telepresense

Not having the battery on the drone permits to carry a heavier payload. Attaching a screen or a phone onto the Bebop 2 opens many possibilities for telepresence. Scalable Body [11] attaches a camera on a scalable pole to a movable robotized base. This allows to reflect more accurately the remote operator 's height while also piloting the robot. Falconer reproduces the same effect but with a drone. The remote user can operate the drone to explore and experience the same landscape as the local users. For indoor usage, the grounded power source can either be directly connected to an outlet, providing unlimited flight time but limited mobility within the range of the wire. Whereas for outdoors, like previously mentioned, the battery pack can be stored in the user's backpack.

DISCUSSION

The current state of Falconer is quite limited at the moment. The different topics outlined through out the paper shows how versatile a tethered drone can be.
With the current prototype, the cable linking the drone to the power supply can not vary its length, meaning as the vehicle flies closer to the user, unnecessary wires are left on the floor. In the near future, we would like to implement a system that would wind back the cable to minimize the tension as well as the length of the wire left between the drone and the battery.
As we want to implement a relative position control [5] to be able to control the UAV precisely without hindering the experience, other type of tracking should be considered such depth sensing cameras or SLAM. Additionally, by knowing how much wire has been released, we could calculate the distance separating the drone and the user. It would therefore give us more information to help maneuvering the vehicle autonomously around the user. With a decent localization system, the wearable drone would be able to self-takeoff and self-park onto the user's backpack with great accuracy.
Without a battery on-board, the system completely relies on the connection from the power source to the quadcopter. Adding a small capacity battery can prevent disastrous crashes if the main power system fails. If the capacity allows it, implementing a similar design as Evercopter [9] could widen the possibilities of Falconer. The drone would connect to the power source through a magnetic link and would be able to disconnect itself and fly-out independently for a short among of time.

CONCLUSIONS

Tethering a drone greatly opens new applications for professional uses. However, in this paper, we explored how such system can be beneficial to an individual. Falconer is a prototype of a platform for a personal aerial companion. We dived into how it can enhance one 's personal space by augmenting the human vision as well as bringing closer humans with more engaging interactions through telepresence. In the next iteration, we will be addressing the different key components discussed in the discussion section along with refining the design of the current system.

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Integrated Apparatus for Empirical Studies with Embodied Autonomous Social Drones

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ABSTRACT

Current use cases for drones often involve a remote human operator and/or an environment which is inaccessible to humans. Social drones, which we define as autonomous drones that operate in close proximity to human users or bystanders, are distinct from these. The design of social drones,

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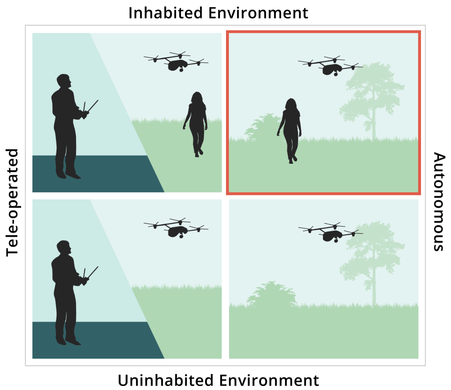

Figure 1: We use the term *social drones* for applications where an autonomous drone operates in an inhabited environment. (Figure from [7].)

in terms of both aesthetics and behavior, can involve particular human factors that require further study. Currently, in lieu of empirical studies with autonomous embodied agents, approaches such as Wizard of Oz methods, questionnaires, videos, and/or makeshift mechanisms are often employed to investigate interactions with social drones. For empirical design research using embodied, co-located drones, we have been developing an experimental setup that enables high precision drone control, as well as rich multimodal data collection and analysis, in an integrated fashion. We present this apparatus and its rationale in this paper. Using this setup, we aim to advance our understanding of the psychology and ergonomics of interacting with autonomous social drones through experiments, and extract design implications.

KEYWORDS

Drones, social drones, autonomous drones, empirical studies, experimental setup, motion capture, motion tracking.

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Mehmet Aydın Baytaş, Mohammad Obaid, Joseph La Delfa, Asım Evren Yantaç, and Morten Fjeld. 2019. Integrated Apparatus for Empirical Studies with Embodied Autonomous Social Drones. In . ACM, New York, NY, USA, 9 pages.

INTRODUCTION

In the near future, the drone has the potential to become a paradigm of human-computer interaction in itself [7, 13]. Taking advantage of the drone's ability to maneuver beyond human reach, many current use cases for drones involve a remote human operator and/or an environment which is inaccessible to humans (see [1, 12, 24]). Conversely, drones may also operate autonomously in close proximity to human users or bystanders (see Figure 1). We use the term *social drones* to describe this emerging class of applications [7]. Design and development in the context of social drones requires foregrounding human factors, some of which may not have been consequential when a drone is under human control or operating in uninhabited environments.

In previous work, researchers have investigated various aspects of the experience of interacting with social drones, considering the influences of various design dimensions on human experience outcomes (see [7] for a review). However, even though these studies aim to find out more about interaction with embodied autonomous agents, in many of these cases, researchers have not carried out studies using actual autonomous drones. Instead, many studies rely on other techniques: e.g. Wizard of Oz (WoZ) methods, questionnaires, virtual reality (VR), videos, and makeshift mechanisms. In turn, empirical design research with embodied prototypes can yield sophisticated insights into the psychology and ergonomics of interacting with social drones. To be able to conduct such studies, we have designed and implemented an experimental setup for real-time drone control and multimodal data collection in tandem. In this paper we present the rationale for this design, provide a description of the setup itself in sufficient detail for researchers looking to implement one like it.

RELATED WORK AND MOTIVATION

In empirical design studies[1][-5cm], there must be congruity between study methods and the purpose of the study (e.g. the design stage being addressed). For example, online surveys and various flavors of brainstorming, which rely on participants' faculties of imagination and articulation, can cater to earlier stages of design characterized by exploration, ideation, and lower-fidelity prototyping. Conversely, experiments with embodied autonomous agents are apt for evaluating design ideas at a higher-fidelity, e.g. capturing correlates of different aspects of the human experience and ergonomics, and efficiently uncovering quantitative design parameters.

Empirical studies with social drones could be said to have emerged as a sub-genre of research literature in more recent years, due to the availability of drone platforms as a consumer commodity. Examining a diverse and representative selection of works from this body of works, we have identified three main strands (see [7] for more detail). The first relates to more general issues of human-drone communication and user experience with social drones [9, 11, 16, 26, 27, 32, 32, 35]. Here, researchers have addressed high-level drone control by co-located humans (as opposed to real-time low-level piloting), conveyance of drone intentions and state through various modalities including motion qualities, and perceptions of comfort and safety in human-drone interactions; aiming to uncover design parameters for intuitive and efficient human-drone communication. A second strand of research deals with use cases involving navigation, assistance, and companionship; employing drones to improve or augment experiences of outdoor wayfinding, exercise and sports spectatorship, and living with sensory disabilities [4, 5, 10, 17, 20, 25, 28]. Finally, social drones have also been utilized to realize novel interaction designs for implementing different flavors of mid-air displays, haptic feedback devices, and interactive tangibles [2, 3, 8, 14, 15, 19, 29–31].

While the aforementioned studies are ultimately about interactions with embodied autonomous drones meant to be co-located with human users or bystanders, only a minority of the published studies utilize actual autonomous drones [16, 18, 25, 33]. In lieu of such high-fidelity prototypes, approaches reported in the literature include online surveys [10, 16, 17, 32], interviews (mostly semi-structured) [3, 5, 9, 11, 16, 20, 28, 31], design studies (including a broad variety of approaches, e.g. ideation sessions, focus groups, and expert critique) [17, 26, 35], WoZ studies [3–5, 9–11, 20, 26–28, 31, 32, 35], and user studies in VR [17].

[1]"According to one definition, empirical means *originating in or based on observation or experience*" [23]. In the context of this paper, we use the term "empirical studies" to denote studies that involve collecting data from (i.e. observing) human participants. In addition to controlled experiments, this includes "interviews, field investigations, contextual inquiries, case studies, field studies, focus groups, think aloud protocols, storytelling, walkthroughs, cultural probes, and so on" [23].

RATIONALE

As indicated above, empirical studies with social drones is a growing research agenda. However, in the literature so far, studies with fully autonomous drone implementations are not as common as other kinds of studies. Our experience suggests that implementing drone behaviors and related data collection in a robust manner can require engineering prowess and time, which may pose a high barrier to entry for design researchers. In response to this issue, we aimed to construct and document an apparatus which would be able to collect and respond to highly detailed, multimodal data while implementing precise drone motion control. Based on our learnings from the literature discussed above, and our prior experience with stimulus presentation and data collection apparatus in behavioral experiments, we desired our setup to accomplish the following:

Drone control. The drones' position, orientation, and velocity profile should be controllable, to an appropriate level of precision, through pre-programming movement patterns and responding to events in the scene (e.g. following a human subject or props) in real time. In other words, autonomous flight must be possible, in lieu of a WoZ operator.

Drone capture. The setup should allow for recordings, at an appropriate precision, of the position, orientation, and other relevant behavior of drones. For some studies, for example, a video recording may suffice, but this must be synchronized with motion control to facilitate subsequent analysis. Studies requiring high-precision data or efficiently looking for quantitative design parameters (e.g. [21]) can benefit from more precise position tracking.

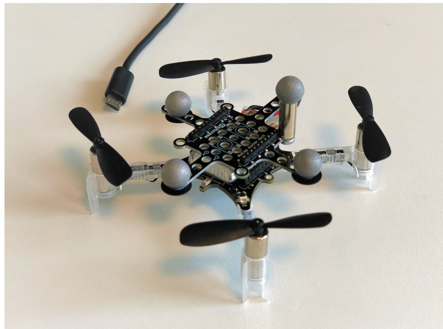

Figure 2: Our Crazyflie drone with MoCap marker deck and markers installed; Micro-USB connector used to charge the drone is in the background, for scale.

Human capture. It should be possible to record and respond to movements and other behavior of human participants, at reasonable precision. Behavioral measurements may include sophisticated data like motion capture, eye tracking, and physiological measurements (e.g. heart rate, skin conductance, electroencephalography, and electromyography), but may also be due to simpler means—for example, in studies on the psychology of musical perception, researchers have used simple linear potentiometers to acquire real-time, continuous measurements of tension experiences [6, 34]. The overall system must be able to accommodate and synchronize with such instruments.

Environment capture. The setup should be able to record and respond to any relevant happenings in the environment, e.g. positions of props or different sensor readings. In the future we expect social drones to surpass human sensory capabilities in many modalities, and communicate with other devices more efficiently [13]. We wish to provide the means for incorporating such novel capabilities.

OUR APPARATUS

While many simple sensor systems may be used to control and record drone behavior, such solutions often do not provide the flexibility we were aiming for, in that it is not straightforward to track arbitrary configurations of drones, human subjects, and props within the same coordinate system using such systems. Thus, we opted for an optical motion capture as the centerpiece of our control and data collection apparatus.

We utilized a motion capture studio equipped with a Qualisys[2] system, including 12 high-speed marker cameras, 2 spatially calibrated video cameras, and Qualisys Track Manager software (QTM).

[2]qualisys.com

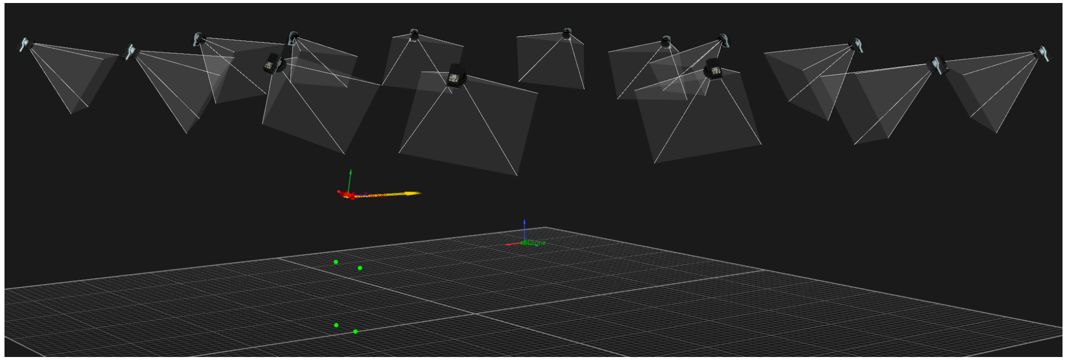

Figure 3: We used optical motion capture to handle drone motion, human movements, and eye tracking within the same spatial coordinate system. This screenshot taken from the motion capture software shows 6DOF tracking of the drone and the human head, point tracking of the hands and feet, and the gaze vector from the eye tracker.

The system was readily configured for optimum coverage, mainly for biomechanics and animation performance use cases. The total size of the room was 14 m × 10 m × 4 m, while the motion capture system was able track a capture volume of approximately 9 m × 8 m × 2 m in the middle of the room. This motion capture system was configured to track at 100 Hz and used both for data collection and closed-loop control of the drone.

Integration of the motion capture system and the drone was implemented in Python scripts using the open-source cflib[3] and qtm[4] libraries. We have made these scripts available online as open source, under a permissive license[5].

We used a Bitcraze[6] Crazyflie 2.0 drones, with chassis dimensions of approximately 10 cm × 10 cm × 2 cm. Four spherical infrared-reflective motion capture markers, 9.5 mm in diameter, were attached to the drone using a "MoCap marker deck" fabricated from the same printed circuit board material as the frame of the drone. QTM was configured to track this marker set in 6DOF as a "rigid body." (As an implementation detail, we note that proper 6DOF tracking requires the markers to be attached asymmetrically.)

We incorporated a Tobii Pro[7] Glasses 2 wearable eye tracker into our setup. This device was equipped with 6 motion capture markers of the same size as on the drone, again configured for 6DOF tracking. In QTM, gaze vectors for both eyes were overlaid onto the motion capture data (see Figure 3).

[3] pypi.python.org/pypi/cflib

[4] pypi.python.org/pypi/qtm

[5] github.com/qualisys/crazyflie-resources

[6] bitcraze.io

[7] tobiipro.com

Along with head and gaze tracking, attaching other markers to participants can provide information on participants' reflexive reactions to drone behaviors, and may be used to enable gesture control or other responsive drone behaviors. In addition to motion tracking, we incorporated a wired trigger button used to obtain binary input and record it with precise timing. This button was connected directly to the motion capture system on a hardware level to minimize signal latency.

Finally, we considered safety measures. Our experience has been that our drone is small and lightweight enough to be incapable of damaging clothes or skin upon contact. To protect participants' hair from possible contact with the drone's propellers, we procured a hair net. Eye protection was provided by a clear plastic attachment fitted onto the eye tracker.

EXPERIENCES, LIMITATIONS AND FUTURE WORK

A subset of the apparatus we propose in this paper has been used to implement a technical demonstration that explores how a small drone can be used to facilitate meditative movement exercises [22]. We also note that fundamentally similar equipment has been used by other researchers to prototype and demonstrate free-flying tangible user interfaces [15, 29].

Our preliminary work with the apparatus has revealed a set of improvement possibilities. So far, we have only been using the Crazyflie drones, which are smaller compared to drones used in much of previous work, and thereby have limited use cases. Future work can address developing the software to integrate different drones in the setup, and identifying different use cases where the smaller drone is more appropriate. Furthermore, while the particular motion capture system we had at our disposal has advantages in terms of precision and flexibility, such systems are costly. Systems with different cost/performance characteristics can be substituted in its place, but the software will need to be reworked—a more general software framework to interface motion tracking, drone control, and other systems can be explored in future work. Lastly, future work can also investigate adding further data acquisition capabilities. For example, sensors for recording electrodermal activity (a.k.a. skin conductance or galvanic skin response) or other physiological measurements could be introduced.

CONCLUSION

In this paper, we have presented our design and implementation of an experimental apparatus for empirical research on human factors in social drones. This apparatus supports integrated multimodal data acquisition at high spatial and temporal resolution, and real-time closed-loop drone control with high precision. Here, along with details of the setup itself, we reported on its design rationale and how various aspects of it relate to previous work. Through this report, we have aimed to share a description of our apparatus at some detail, in order to serve as a resource for other researchers looking to undertake similar studies. We would also like to open up our approach to critique; and we invite others in the field to provide feedback and share experiences regarding how future work on the apparatus can better serve the community.

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Investigating users' natural spatial mapping between drone dimensions and one-hand drone controllers

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ABSTRACT

Using remote control transmitters is a common way to control a drone. For the future, we envision drones that are intuitively controllable with new input devices. One possibility could be the use of one-hand controllers, e.g. 3-D mice. While developing such a device, we investigated the users' natural spatial mapping between controller and drone dimensions. In this paper we present our insights about this mapping and show why relative position control is an important control concept for novice users.

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Figure 1: Currently, most non-autonomous drones are controlled by more or less complex remote control transmitters (RCT). The image shows one of the complex models.

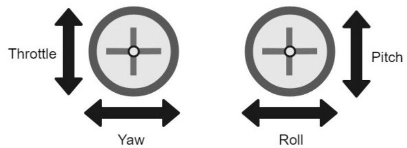

Figure 2: Even though there are numerous different control devices available, the control concept follows in most cases the image shown above. This concept shows the difficulties of mapping two planes on the four degrees of freedom (DOF) of a drone.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **Interaction devices**.

KEYWORDS

human-drone interaction, unmanned aerial vehicle, 3-D mouse, spatial mapping

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INTRODUCTION

In recent years, drones (also known as multicopters or unmanned aerial vehicles), are widely available and have become increasingly popular due to the growth of low-cost hardware (e.g. sensors). They are utilized in multiple applications such as film and photography, leisure activities, search-and-rescue, product delivery, or industrial maintenance. Apart from completely autonomous drones, using two-hand drone remote control transmitters (RCT) is a common way to control a drone. Using classical RCTs tend to be difficult to use for a non-experienced user, requiring a long period of both training and understanding how the drone will react to user inputs. To create more intuitive interfaces and a better user experience while controlling a drone, we envision semi-autonomous drones that are controlled by new input devices. In this context, we develop a first exploration that uses a 3-D mouse (also known as space navigator) to manually control a semi-autonomous drone with a single hand. When using this input device, it is essential to find a mapping between the spatial dimensions of the 3-D mouse and the dimensions of the drone that feels natural to the users (compare [10]). In this paper we present first insights about our investigation of the users' natural spatial mapping.

STATE OF THE ART

There are different strategies for controlling drones, depending on its specific use case. The requirements range from completely autonomous drones (e.g. for delivery) over semi-autonomous drones, where users can influence movements of an autonomous drone (e.g. the concepts shown in [2]) to manual controlled drones, where actively flying the drone is part of the experience (e.g. drones for leisure activities). This section gives an overview of the state of the art of human-drone interfaces.

Remote Control Transmitters (RCT)

The most common way to manually control a drone is using an RCT (see Figure 1). These transmitters are devices held with two hands, ranging from very small ones with only few buttons to complex programmable models that have displays and numerous additional input controls, such as buttons and slide controls. Typically RCTs consist of two separate control sticks. Each stick has two degrees of freedom (DOF) allowing the user to have four DOF inputs in total. The stick on the left is used to send commands for throttle (drone moves up and down) and yaw (drone rotates around z-axis). The second stick on the right is used to send commands for pitch (drone moves forward or backward) and roll (drone moves sideways left or right). The mapping of the stick movement to the drone is illustrated in Figure 2. RCTs require the coordination of both hands for the 2-D degrees of motion of each stick to transform into the variety of motions available in a 3-D space. Obviously, it is impossible to find a natural mapping of these dimensions and the mapping described above is a convention which requires inexperienced users to learn how to control the drone.

Tablets or Smartphones

Smartphone or tablet applications have been used to replace RCTs, especially for low-cost drones for leisure activities. The control concept of the applications is usually the same as of RCTs: two virtual control pads replace the two sticks. While this control concept has haptic restrictions, the screen of smartphones and tablet offers further features, e.g. to show live images of the drone camera.

One-hand Controllers

As described above, two-hand controllers require a certain coordination of both hands. Such coordination might pose a challenge to inexperienced users or people with physical disabilities (compare [8]) and restricts the use case as well, if the user needs to perform additional tasks, while manually flying the drone. Furthermore, the mapping between the 2-D controls and the 3-D drone movements are not intuitive. Consequently, there were efforts to develop one-hand devices for better interaction with drones. One concept first published in 2016 by the South Korean company “this is engineering Inc.” [13] is the drone controlling system Shift that allows to control a drone with a stick held in one hand and a ring that is worn on the thumb of the same hand. Moving the thumb in relation to the stick controls the drone. While this concept created huge interest on the crowdfunding platform Kickstarter and was funded, the project was canceled at the end of 2016 and since then, there has no been any further notice about its sales launch [6]. A second successful Kickstarter campaign relates to the development of the “FT Aviator Drone Flight Controller” that, according to the developers, will be launched until mid-2019 [7]. The controller can be used with only one hand by using a normal joystick to navigate pitch, roll and yaw and thumb and index fingers to control the throttle value. Using a thumb to control the throttle can eliminate the complexity and the need of using two hands with natural and cognitive translation of hand-to-device movement. The glove-based controller PULSIT is another one-hand controller that is currently under development by the French startup WEPULSIT

Figure 3: The device SpaceMouse® Compact from 3Dconnexion [1] was used for our exploration.

Figure 4: Degrees of freedom (DOF) of the 3-D mouse used in our exploration (Figure based on [12]).

[14]. Wearing PULSIT, users can control a drone by moving their hand and making specific gestures with their fingers. In summary, it can be said that one-hand controllers are currently still in a development stage.

Natural Drone Interactions

Beyond physical controllers, different natural interaction techniques have been proposed to interact with drones more naturally, such as control by hand or full-body gestures or language control. Cauchard et al. [2] analyzed natural ways of interacting with drones in a Wizard-of-Oz study. They found out that interpersonal gestures are intuitively used by people, e.g. if a drone should be stopped or fly back to the user. Fernández et al. [4] used a leap motion controller [9] as an input device for gesture control. Compared to the work of Cauchard et al., their defined gestures have no meaning in interpersonal communication. Rather they map the movements of the hand to the movements of the drone. They state that users had to get used to this interaction first, but "experiencing the connection of the hand with the drone made this [...] natural and fun" [4]. The same authors also explored the use of voice commands [4]. Peshkova et al. [11] provides an overview on different natural interaction techniques for drones, which also includes approaches with gaze trackers or brain activity. But natural drone interaction possibilities are not only a topic for research. First consumer products are already in the market that realize the gesture control concepts described above: DJI's consumer drone Spark has an optical system for tracking users' gestures for controlling the drone and for taking photos with the built-in camera [3] using gestures similar to the work of Cauchard et al. [2].

EXPLORATION: 3-D MOUSE AS DRONE CONTROLLER

While classical remote control transmitters are a suitable input device for experts and – as mentioned – for some hobby pilots, where expertise contributes to the experience, we envision a future, where a lot of drones can navigate autonomously. In that world, operators of drones will only fly manually if necessary. Our use cases relate to industrial settings, such as plant monitoring. If, for example, an operator visually inspects a plant with a drone and wants to navigate to a certain spot, he might manually control the drone while his eyes are focused on a screen. In this scenario a natural and intuitive one-hand controller might be a good choice. We therefore want to explore possibilities of a 3-D mouse as drone controller. 3-D mice are originally designed for navigating through computer-generated 3-D imagery and commonly utilized in Computer-aided Design (CAD), 3-D modelling and 3-D visualization. For our exploration we use the 3-D mouse SpaceMouse® Compact from 3Dconnexion [1] (see Figure 3). This device has six DOF (see Figure 4) and is to be operated with one hand. It has two additional buttons and can be connected with a computer via a USB port.

UNDERSTANDING THE NATURAL SPATIAL MAPPING OF USERS

A typical drone has four DOF, which are composed of the three dimensions of movement in the physical space and the possibility of rotating the drone around the own z-axis (some drones can also flip over, which corresponds to another dimension, but this is uncommon for larger industrial drones, so we excluded this 5th dimension from our consideration).

During the development process of our exploration, we involved potential users to evaluate whether users could intuitively use the drone with the 3-D mouse and to find a natural mapping between the six DOF of the 3-D mouse and the four DOF of a drone. Furthermore, we wanted to understand whether users consider themselves or the drone as reference point for the movements.

Method

Figure 5: Study setup. During the study, the participant sat in front of the 3-D mouse and had to control a simulated flight.

To find answers on these questions, we ran a Wizard-of-Oz (WoZ) experiment in our lab. In the experiment, users had to take a simulated flight with the 3-D mouse, without receiving any prior information about the 3-D mouse. The setup is shown in Figure 5: The participant sat behind the table in front of the 3-D mouse. The drone was placed in front of the user. The observer sat next to the user and told the user to do seven specific drone movements (e.g. "Start the drone straight up in the air," "Fly one meter into the direction of the telephone," "Fly sideways to the right. During the flight turn the drone 90° to the left.") The movements on the controller were observed and at some points questions were asked, such as "What would you expect to happen to the drone, if you release the controller now?" An assistant carried the drone through the room to simulate the flight according to the commands. After this simulated flight, the users were asked about the possible movements with the 3-D mouse to find out whether users understood the device without any introduction. Afterwards, Figure 4 was shown and users were asked how they would map these dimensions to the drone dimensions. Obviously, this second mapping was different from the mapping observed in the experiment, since most participants did not recognize all axes of the 3-D mouse during the experiment.

For the experiment, we recruited 9 participants (1 female, 8 male), aged 24 to 36 ($\mu = 30.6$, $\sigma = 3.5$), all employees of our institute, but none of them involved in any projects related to drones. 4 of the participants had never flown a drone before, 3 had tried out a drone before (2 with RCT, 1 with tablet) and 2 own a drone (1 with RCT, 1 with smartphone). 7 participants had never used any 3-D mouse before, 2 had experience with this device (1 from CAD applications, 1 from controlling a robot).

Results

Even though there were only a small number of participants, the results show a trend about the users' intuitive understanding of the controller and the natural mapping.

Point of Reference. First, we analyzed the users' understanding of the point of reference. Common drones need to be controlled in a way that takes the drone as point of reference for the movements ("direct position control", see [5]). With this mode, steering left means that the drone moves left from its own perspective. Our experiment showed that about half of the users (5 out of 9, including the 2 participants, who own a drone) used the controller in this way. However, the others (4 out of 9, most of them inexperienced with drones) used the devices as "relative position controller" (see [5]), so they steered left, if the drone had to move left in relation to the user. These results show a strong need for supporting relative position control, if a drone controller is designed for novice users.

Intuitive Understanding of the Input Device. Considering the supported DOF of the input device (see Figure 4), most participants intuitively understood the directions Tilt (all), Spin (8 out of 9), Roll (all), and Pan down (7 out of 9). However, only 3 participants recognized that they could move the controller upwards (Pan up). One of them showed doubts: "Maybe I can move it up. I don't want to destroy it." The directions Zoom and Pan left / right were only used by the participant who had controlled a robot before with a similar device. The other 8 participants did not use or recognize these dimensions for the drone movement.

Natural Mapping between 3-D Mouse and Drone. Most participants (8 out of 9) used Tilt and Roll to move the drone forwards, backwards, and sideways right and left as mentioned above with different points of reference. Only one participant used Zoom and Pan left/right instead. Also, turning the drone around the z-axis was done by most participants (8 out of 9) with the Spin action. The participant who did not recognize the Spin function of the controller explained that he would have expected a button for turning the drone. The results for starting and landing were more diverse: 2 participants used the Pan up function, 3 used a button for the start, 2 used the Pan down function (1 explained that he would push the button down as long as the drone should be in the air), 1 assumed that he can control the height by turning the controller (Spin) and 1 participant assumed that the drone starts automatically, if he starts to move it forward with Tilt. In the same way, participants had different ideas about how to land the drone. Most participants (4 out of 9) expected the drone to land with a button on the device. Even though most users recognized the possibility to pan the button down, only three used it for landing, since the others had used this function already for other flight maneuvers. One participant used the button for flying and stated that he expected the drone to land as soon as he releases the button. One participant used a double-click on the controller (Pan down) as an input for landing.

Implications for Design. Our study reveals the strong need for relative position control if a drone controller is designed for novice users. Mapping the spatial dimensions of the 3-D mouse simply with the drone movement is not as intuitive as it might seems at first glance. Especially movements up-and downwards were not intuitively understood by the participants. With drones becoming more autonomous, we suggest to control starting and landing operations with buttons separate from the control. The same is valid for ascending and descending movements. Finally, for our particular device, we suggest to make no difference between Tilt and Zoom and between Roll and Pan left / right, since users were not aware of this difference and controlling the dimensions independently requires prior training with the input device.

SUMMARY AND CONCLUSION

In this paper, we investigated the natural mapping of users between the spatial dimensions of a 3-D mouse and the dimensions of a drone. This investigation was a first step towards the development of a one-hand drone controller. While the development of our specific controller is ongoing work, we could gain important insights in users' intuitive mapping, which is important knowledge when designing controllers in general. We argue that future semi-autonomous drones will be controlled by more intuitive devices than contemporary RCTs. Considering our results, relative position control should be the standard control concept for novice users.

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Issues of indoor control of a swarm of drones in the context of an opera directed by a Soundpainter

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ABSTRACT

Among the many issues one encounters today with drones, and especially with swarms of drones, positioning has become more and more crucial. Even though technologies such as GNSS and sensor based location systems have become mature, they are only efficient, *i.e.* accurate, outside of buildings and in environments that are not adverse (no jamming). In this paper, to go beyond the state of the art, we present the issues of indoor and adverse locations and provide retex based on our previous and current research work. Our use case is an indoor show using a swarm of drones directed by a Soundpainting artist.

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(1) Give the drone the location of the target point it must go to.
(2) Make it possible for the drone to determine its precise location.
(3) Make the system self contained, *i.e.* we do not want (as far as possible) the drone to rely on some external setup, it must be autonomous.
(4) Make the overall system must be resilient to the loss of communication.

Figure 1: The four main challenges that we address

CCS CONCEPTS

• **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; **Fault-tolerant network topologies**; • **Networks** → Network reliability; • **Human-centered computing → Gestural input**.

KEYWORDS

Drones, swarm, indoor positioning, GPS denied environment, Soundpainting, human drone interaction, Smart and Empowering Interfaces

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INTRODUCTION

Drones are becoming more and more common in many areas such as search & rescue, surveillance, etc. They are used in so-called D3, *i.e.* Dull, Dangerous and Dirty situations where a human would be less efficient or at risk. It has quickly appeared that using several drones combined together as a swarm offers many advantages over a single drone [4]: continuous flight, combination of different sensors, security (by lowering the radio footprint of each individual aircraft), etc. The authors have been working on swarming for some 10 years, on both aerial only use cases (*e.g.* CARUS and ASIMUT EDA funded project [3]) but also on combinations of heterogeneous systems, combing aerial and ground vehicles (*e.g* the Green Sword park cleaning system [2]). In recent years, drone swarms have become increasingly popular in the entertainment industry. For instance, companies such as Verity Studios [1] have developed technologies for controlling a swarm of drones (equipped with LED lights) in a variety of live shows under indoor and outdoor locations. However these swarm of drones have been choreographed in advance, or else are being controlled by people with joysticks or teleoperators.

Combining a (possibly) large number of systems together raises a number of issues among which the control of the system has become crucial. This raises a number of issues listed in Figure 1. First, one must be able to give orders to the drone so as to let it know that it has to move to a given location. Second, it must be possible acquire the locate the drone so that the given directions can be applied (moving to a location only makes sense if the notion of location exists in the system). One additional issue in our context is that we are talking about autonomous systems, not about remotely piloted systems (which is the common approach in most if not all of the commercial uses cases that have been developed in both civilian and military context). It means that the drone must have self awareness

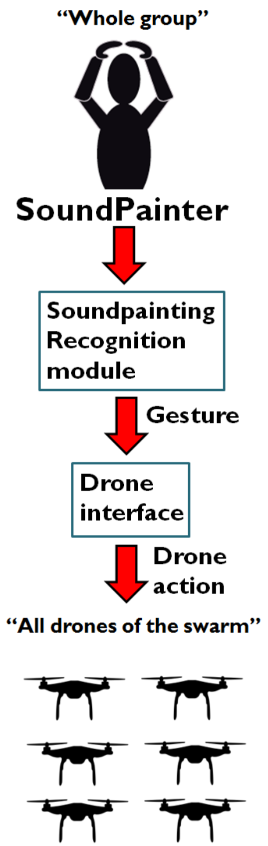

Figure 2: System architecture to control a swarm of drones using Soundpainting language

(autonomous knowledge) of its location. Eventually, being given a large number of drones are used, resilience must be considered [5].

ADDRESSED PROBLEMS, RETEX ON PREVIOUS WORK AND DIRECTIONS TO EXPLORE

GNNS based approaches: retex on our own previous work and associated limitations.

In the previous use cases/research projects described above (CARUS, ASIMUT, Green Sword), we have been running the systems outside buildings, on dedicated (military) fields of experimentation. We thus heavily relied on Global Navigation Satellite System (GNSS). Nevertheless, the hardware we were using add a limited accuracy, and thus we had to leave a significant amount of space between the drones so as to avoid any issue/crash. We still depended on the reception of the GPS signal that we could not guarantee depending on the weather and on possible adverse jamming.

Technologies that make sense to explore.

Most of drone control technologies currently use traditional global GNSS (mainly GPS) systems to provide real-time drone localization. However, such systems, as described above, are not reliable/accurate enough to operate a swarm of drones since they can possibly lead to crashes [6]. In addition, GNSS systems cannot be used in indoor conditions due to signal reception occlusion [12]. Because of these limitations, recent projects have explored different technologies to deal with a swarm of drones that do not rely on some global localization system like satellites. There are for instance motion capture systems [10], ultra-wideband (UWB) signals [8], Simultaneous Localization and Mapping (SLAM) techniques [9] and optical flow technologies [11].

THE USE CASE: AN INDOOR LIVE OPERA PERFORMED BY A SWARM OF DRONES CONTROLLED BY A SOUNDPAINTER

According to artistic director, the objective is to create a form of a live opera in which musicians and drones can collaborate in order to generate together, by improvisation, an original musical composition. A swarm of drones would be used as moving sound sources to produce spatialization of the sound in three dimensions. These drones will generate different movements and sounds according to body gestures performed by a composer, called Soundpainter. In the proposed study case, we explore the use of automatic recognition of SoundPainting gestures for efficiently controlling a swarm of drones.

The Soundpainting is a gestural language, proposed by Walter Thompson [13], consisting of a well-defined grammar for conducting a large ensemble of improvising artists (musicians, actors, dancers and visual artists) without the use of any score. The advantage of Soundpainting is that it already integrates the notion of groups of entities and makes it possible to control one single entity of a set/subset and to control the set as a whole. Indeed, Soundpainting allows a real exchange and an

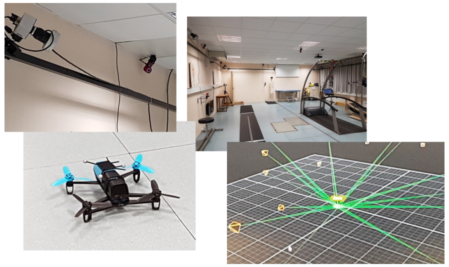

Figure 3: A motion capture system and its output

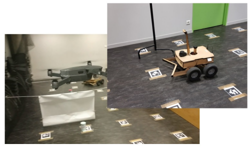

Figure 4: SLAM supplemented with tags

adaptive dialogue between the Soundpainter (here is the pilot) and the group, enabling contextual interpretation by each individual, and generating rich interaction and dialogue. The grammar used in Soundpainting is a set of gestures classified in four subsets: *Who*, *What*, *How* and *When*. A gesture *Who* indicates who is chosen by the Soundpainter. A gesture *What* indicates what Soundpainter wants to be done (e.g., hold a note). A gesture *How* indicates how Soundpainter wants the action to be done (e.g., in the case of sound, loud, fast or high). A gesture *When* indicates when the Soundpainter wants the action to start and/or stop. The expressive power of the Soundpainting language in the context of controlling the movements and the sounds of drones was shown in [7].

OUR APPROACH TO CONTROL (A SWARM OF) DRONES IN AN INDOOR CONTEXT

Research directions for issue 1 : controlling the drones/swarm of drones

According to our study case, the Figure 2 shows the proposed system architecture to control a swarm of drones using Soundpainting language. First, the Soundpainter performs a Who gesture ("Whole Group" here) in front of a gesture recognition software. Second, the recognized gesture is sent to the drone interface that controls the drones. Finally, the swarm reacts to the gesture "Whole Group", then stands ready to react to the next one. In the gesture recognition software, the body movement is grabbed via a non-intrusive motion capture system (e.g., a Kinect sensor). Then a machine learning model would be trained to recognize, in real time, Soundpainting gestures from the 3D joint coordinates extracted from the motion capture sensor. The result is the recognized gesture that is sent to an interface in charge of transforming it into instructions interpretable by drones (ARDrones modified to UDP client). Here is the main problem ; how to locate drones correctly in an indoor environment to compute movements?

Research directions for issue 2 : making the drone aware of its location

Motion capture. Using a motion capture system can be a very efficient approach as far as precision is concerned (see figure 3). Nevertheless, the drones must be equipped with sensors that are detected by cameras that have to be installed all over the flying area. This makes it possible to have a very precise location but the price to pay is in terms of instrumenting the drones, instrumenting the area and calibrating the system before use. Additionally, the number of cameras must be very important so as to avoid obfuscation between the drones.

SLAM. The Simultaneous Location and Mapping is an approach that consists of building a map of the flying area in real time so as to achieve location relative to this reconstruction. It requires to have a camera on the drone and enough computing power to run the SLAM algorithm inside the drone (required because we want to operate in real time) (see figure 4). Additionally SLAM only works properly provided a significant number of POIs (Point Of Interest) can be captured which is an issue in some situations and requires a lot of calibration to adapt to a given environment. In case the environment is not adapted (because of bad lighting for instance) the system can be augmented with external tags. We have experimented this approach in our Green Sword use case that consists in cleaning a green park with a swarm of air and ground vehicles and we obtained a correct location, even though not as good as what we had with motion tracking.

Technology	Accuracy
GPS	6m-10m
Infrared	1m-2m
Wi-Fi	1m-5m
Ultrasound	3cm-1m
RFID	1m-2m
Bluetooth	2m-5m
Zigbee	3m-5m
FM	2m-4m

Table 1: Comparison of the accuracy of the major radio technologies (source [14])

UWB. Many Ultra Wide Band or other radio-based approaches have been developed and experimented as shown in table 1. Most of them (if not all) suffer from the variability of their output and from their dependence on the environment. It is thus required to have the radio nodes to remain in place for a very long time so as to acquire a footprint of the location in terms of its "radio behavior" before it can be used to efficiently position a moving target (drone).

Sound based location. Using sound waves instead of radio waves seems to be a good alternative because sound waves are less subject to radio noise, even though it is of course subject to noise (in terms of sound noise).

Figure 5: A rehearsal of the opera with drones and musicians directed by a Soundpainter

Research directions for issues 3 and 4: building a self-contained system and making the system resilient

How can a system without external setup locate itself ? Building a self-contained system is probably one of the most challenging issues and it is a key to future applications of drones. This problem is listed here for the sake of completeness, but it is not an issue in our use case (more precisely, should this be impossible we can instrument the area where the show has to take place). Regarding resilience, the reader is referred to [5].

PRELIMINARY RESULTS AND CONCLUSION

The different projects that we have carried out in the recent years and that required precise location of the drones have raised a number of issues in terms of precision, stability, etc. It has basically been impossible to have a location more accurate than a few meters. To develop these use cases we thus had, each time, to setup dedicated approaches that most of the time led to lower our expectations in terms of scenario (making the drones fly far away from each other, forbid some moves, etc.). In the current use case, the Soundpainter directed opera, accuracy is required; there is no way to lower our expectations in terms of freedom of the director. Therefore, we have begun experimenting four directions: firstly, testing new radio based location systems; secondly, adapting the flight path of the drones in the swarm so that we require less accuracy; thirdly, changing/limiting the scenario that can be run by the director; and fourthly, experimenting the sound location.

The goal of this paper is to open a discussion with the community regarding one of the key issues linked to the interaction with an semi-autonomous swarm by gestures: the positioning. Even though technologies have become mature, we shown that it remains issues of indoor and adverse locations and we showed that the problem is four-folds (Figure 1). Our use case, an opera with drones and musicians (see figure 5) directed by a Soundpainter, leads to a real exchange and an adaptive dialogue between the Soundpainter (that could be seen as a pilot) and the swarm, enabling contextual interpretation by each individual, and generating rich interaction and dialogue. This usage requires precise location of the drone and needs an efficient positioning technology.

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Little Helper: A Multi-Robot System in Home Health Care Environments

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ABSTRACT

Being able to live independently and self-determined in one's own home is a crucial factor for social participation. For people with severe physical impairments, such as tetraplegia, who cannot use their hands to manipulate materials or operate devices, life in their own home is only possible with assistance from others. The inability to operate buttons and other interfaces results also in not being able to utilize most assistive technologies on their own. In this paper, we present an ethnographic field study with 15 people with motor disabilities to better understand their living environments and needs. Results show the potential for robotic solutions but emphasize the need to support activities of daily living (ADL), such as grabbing and manipulating objects or opening doors. Based on this,

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we propose Little Helper, a tele-operated pack of robot drones, collaborating in a divide and conquer paradigm to fulfill several tasks using a unique interaction method. The drones can be tele-operated by a user through gaze-based selection and head motions and gestures manipulating materials and applications.

KEYWORDS

multi-robot system; healthcare environment; ethnographic study; activities of daily living; people with disabilities

INTRODUCTION

Robotic solutions can make a significant contribution to improving care by relieving and supporting care assistants (e.g. nurses or relatives) and having the potential to improve the quality of life of those in need of care [2]. The use of robotic systems benefits in particular people with severe physical impairments, such as people with tetraplegia, who can not use their hands to interact with physical materials by proving alternative interaction mechanisms. Many people with severe physical impairments wish to be able to live independently and self-determined in their own home instead of being cared for in inpatient facilities. The wish for outpatient care is supported by Article 19 “Living independently and being included in the community” of the UN Convention on the rights for people with disability[1]. This is also reflected in national law, e.g. in the German law the social security statute book XII provides the principle “Outpatient care over inpatient care” §13 (1) SGBXII[2]. Physical impairments, which are associated with loss of function in the arms, hands and possibly the mobility of the upper body, limit the ability to live independently considerably. Activities of daily living (ADLs) like eating and drinking, moving around or to occupy oneself can only be achieved with assistance from others. For instance, the persons concerned are dependent on getting drinks and meals prepared, provided and presented. Outpatient care is needed many hours a day or 24/7. This group includes people with tetraplegia, multiple sclerosis, muscular dystrophy, and diseases with similar effects. There are currently several assistive technologies that are designed to enable independent eating and drinking - including eating utensils placed on a table (e.g., iEat, Obi) or robotic arms attached to an electric wheelchair (e.g., JACO, iArm). These products have in common that at least residual functions in either hands, arms and upper body are needed to operate the devices. Recent and ongoing research projects take up this problem and aim to develop robotic solutions for independent living for these usergroups. Examples are the Robots for Humanity Project (testing the PR2 Robot as an assistive mobile manipulator) of Chen et al. [5], AsRoBe Project (testing a mobile service robot with people with a physical disability in a real live environment) [6] and the research of Fattal et al. about SAM, an assistive robotic system to assist people with quadriplegia [7]. These projects have in common, that such a robotic device is designed to assist with several activities of daily living. The robotic device is usually very large,

[1] http://www.bmas.de/SharedDocs/Downloads/DE/PDF-Publikationen/a729-un-konvention.pdf?__blob=publicationFile

[2] https://dejure.org/gesetze/SGB_XII/13.html

consisting of a robotic arm on a mobile module. Theses robots require a barrier-free environment and rooms with sufficient space to fit in and to be able to move around safely. It can be expected that not all buildings will meet these requirements. On the other hand, smaller technological devices that may support certain activities of daily living, e.g. reading or eating, are bound to certain locations and positions and do not offer the same flexibility a human assistant can provide. However, people with these severe impairments are often reluctant to ask their human assistant continuously for small tasks.

In this contribution, we first present an ethnographic field study with 15 people with motor disabilities, aimed at understanding their living and support environment as well as their needs. Based on the results, we suggest Little Helper, a mobile multi-robot system which enables flexibility and enhances a human's opportunities regarding different tasks. In contrast to drones in the context of an unmanned aerial vehicle (UAV), Little Helper uses, for the most part, unmanned ground vehicles (UGV) to perform tasks on tables and floors. The interaction design is assignable between both kinds of drones.

RELATED WORK

In this abstract, we draw upon two strands of related work. First, we review approaches which deal with experiences with flying drones. Second, we present work that exploits the multi-agent system as a mechanism for allocation of duties.

Previous research in flying drones delivered a great amount of knowledge in human-drone interaction. Cauchard et al. found in their research, that the user should always have a feeling of naturalness, safety, and perceived control over the drone, also in autonomous performed tasks [3]. In addition, they observed "Interacting with a person" and "interacting with a pet" as the preferred high-level design metaphor. On the feedback side, Cauchard et al. found that human interpretations of drone behavior are often based on expectations formed by animal behavior [4]. Yeh et al. observed an increase of the mental stress of any human in the vicinity of the drone if it produces noise [13]. Moreover, they found that on average, the personal space of the drone and human was closer when compared with the personal space between human and human. Further, visual feedback, e.g. a lighting ring around a drone to communicate navigation parameters, can significantly improve the perception of the robot as a work partner [10]. To reduce privacy-related fears, Uchidiuno et al. did research in providing privacy-preserving technology, e.g. preventing the capture of data by blocking, obstructing, or re-orienting the drone [11]. Furthermore, head-mounted displays in an augmented reality context can significantly improve user understandings of robot intention and increase objective task efficiency [12].

To organize and coordinate such a group of mobile robots in a common space, multi-agent systems (MAS) are a good approach to reach this goal [8]. In a MAS, each subsystem has a specific goal and deals with that goal only. Once all the small tasks are accomplished the big task is accomplished, too.

However, the necessary organizational structure of MAS does not necessarily derive from explicit structuring, but can also be implicit in emergent behavior [9].

USER STUDY

In order to understand the living and care environments of the intended user group, we carried out an ethnographic analysis with 15 persons with tetraplegia, multiple sclerosis, Locked-In Syndrome, and similar diseases. All of them were living in their private homes supported by care assistants. The study focused on participatory observations of activities of daily living, such as eating and drinking, which were recorded with videos and photos, semi-standardized qualitative interviews took place. The chosen method allowed not only a comprehensive recording of the requirements regarding drinking and food intake but also gave a deeper insight into the life situation and further unmet needs. The 15 interviews have been analyzed qualitatively.

All participants emphasized the wish to live more independently, meaning to be able to be on their own for several hours without the need of a care assistant. All interviewed participants welcomed robotic solutions in order to gain increased autonomy, wishing that the robotic aid should assist with several activities of daily living. Furthermore, participants appreciate the possibility that a robotic aid relieves the care assistants, too. Another result of the analysis is, that although eating and drinking is an important subject, the participants mentioned a variety of other unmet needs. The most commonly mentioned wish was to be able to grab and manipulate objects, e.g. picking things up or open doors. This would also enable to fulfill tasks related to eating and drinking, like setting the table, meal preparations/cooking or to add some seasoning. Other expressed wishes related to leisure activities or basic care. Robotic aids for leisure activities are mainly wished for activities like reading (flip pages) or computer and video games (using a game console). Mentioned issues of basic care are to comb one‘s hair, to be able to scratch one's self (e.g. scratch the nose) or to clean one‘s tooth. Participants complained that it is more than annoying to ask for help for any task. This plays a crucial role with respect to drink sufficient amounts of liquids per day, where they preferred to rather gulp huge amounts instead of sips distributed over a longer time.

The ethnographic analysis showed, that not all homes have the sufficient space for large, mobile robotic devices like the ones mentioned above. Also, people with tetraplegia and similar diseases often have other huge devices such as lifting systems, additional wheelchairs or shower chairs which need sufficient storage spacer [1]. Participants emphasized that robotic aids should not be too big and require to much space. Also, some were concerned a robotic arm on a rather big platform might need a large charging station and have a high power consumption. Some would prefer a robotic arm attached on their wheelchair. This way they would have the robotic arm with them where ever they are. Others do not like to have to carry an aid (robotic or other) close to their body or attached to the wheelchair. This group also mentioned that they wanted a robotic aid that they can use while resting in their bed. Another concern towards using a robotic arm as drinking aid was, that it is stigmatizing if the arm is too big and/or the design to appalling or showy. Instead, the participants would prefer a robotic aid which is small and lean and designed like a "cool" lifestyle product (e.g. such as the Apple iPhone). Further concerns mentioned were safety and data protection as well as a complex and time-consuming usage of a robotic aid. Two participants asked if they would need technicians as assistants rather than care assistants in the future. All participants said, that they need robotic aids which are easy to use and do not need many instructions on how to use them ("plug and play"). It is important that not only the user but also the care assistants easily understand how the robotic aid works.

LITTLE HELPER

The results of the study suggest to concentrate on an approach focusing on simple robotic solutions for specific tasks instead of pursuing single, monolithic systems. We propose a distributed system of Little Helper which operates according to the principle of "divide and conquer", in which tasks are processed jointly by different robotic solutions. In addition, robotic solutions no longer need to operate e.g. a light switch but can simply interact with smart-home devices over the network. The distributed system would also allow the integration of a wide range of sensor information from different individual bots in task planning and execution. For this purpose, easy-to-use control software is needed, which allows non-technicians to network the individual systems at the touch of a button. The individual bots in such a system would be much simpler in their complexity and thus cheaper to produce. Bots of different types could also have very different components and functionality. This allows small but specialized devices, focusing on different activities of daily living, as proposed by the participants of the user study, such as setting the table, meal preparations/cooking or to add some seasoning and comb one‘s hair, to be able to scratch one's nose, or to clean one's tooth. In turn, a gripping bot can be designed in different forms for specific gripping tasks, such as the provision of a beverage bottle or the opening of a can. The aim for these different bots is to act in concert, thereby being capable of performing much more complex tasks. For the user, however, the access has to remain simple and transparent, without the latter having to consider which bot they operate for which task.

As an example individual bot, we present SwipeBuddy (see Figure 1). SwipeBuddy is a physical robotic device that acts as a mobile ebook reader and photo browser and can be controlled by using head movements. Its main tasks are to a) hold a digital device (e.g. Amazon Kindle) b) provide an interaction mechanism with the device to swipe pages and c) flexibly move around so that it does not interfere with parallel activities (e.g. eating). The SwipeBuddy acts as an r-c mobile ebook-reader that can be positioned using head movements. The SwipeBuddy consists of two main parts. The mobile robotic device itself and the interaction interface. The prototype of SwipeBuddy was built with parts of the Makeblock kit.[3]. The interaction concept consists of a **M**agnetic-**A**ngular**R**ate-**G**ravity

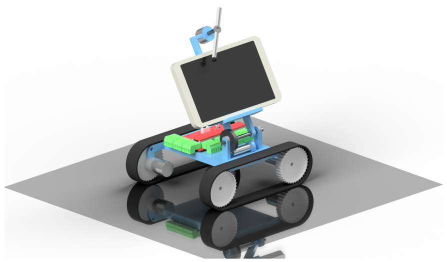

Figure 1: Draft concept of the SwipeBuddy. To increase mobility the robot is equipped with a continuous track vehicle propulsion. Furthermore, it features a tilting platform to change the tilt and therefore view-angle of the mobile device.

[3]Ultimate 2.0 — 10-in-1 robot kit (https://www.makeblock.com)

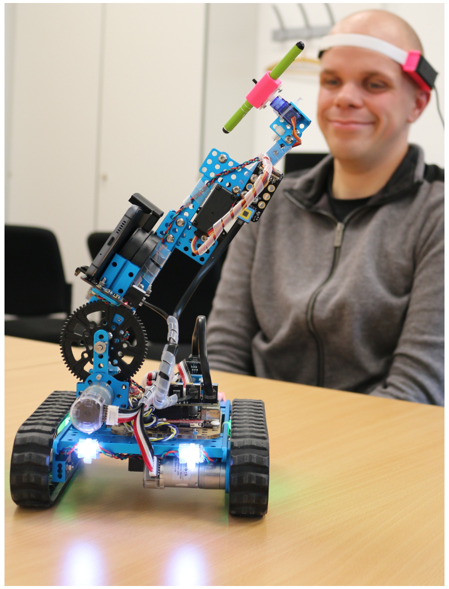

Figure 2: The user is steering SwipeBuddy by his head movements. The white headlamps are turned on.

(MARG) sensor that is mounted on a headband. We choose a continuous track vehicle propulsion (caterpillar track) for high maneuverability, i.e. turning around its own axis. The mobile device is placed on a tilting platform that allows the user to easily manipulate the view-angle of the device. The swiping mechanism consists of a tip of a stylus for capacitive touch displays and a motorized arm which provides contact pressure for swipe and scroll. In our interaction design, the user can switch between different modes to steer the robotic platform, change the tilt angle of the electronic device, and perform a forward or backward swipe action. Using a mechanical swipe mechanism enables a user to activate a swipe action with any application and with any device. A software controlled swipe would be device dependent and thus less flexible. Additionally, an idle mode is available to block all interactions to put the sensor headband on or off. In particular, the user is switching modes by performing a movement along the yaw-axis, while movements in roll and pitch axis are used in each mode differently, e.g. to tilt the device or swipe pages. To provide a visual feedback to the user about which mode is selected and to help to orient, 25 RGB LEDs are installed and used in a way that supports intuitive insight. Furthermore, all LEDs are mounted at special positions and on special parts of the robotic system where they could be recognized easily (see Figure 2).

CONCLUSION

With the Little Helper we presented a concept of a self-organizing and self-coordinating collection of assistance robots for people with severe physical impairments. It does not aim to replace care assistants but supports the user group for very specific tasks where users might not feel comfortable constantly asking for help. Thereby, it helps to empower people with such functional losses to increase the degree of an independent life. Our conceptional approach allows the integration of many activities of daily living, e.g. moving things, opening bottles, opening and closing doors. The interaction for users with tetraplegia will be based on hands-free input modalities, such as speech, gaze-based, or head-based interaction.

ACKNOWLEDGEMENT

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Lure the Drones: Falconry Inspired HDI

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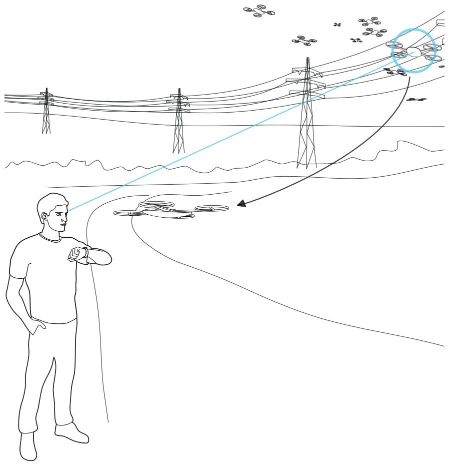

Figure 1: Interacting with individual units in a swarm of drones can be challenging. This paper proposes an interaction metaphor derived from falconry to provide GUI-free control over drones in the field.

ABSTRACT

The following paper proposes a concept regarding Human Drone Interaction (HDI) based on the traditional profession of falconry. For more then 2500 years humans already practice the interaction with flying agents for hunting and caretaking tasks. Based on the metaphor of the falconer we propose the following system which enables gaze control of drones utilizing a wearable eye-tracker. By taking the "looking at the watch"-pose, which is reminiscent of the "falconer luring its bird"-pose, the eye tracker gets implicitly positioned in front of the user's face. A combination of body posture and eye gaze allows for GUI-free interaction in the field and during physically demanding tasks.

CCS CONCEPTS

• **Human-centered computing** → **Interaction design**.

KEYWORDS

human drone interaction, falconry, interaction metaphor, eye gaze, smartwatch

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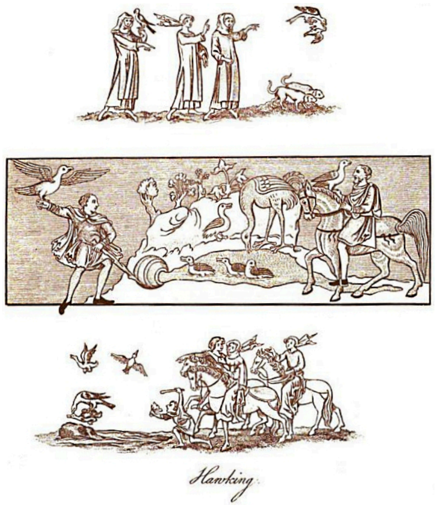

Figure 2: Trained birds have been an important element of hunting for many centuries. This craft originated from China and spread all over the world and various cultural contexts. In addition to the practical character of the bird, it also functions as a status symbol representing the power and influence of the owner. | Joseph Strutt "The sports and pastimes of the people of England from the earliest period" (1801). wikimedia.org

TIMELINE

680 BC: First records for falconry in China.
200-400 AC: Goths learned falconry.
500 AC: Roman mosaic pictures falconry.
700 AC: Falconry established in Arabia.
2010: Falconry accepted as Intangible Cultural Heritage of Humanity by the UNESCO.

INTRODUCTION

In the near future mobile agents or drones could be a substantial aspect of many jobs and everyday tasks. From supervising swarms performing maintaining tasks or coordinating agents in inaccessible territories or dangerous situations drones will broaden the capabilities of such professions and lead to safer and more effective work conditions. When looking back in time, one can see parallels to an ancient profession that also widened capabilities by taking advantage of mobile agents. Hunters and caretakers used trained birds to assist their tasks (see Figure 2). This craft is called falconry and is still used today for hunting purposes but also for keeping public spaces free of vermin and thus pollution or to frighten away swarms of birds from airports to prevent collisions with planes. In this paper the authors propose a HDI concept that builds upon this traditional way of interacting with mobile agents. Furthermore, scenarios are described in which such new interaction techniques could turn out to be beneficial compared to established GUIs.

RELATED WORK

Human Drone Interaction is an expanding field of research in the Human Computer Interaction (HCI) community. Many projects investigate intuitive ways of interacting with drones. Cauchard et al. [3] already explored natural interaction with drones based on gestures participants performed intuitively. Their findings show that a lot of persons automatically tend to interact with drones similarly as they would do with pets or humans using e.g. gestures for beckoning.

In addition, other research projects explored how to use gaze [5] as a potential input technique for the interaction with drones. Yu et al. [8] implemented a system that allows for direct remote control of a drone via gaze input. Gaze in this project was used to control the movement comparable to a remote control allowing for the manipulation of the absolute position (move: right, left, up, down) and not to send to specific locations (go to: desk, door, wall, ...). In contrast, Alapetite et al. [1] implemented a system that uses gaze to control a drone from 1st person perspective using point of regard on a screen that pictured the drone’s live stream.

A comprehensive overview of the current state of HDI techniques such as gestures, gaze direction and speech is given by Peshkova et al. [7]. Also the combination of input techniques such as gestures and speech with GUIs was already explored by Fernández et al. [4] in the context of in indoor scenarios.

Falconry inspired interaction? [6]

INTERACTION METAPHOR

The falconer recalls its bird by using the lure and offering the bird its arm for landing. The lure is typically consisting of feathers as well as bird food and is used during the trainings-process to condition and later to trigger the bird by a motion pattern to return or signaling when to return to its

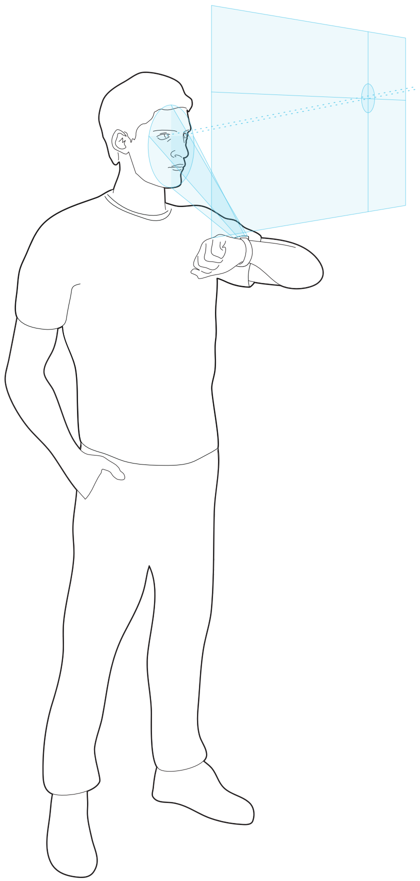

Figure 3: Via wearables, such as smartwatches, gaze direction is tracked and used to select single drones out of a swarm and lure it back to the operator. The position taken is reminiscent of a falconer luring one of its birds offering its arm for landing.

owner. Luring drones obviously does not need conditioning based on food rewards but nevertheless we can transfer the pose of offering the arm for landing as a sign for recalling the drone. In addition when interacting with multiple drones at once, the selection process of which drone to recall (by falconers typically done by using individual lures for each bird) could be achieved by looking directly at a specific drone. By the nature of the pose (see Figure 3) eye-tracking could be implemented with wearable devices such as smartwatches. Further, to allow the user to perform various gaze-based interactions with the drone, static hand poses can be used for task distinction. Such hand poses are differentiable by electrical impedance tomography as implemented by Zhang and Harrison [9] and are to be performed with smartwatches in the near future.

INTERACTION AND SCENARIOS

The following tasks can be performed with gaze combined with static hand poses (see Figure 4) and are based on or derived from the interaction metaphor:

- **Selecting from the Swarm**: Selecting a specific drone from a swarm to get further information on a handheld device. The drone will stay at its current position. Available options for operators include displaying status information on the mobile device or introducing further instructions for the drone. A gesture with the arm initializes a selection, see Figure 3.
- **Luring Home**: Selecting a specific drone from a swarm and recall it to the controller. The drone will leave its current position and return to the operator.
- **Sending to Position**: Selecting a specific drone from a swarm and sending it to a new position. The drone will leave its current position and head towards a new target.

The following three scenarios identify use cases where controlling drones with eye gaze could be beneficial. Some of the following scenarios could also benefit from combinations of gaze, postures and gestures:

- **Hands-free Interaction**: Activities as sport climbing but also industrial climbing often requires both hands of the user for handling equipment or securing. Thus, controlling a swarm of drones is not possible by touch-controlled GUIs displayed on hand-held devices such as tablets or phones. Interacting with the drones by visual contact keeps the hands free for other tasks.
- **Focus on Surrounding**: During tasks with a high security risk, such as firefighting or everyday tasks as driving, the user's visual focus should remain on its surrounding. GUIs can distract the user's attention for longer time spans than recommendable. Therefore, the possibility of controlling and commanding drones with gaze could be beneficial for keeping the surrounding in the user's peripheral field of view.
- **Hindered Orientation**: Drones already showed to be useful tools in the context of rescue missions [2]. But furthermore, catastrophes such as avalanches, floods or earthquakes can

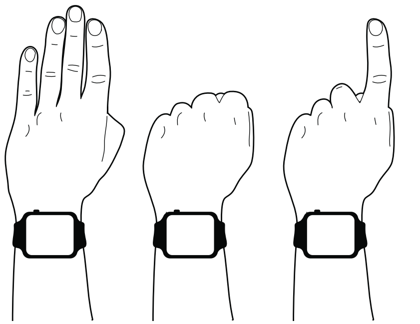

Figure 4: "Selecting from the Swarm" inspired by the "stay" hand signal performed with dogs, "Luring Home" inspired by falconry, "Sending to Position" inspired by typical pointing. (fLTR)

Figure 5: During catastrophes map material can differ drastically from the situation on site. Therefore, the assignment of drones indicated on GUIs with drones seen in the field may turn out to be difficult to almost impossible. Selecting drones with gaze could turn out to be beneficial in such situations.

cause map materials to become unrecognizable (see Figure 5). Missing landmarks, covered by water, snow or mud, as well as destructed reference points as prominent buildings hinder the orientation on GUI based systems. In such scenarios selecting, controlling and commanding drones by gaze direction can be useful as well as indispensable. A conceivable example would be the selection of a specific drone to watch its video stream on a portable monitor during rescue. This could be useful for searching for survivors of avalanches of floods in inaccessible areas.

CONCLUSION AND OUTLOOK

We propose to use gaze as modality for human-drone interaction. To that end, this work presents a novel interaction metaphor inspired by falconry. A wearable (e.g., smartwatch) detects and selects a drone corresponding to user's focus. An arm-gesture inspired by inviting a bird to land is therefore adopted from falconry. Furthermore, we suggest supporting luring, sending and selecting of drones via gaze control and optional hand gestures (fist, pointing and flat hand). Additionally, we motivate our interaction metaphor by listing three corresponding scenario settings which could benefit from implementing gaze controlled HDI (hands-free interactions, focusing on surroundings and scenarios with hindered orientation).

However, accuracy, selection speed and reliability are crucial aspects which need to be considered when implementing the concept. Since individual drones are moving constantly selecting a specific drone in a swarm requires a high level of accuracy. As of now, there is a lack of knowledge regarding appropriate specifications for selection speed and accuracy. Moreover, reliability, acceptance and comprehensibility should be investigated within future user studies. While we argue for a concept, a working prototype remains an open research challenge.

We state that our proposed approach could ease critical situations, e.g. industrial climbing, fire fighting or finding POIs in flooded areas. Besides, it could support sports e.g. climbing or everyday tasks such as driving. Hence, our concept might foster safety and comfort during safety-critical maneuvers as well as leisure time activities while applying a familiar interaction metaphor known from falconry.

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Priority List: What Users Want to Know About a Drone

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ABSTRACT

With the decrease in the price of aerial robots and advances in technology, more groups of people are using aerial robots, including hobbyists, bridge inspectors, photographers, etc. As a result, more people are being exposed to aerial robots both as direct robot operators/pilots and also as bystanders and/or people having unwanted/unplanned interactions with aerial robots. For example, if a hobbyist flies a robot in a neighborhood, neighbors may be involved in the interaction just because they are in the same environment as the robot. As these interactions become more commonplace, it is critical to intentionally design robots around both explicit and implicit interactions. To this end, we are interested in learning more about what type of information users might want to know while interacting with aerial robots. We created videos of a user interacting with an aerial robot and collected user responses regarding possible information a user might want to know about the robot in a survey with 50 participants on Mechanical Turk. While some of our results support findings in prior work in human-robot interaction, they also reveal several new priorities for drone researchers to consider in improving human-drone interactions.

KEYWORDS

aerial robot, user study, priority list, human-drone interaction

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INTRODUCTION

In the last few years with the advances in technology, robots are used more than anytime and this is still growing. Aerial robots are going to be used for to go where users can't go e.g., bridge inspection [8], help astronauts on the international space station (ISS)[5], for package delivery [9], etc. Other than traditional industrial robots which only exists in cages, there are new mobile industrial robots which move around the factories and warehouses and perform a variety of tasks such as moving payload or shelves [17]. Some of these mobile base robots have a manipulator and can perform a manipulation task [10, 12]. In a human-human interaction, people are good at interpreting the signals coming from the opponent e.g., if two people passing by each other in a narrow hallway, often they are good at signaling/interpreting signal which path (right or left) are they going to take. If they can not perform a good job, the mentioned interaction would become an awkward situation. For a good interaction, both human and robot should have a basic understanding of each other. It is essential for a human to know more about the state of the robot and it is necessary for the robot to convey needed information to the user.

There is a large amount of literature about human's mental model [2], the works that have been done to convey specific information [3, 4] and what signals to use to convey specific information[7]. As an example to convey "where the robot is moving next", Szafir et al. used gaze and lights [14], other researchers used Augmented reality [11, 13, 15, 16], Cha et al, used sound [6].

In this paper instead of "what medium to signal specific information?" , we are curious about "what information should the robot conveys?". This is an important question for designers/researchers to keep in mind while making a robot. Other than specific use cases e.g., designing the bomb defusing robots [1], to best our knowledge no one asked what type of information users needed to know about the robot.

We recruited 50 participants in 3 groups on Mechanical Turk. We asked them about the information they want to know about the robot and we would share our finding in the result section.

SURVEY AND PROCEDURE

We designed a survey with 4 sections. In the first section, participants watched two short videos, each approximately 30 seconds in duration. Both videos depicted a user completing a pick-and-place task while sharing an environment with an aerial robot (Figure 1). There are two tables in the environment. One table contains the user instructions and two boxes, while the other table contains various wooden blocks with associated numbers. The instructions required the user to follow a sequence of steps in

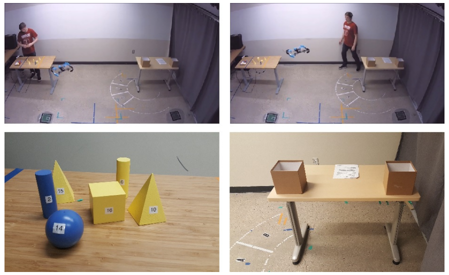

Figure 1: Top left: The robot doing a supervisory task. Top right: The robot intentionally interferes with the path the user is taking. Bottom: Pick and place task that the user is performing in the videos.

which they selected a specified block from one table and placed it in one of the boxes in the other table (e.g., "1. The yellow pyramid with number 15 should go in Box A").

In both videos, the robot acted as a supervisor, which meant that it occasionally flew over the tables and checked the current status of the task (e.g., how many objects were in a box or whether objects were placed in the correct box). In the first video, the robot was on the opposite side of the table and completely isolated from the user (Figure 1 top left). However, in the second video, the robot flew on the same side of the table as the user and thus at times was in the way of the path that the user tried to take (Figure 1 top right). Our goal in designing these two videos was to highlight scenarios in which users may simply coexist in shared environments with drones (i.e., bystander interaction) as well as scenarios requiring more direct interaction (e.g., to resolve right-of-way issues) as the information that users desire from the robot may depend on the amount and type of interaction.

After watching the videos (participants could re-watch videos at anytime of the survey), participants ranked 22 items, each of which corresponded to some sort of information that the robot might convey, in order of how important the participant perceived this information to be were they to interact with a robot as in the videos they had just watched. These items were drawn from a list of possible information that users might want to know from the robot created by reviewing prior HRI literature and a series of brainstorming sessions with expert roboticists with at least 5 years of experience.

We can roughly categorize the items in 3 major groups. First, several items correspond to various information the robot might convey about itself, such as “The robot conveying whether or not its camera is recording” or “The robot conveying when and in what direction robot would move next” etc. The second group represents information that the robot might convey about the task it is doing, for example “The robot conveying a list of successfully/unsuccessfully completed tasks (task history)” or “The robot conveying whether or not any faults/errors are detected (e.g., electric circuits damaged, payloads/sensors not mounted correctly, etc.).” Finally, the third group corresponds with information related to whether it is safe and/or appropriate for human interaction, such as “The robot conveying whether or not it is safe to get close to it” or “The robot conveying whether or not it currently knows where you are.” For each participant, the list of items was presented to participants randomized in order to reduce the potential for initial placement bias. Participants were tasked with re-ordering the list of items in order of their perceived priority.

In the next section, participants were asked to provide a 1–7 Likert-type rating regarding their perceived importance for each item they ranked in the previous section. Here 1 was defined as “not important” and 7 was defined as “very important.” This section of the survey served two primary purposes. First, this section helped provide supplementary information on perceptions of absolute importance to contextualize the information on relative importance from the previous section (e.g., even items ordered near the end might be perceived as highly important by participants). Second, these questions provided a validation method for the items in the previous section (i.e., items ranked

Most important			
Rank	The robot conveying ...	Mean	SD
1	whether or not it is safe to get close to it.	8.0	5.2
2	whether it is currently acting autonomously or being controlled by a person.	8.3	6.1
3	what it knows about the surrounding environment.	8.8	4.3
4	whether or not any faults/errors are detected.	9.6	5.8
5	when and in what direction robot would move next.	9.7	5.7

Least important			
Rank	The robot conveying ...	Mean	SD
18	its most recent maintenance report.	13.9	5.5
19	its total flight duration.	13.9	5.7
20	how to look up more information about the robot.	15.5	6.4
21	the current time and date.	15.9	6.1
22	contact information for how to leave feedback about the robot.	15.9	6.8

Table 1: List of the most important items based on participants ranking for aerial robot

lower in the prior section should also receive an equal or lower score in this section). This validation helped us identify and control for the quality of participant responses.

While we created a large sample of items corresponding to different types of information it may be useful for a robot to convey, we recognize that our list is not exhaustive and might be missing potentially critical aspects. As a result, the next section of the survey provided participants with open-ended questions where participants could suggest any other information they think would be helpful to know about the robot or useful for the robot communicate to them. For each suggestion, we also asked participants to provide a Likert-type rating of 1–7 regarding how important they believe this suggested information might be. Each participant had the option to provide and rate 3 new suggestions.

In the last section of the survey, we collected demographic information regarding age, gender, education and the level of familiarity of participants with robots in general. We also included a question about obvious features in the two videos, in this case, we asked the number of boxes on the table in order to ensure that participants actually watched the videos.

With IRB approval we deployed the survey on Amazon Mechanical Turk and collected responses from 50 participants. After initial validation analysis, we removed data from 2 participants who didn't pass the video sanity check and 11 participants with inconsistencies across the ranking and rating sections. As a result, we ended up with 39 responses for full analysis.

RESULT AND FINDING

Among valid responses, 16 participants identified themselves as female while 34 identified as male. Average participant age was 33.7 (SD = 9.6), with a range of 22 - 70. On a seven-point scale, participants reported a moderate prior familiarity with both aerial robots (M = 3.8, SD = 1.4). The ranking table can be find in **??**. Safety and privacy are the most important concern of the participants and information about robot was the least important. Category wise Both safety and privacy (M = 5) is the most important followed by Interaction (M = 14), task (M = 14.2) and Robot (M = 16.28) is the least important category.

For the open-ended questions, 45 answers were received from 28 participants (M = 1.21). 17 participants provided a suggestion, 5 provided two suggestions and 6 participants provided 3 suggestions. Annotators group the responses in the following categorise: navigation (%8.8 of total responses and Avg score = 5.75) , safety (%26.6, Avg = 5.6), robot capabilities (%17.7, Avg = 4) , communication (%20, Avg = 5.3), environment (%6.6, Avg = 3.33) and privacy (%11.11, Avg = 4.6). Some of the user responses are as follow:

(1) Navigation
- **Participant 36, importance 5:** "How quickly will the robot move?"

	List of all items
	The robot conveying ...
1	whether it is currently acting autonomously or being controlled by a person.
2	whether or not it is safe to get close to it.
3	what it knows about the surrounding environment (i.e., the objects and people it can sense).
4	whether or not it needs assistance.
5	whether or not any faults/errors are detected (e.g., electric circuits damaged, etc).
6	whether or not its camera is recording.
7	when and in what direction robot would move next.
8	its battery life remaining in time (hours/minutes/seconds).
9	whether or not there is a problem with the engines/motors.
10	whether or not it currently knows where you are.
11	its current task progress (as a percentage of the whole task).
12	its wireless signal strength.
13	when it will change its altitude.
14	a list/schedule of upcoming/planned tasks (task queue).
15	the name of its current task along with a short description.
16	a list of successfully/unsuccessfully completed tasks (task history).
17	its remaining battery life as a percentage.
18	its most recent maintenance report (e.g., last time propeller was changed).
19	its total flight duration (from takeoff to the current moment).
20	how to look up more information about the robot (e.g., where to find a manual).
21	contact information for how to leave feedback about the robot.
22	the current time and date.

Table 2: List of all the items to rank in the survey

- **Participant 46, importance 6:** "What direction it is facing."
- **Participant 41, importance 6:** "Overall flight path"

(2) Safety
- **Participant 37, importance 6:** "It could tell me when it is too close with a beep or similar."
- **Participant 33, importance 6:** "Anything that is shaking the robot due to a failing part."
- **Participant 45, importance 7:** "If the robot is on a collision course."

(3) Robot Capabilities
- **Participant 22, importance 2:** "If the robot is on a collision course."
- **Participant 50, importance 4:** "How new is it's technology and how well it operates."
- **Participant 21, importance 6:** "What it is made out of."

(4) Communication
- **Participant 5, importance 6:** "If the robot can change objectives before completing one."
- **Participant 45, importance 5:** "How the robot perceives my actions."
- **Participant 38, importance 7:** "if it can react to my questions or concerns"

(5) Environment
- **Participant 15, importance 2:** "Rain or Water alert"
- **Participant 20, importance 5:** "Whether it is entering a restricted area."
- **Participant 15, importance 3:** "Heavy Wind alert"

(6) Privacy
- **Participant 34, importance 6:** "What is the robot doing in relation to me? Is it guarding something, is it recording me?"
- **Participant 4, importance 5:** "The distance from what it is recording from"

CONCLUSION

To summarize, in this paper we tried to answer a basic question "what information naive users want to know about a robot?". We believe this is a critical question and help the robot designers, design robots with knowing their needs. Often, we see this is not happening in the design process. We ran an online study of 50 participants on Mechanical Truk and asked them to rank a list of information they want to know about a robot. We find out that naive users have concerns about safety, navigation around robot and privacy.

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STOP! Enhancing Drone Gesture Interaction with Force Feedback

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ABSTRACT

Gesture interaction is a common way to control drones. Often it is done by mid-air gestures i.e. the operator does not need to hold any controller. Hence, such interaction is lacking force feedback while the other senses are overloaded by the noise of the drone or occupied by following the behavior of the drone. Therefore, we present an approach in which we use electrical muscle stimulation (EMS) to provide force feedback for controlling drones. We build on existing gesture sets and discuss different feedback options for operating drones.

KEYWORDS

Drone, Gesture Interaction, Force Feedback, Electrical Muscle Stimulation (EMS)

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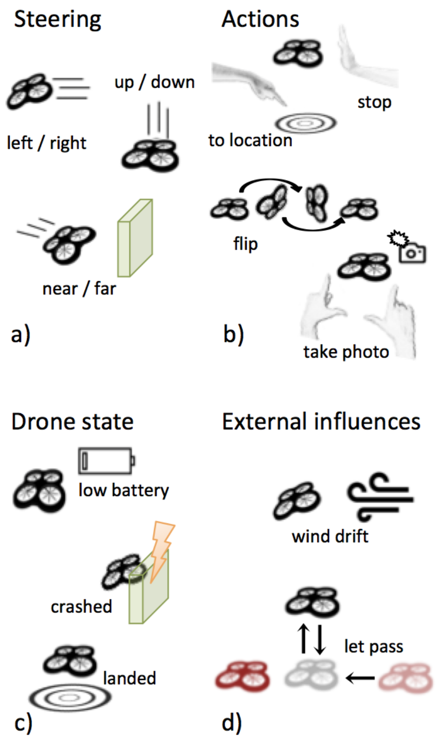

Figure 1: Drone feedback space: a) Steering commands, b) action commands, c) state of the drone, and d) external influences

INTRODUCTION

Nowadays, drones are available in various sizes and are used for different application scenarios, indoors as well as outdoors. In many cases, drones share the physical space with their users (their operators) and other people to fulfill specific tasks. The main actions operators use to control drones are for performing simple movements (e.g., up, down, left, right, near, far, rotate) and specific action commands for drones such as take-off, landing, or photo and video recording [11].

One popular way to perform such inputs is to use gestures [11, 12, 16]. Users perform gestures in mid-air either with their hands [10], arms [16], or their full body [1]. Cauchard et al. [2] explored how users interact with drones in a natural way. They found that users treat drones either like individual persons, a group, or as a pet. The replication of [2] study showed that Chinese participants also treated drones similar to their US counterpart. Jane et al. [5] investigated the social impact on such gesture sets. An overview of hand and upper body gestures is given by Peshkova et al. [12].

When interacting with drones, the user can immediately see the result of the command (i.e., the drone moves in the intended way) as long as the drone is within the line of sight. As soon as the drone is not in the user's field of view, the user can not receive any feedback on the movement of the drone directly. One way of enhancing the feedback associated with mid-air gestures is to introduce force feedback via electrical muscle stimulation (EMS) [8, 9, 13, 14, 18]. This approach has already been explored for mid-air input on public displays [14]. Moreover, EMS has been used to notify [3] users about important events, communicate affordance of objects [9], and support mid-air target selection [15] of 3D objects.

In this work, we introduce a novel way to provide force feedback for gesture-controlled drones using EMS. We use gesture sets proposed in related work and extend them with feedback. We discuss how such feedback can be designed and what benefit it might provide.

DRONE FEEDBACK

Drones provide feedback to users on several different occasions. This includes feedback as a response to commands performed by the user and feedback generated proactively by drones.

Steering Commands. While controlling a drone in a restricted area (e.g., inside a building, in a forest), an operator can perform commands that might result in crashing the drone into an obstacle. This could happen through any steering command e.g moving the drone up or further away (see Figure 1 a). Thus, this crash potential needs to be communicated to the operator so that the operator can stop the command prior to an incident.

Action Commands. Besides steering commands, operators also perform action commands such as controlling a camera or another adjacent device (e.g., taking a picture, starting a video) or doing a

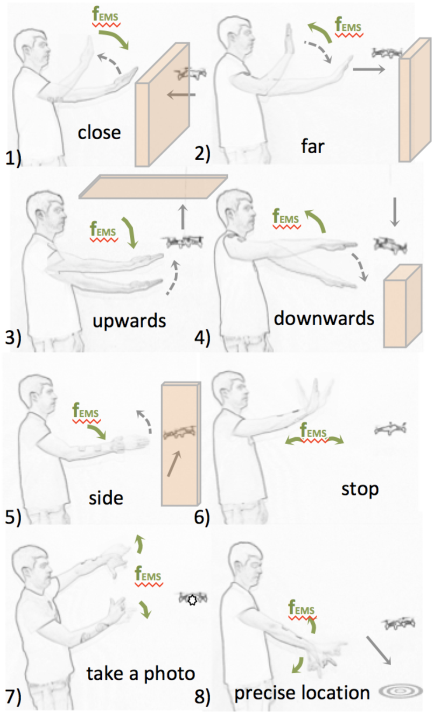

Figure 2: EMS force feedback (f_{EMS}) for gesture-based drone control: 1) Close, 2) far, 3) up (including taking off), 4) down (including landing), 5) side, 6) stops, 7) take a photo, and 8) flight to a location

special move (e.g., fly to a location, land or flip the drone) as shown in Figure 1 b. For each command, the operator needs to perceive feedback [17].

State of the Drone. The current state of the drone is also important information that needs to be communicated to the user (see Figure 1 c). The level of the battery, the connectivity, or the selected flight mode might need to be communicated to the user in certain situations. To provide this information, one option would be that the operator triggers the feedback. For example, the operator could request the current flight mode. Another option could be that the drone proactively provides such feedback if e.g. the battery level becomes low. The type of information that needs to be communicated differs from state to state. While a proactive message of a low battery might be binary information, an operator request for the battery level might rather be a continuous value.

External Influence on the Drone. Drones are influenced by their environment (see Figure 1 d). For example, the wind might influence the drone so that it needs to compensate. Another external influence could be a moving object (e.g., other drones, other people) the drone has to avoid. The drone might communicate this maneuver to the operator in a proactive way.

EMS FEEDBACK FOR GESTURE-BASED DRONE CONTROL

In the first step, we identified gestures for drone control and combined them in a set. We derived the gesture set from related work (i.e., Peshkova et al. [12], Obaid et al.[11]). The used gesture set is depicted in Figure 2 and contains eight gestures for the most common commands. Next, we identified EMS movements suited as feedback for this gesture set.

Feedback for Steering Gestures. Steering gestures include gestures controlling the drone on each axis in 3D space. This is done by moving the arm in a dedicated direction (cf., Figure 2 1-5).

The general idea of the EMS feedback group for these gestures is to generate a counter movement to the gesture performed by the operator to slow down, stop or invert the gesture. As soon as the drone comes too close to an obstacle (e.g., a wall when flying indoors or the operator him-/herself when the drone is flying towards him or her), EMS actuates the arm of the operator in the opposite direction. This either stops the drone or brings it back to its previous position.

Note that, with EMS, the operator is still able to override the force feedback and to further perform the respective gesture command. The *closer* and *further* commands require the user to move his hand closer or further away from him-/herself (Figure 2 1-2).

For the *closer* command, the counter force feedback is generated by actuating the triceps muscle. This stops the operator from moving the drone towards him-/herself or an obstacle (Figure 2 1). The biceps is actuated to induce counter force feedback of the *further* command (Figure 2 2).

Accordingly, the *up* command requires the operator to raise his/her whole arm which involves muscles in the shoulder, in particular, the deltoid muscle. Thus, the counter-movement would be to pull the arm down, which could be realized by actuating the infraspinatus muscle (Figure 2 3). Similarly, for the *down* command, the operator decreases the tension of the muscles of the shoulder and lets gravity sink down the arm. By actuating the deltoid, this movement could be slowed down or stopped, or the arm could even be raised again (Figure 2 4). For moving the drone *left* or *right*, the operator needs to move his/her hand to the left or right. The movement to the inside (i.e., left for right-handed operators) is achieved using the flexor digitorum profundus muscle, thus the counter movement (i.e., right for right-handed operators) can be created by actuating the extensor digitorum muscle. The other way around, the counter-movement to the outside of the operator (i.e., right for right-handed operators) could be generated (Figure 2 5).

Feedback for Action Gestures. We propose using the following feedback for action gestures. The *stop* gesture is done by raising the arm and the hand in front of the operator (Figure 2 6). This action may be triggered when the operator wants to stop the drone immediately. If the command was executed successfully, the hand of the operator can be moved slightly forward and backward by actuating the flexor digitorum profundus muscle and the extensor digitorum muscle alternating.

The *take a photo* or *'selfie'* gesture is done by opening the thumb and index finger of both hand and forming the shape of a frame in front of the operator (Figure 2 7). The EMS-based force feedback after the drone takes the photo could be realized by opening the hands slightly by actuating the flexor carpi ulnaris muscle and extensor carpi ulnaris muscle.

The *fly to a location* gesture involves a pointing gesture to a certain location [2] (Figure 2 8). The EMS feedback could be similar to the response for the stop gesture. The hand could be moved slightly forward and backward. In general, this type of *'acknowledge'* feedback could function to confirm certain action gestures but also enhance flight control gestures, such as confirming a successful landing or take-off maneuver.

This considered gesture sets does not include gestures for requesting feedback on the *state of the drone* or reacting to *external influences* [11, 12, 16]. The feedback that describes the *state of the drone* could be an *'acknowledge'* gesture as a response to the user's request gesture. In the case of a simple response, as discussed in the work of Duente et al. [4]. In the case a discrete value or progress is communicated, the hand of the user could be raised to indicate the value similar to the work of Lopes et al. [8]. For more complex output [6, 9] or disambiguation, gestures [7] could be used to represent the state or the behavior of the drone.

For *external influences* on the drone, feedback could be designed to be similar to the motions of the locomotion system. For example, if the drone is drifting due to wind while the operator controls the direction of the drone, the operator's arm could be stimulated to slightly follow this drift, as discussed above.

CONCLUSION

We propose EMS as a force feedback technology for drone-controlling gestures. For the existing gesture sets, counter-movements through EMS feedback could be used to slow down, stop, or revert the operator's gestures. However, the operator should always be able to override the EMS feedback with his or her own muscle force e.g. if the operator would like to fly closer to an obstacle than the system allows. EMS is particularly suited for this situation since it is light-weighted and could be included in wearable devices [13]. Upcoming electrode suits, such as the Tesla suit[1], and auto-calibration using electrode grids will reduce the time to set up such a force feedback system. In the future, a full working prototype should be implemented and tested with drone operators.

[1]Tesla-suit: https://teslasuit.io/

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Shooting Swimmers Using Aerial and Underwater Drone for 3D Pose Estimation

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ABSTRACT

Methods of 3D pose estimation using RGB cameras have been studied in recent years. They are used for sports to improve athletes' abilities and techniques by providing visual feedback. However, they still can be difficult to be used for swimming. This results from several problems, such as the difficulty of camera installation or tracking and the disturbance of bubbles and other optical issues due to the characteristics of water. To address these issues, we propose a method for shooting videos of swimmers using multiple drones. We aim to realize 3D pose estimation by using videos shot from the top and under the water with aerial and underwater drones.

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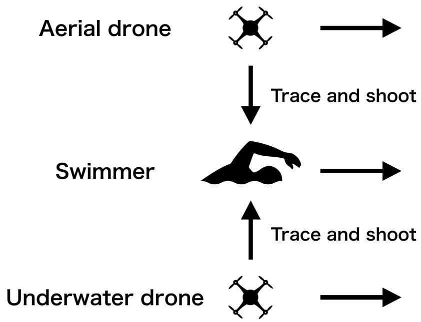

Figure 1: The system to shoot a swimmer using aerial and underwater drones.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; • **Applied computing** → **Computers in other domains**.

KEYWORDS

Sports Assistant, Pose Estimation, Aerial Drone, Underwater Drone

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INTRODUCTION

3D pose estimation is an important approach and technique for analyzing human motions.

Methods of 3D pose estimation with RGB cameras have been studied in recent years and presented remarkable results by using monocular cameras [2, 3].

Although these techniques for 3d pose estimation using RGB cameras have been used in the field of sports, using them for swimming may still be difficult. This results from several problems, such as the difficulty of camera installation or tracking and the disturbance of bubbles and other optical issues due to the characteristics of water. Therefore, motion capture techniques using sensors or markers have been used for 3D pose estimation of swimmers [4]. However, when a swimmer wears sensors or markers on their body, it may produce resistance of water. Furthermore, preparing such as motion capturing equipments are difficult in general (e.g. expensice or requires large equipments to be installed). To address these issues, we propose a method for taking videos of swimmers using multiple drones and to estimate the 3D pose.

Applications of using a drone for sports and pose estimation have been investigated in recent years.

Higuchi et al. proposed a system for a drone to autonomously track the target, and to capture athletes' external visual imagery to support soccer and other sports [1]. Flycon is a method for environment-independent estimation of human poses in real-time with aerial vehicles [5]. Swimoid is an underwater buddy robot to support a swimmer by following them and to present visual feedback with a display [6].

We aim to take videos of the swimmer from the top and from under the water using the aerial and underwater drones. Figure 1 shows the overview of the proposed system we propose. By using these videos, we can acquire 3D pose for swimming activities.

Figure 2: An image of a swimmer from the top using DJI Spark.

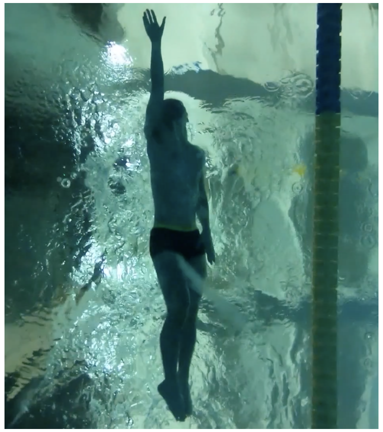

Figure 3: An image of a swimmer from under the water using GoPro HERO 6.

METHOD

As a pilot study for using two drones to take videos of swimmers, we took videos of the swimmer from the top using a drone and from under the water using an action camera installed at the bottom of the swimming pool. We used a DJI Spark and its integrated camera to take videos from the top and GoPro HERO 6 installed at the bottom of a pool to take videos from under the water. Figure 2 shows an image shot from the top of a swimmer using DJI Spark and Figure 3 shows an image shot from under the water using GoPro HERO 6.

DISCUSSION

Swimmers can observe themselves from external point of views by using drones for video shooting. Moreover, drones allow swimmers to see themselves from an unusual perspective such as from directly above them. This may help swimmers to perceive some amendable flaws which are not detected in the ordinary workout. On the other hand, there are some problems to shoot videos using drones. The sensors on the drone may be disturbed due to the fluctuation of the water face.

FUTURE WORK

Tracking the Swimmer

Currently, we control the drone manually to trace the swimmer. For future work, by using a swim cap or a swimsuit as a marker for the tracking, we can track a swimmer without specific equipment. Using this system, swimmers can shoot their swimming style by themselves.

Using an Underwater Drone

In our pilot study, we use an action camera installed at the bottom of the pool to shoot the video from under the water. However, a fixed camera may only shoot a swimmer for a short duration when they pass through the camera. Therefore, we consider to use an underwater drone to shoot the video from under the water so that they can trace a swimmer moving through a pool.

Feedback to the Swimmer

We also plan to apply 3D pose estimation to videos shot by aerial and underwater drones. By using 3D poses, we can present and visualize the differences between themselves and experts. Accordingly, swimmers can understand how they should fix their swimming styles.

CONCLUSION

We propose an approach to shoot videos of a swimmer from the top using an aerial drone and from the bottom using an underwater drone. By using drones to shoot a swimmer, they can observe themselves from an external point of view and check their swimming styles. Moreover, multi-view videos shot by aerial and underwater drone may be used for 3D pose estimation and this allows us to estimate 3D pose in swimming using RGB cameras without specific equipment such as sensors or markers.

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Tactile Human Drone Interface for End-Users and Qualified Pilots Collaboration

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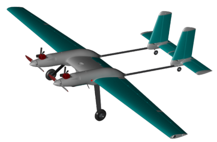

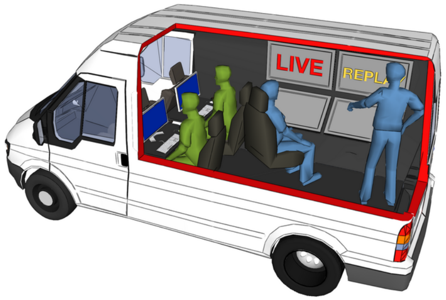

Figure 1: Van from 3i UAS

ABSTRACT

During the 3i European project for maritime surveillance, a solution has been designed to support crew collaboration in Unmanned Aircraft System. This study focuses on Human Drone Interface usability and raises issues about how it could help end-users to collaborate with pilots. Software architecture and interaction tricks are explained. As we particularly paid attention to give to the end-users the capabilities to easily submit maneuvers to the pilots, we assessed the usability of this new solution. We found limits and perspectives, and also opened discussion about end-users / pilots collaboration issues.

CCS CONCEPTS

• **User studies**; • **Empirical studies in interaction design**;

iHDI '19 - International workshop on Human-Drone Interaction, CHI '19 Extended Abstracts, May 5, 2019, Glasgow, Scotland, UK, http://hdi.famnit.upr.si

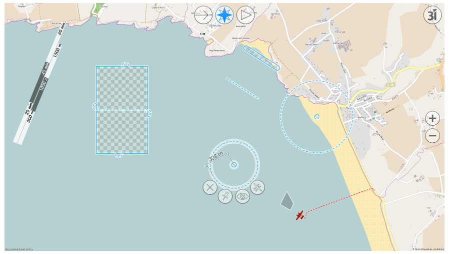

Figure 2: 3i tactile HMI display overview

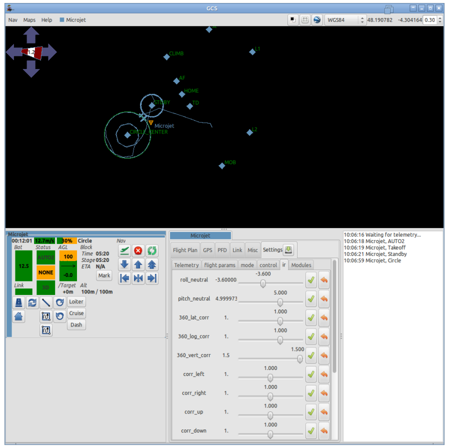

Figure 3: The paparazzi GCS display

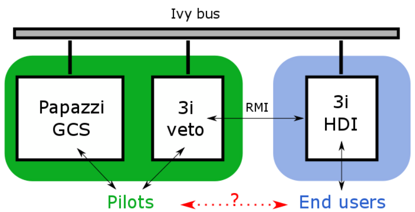

Figure 4: Architecture of the 3i UAS HDI

KEYWORDS

Human Drone Interaction, collaboration, end-users, pilots, usability

ACM Reference Format:

Mathieu Simonnet, Philippe Tanguy, Francois Legras, and Gilles Coppin. 2019. Tactile Human Drone Interface for End-Users and Qualified Pilots Collaboration. In . ACM, New York, NY, USA, 6 pages.

INTRODUCTION

Recently some studies focused on new ways to interact with drones [6], on how an operator could manage multiple Unmanned Aircraft Vehicules (UAV) at the same time [3] and on how multiple operators could collaborate to manage one drone to properly complete a common mission [7]. The 3i project focused on this third case where a team manage a unique UAV. It was an INTERREG project from 2012 to 2014 which aimed to set up a Unmanned Aircraft System (UAS) for maritime surveillance. The system is composed from a van (figure 1) included a tactile HDI (Human Drone Interaction) (figure 2), a Ground Control Station (GCS) (figure 3), a video display and a long range UAV. Although the project has already ended, interactions issues between humans, interfaces and the drone are still current.

The 3i tactile HDI runs computer using a touch screen for user interaction. It is a software designed to allow laymen operators, so-called the **end-users**, to manage UAV missions. More precisely, these end-users need to easily move a video camera in the air to complete observation missions. By this respect, it has to be done under the control of qualified experts, so-called the **pilots**, to deal with aviation regulation, weather constraints and technical capabilities of the UAV on flight. Thus 3i tactile HDI has been designed to provide the end-users with the option to easily draw flight primitives and then submit them to the pilots. These pilots actually used the paparazzi ground station (GCS) running on another computer to set up the flight plans and manage UAV behavior during missions [4]. The paparazzi GCS is where the pilot interact with the UAV. It provides feedback about UAV activity, allows command and control of the aircraft and has a method of override control for the system (https://wiki.paparazziuav.org/). In the 3i project, pilots accept or reject submitted maneuvers thanks to another component: the 3i Veto HDI. This organization raises at least 3 questions:

(1) Which UAS architecture can afford flexibility and safety for end-users / pilots interactions?
(2) Is the 3i HDI really more usable than the paparazzi GCS for the end-users?
(3) How communication between end-users and pilots could be enhanced?

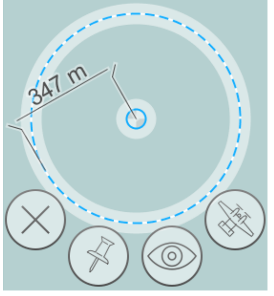

Figure 5: The circle maneuver

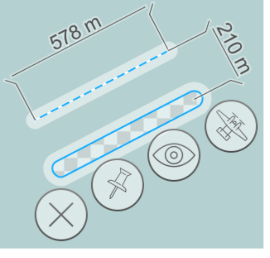

Figure 6: The line maneuver

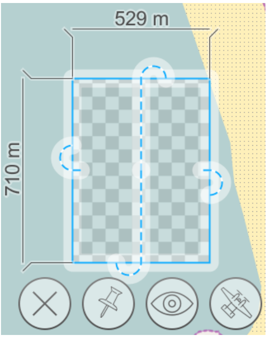

Figure 7: The box maneuver

THE UNMANNED AIRCRAFT SYSTEM

Interface

As mentioned above, two computers are involved in the communication between the 3i HDI and the Paparazzi GCS (figure 4).

- The computer 1 (in blue on the right in figure 4) is dedicated to the end-users. Here, they use the 32" touch screen and the 3i HDI to manipulate maps and submitted maneuvers.
- The computer 2 (in green on the left in figure 4) is dedicated to the pilots. Here they control the UAV with the paparazzi GCS and also receive new maneuvers the end-users submitted via the local network. These maneuvers are displayed on the Veto HDI and can be transmitted to paparazzi GCS id accepted.

An Ivy communication protocol put the 3i tactile Interface, the paparazzi GCS and the UAV in relation.

The main goal of the 3i HDI is the simplicity. Here, a non-specialist could plan and manage a flight mission by using this interface. When launched, the interface displayed a map in full screen (figure 2). On this map, user can switch between the 3 following modes within buttons.

(1) The **Map mode**. This is the default mode where it is possible to interact with the map: pan and zoom using the "plus" and "minus" buttons.
(2) The **Maneuver mode**. Here, the end-users can define maneuvers to be sent to Paparazzi. To differ from the previous display, a grid is shown on the map.
(3) The **Replay mode**. This mode is designed to control the video replay. When this mode is on, a time line appears at the bottom of the screen (https://videopress.com/v/TGtY9IfQ).

End-users maneuvers and interactions

To define a maneuver, end-users have to use the maneuver mode and draw on the map the point, the line or the area that they want to see with the camera. The system was designed to be "camera-centered" and not "drone-centered".

3 simple maneuvers can be used in the 3i HDI in the maneuver mode.

(1) The **circle maneuver**: The drone turned around the center. (figure 5)
(2) The **line maneuver**: The drone performs round trips on the defined line. (figure 6)
(3) The **box maneuver**: The drone performs round trips inside the defined area. The round trips can be defined as North-South or West-East (figure 7).

Each new maneuvers offers 4 buttons (figures 5,6,7).

(1) The **cross button** deletes the maneuver.
(2) The **pin button** stores a maneuver between two or mode sessions.

(3) The **eye button** shares the maneuver with the pilots. The maneuver appears on its own interface and a discussion can be performed with him: feasibility, modifications needed, etc.
(4) The **aircraft button** is nearly the same than the eye button - the maneuver is shared with the pilots - and an execution of the maneuver is asked. The maneuver can be accepted (the color becomes green) or rejected (red).

Veto HDI

The 3i Veto HDI is a very simple interface (even more than the main interface) dedicated to the pilots. Its main goal is to supervise maneuvers defined by the end-users on the main interface. The 3i Veto HDI display a map. At least, the following two use-cases do exist :

- In the first one, the end-users need the technical opinion from the pilot: feasibility, modifications needed, etc. This use-case is linked to the eye button in the main interface. The defined maneuver is sent and displayed on the 3i Veto with information about size (radius, length) and localization on the map. When a maneuver is shared, the screen is automatically centered on the maneuver. No action is needed, it is just information, both of them can discuss about this maneuver.
- In the second use case, the end-users want to execute a specific maneuver. As in the first use-case, the maneuver is sent to the 3i Veto HDI and displayed on it. In this case an action is expected from the pilots: acceptance or rejection of the maneuver. If the maneuver is accepted, it becomes green on the end-users HDI and red if it is rejected (figure 8).

If the maneuver is accepted, it is transmitted to the GCS running paparazzi (figure 3)

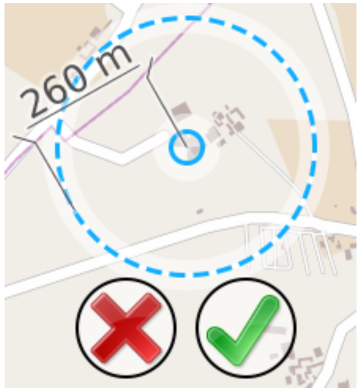

Figure 8: The veto HDI for pilots

USABILITY STUDY

In the usability study, we focused on 10 end-users. They performed a simple activity in simulation condition. They actually managed 3 maneuvers directly with the paparazzi system on the one hand, and with the 3i HDI on the other hand. We collected System Usability Scale (SUS) Scores [2]. The global overview showed that the 3i tactile HDI obtained an average of SUS scores about 86. This suggests a good user experience [1]. Here, Paparazzi only obtained 58. Analysis also revealed a statistically significant difference (Wilcoxon test, $V=55$ $p<.01$). More precisely, 9 users had a higher score than the SUS average (*i.e.* 68) using the new tactile 3i HDI whereas only 4 of them crossed this boundary using existing paparazzi GCS. This result is not surprising since Paparazzi GCS is designed for pilots, flight plans and technical aspects whereas HDI specifically targets end users. However, focusing on details, this experience is such an opportunity to better understand the features which still could be increased in HDI and paparazzi GCS. In order to better explain why 3i HDI was more usable, we tried to correlate SUS results with the remarks some users made during the tests.

Managing maps

Almost every user complained when they experienced zoom and pan actions in Paparazzi GCS. About zooming in paparazzi, map tiles were in a low resolution and force the users to zoom in and out often to understand the environment. About panning, map tiles did not refresh automatically in paparazzi. In comparison, the 3i map tiles were clearer and refreshed automatically very fast. This map management advantages in 3i HDI seemed to explain why the users found paparazzi more cumbersome than 3i. It appeared obvious that the experts would appreciate to get rid of these multiple actions to explore the environment features. Moreover, this would widely participate to improve the "situation awareness" which we recall "is the perception of environmental elements with respect to time and/or space" [5].

Creating maneuvers

Another critical function of this UAS was the maneuvers creation. Some users told they found tedious the Paparazzi procedure to do so. Indeed, using Paparazzi GCS, end-users had to first move the waypoints of the attempted maneuver. Each waypoint displacement required a confirmation in dialog box displaying coordinates. Then, even if the maneuver was not directly drawn on the map, they had to find the right block in the flight plan to launch the maneuver. To perform the same action in 3i HDI, users had to activate the maneuvers mode, draw the primitives (circle, line or box) which will be clearly drawn on the map and click on the button representing the UAV. This difference could explain why users answered that 3i HDI functions were better integrated than the paparazzi GCS ones. It is also possible that this procedure led end-users to answer that 3i HDI was less complex and required less things to learn. Thus, the two main functions: "managing maps" and "creating maneuvers" were perceived as more simple in 3i HDI and could explain why this new application provides the end-users with an HDI which seems more adapted to their needs.

Usability Limits

To conclude about HDI usability, it is important to recall that the task the users were asked to do was very simple and did not aim at using advanced features of paparazzi GCS or 3i HDI. Taking this into account, we mean that 3i HDI is more adapted to the end-users to complete simple tasks without any knowledge in UAV, but this does not mean that Paparazzi GCS does not work properly. The latest offers much more possibilities and is particularly suitable for UAV specialists (*i.e.* the pilots). Eventually, this study allowed end-users to suggest some perspectives to improve 3i HDI. The first remark was the automatic switch between the map mode and the control mode. To date, to create a maneuver, the user has to click the maneuvers button. As soon as the maneuver is drawn the HDI automatically switches back to the map mode. Certain users tried to draw a second maneuver without re-click on the maneuver button because they did not notice that the HMI state went back to the map mode. Although there is already a grid on the map to show that we are in the map mode, one suggestion was to make a bigger difference between the display in map and maneuver modes. Users suggested graphical animations and/or sounds to help to notice the automatic switch. They also suggested a sort of negative color when in maneuver mode.

END-USERS / PILOTS COLLABORATION PERSPECTIVES

To the question "Which UAS architecture can afford flexibility and safety for the end-users / pilots interactions?", it seems that the UAS composed of paparazzi GCS and the 3i HDI with the Veto is a suitable solution. It is at least technically robust and the link provided by the Veto ensures the end users to submit maneuvers under control. The remaining question is "How communication between end-users and pilots could be enhanced?" Indeed, although the end-users are able to submit different maneuvers to the pilots, some circumstances could imply temporal pressure or need higher precision's feed backs. In such cases, one could ask whether simple veto (*i.e.* "validating system") is enough to support efficient collective decision. In other words, should we encourage free "end-users/pilots" verbal discussions during missions? Or could crew take greater advantages from other interaction tricks? An interesting debate could be opened to try to position the cursor on the most legitimate level on a continuum between constraints and freedom for collaboration.

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Tactile Interaction of Human with Swarm of Nano-Quadrotors augmented with Adaptive Obstacle Avoidance

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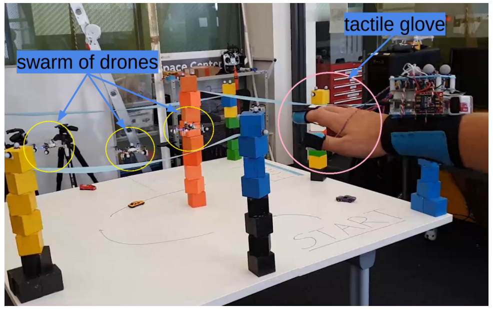

Figure 1: Swarm of three drones guided by a human operator through the labyrinth. Robots change their position according to a human hand movement.

ABSTRACT

This paper presents a human-robot interaction strategy to solve multiple agents path planning problem when a human operator guides a formation of quadrotors with impedance control and receives vibrotactile feedback. The proposed approach provides a solution based on a leader-followers architecture with a prescribed formation geometry that adapts dynamically to the environment and the operator. The presented approach takes into account the human hand velocity and changes the formation shape and dynamics accordingly using impedance interlinks simulated between quadrotors. The path generated by a human operator and impedance models is corrected with potential fields

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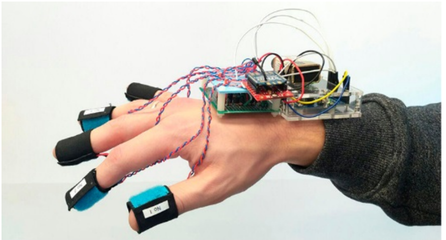

Figure 2: Wearable tactile display.

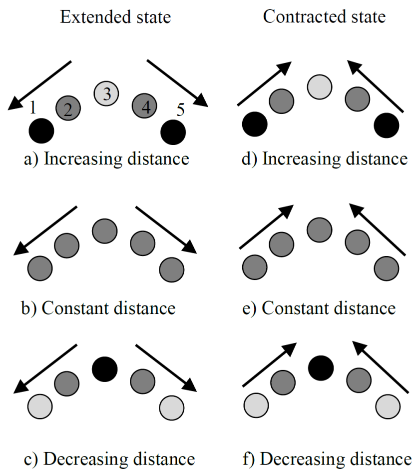

Figure 3: Tactile patterns for representing the state of the formation in terms of drone-to-drone distance and swarm displacement. Each circle represents the finger of a right hand (view from the dorsal side of the hand). The gray scale color represents the intensity of tactor vibration.

method that ensures robots trajectories to be collision-free, reshaping the geometry of the formation when required by environmental conditions (e.g. narrow passages). The tactile patterns representing the changing dynamics of the swarm are proposed. The user feels the state of the swarm at his fingertips and receives valuable information to improve the controllability of the complex formation. The proposed technology can potentially have a strong impact on the human-swarm interaction, providing a new level of intuitiveness and immersion into the swarm navigation.

CCS CONCEPTS

• **Human-centered computing → Laboratory experiments**; **Haptic devices**; • **Networks →** *Network design and planning algorithms.*

KEYWORDS

Human-robot interaction, tactile display, wearable computers, robot formation motion planning, impedance control, potential fields

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INTRODUCTION

Due to a wide range of applications (surveillance, cooperative mapping, etc), multi-agent formations have become one of the most interesting topics in robotic research. The main difficulty for robotic formations is to maintain a pose for each individual agent depending on the poses of other robots and obstacles with a common objective to reach the desired goal. For many kinds of missions, autonomous formation flight is suitable. However, for some specific applications, fully or partially guided group of robots is the only possible solution. The operation of swarm represents a significantly more complicated task as a human has to supervise several agents simultaneously, Fig. 1. In order for the human to work with the drone formation side by side, robust and natural interaction techniques have to be developed and implemented. Human-swarm interaction (HSI) combines many research topics, which are well described by authors in [1]. Here, we focus on the interface (control and feedback) between a human operator (leader) and a swarm of robots, addressing the nascent and dynamic field of HSI.

For the cases when the human is considered as a leader, standard control techniques have been developed in the last decades. Applications could include single robot-human interaction and multi robot-human interaction, both in the framework of centralized and decentralized architectures. A survey [4] shows some of the control approaches. To make human-swarm and human-environment

Percentage, %	Subject Response					
Actual pattern	*CD*	*CI*	*CC*	*ED*	*EI*	*EC*
Contracted state, Decreasing distance (CD)	**98.3**	0	0	0	1.7	0
Contracted state, Increasing distance (CI)	3.3	**86.7**	8.3	1.7	0	0
Contracted state, Constant distance (CC)	10.0	5.0	**85.0**	0	0	0
Extended state, Decreasing distance (ED)	1.7	0	0	**86.7**	0	11.7
Extended state, Increasing distance (EI)	3.3	3.3	0	8.3	**66.7**	18.3
Extended state, Constant distance (EC)	0	0	0	3.3	3.3	**93.3**

Figure 4: Confusion matrix for patterns recognition.

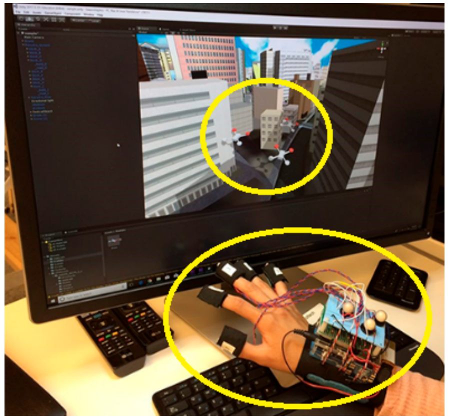


Figure 5: Swarm of drones controlled in virtual reality with the help of the tactile glove.

interaction natural and safe, we have developed impedance interlinks between the agents. In contrast to the traditional impedance control [6], we propose to calculate the external force, applied to the virtual mass of impedance model, in such a way that it is proportional to the human hand velocity. The impedance model generates the desirable trajectory which reacts to the human arm motion in a compliant manner, avoiding rapid acceleration and deceleration.

Changes in the current state of the formation have to be estimated by a human operator. The importance of this statement increases with the number of robots. Haptic feedback can improve the awareness of drone formation state, as reported in [3], [2], and [9]. S. Scheggi et al. [8] proposed the haptic bracelet with vibrotactile feedback to inform an operator about a feasible way to guide a group of mobile robots in terms of motion constraints. In contrast to the discussed works, this paper presents a vibrotactile glove for the interaction of the human with a swarm of aerial robots by providing an intuitive mapping of the formation status to the human finger pads.

In our previous work, [10], we have met the challenges of obstacle avoidance. In order to overcome this problem, the algorithm based on artificial potential fields [7] is proposed in this paper as a local robots trajectories planner.

SWARMGLOVE: VIBROTACTILE WEARABLE DISPLAY

The navigation of the robot with the help of a human operator is inherently a visual process: users identify robots' positions and obstacles through their visual appearance. However, this can get cumbersome and is not feasible in every situation. In particular, if the robot is outside of the user's field of view, occluded by other objects, visual feedback is not enough for reliable control, especially in a 3-dimensional environment, [5]. The main goal of the Vibrotactile Wearable Display usage is the augmentation of human awareness about robots positions and a map.

Tactile patterns

During swarm manipulation by the operator, the formation can change its shape, becoming contracted or extended relative to a predefined geometrical configuration. The state of the formation could be changed due to obstacle avoidance with potential fields or impedance interlinks as described in the lower sections. For such an adaptive formation which could reach dozens or even hundreds of robots, it could be challenging for the operator to estimate the dynamics of the whole fleet. That is why we designed the tactile display SwarmGlove, shown in Fig. 2, and tactile patterns, that could be seen in Fig. 3, for presenting the feeling of the swarm behavior at the operator's fingertips. The glove is equipped with five vibro-motors that become active when the formation shape is getting deformed. The inter-robots distance is presented by the gradient of the tactor vibration intensity (depicted by grayscale shade on Fig. 3). If the formation is extended, then side vibration motors have a higher

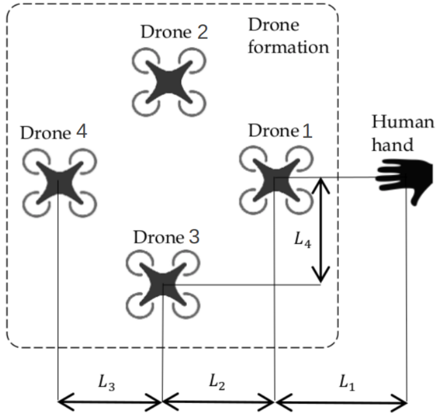


Figure 6: Formation of four drones controlled by a human operator.

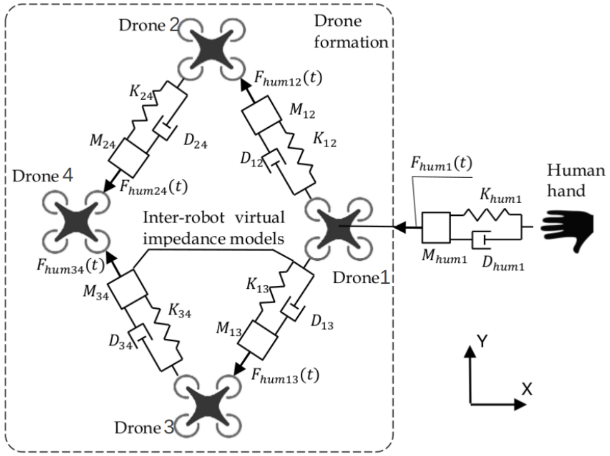


Figure 7: Position-based impedance control links between agents in four drones formation, and human operator and leader drone.

intensity than the middle one. The dynamic change of the distance between robots is presented by the tactile flow propagation, e.g., if the distance is increasing, the flow goes from the middle finger to the side ones (represented by arrows on the Fig. 3).

SwarmGlove experimental evaluation

The experiment was conducted to evaluate the detection of multi-modal patterns. The statistical analysis of the user study revealed the easiest to recognize patterns which were used during the flight evaluation of the tactile interactive display, [10]. The results of the experiment revealed that the mean percent of correct scores for each subject averaged over all six patterns ranged from 78.3 to 96.7 percent, with an over-all group mean of 86.1 percent of correct answers (Fig. 4). The ANOVA results showed a statistically significant difference in the recognition of different patterns ($F(5, 30) = 3.09, p = 0.023 < 0.05$).

During the flight experiments, we used SwarmGlove to deliver the information about the contracted or extended state of the swarm and about the displacement of the formation center of mass. We asked the users to smoothly guide the formation throughout the set of obstacles trying to keep the prescribed shape of swarm using one of two types of feedback: visual and tactile. The results demonstrated that it is possible to navigate the swarm of drones in a cluttered environment using only tactile feedback with low degradation in the quality of navigation. For example, the mean area error (which is defined as default area subtracted with the current area of the formation) for the tactile feedback was 0.01 m^2, while for the visual feedback it was 0.007 m^2.

FORMATION CONTROL

Formation of drones repeats glove trajectory with a spatial scale while being guided by a human operator. Robots' trajectories are also corrected with impedance control technique and an obstacle avoidance algorithm.

Impedance control of the leader-based swarm

To implement the adaptive manipulation of a robotic group by a human operator, such as when the inter-robot distances and formation dynamics change in accordance with the operator state, we propose a position-based impedance control. Mass-spring-damper link between an operator and formation leader (drone 1) is introduced as shown in Fig. 7. External force, applied to the virtual mass of the leader drone, is calculated in such a way that it is proportional to the operator hand velocity. While the operator is guiding the formation in space, impedance models update the goal positions for each flying robot, which changes default drone-to-drone distances. As a result, the operator pushes or pulls virtual masses of inter-robot impedance models, which allows the shape and dynamics of the

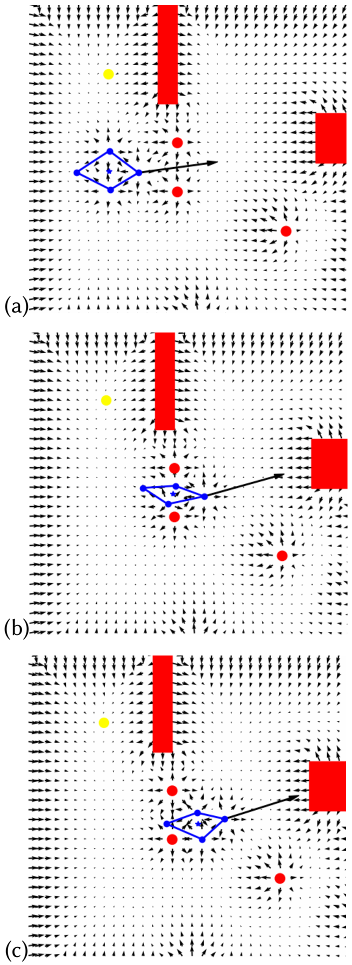


Figure 8: Four robots formation guided through a narrow passage. Potential field map is depicted on each figure (a)-(c) for the left-most drone. A long arrow represents the leader's movement direction.

robotic group to be adaptive in accordance with the human hand movement. In order to calculate the impedance correction term for the robots' goal positions, we have to solve a second-order differential equation (1) that represents the impedance model. Similar equations are solved for each involved pairs of agents as well as for each dimensional axis.

$$M\ddot{\vec{p}}_{imp} + D\dot{\vec{p}}_{imp} + K\vec{p}_{imp} = \vec{F}_v(t), \tag{1}$$

where $\vec{F}_v(t) = K_v\vec{V}_{human}(t)$ is a virtual force, proportional to swarm operator's hand velocity, denoted as $\vec{V}_{human}$, K_v is a scaling coefficient, which determines the effect of the human operator velocity on the formation. The method described above is used to calculate the impedance correction vector, $\vec{p}_{imp} = [x_{imp}, y_{imp}, z_{imp}]^T$, for the current position of the virtual body of each impedance model. The main goal of the proposed impedance control-based model is to make drones trajectories smooth, introducing a delay between the human hand commanded setpoints and robots response. For the case of four controlled drones in the swarm, their goal positions along X, Y, and Z-axis are determined as follows (see the structure presented in Fig. 6, 7):

$$\begin{bmatrix} x_{1\_g} \\ x_{2\_g} \\ x_{3\_g} \\ x_{4\_g} \end{bmatrix} = scale \begin{bmatrix} \Delta x_{hum} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} x_1 \\ x_1 - L_{12} \\ x_1 - L_{13} \\ \frac{x_2+x_3}{2} - L_{34} \end{bmatrix} - \begin{bmatrix} |x_{imp\_hum1}| \\ |x_{imp\_12}| \\ |x_{imp\_13}| \\ |x_{imp\_24} + x_{imp\_34}| \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} y_{1\_g} \\ y_{2\_g} \\ y_{3\_g} \\ y_{4\_g} \end{bmatrix} = scale \begin{bmatrix} \Delta y_{hum} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} y_1 \\ y_1 + H_{12} \\ y_1 - H_{13} \\ \frac{y_2+y_3}{2} \end{bmatrix} + \begin{bmatrix} y_{imp\_hum1} \\ y_{imp\_12} \\ y_{imp\_13} \\ y_{imp\_24} + y_{imp\_34} \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} z_{1\_g} \\ z_{2\_g} \\ z_{3\_g} \\ z_{4\_g} \end{bmatrix} = scale \begin{bmatrix} \Delta z_{hum} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} z_1 \\ z_1 \\ z_1 \\ \frac{z_2+z_3}{2} \end{bmatrix} + \begin{bmatrix} z_{imp\_hum1} \\ z_{imp\_12} \\ z_{imp\_13} \\ z_{imp\_24} + z_{imp\_34} \end{bmatrix} \tag{4}$$

where x_{imp_ij}, y_{imp_ij}, and z_{imp_ij} for $i, j = hum, 1, 2, 3, 4$ are corresponding impedance correction terms, L_{ij} for $i, j = 1, 2, 3, 4$ are displacements for the quadrotors, as could be seen in Fig. 6, and x_i, y_i, z_i for $i = 1, 2, 3, 4$ are the actual positions of UAVs. Equations 2 to 4 consist of three parts. The first part is simply a spacial mapping with the coefficient *scale* between the human position and the formation leader (drone 1) motion, where the values $\Delta x_{hum}, \Delta y_{hum}, \Delta z_{hum}$ denote, how far the human moved his/her hand from an initial position along each Cartesian axis. The second determines the default geometrical shape of the formation (rhomb which is placed in XY-plane in our case), and

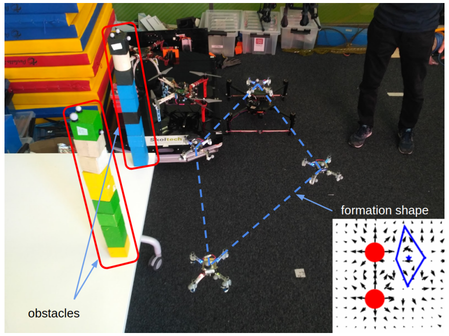
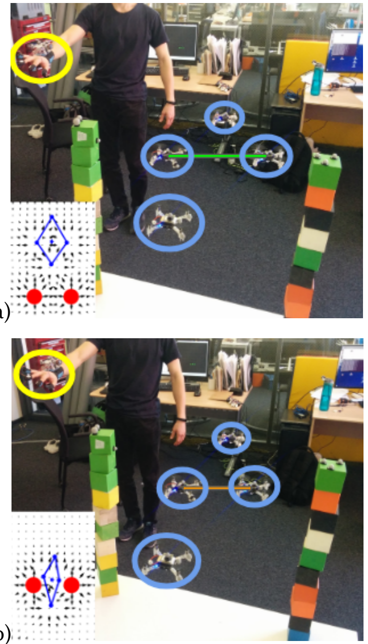


Figure 9: Change of the swarm formation shape due to the presence of obstacles.



(a)

(b)

Figure 10: Four drones adaptive formation guided through the passage.

the third describes the impedance interlinks between the agents. The impedance control part of the equations could be designed separately, following the specific application needs. In particular, when the formation is moving fast, we want the drones to always split apart in the negative direction of X axis (from the human), that is why we subtract the absolute values of impedance terms in (2). On the other hand, considering motion in Y and Z axis, the formation has to be shifted in different directions, with respect to the human motion.

Potential fields-based obstacle avoidance

The basic idea of potential fields-based obstacle avoidance algorithm is to construct a smooth function over the extent of robot's configuration space which has high values when the robot is near to an obstacle and lower values when it is further away. This function should have its the lowest value at the desired goal location and its value should increase while moving to configurations that are further away. Ones such a function is constructed, its gradient can be used to guide the robot to the desired configuration [7]. In our case of the human-guided swarm, a point of attraction (desired location) for every drone is defined relative to the leader-drone position with prescribed formation shape. Each robot and obstacle on the known map possesses its own local potential which contributes to the global field. These artificial potentials define interaction forces between neighboring robots and obstacles. Fig. 8 represents four drones formation (blue connected circles) movement through the passage defined by two static obstacles (red circles). Obstacles map is depicted in red, while small black arrows represent here the gradient map for the left-most robot. The algorithm tracks static as well as dynamic obstacles (other drones in the formation).

In the implementation phase, the centralized control approach was used. In this case, one main computer receives all the information through sensors and communicates the decisions directly to the robots. A motion capture system was used to track the drones forming a swarm. Four drones swarm guided through a passage between two static obstacles is depicted in Fig. 10. It can be noticed, that formation adopts its shape in order to avoid collisions, Fig. 9, Fig. 10(b), and drones do not fly too close to obstacles.

CONCLUSION

A novel system has been proposed, which integrates impedance control, potential fields and tactile glove for intuitive and effective swarm control by an operator. The impedance links between agents and adaptive obstacle avoidance algorithm allow the swarm to not only execute safe trajectories but also to exhibit a life-like behavior. We also designed the tactile patterns for the glove and conducted experiments to reveal more distinguishable ones. The possible application of the proposed system is the navigation of swarm in the city with skyscrapers (Fig. 5) and for rescue operations.

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TrayDrone – A Flying Helping Companion for in-situ Payload Delivery in the Smart Home

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ABSTRACT

The vision of using drones for instant delivery is not very far out anymore. Press releases from companies like Amazon are already suggesting that this technology will re-define the last hop of delivery to end users. This paper explores this concept in a much smaller scale: The use of a flying tray for micro payload deliveries in the context of the smart home, in particular the kitchen. We built a custom made drone that carries a roundly shaped tray that can carry up to 1 kg payload. In this paper, we share our experience of deploying our TrayDrone prototype in a kitchen booth at an international kitchen fair. Our findings underline the convenience of TrayDrone but also identify issues that need improvement.

KEYWORDS

Human-Drone Interaction; delivery drone; smart home; voice-user interaction

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Figure 1: TrayDrone is carrying a box to be delivered to the user in a smart kitchen environment.

INTRODUCTION AND BACKGROUND

As voice assistants enter more and more households the idea comes easily to mind to have new types of actuators nearby that receive commands and do something for you. Either for convenience reasons or to create special experiences in your current context. E.g. a user sits on the couch reading a book feeling too lazy to go to the storage room to get a can of juice. Why not saying "Alexa, bring me a can of juice!". And shortly after, the juice can is brought to you without any person having to do something. This may be a situation where the TrayDrone as a helping companion in a user's smart home sounds plausible.

Regarding the interaction with such a flying companion for a smart home, we decided to use a voice assistant (as most smart home devices do today). Interacting with a drone by voice, on the first glance seems like an impossible endeavor as the rotors create a very loud sound already. However, Fernández et al. [4] are using voice commands for interacting with a drone. While Wang et al. [11] equip a drone with microphones to filter rotor noises out, they can follow a person that is speaking with a drone – although the drone creates noise. Landau and van Delen [8] even enable positioning a drone using voice commands.

While Human-Drone Interaction [5] is becoming more prominent [3] for directly interacting with a user - most projects in the HCI community focused on either equipping a drone with a projector [2, 7] or a display [9, 10]. Using drones as a device for delivering micro payloads in a smart home context is yet underexplored. We build on research that suggests using drones as a companion for the smart home. E.g. Karjalainen et al. [6] suggest a friendly design for a smart companion drone. Most prominently, Agrawal et al. [1] suggested building drones into pieces of furniture to provide them on demand in a smart-home environment for delivering a desk or a lamp when it is needed.

While some concepts of always available delivery drones have been already introduced (e.g. JerkyBot[1]), we specifically developed TrayDrone to be a micro payload delivery drone that is used in a voice controlled smart home.

THE TRAYDRONE SYSTEM

In order to build the TrayDrone we collaborated with a Drone-Design company named Artfantasie. They created the mechanical design for us, manufactured the device, integrated the electronic parts as well as the flight controller. The drone comes with designed protectors for protecting the users and the environment from the drone's blades in case of a collision or crash. The flight controller is programmed in such a way, that even when bumping into a cupboard the TrayDrone will automatically bounce back and keeps flying. The tray itself has an air permeable honeycomb design in order to allow maximum air circulation (Figure 2) and measures a diameter of approx. 40 cm. The tray is positioned 10 cm above the rotors in order to allow adequate air flow even in cases when the tray may be completely covered with payload.

[1]JerkyBot: http://www.shendrones.com/jerkybot/
(last accessed 02-20-2019)

Figure 3: TrayDrone passing the drone-sluice.

Figure 2: The design of our TrayDrone uses a tray that is designed after an air permeable honeycomb design. Further it comes with designed protectors for protecting the users and the environment from the drone’s blades.

Figure 4 TrayDrone landed on kitchen table.

EVALUATING TRAYDRONE INTEGRATION IN A SMART HOME

For evaluating TrayDrone, we integrated our prototype in a smart kitchen environment that is voice controlled. The purpose of this proof-of-concept study was to let people experience the TrayDrone flights live. Both interpretation and reaction to voice commands and drone control was done by a study assistant that acted as a Wizard-of-Oz.

We presented the following scenarios to passersby that were interested in interacting with TrayDrone:

At a kitchen fair, our industrial partner had a complete kitchen room with fully furbished kitchen furniture. Large glass doors on one side of the kitchen prevented other visitors to enter the kitchen during the flight of the TrayDrone. On one side of the kitchen-wall, we built an automatic sluice door with a size of 120 cm in height and 120 cm width (see open drone-sluice in Figure 3).

Procedure: After our protagonist - who was standing inside the kitchen - said the words: *"Alexa, bring me my food package"* the sluice door opened and the TrayDrone entered the Kitchen flying through the kitchen room toward the kitchen table and smoothly landed on it (see Figure 3 and Figure 4). While the rotors were moving slowly the protagonist took the food package off the TrayDrone. The package included a box of noodles, salad an apple and some potato chips. Shortly after, the drone left the kitchen through the drone-sluice door into a dark room that was built next to the kitchen and landed on a table there. After that the drone-sluice door closed automatically (Figure 6). Due to the darkness of the room visitors could not look inside where the drone pilot was positioned and could not see where he always newly loaded the TrayDrone before it took off for the next flight.

The drone pilot was able to oversee the entire flight with his own eyes as he had to be able to maneuver the drone quite accurately and thus be able to react instantly if the drone would get out of control. During the day, we performed several TrayDrone-flights where approx. 50-60 spectators kept standing each time in front of the kitchen-showroom. We changed the payload flight by flight. Beside the food package, we delivered apples, vegetables, coke cans, pizza slices, and flowers (see Figure 5). A video of the TrayDrone in action can be found on Youtube (https://youtu.be/DbN02-532gk)

Figure 5 Various TrayDrone loads that we used during our proof-of-concept study where we integrated TrayDrone in a smart-home scenario.

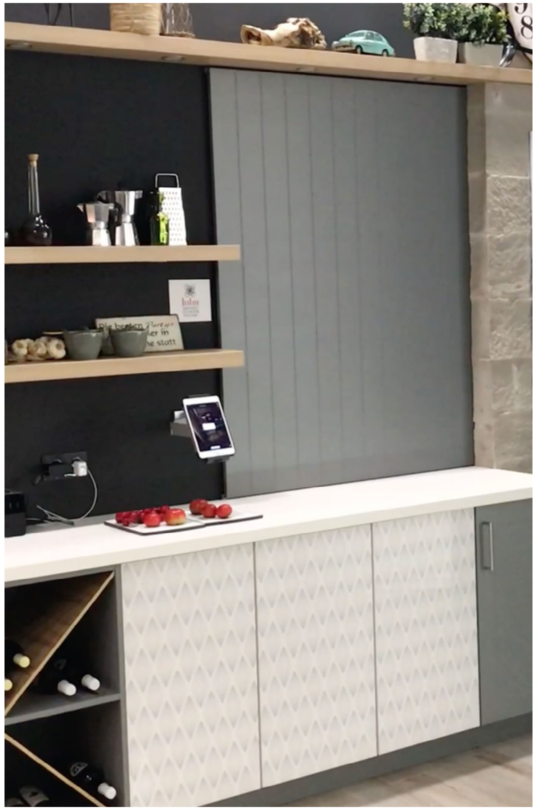

Figure 5 closed grey wooden drone-sluice

User statements:

Most visitors that saw the TrayDrone delivery live where stunned by the experience, telling that now the concept of delivery drones has become much more realistic and prominent in their own mind. However the big noise of the drone causes unease and may reduce the chances of deployability of such a drone system inside the house for everyday situations. However some elderly men stated that telling *„Alexa, bring me a beer“* sounds intriguing – but could become a reality.

Problems that we encountered during the experiment:

Strong air circulations. A drone of the size as we deployed creates a lot of wind due to strong air circulation caused by the drone’s rotors. This mean in the kitchen all things standing around needed to be heavy enough to keep standing and all other things needed to be kind of fixed. In a real household as we know it until today, this is not the normal case and pose problems to a clean and order kept kitchen.

Obstacles. Obstacles in the kitchen can cause air cushion changes that affect the stability of the drone path. E.g. if the drone came near the kitchen table, the wind circulation under the drone changed thus the rotors had to bring different lifting power to the drone. This brings different kind of requirements to the drone’s flight control system as compared to outdoor flights.

Staying in the same room. Not only a rather loud noise of the TrayDrone is a problem, but also the chance to collide with a TrayDrone is seen as a risk.

RESULTS AND DISCUSSION

Autonomous flight. In order to make TrayDrone more usable it must be able to fly autonomous. Thus an indoor navigation system needs to be available in the house that delivers highly accurate position data in real time with high frequency. That system should be installable with limited efforts and should blend into the kitchen environment.

Loading the drone. In contrast to our showcase where we manually loaded the TrayDrone by hand, an automatized system would be sensible. This could be a robot with grasping arms that fetches things from a shelf or table and lays them on the TrayDrone once the tray comes close. Another idea could be many readily loaded trays that are stationed in a storage room in such a way that the drone can fly underneath and by lifting it picks up the tray and flies to the destination.

Battery size and weight. As flight time of one TrayDrone delivery cycle may typically be short in the smart-home context (in our fair scenario it was maximum 1 minute), the battery can be kept at minimum size in order to reduce the total weight of a TrayDrone system – thus allowing more payload compared to delivery drones used for longer distances outdoors.

CONCLUSION

In this paper, we presented TrayDrone, a drone for delivering micro payload in a smart home environment. Through a proof-of-concept study at a booth of a trading fair, we elicited first reactions of passersby when seeing our system in action. Further, we identified benefits and challenges regarding using a drone in an indoor environment in a smart-home context.

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Understanding the Socio-Technical Impact of Automated (Aerial) Vehicles on Casual Bystanders

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ABSTRACT

Automated vehicles are coming to our streets and into our air. These automated vehicles are not acting as fully independent entities but are embedded into our social space and are affecting humans with which they interact. Recent advances are looking at the direct cooperation of human and machine in concrete interaction scenes such as steering a semi-automated drone or interacting with an automated car as a pedestrian. What we do not understand yet, is the reaction of automated systems on individuals that are casual bystanders of the automated systems. Cooperation and social acceptance of the casual bystanders are crucial in many situations. Affects such as irritation, anxiety or frustration may be easily invoked by the automated object. We need to anticipate effects on bystanders and include this into the interaction design space.

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Figure 1: Person interacting with a drone showing it to move sideways.

Figure 2: Person interacting with automated vehicles in a VR Simulation - interacting with an automated vehicle to indicate it should give way.

CCS CONCEPTS

• **Human-centered computing** → **Interaction paradigms**.

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INTRODUCTION

Understanding an automated vehicle is challenging and can cause negative side effects, such as anxiety or frustration. Because today's automated vehicles omit the human side of person-to-person communication: when communicating with an automated vehicle, users and bystanders cannot rely on established practices as in communicating with other individuals. While the automated vehicles of today are being designed to work properly, robustly and safely, they do not yet act socially. Two humans that can see each other, such as a pedestrian and a driver, still use many subtle cues to cooperate and indicate each others intention. This may not be true for a full automated vehicle in cooperation with a pedestrian, who may not understand it, not trust it, or just be surprised by the automated vehicles' behavior. Similarly, drones might distract or surprise bystanders and even cause anxious behavior, as when a drone approaches a person that is not expecting it and cannot understand the intention of the drone.

We propose that a systematic exploration of the design space is needed for automated vehicles. This includes their appearance and actions to communicate intent to casual bystanders in everyday situations and increase cooperative, prosocial behavior. We hypothesize that bystanders and affected persons not only need to recognize the automated vehicle but clearly understand its intentions and upcoming actions to increase social acceptability and successful cooperation.

STATE OF THE ART

The interaction between humans and drones is a field in its beginning. Nevertheless, drones are more and more becoming automated (aerial) vehicles. We are convinced that the work on interaction between other types of automated vehicles and pedestrians and other traffic participants will be inspiring and supporting for the work on human-drone interaction. Research and industry are already making first proposals and showcase concept studies of communicating with bystanders to inform them and to keep them in the loop. In consequence it is timely and topical to conduct research on the effect of (automated) drones on casual (human) bystanders.

Rothenbücher et al. [26] developed a Wizard-of-Oz technique for investigating the interaction between automated vehicle and traffic participants (or bystanders) by hiding the actual driver (the "Wizard") of the car. They considered how pedestrians interacted with the car at crossings in the

Stanford University Campus and found that most pedestrians were able to decide whether to cross the road or not without explicit communication, but also that it remains relevant to acknowledge that a pedestrian was noticed. However, this was a first experiment in a confined campus setting where people are expectedly open to technological innovations and with less of a surprising effect than in a narrow urban road scenario in Europe. Similarly, Petterson et al. [23, 24] report on explorations of social situations between (seemingly) autonomous cars and pedestrians using similar techniques where the actual driver was hidden behind a cover resembling a car seat (c.f., Habibovic et al. [14]). They uncovered two-fold, specific information needs: information the pedestrian may need from the autonomous vehicle in certain situations, and vice versa. Chang et al. [8] equipped cars in Virtual Reality (VR) with eyes to help pedestrians assessing if they were acknowledged. Their experiment showed that pedestrians made quicker decisions and felt safer when they could see where the car is "looking". Mahadevan et al. [19] explored possible interfaces and designs for explicit vehicle-pedestrian communication and tested them with an equipped car and a Segway. They could show that explicit signals help pedestrians to make faster decisions. While reviewing, relevant literature shows that research towards cues and signaling of automated vehicles exists, there are still no common communication strategies or even standardized designs. Also, current research focuses on functional traffic interaction such as crossing a road but does not necessarily investigate how cues need to be designed for prosocial behavior and inclusion of effects on casual bystanders.

The social acceptability of drones as guidance vehicles for navigating persons with visual impairments has been explored by Avila Soto et al. [1]. They investigated both, the (visually impaired) user's perspective, and the perspective of (sighted) casual bystanders, and note that knowledge about the purpose, functioning, and benefits of the guidance drone are relevant for social acceptability. However, they did not elaborate on autonomous behavior of the drone and on how the drone interface might communicate its intent. Communication of usage purpose and intention has been explored in the area of body-worn cameras [18]. In this context, design strategies including physicality, signaling, as well as transfer of control have been explored to create a sense of situational awareness for the bystander, and justification on the device user's side. The authors also explored how bystanders can take over control by using gestures to explicitly express consent (Opt-in) or disapproval (Opt-out) with being recorded by a body-worn camera [17]. Similar technologies could be used for drones when people might want to use explicit consent to be recorded or not.

In our own previous work, we have been designing and evaluating multimodal interfaces that form the foundation for communicating information about upcoming tasks and objects in pervasive spaces by multimodal cues. We systematically explored different sensor modalities in pervasive user interfaces: light-based interfaces [20], projection-based interfaces [4], auditory interfaces [16], and haptics and vibro-tactile interfaces [5, 25, 27]. For many years now, we explored assistance systems with increasing levels of automation. We studied the effect of multimodal cueing for situation awareness and spatial awareness in supervisory tasks [10] and attention shifting to other work tasks [21]. We studied how wearable technology can give feedback on biosignals using visual, audio, and haptic modalities [11]. We have been designing multimodal cues for take over in highly automated driving [2] and priming individual with information about the upcoming task after taking over [3]. In recent work, we investigated how we can shift attention in larger cyber-physical system and environments to (automated) objects that are currently out of view [13, 28].

To date, research on human-drone interaction has aimed to communicate the intent of a drone, such as using LEDs around a quadcopter to communicate direction [30] or modifying the drone's flight path, using techniques such as arcing, to communicate directional intent [29]. We find that several works that looked at the adequacy of multimodal interaction with drones [6], or how drones might convey information about themselves. As one example, Cauchard et al. [7] modified the flight path of the drone to communicate the drone's emotions. However, none of this work investigated the automation level of the drone and how it could handover control to passersby or provide the option to listen to their command. As with autonomous cars, the technology's current level of automation for a task is not conveyed to passersby. It is crucial for the autonomous vehicles to become more transparent so that they can be accepted into our environments. In order to explore concepts and interaction designs, this research can be inspired by different levels of simulation of automated situations which enables us to obtain higher levels of mundane realism [23], to evaluate designs for interaction with automated vehicles in different traffic scenarios.

PROSOCIAL BEHAVIORS IN HUMAN-AUTONOMOUS VEHICLE COMMUNICATION

So far, research and industry has shown interesting prototypes and design concepts of such displays outside the vehicle. However, commercial products coming with a standard set of communication patterns have not been developed. Here, the industry has not yet demonstrated a clear understanding of a cooperative and understanding interaction between automated vehicles and individual bystanders. To better understand the impact of the role of bystanders for the design of automated (aerial) vehicles for acceptance and cooperation of automated vehicles with casual bystanders we need to understand how an automated (aerial) vehicle and its goals can be recognized and understood. We need to design for prosocial behavior with the automated vehicle and how cues and signals of the automated vehicles can support cooperative behavior and communication with bystanders. We identify three core aspects of that form the basis for a successful interaction between an automated vehicle and bystander(s):

Situational Awareness (SA)

One aspect is the Situation Awareness of the automated vehicle by the bystander. We are following Endsley's well established notion of Situation Awareness [9], in which SA comprises the perception of the objects in the environment, understanding their behaviour and the individuals' projection of future states and events. We propose that the following questions need to be answered to understand which cues and signals issued by the automated vehicle are good prerequisites to increase the situation awareness of the vehicle:

- How to make the bystander aware of the automated (aerial) vehicle?
- How to allow the bystander to identify whether a present automated (aerial) vehicle is affecting her/him?
- How can one tell what the automated (aerial) vehicle does and for what purpose and by whom?

Affordance

Based on the longstanding knowledge from the field of human computer interaction, we know that interaction is more successful and satisfying if the object of interaction offers affordance on how to interact with it [22]. As an attribute of interaction design, an affordance is a feature that is offered to the user, what the interaction design provides or furnishes [12]. We want to understand what kind of physical (real) affordance, cognitive (perceived) affordance, and functional affordance [15] the automated vehicle can offer to the bystander, such that it easily reveals its functions and actions. With such an affordance concept, the bystander can understand if and how they may be able to interact with the automated (aerial) vehicle such as allowing it to come closer or to stop.

- Do the automated (aerial) vehicle’s features help the bystander to understand what it does/and provides?
- Does the automated (aerial) vehicle reveal if it is ready to receive inputs and if a bystander may interact with it?
- Does the automated (aerial) vehicle offer functions to interact with it?

Conversation

The interaction with an automated vehicle might not be a one-shot or uni-directional interaction, but rather an actual negotiation between an individual and an automated (aerial) vehicle. For example, in the case of a car, the determination of who will go first and decide that the individual may interfere and signal a decision (c.f., Figure 2). In the case of a drone, the person may want to tell the drone that they do not want to appear in recorded footage, provide instructions for guidance and navigation aids, or acknowledge receipt of a delivery.

- How does the automated (aerial) vehicle get into a conversation with a bystander?
- How can the bystander ask and get explanations on the intentions and actions of an automated (aerial) vehicle?
- How to interact with the automated (aerial) vehicle such as asking it to come closer?

Key Factors

We hypothesize that are three key factors that are core to such communication aspects for moving automated vehicles, such as cars and drones, as described above. These core factors, that we envision to be addressed by future research are:

(1) Physicality. The device itself may have a form, shape and (aesthetic) appearance that is self-explaining its functions and potential actions. What role does the shape of the device play for the acceptance of the automated devices' actions? Can the intended function already be encoded in the appearance?
(2) Signaling. Beyond the actual appearance, the device can use integrated and added displays to signal its behavior to the bystander. It needs to be further investigated what and how should it signal with visual and auditory displays?
(3) Movements. As the automated vehicle is moving, it is in demand to better understand how to express cooperative behavior with movements. How should such vehicles approach a person to express intent of communication?

CONCLUSION

HCI research with autonomous devices is still in its early stages. Autonomous cars are increasingly being studied and have an obvious widespread reach as we saw companies like Uber using autonomous taxis driving passengers from 2016 to 2018. On the other hand, drones are just reaching the point of technological maturity for them to interact with people. We posit that the research done in autonomous devices can be designed with similar methodologies for cars and drones. In particular, we show the importance of including methodologies taking in consideration passerby and not only designated users. This will be crucial for the technology to become acceptable to all.

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"Come To Me Nice Butterfly" Drone Form in Collocated HDI

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Figure 1: artist's rendition of drone form in collocated HDI (sketches courtesy of *Norm*)

ABSTRACT

Recent human-drone interaction (HDI) research is shifting away from the remote-control paradigm and increasingly exploring collocated interaction between people and drones. We are interested in intimate aspects of this new design space: in collocated interaction that affords tactile interaction and emotive touch. In this position paper, we briefly motivate emotive collocated HDI, present preliminary design ideation, and propose a research outline for further exploration using immersive collocated HDI simulations.

KEYWORDS

collocated human-drone interaction, natural interfaces, intimate interaction with drones

INTRODUCTION

Humans have an established set of interactions with volant (flying and gliding) animals, which has previously inspired human-drone interaction (HDI) design [3]. A small subset of these includes collocated interactions, for examples, dealing with flying insects, petting bats, or falconeering. With

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"Come to me, nice butterfly.
Sit with me,
in the palm of my hand.
Sit, rest, don't fear.
and fly away again."

From: "Come to Me Nice Butterfly", by Fania Bergstein (translated from Hebrew [6])

Figure 2: From the cover of Fania Bergstein's "Come to Me Nice Butterfly" [6]

few exceptions, collocated interaction between people and flying animals is awkward, bothersome, and undesirable. On the other hand, cultural context can provide positive perspective, for example when interacting with pet birds [5], butterflies (Figure 2, [6]), or fairies.

We expect collocated HDI to emerge in both domestic and work environments, for functional uses, such as delivery of goods, or search-and rescue, and for fun and leisure, such as in photo and videography. When considering this new design space we see the realistic negative context of interacting with volant animals as a design challenge, and turn to the much more positive, and unrealistic, cultural contexts for inspiration. We envision future drones that will share space with people, providing functionality and playing social, emotive and intimate roles, taking physical forms that convey positive relationship, inspired by cultural contexts (Figure 1).

Such interactions are often seen in the popular culture, in movies and anime. For example, in Grave of the Fireflies [7], we see the main character, within a cloud of fireflies, trying to catch and hold them, later using the fireflies for light when needed. We envision similar behaviors with swarms of drones, where people could catch one in their hand before releasing it to the swarm.

Our vision is hindered by the current technical boundaries of flying machines. Drone technology, while advancing by leaps and bounds, still accounts for entities that become smaller in size but are still noisy, mechanical looking, and even dangerous. In order to explore the benefits and limitations of intimate collocated interaction with drones we propose the use of immersive simulations, and argue that the first challenge should be the exploration of drone form. In the following sections we provide a brief reflection on the state of the art of collocated HDI, describe our current low-fidelity ideation, present an exploration methodology and our proposal for an immersive simulation testbed.

RELATED WORK

Prior work on interaction with small-sized drones explored control mechanisms for collocated interactions including voice [8,9], gestures [2,3,10,11,12], gaze [13], and touch [4, 14]. Several feedback mechanisms have been proposed such as using a screen, a projector, or using the flight path to convey affect and emotions [1, 15]. Affect and emotion have been specifically investigated as a first step towards integrating drones into humans' social environments. In their preliminary results, Arroyo et al. [15] show that different emotional states can be recognized and suggest that HDI can be improved if the drone conveys different emotional states. Cauchard, et al. [1] explored how a drone's emotions could be conveyed through different behaviors and flying paths. They showed that people can accurately associate emotional states to a drone. Recently, researchers have been working towards design guidelines for social drones suitable for interaction and companionship. Kim et al.'s ideal companion drone [16] presents "adorability" features. Yeh et al. [17] proposed a blue oval shaped drone and discussed how a tablet can be used to display a "friendly face". Karjalainen et. al. [18] investigated several features and found that emotional characteristics were desirable, and they also suggest that the drone appearance should be a round shape with a face. The above literature shows that appearance and behavior is a central aspect of designing social drones intended to interact with people. We propose an investigation of this new HDI design space by liberally exploring unrealistic cultural contexts of interaction with collocated flying entities. We further suggest that this early design exploration should be unhindered by current drone technology, and instead conducted first within immersive simulations.

EXPLORING FORM IN IMMERSIVE COLLOCATED HDI

We are planning to design and implement a collocated HDI immersive simulator that would allow users to perform various simple tasks while interacting with a collocated drone. The simulator will be implemented in VR, though an AR iteration is also possible. The simulator will include 3D visual features relating to the drone, the setting (e.g. domestic environment, or a workplace) and the task. The testbed will include haptic feedback supporting intimate interactions: touching the drone, sensing its landing on a palm or taking off (note that others proposed the use of physical drones to provide such haptic feedback [20,21]), and possibly synchronized air flow device (e.g. fan [19]), enabling sensation of the drone rotors in proximity. The simulator will allow iteration of various collocated HDI form and behavior approaches, ranging from interaction with drones that look, for example, like butterflies, fairies, and birds (see Figure 1 for artist renditions of some of our current design ideas). The drones rendered in the simulator can take a range of forms, rendered as naïve entities, or as mechanical looking and moving flying machines. The simulator will support different drone behavior and varying flight characteristics (speed, acceleration and jerk) and proxemics behaviors. The simulator will support single drone as well as a group of drones moving individually or as a flock or swarm. The simulated drones will be sensitive to the user's pose and gestures, as well as their voice and gaze. The testbed will also allow the simulated drones to express themselves, using body and wings gestures, gaze, "facial" expression, chirping, and voice.

LIMITATIONS

Our proposed collocated HDI simulator stops short of practical reflections on the many potential technical limitations and bottlenecks derived from some of our design ideas. Implementing drones for collocated interaction is a hard technical challenge, and it is questionable how many of our simulated design ideas could be scaled to the physical realm and implemented as collocated drones, in the short-term.

CONCLUSION

Realistic interaction between people and collocated volant animals is very limited at best, and undesirable in most practical cases. However, collocated interaction with flying entities in cultural contexts, in literature, film, media and the arts, while often unrealistic, can be quite positive. We suggest an exploration of the realm of purposely unrealistic collocated HDI metaphors, starting from drone form and behavior. We propose an immersive simulation testbed that would allow people to interact with different forms of collocated drones in various settings and tasks. Lessons drawn from the testbed could inform the design of the form and behavior of future drones, and be used in the design of more natural HDI.

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