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Physical Robot Swarm Testbed at ARL: Specifications and Experimental Design Possibilities

by James Humann, Kimberly A Pollard, Susan G Hill, Oluseyi A Ayorinde, Ashley N Foots, and Suya You

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The Arena for Indoor Research on Swarm-Human Interaction Performance (AIRSHIP) testbed is a human–swarm interaction testbed located at ARL-West in Los Angeles, California. It currently features 10 small quadcopter unmanned aerial vehicles with indoor localization capability, open-source firmware, and communication with a native PC client. A physical testbed was deemed necessary for human–multirobot interaction studies because it would accurately reflect the human psychophysiological response to interaction with physical robots, the variability and stochasticity of environmental factors, and true hardware constraints on proposed algorithms. This report details the current status and future vision for AIRSHIP. We developed the testbed with a focus on enabling research in these areas: user interfaces, interaction modalities, agent hardware and algorithms, system scalability, and human variability. A set of possible scenarios for human subjects studies is also given, such as search and rescue, monitoring, and construction.</td></tr>
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1. Introduction

1.1 Purpose of Report

The purpose of this report is to describe a physical testbed for human–swarm interaction research at the US Army Combat Capabilities Development Command (CCDC) Army Research Laboratory West (ARL-West) in Los Angeles, California, and present opportunities for future capabilities and experiments using this testbed. This has come about because of the FY19 ARL swarms project, which was part of a Department of Defense-funded effort to examine humans interacting with swarms.

1.2 ARL Swarms Project

The ARL swarms project described here is a joint effort of ARL's Vehicle Technology Directorate (VTD); Sensors and Electron Devices Directorate (SEDD, now the CCDC Data & Analysis Center [DAC]); and Human Research and Engineering Directorate (HRED). We define a swarm as a group of fully or largely autonomous agents interacting in a collective fashion to perform a task. In our working definition, we will also occasionally reference scenarios wherein agents are operating cooperatively but not necessarily as a collective whole (e.g., when robots are assigned individual tasks that form the building blocks of the cooperative goal). These are often called multiagent or multirobot systems. The group of agents may be homogeneous or heterogeneous.

Combining team members' experience in vehicle technology, sensors/machine vision, processor chips and power consumption, human factors, and perceptual/cognitive psychology led to insights on human–swarm interaction and the impetus to build a human–swarm interaction testbed. A major insight from our collaboration was the fact that power needs, chip limitations, and sensor abilities may significantly impact human performance or human response with swarms or other multiagent systems, but they are rarely adequately considered in models of human-autonomy–swarms interaction. To advance research and lay groundwork for continued exploration in these and related areas, the ARL swarms team created a physical swarms testbed at ARL-West: the Arena for Indoor Research on Swarm-Human Interaction Performance (AIRSHIP). This testbed will allow research on how interfaces, physical constraints, human factors, and their interactions affect human–swarm task performance and human psychological/physiological responses. To accommodate a broad range of experimental possibilities, the testbed is highly customizable for a range of task scenarios, number and diversity of autonomous assets, and inherent and imposed physical constraints.

Insights from our discussions and literature reviews, from the virtual testbed developed by the Institute for Creative Technologies (ICT), and from modeling work (e.g., Humann and Pollard 2019) highlighted the need to develop a physical testbed for addressing human–swarm interaction research questions. In our design of the testbed, we aimed for the following characteristics: indoor, small, portable, highly customizable, and flexible to accommodate a wide range of experiments.

Here we describe the existing capabilities of the AIRSHIP testbed and elucidate the kinds of experiments that can be performed in such a physical testbed, given the hardware and software currently available, as well as future possible enhancements to the testbed.

1.2.1 Associated ICT Project

An allied project on human–swarm interaction is being performed by ICT, an Army University Affiliated Research Center (UARC) governed by the University of Southern California. This project is researching the use of a natural language dialogue interface with a virtual human spokesperson, which acts as an intermediary between the human operator and the swarm. With input and guidance from ARL, ICT created a simulation-based testbed in which to collect natural language data from users as they interact with the virtual spokesperson and with the swarm.

The simulation-based testbed runs a virtual search and rescue scenario in which the human user commands a heterogeneous team of unmanned aerial and ground vehicles (UAVs and UGVs, respectively). In the simulation, a small town is threatened by encroaching wildfire, and town residents must be saved by harnessing the UAVs and UGVs in different ways. For example, some residents are lost and must be instructed to follow a drone to safety. A UGV must be dispensed to remove a road blockage. A "stubborn couple" cannot be saved unless the human commander patches his or her voice through a nearby drone and talks to the couple personally. A virtual human spokesperson is available to act as an intermediary between the human commander and the autonomous vehicles, but the human can also instruct the assets individually. The wildfire spreads over time, and the goal is to rescue as many town residents as possible. The different residents and other challenges can be distributed randomly across the town map, and modifications can be made to change the number of available assets, the speed and direction of the encroaching wildfire, and to add further challenges (such as loss of a UAV). The human commander uses a voice microphone and two computer screens to interact with the system. One screen displays the virtual human spokesperson, and the other screen displays a map of the town. (See Fig. 1 for the commander's workspace.) The progress of the fire is visible on the map if the participant has assigned some of their UAVs to provide overwatch. The drones' behavior and virtual human spokesperson's behavior are controlled by two Wizards of Oz behind the scenes. An early version of this testbed was described in Chaffey et al. (2019).

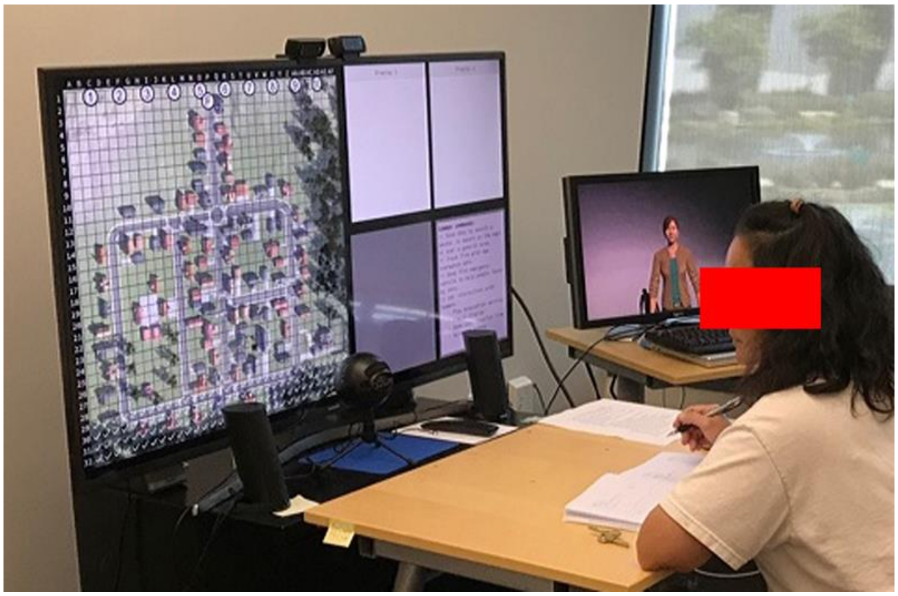

Fig. 1 ICT's human–swarm interaction virtual testbed, showing wildfire map, simulated drones, and virtual human spokesperson that interacts with the user via natural language

1.2.2 Need and Concept for Swarm Testbeds

Virtual testbeds have many advantages, including portability, rapid modification, and in some cases lower cost. However, the human response to simulated robot swarms differs from the human response to physical robot swarms. This was shown by Podevijn et al. (2016a, 2016b), where psychophysiological markers of stress were elevated when interacting with physical robots compared to simulated robots. Interacting with larger swarms versus smaller swarms yielded a similar pattern (Podevijn, et al. 2016a; Podevijn et al. 2016b).

A virtual swarm may appear identical to a virtual representation of a real swarm, provided the commander is not physically collocated with the actual agents. However, in many scenarios human commanders and other interacting humans would be at the tactical edge and on site with the robotic agents. Findings derived from virtual simulated swarms for these scenarios may not be entirely representative of findings with actual physical swarms and are perhaps best considered preliminary findings until replicated in a physical swarm testbed.

Another reason to use a physical swarm testbed is to better include real-world challenges of working with robotic agents—namely, their physical needs and limitations. Heterogeneous teaming simulations can easily make unrealistic assumptions about flight time, power usage, mechanical robustness, payload capacity, camera resolution, and so on. When these unrealistic assumptions are implemented in the simulation, the result is a scenario that fails to replicate many of the significant challenges in human–multiagent teaming. We acknowledge that careful consideration of these parameters can allow them to be implemented more faithfully in simulations, and we also acknowledge that our physical testbed cannot completely replicate all these issues. For example, using tiny, low-cost, portable UAVs comes with the caveat that they cannot be flown outside. Actual weather effects therefore cannot be included in our testbed. However, our testbed innately provides realistic physical constraints on flight time, power usage, payload capacity, mechanical robustness, and so forth.

A variety of virtual and physical heterogeneous teaming testbeds have been developed for different experimental purposes. We will highlight a few key examples in the following section.

1.3 Related Work

In this section, we provide a noncomprehensive overview of research projects with multirobot/swarm testbeds that can examine human–swarm interaction performance. A comprehensive review is outside the scope of this report, so here we only provide details of projects closely related to or in collaboration with ARL research.

A versatile virtual reality (VR) testbed for human–multiagent interaction is the Accelerated User Reasoning for Operations, Research, and Analysis (AURORA)-XR interface, which is under development by ARL for the Internet of Battlefield Things (Dennison et al. 2019). AURORA-XR currently features a virtual city block with an array of sensors and agents that can virtually detect movement of virtual friendlies and adversaries. The human commander can pull up views from the visuospatial perspective of different sensors and unmanned vehicles via virtual camera feeds and virtual sensor data. This setup can be seen in Fig. 2. The simulation can be modified for the performance of different simulated tasks and is proposed to be used by HRED for studies of training humans in skills relevant for human–agent teaming (e.g., uncertainty quantification and visuospatial perspective taking).

A main goal of AURORA-XR is to serve as a visualization tool and off-site collaboration tool (via AURORA-NET), wherein multiple humans at different locations can simultaneously interact with the sand-table representation in VR to engage in collaborative decision-making for multi-domain operations.

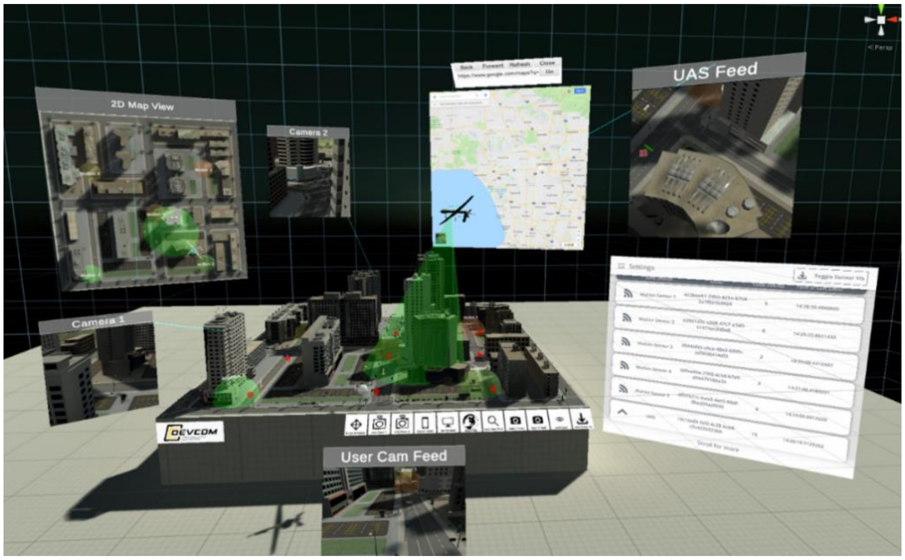

Fig. 2 AURORA-XR interface with example feeds and camera angles

The Mixed Initiative Experimental (MIX) testbed (Barber et al. 2008) combines simulations of unmanned vehicles and cameras with an Operator Control Unit (OCU) interface, shown in Fig. 3, that allows the user to control the unmanned systems. The OCU is customizable, and the underlying autonomy simulator software (Unmanned System Simulator [USSIM]) can be used to simulate a variety of mission types with varying levels of automation, including reconnaissance, target identification, and route-planning scenarios. MIX has been used in a variety of studies, and modified OCUs for intelligent agents have been the subject of extended research as well (Chen and Barnes 2014; Barnes et al. 2015).

Fig. 3 MIX testbed's OCU interface

In our ongoing work (Humann and Spero 2018; Humann and Pollard 2019), we use a virtual testbed to design appropriate algorithms for human–UAV interaction and choose an appropriate team size. The tool can simulate any number of humans, quadrotor UAVs, and fixed-wing UAVs. Humans are simulated with realistic effects from fatigue and workload. The humans and autonomous assets perform a surveillance mission, where a field must be swept with cameras for possible dangers such as vehicles and fires (performed by the fixed-wing UAVs) before the points of interest are photographed (quadrotor UAVs) and finally analyzed to assess the threat level (humans). From this analysis, the payoff of adding assets to the system can be analyzed in terms of the overall accuracy and speed of assessing the field. An example screenshot of the simulation is shown in Fig. 4.

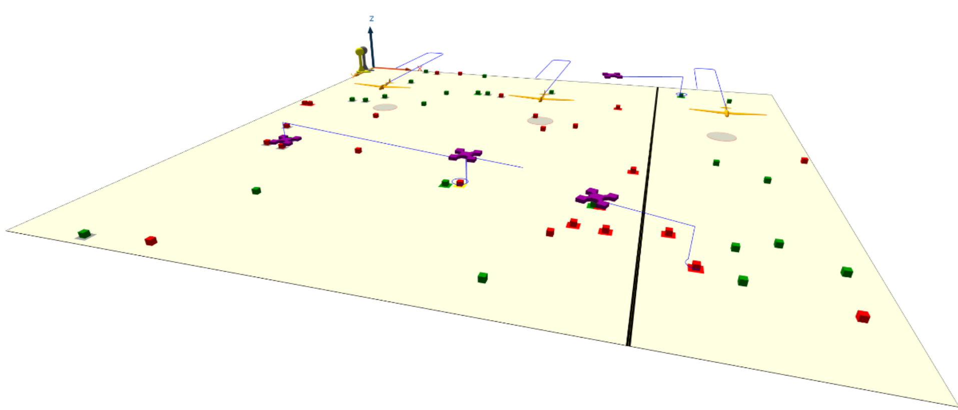

Fig. 4 Screenshot of simulation (Humann and Pollard 2019), showing three fixed-wing UAVs, four quadrotor UAVs, and two operators cooperating to perform a surveillance task

There are two ongoing efforts at ARL involved with multiple, distributed intelligent assets that are developing testbeds for future work. The first is the Distributed Collaborative Intelligent Systems and Technology (DCIST) collaborative research alliance. This project will "create Autonomous, Resilient, Cognitive, Heterogeneous Swarms that can enable humans to participate in a wide range of missions in dynamically changing, harsh, and contested environments" (www.dcist.org). The DCIST performers have discussed building a testbed (virtual and/or physical) to test intelligent systems algorithms. While many of the participating academic institutions have their own testbeds for individual research use (e.g., Pickem et al. 2017), a goal of the DCIST testbed is to enable integrated experimentation of research products from across partner sites.

The second ongoing effort at ARL is a potential testbed for exploring human interaction with intelligent systems combining different human-interaction modalities with reinforcement learning, called the Cycle-of-Learning framework for autonomous systems (Waytowich et al. 2018; Goecks et al. 2019). They have implemented a simulation to explore the use of human demonstration to improve intelligent system capabilities (in the cited case, a small quadcopter UAV). They plan to continue research on reinforcement learning for joint interactions on a physical testbed using Crazyflie UAVs.

Researchers affiliated with USC and ICT have demonstrated coordinated behavior of multiple robots in ongoing research (Tran et al. 2018), flying up to 49 micro UAVs simultaneously and autonomously (Preiss et al. 2017). They have also demonstrated user interactions among up to three humans and six UAVs navigating through rooms in close proximity to each other (Phan et al. 2018).

2. Components and Capabilities Available in AIRSHIP

In this section, we provide a description of physical components available in the AIRSHIP testbed.

2.1 Mini-UAVs

The foundation of the AIRSHIP testbed is a group of mini-UAVs. Currently we have 10 Crazyflies, manufactured by BitCraze. These are very small (approximately 92 mm across) commercial off the shelf mini-quadcopter UAVs with small plastic propellers, suitable for flying in indoor spaces. They weigh 27 g with a battery, and their payload capacity is limited to about 15 g, which is enough for a tiny camera or other very small electronic payload. Out of the box, these mini-UAVs have onboard gyroscopes to sense tilt and barometers to provide rough altitude sensing. The Crazyflies can communicate with a CrazyRadio antenna via a

2.4-GHz radio. The battery life is approximately 15 min when flying without a payload. Adding payload quickly reduces battery life. Figures 5–7 show the Crazyflie hardware in flight and the suite of 10 available aircraft.

Crazyflies are very simple to assemble and connect to a smartphone app for rudimentary control. Within approximately 1 h, a user can build the UAV, install the Crazyflie PC client, and begin flying via a video game controller (gamepad). In its default state, the Crazyflie is self-leveling but cannot hold position or altitude. Thus, manual flight requires a considerable amount of skill to maintain steady, precise flight. A typical user will require approximately 4 h of practice time to be able to reliably fly manually.

For autonomous maneuvers, the UAVs are configured to respond to commands through Python, but this is not of much use without stable autonomous flight. For this, the UAVs will rely on the arena’s position system. The Loco Positioning System (LPS) includes eight wall-mounted anchors that demarcate the boundary of a flight zone. Onboard, the Crazyflies use LPS decks to communicate with the anchors. Since the anchor positions are known and constant, the UAVs can use the Two-Way Ranging (TWR) or Time Difference of Arrival (TDoA) protocol to triangulate the position of the deck. Choosing between the two algorithms requires a tradeoff between accuracy and scalability: TWR can achieve tighter accuracy but is limited to one Crazyflie at a time as it relies on precisely timed two-way communication with the anchors, whereas TDoA can support multiple simultaneous UAVs with 10-cm position accuracy with one-way broadcasting from the anchors.

The control software is custom firmware supplied by the manufacturer, but it is fully open source, allowing us to modify it at will. It runs on a STM32 microcontroller unit at 168 MHz. There are packages available to integrate the controller and positioning system with ROS (Robot Operating System) (Hönig and Ayanian 2017), which is a standard open-source operating system for robotics research and is used in other ARL research (Bonial et al. 2017; Lukin et al. 2018), allowing opportunities for cross-compatibility with other existing projects.

2.2 Payloads

Due to weight restrictions, the payloads are limited to a maximum of one or two of the capabilities listed in this section for each UAV. Current payloads and capabilities include the following:

- Loco Positioning deck: allows UAV to localize itself in 3-D space for autonomous flight.

- Flow deck: visual flow sensor and altitude sensor to autonomously hold position in 3-D space.
- Multiranger deck: allows detection of large objects in front/back/left/right of the UAV.
- LED ring: ring of multicolored programmable LED lights; these can be used to visually indicate to the user the individual identity of the UAV, the battery or flight time status, or any other UAV attribute.
- Wireless charging deck: Qi-compatible wireless charging; this allows the UAVs to charge themselves by returning to their home base with no need for a human to plug them in.
- Micro camera: lightweight visual light camera with built-in antenna for analog video broadcast. It has a 120° field of view and can be mounted in any orientation but cannot be moved during flight.

By varying the payloads of each mini-UAV, a heterogeneous swarm can be created where different UAVs have different capabilities. Payloads can be mounted, unmounted, and remounted to different individual mini-UAVs. By mixing and matching the payloads, a wide variety of different capabilities and distribution of capabilities can be achieved to model different human–swarm interaction task scenarios.

Payload capacity may be expanded by in-house modification of Crazyflies to add extra propellers. We also possess a "Big Quad deck," which is a beta product from Bitcraze allowing the Crazyflie controller and accessories to control larger quadcopter form factors. Thus, there are options to expand on the Crazyflie using 3-D-printed structures while maintaining compatibility with the same software systems, sensors, and controllers.

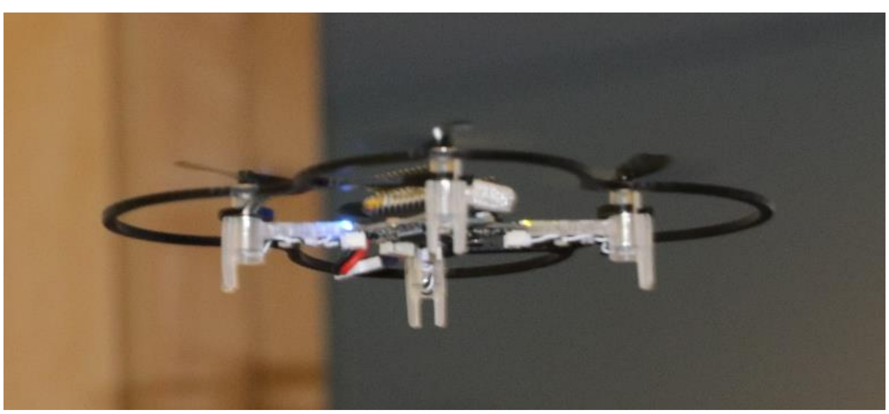

Fig. 5 Crazyflie in flight in Los Angeles office

Fig. 6 Crazyflie being piloted through aerial ring

Fig. 7 Full suite of 10 Crazyflies

2.3 Other Assets

Other possibilities include expanding the testbed to incorporate a more heterogeneous range of autonomous agents. Candidate assets may include other commercial off the shelf robots, such as the Softbank Robotics NAO humanoid robot, or Clearpath Jackal UGV. Additional UGVs and UAVs can also be constructed with the aid of the onsite 3-D printer.

The NAO is a small humanoid-form robot designed for educational purposes and robotics research. The NAO takes commands from a PC client and can perform a variety of tasks such as walking, picking up objects, and transporting objects. It can also be programmed to follow speech commands and to generate speech. The NAO is fitted with cameras and is capable of some rudimentary onboard image recognition.

The Jackal is a 17-kg off the shelf 4-wheeled UGV that can carry significantly larger payloads than the mini-UAVs. A Jackal or similar UGV can be outfitted with payloads such as an RGB camera, infrared Light Detection and Ranging (commonly, LIDAR) obstacle-sensing capability, or a remote-control system. It can be controlled using an Robot Operating System-based system and/or with a game controller. Training for manual control is simpler than that for full manual control of a UAV.

Under construction is a larger UAV with 5-inch propellers that will use the same chip sets as the Crazyflies so that it can be controlled using the same software and related equipment. The payload capacity remains to be tested but is estimated to be 250 g. In addition, with a scalable Loco Positioning system, more standard Crazyflies can always be added to the swarm.

2.4 3-D Printing to Support Physical Testbed

We currently have a LulzBot Taz 6 3-D printer on site, which can print pieces up to 280 × 280 × 250 mm. Pieces can be designed using engineering software such as SolidWorks, advanced 3-D modeling software such as Blender, or more lightweight programs like Paint 3D, which is built into the Windows OS. Pieces commonly designed and printed include mounting brackets and adapters for different payloads, support and protective structures, bodies for new or adapted UAV models, landing and charging pieces, mounts for positioning anchors, or structures for the testbed's environment. Options are virtually limitless. With an indoor environment, easy-to-print but less durable materials like PLA can be used.

For example, we have designed and printed propeller guards for the mini-UAVs. These guards prevent the propellers from coming into contact with walls, floors, environment structures, or other robots. In the event of a collision, the propeller guard takes the stress of the impact, sparing the fragile propeller pieces. See Fig. 5 and Fig. 8.

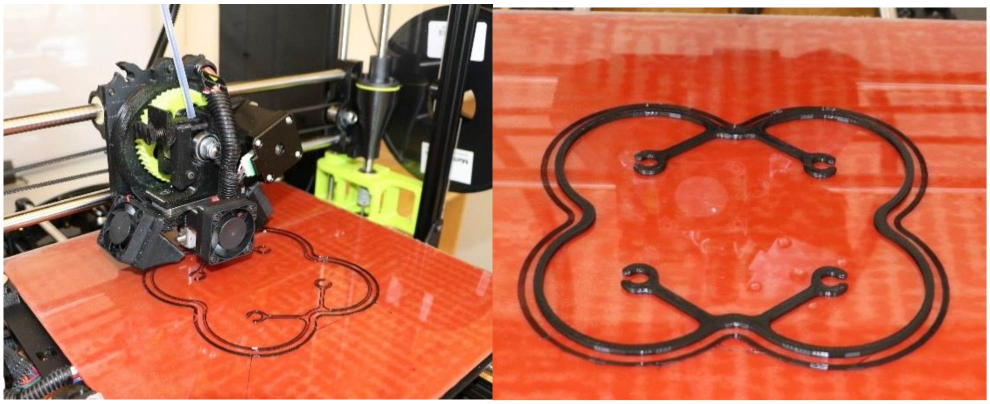

Fig. 8 Left: propeller guard being 3-D printed on LulzBot Taz 6. Right: complete propeller guard (skirt material is scrapped after printing).

We have also used the 3-D printer to design and manufacture custom stands for the positioning anchors. The anchors must be held at least 15 cm away from surfaces or the metal poles of the testbed netting cage, and must be in a vertical orientation. Our current stand design is shown in Fig. 9. While the Crazyflie manufacturer does offer a stand file ready for 3-D printing, their design assumes the stand is connected to a floor or ceiling, not a vertical pole as in our setup, so the ability to design and 3-D print custom parts has been vital to enabling the AIRSHIP testbed's full functionality. We are in the early stages of designing landing ramps for our wireless battery chargers. This will enable the UAVs to land at charging sites and charge themselves; the ramps will guide them into the proper position as they land.

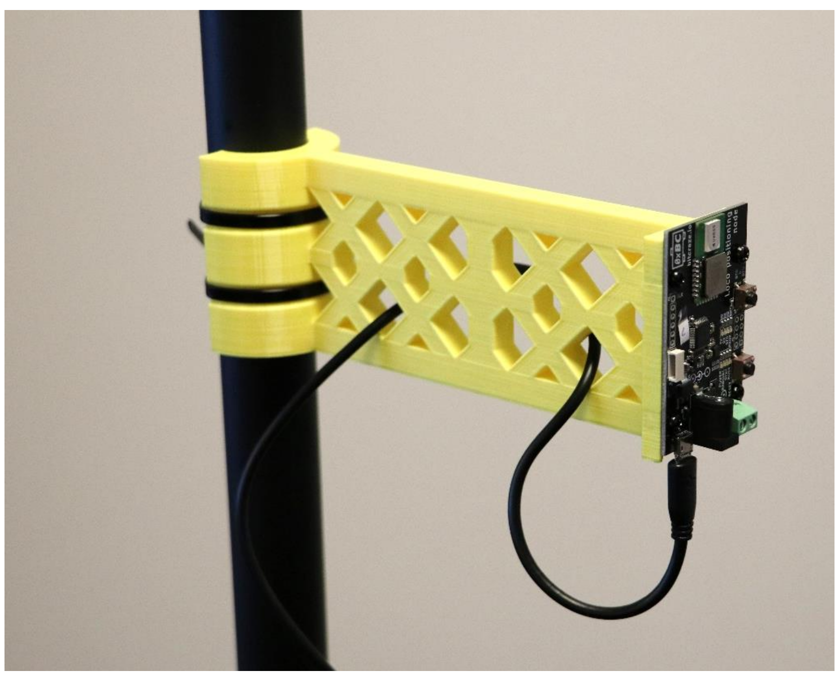

Fig. 9 3-D-printed positioning anchor stand

2.5 Testbed Location and Customization Options

ARL-West has one large room (14 × 14 × 10 ft) that can be used for quadcopter assembly and testing. In addition, there is a portable drone cage with mounting points for the positioning anchors that can be set up in larger rooms or common areas. Two 10- × 10- × 10-ft cages are available, with enough netting to create a continuous space up to 30 × 10 × 10 ft at a maximum. This flexibility and portability allow the testbed to accommodate different experimental scenarios and make it available for demonstrations at different locations and events.

The available spaces can be modified at will to accommodate the setup of a particular experimental scenario. For example, model "buildings" or landscape features can be set up to create a miniaturized version of a city or battlefield for surveillance, detection, monitoring, or search tasks. Complex terrain can be set up for mapping or image stitching tasks. Size scaling can vary based on the needs of the particular experiment. Software can also be used to modify the travel speed of the robots so that the time it takes them to cover a particular amount of simulated terrain can be made proportional to what might be observed in an asset covering a larger outdoor environment. Visible objects and/or infrared beacons can be placed in the environment mockups to represent targets or hazards. Manipulable objects could be placed in the arena for various tasks as well. Such objects could represent items that the swarm assets must move, collect, build with, or physically modify, as dependent on the experimental design.

3. General Classes of Potential Experiments

A wide variety of experiments could be conducted using the AIRSHIP human–swarm testbed. Several general topic areas of interest are explored in this section. They involve the areas of user interfaces, swarm inputs and outputs, hardware options and design, scalability, and human variability.

3.1 User Interfaces

User Interfaces (UI) are the means by which humans and swarm assets (either individually or as a collective) communicate with each other. Traditionally, it has been primarily a means for human control and instruction inputs to be sent to the assets. It is also the means for the assets to communicate back to the human(s) with status information.

Swarm UIs can also be thought about in terms of the interaction modalities that a human would use to communicate with the swarm. Visual displays are the traditional means for presenting information on a UI, but speech and other nonspeech auditory, gesture, tactile, and haptic displays and controls are all feasible and have been shown to be effective for individual asset bidirectional communication. For example, Hill (2017) reviewed literature on multimodal displays for user–robotic-asset one-on-one interaction. Although human interaction with swarm UIs was not specifically addressed, this report does illustrate how various sensory modalities can be used for bidirectional information exchange. The exact design of the UI, and the most appropriate modalities to be used, will depend on the specifics of the task(s) to be performed, the environment and conditions in which the task(s) will be performed, the capabilities of the technology itself, and the capabilities of the human(s) who will be using the UI. Since it is a complex problem, there is no simple answer, making UI development for human–swarm interaction a natural research area to explore in a physical testbed.

3.1.1 UI Appearance and Modalities

There are some new ideas for swarm UIs that could be tried in our testbed. Although implementing the UI in hardware and software is a considerable challenge, once it is available, designing an experiment to assess that concept should be fairly straightforward. General steps for designing a specific experiment given a new UI concept are provided in the following list, using an example of a new type of gesture control:

- Define new concept and the associated user interface. Review relevant research and development literature for information about past efforts and lessons learned. We will consider a gesture interface where control inputs are performed via human gesture.
- Define software and hardware requirements for the next concept UI. For gesture study, pick type of gesture (instrument-based [like a glove] or camera-based) and define how the signal (from glove or from camera) will be processed and fed to the asset as a control signal.
- Define specifics of the UI—what are the necessary commands and information to be exchanged? For example, the need for start/stop/turn-left/turn-right kinds of instructions.
- Identify software developers and obtain hardware with which to work.
- Develop conceptual UI that can be demonstrated and used.
- Perform tests and pilot studies.
- Plan human-in-the-loop experiment. Write experimental protocol and get approval.

- Run experiment when all aspects are ready. Collect data. Analyze data. Document findings.

This layout of general steps illustrates the potential complexities of trying out new UI concepts.

There are survey-based approaches to investigating UIs as well. For example, using the current user interfaces that came with the purchased equipment, we could explore how people actually use the equipment and collect their thoughts on how the current UI could be improved. We could also hypothesize example tasks that a person might need to carry out (sometimes called "use cases") and have the individual participants explore and discuss positive and negative aspects of the existing UI for accomplishing the given use case(s), as well as suggest additions and improvements to the UI to make it better suited to the given tasks.

It is also important to gather information on how individuals would like to interact, particularly for multimodal interaction. So, we could propose to individuals that we are looking to build speech interfaces that accomplish various use cases. The individuals would describe what they believe they would need to do to accomplish those tasks, and then identify the words that they believe should be used and mapped to the task execution.

One way of approaching the use of speech to communicate with swarm assets is to use a constrained set of commands, which use limited vocabulary and must be trained to both humans and swarm. Humans must learn the constrained vocabulary and its meaning. The swarm assets, either collectively or individually, must be programmed to take the constrained vocabulary "signals" and translate them into specific behaviors. They are not intended to be free usage of language, but are developed to simplify the issues of speech recognition (from human to swarm), mapping commands to expected behaviors, and even potentially speech generation (from swarm to human) (Hill 2017).

So, we could develop an experiment to capture ideas of needed tasks for given use cases, and then obtain a list of possible words or phrases that are preferred for use when mapping language commands to expected swarm behaviors. One of the challenges will be to describe what the swarm behavior should be for the words and behaviors suggested. "Start" or "Begin" or "Fly" might all be suggested as the start command, but then one would need to precisely define what it means for the swarm to "start." If we would like the swarm to circle an object, it may be a challenge to specifically describe the behavior well enough to solicit appropriate words to use as commands.

Similarly, we could investigate people's preferences when using gestures to indicate commands. A "circle" gesture might be used to suggest a circle behavior. Identifying a gesture for "fly" might be more difficult. One could also imagine that there will be differences in suggestions between air and land assets. There might also be differences depending on the number of assets within the swarm as well as the size of the assets within the swarms.

How much information to display, and when to display it, are important graphical-user-interface design choices. Swarm control is often indirect, with a time lag between user inputs and the final state of the swarm. Kolling et al. (2015) showed that the negative effects of this latency can be mitigated by providing predictions of future swarm states to the user. In some cases, researchers have found that reporting less information or highly summarized information to the human is advantageous (Amelink et al. 2008; Hocraffer and Nam 2017). Human preferences and limitations regarding these phenomena can be studied in AIRSHIP.

3.1.2 Swarm Inputs and Outputs

Highly related to UI research are questions of inputs and outputs. That is, what does the human input to the swarm system and what does the swarm system output to the human? Human–swarm inputs and outputs can be quite different from one-to-one communication, even if the human is communicating with the swarm as a unit.

Scalable swarm input methods do not require addressing each agent individually. Examples are leader, predator, and stakeholder methods (Pendleton and Goodrich 2013). In the *leader* method, the user directly controls a single member of the swarm. All other swarm members recognize the leader as special and move toward its location while maintaining a flocking formation with each other. In *predator* control, the user-controlled robot repels the members of the flock. This method of influence is less direct but is adept at splitting the formation into separate flocks, which may be beneficial in certain scenarios. *Stakeholder* control gives the user control over a swarm member that is not treated specially by the other members. They will continue to flock and assume formations with the stakeholder as they would with any other swarm member.

A careful balance must be struck when determining how much information the swarm should return. Requiring too much data from individual robots may negate the advantages of a swarm architecture. Swarms are usually chosen to minimize communication and dependence on a central hub. Requiring frequent status updates and data exchange may raise the communication demands to an unacceptable level. The human user can also be overwhelmed if presented with too much data. This can of course be filtered out by a good UI, but to minimize communication, it should not be transmitted in the first place. If swarms consist of aerial assets, with highly restricted Size, Weight, and Power (SWaP), minimizing data outputs is even more crucial. Aggressively cutting down on swarm outputs could restrict human knowledge of the position of the swarm, which would rule out some control methods like leader or stakeholder control, while still allowing autonomous swarming behavior and beacon control (Kolling et al. 2013).

A concept for a specific experimental design would be interrelated with the choice of UI and use case. A skeleton research approach to input/output studies is given here:

- Familiarize subjects with a use case and swarm hardware at their disposal.
- Have subjects identify possible inputs that they would want to convey to the swarm system.
- Have them describe what it is that they are asking the system to do.
- Collect the words and phrases, and their intended meanings, that a human would use to convey inputs to the system and receive outputs.

Conceptually, these words and phrases, with associated meanings and descriptions, could be used in considering needs for user interfaces. They could also inform hardware and communication design to meet only the minimum of input/output requirements for operator comprehension.

Within-swarm sensing and communication is another central aspect in the performance of the swarm. We do not discuss it in depth here as we are primarily focused on human–swarm interaction, but these human–swarm inputs/outputs are coupled with within-swarm interactions (e.g., if decision-making arises as a consensus among swarm members, a human's input is not needed at that time).

3.2 Hardware and Algorithms

Swarm hardware and algorithms are highly constrained (Bonabeau et al. 1999; Rubenstein et al. 2012; Humann and Jin 2013). The large number of robots makes it economically imperative that each robot have simple, inexpensive hardware. In addition, UAVs are highly SWaP constrained, underwater vehicles face significant communications difficulties, and all battery-powered assets must be judicious in their energy usage. For these reasons, experiments that probe the system-wide benefits of more sophisticated, complex, or expensive hardware and algorithms will be of great interest, as will experiments to examine how humans behave and perform under different hardware constraints.

With the ability to modify the software onboard the assets, we can run "hardware" experiments in a simulated fashion, by locking out certain hardware features that would otherwise be available. For example, to study the effects of constrained battery life, we could simply program a robot to cease operations after a preset amount of time, rather than physically installing a smaller battery. Thus, we are not limited to the inherent single set of hardware constraints imposed by any one asset.

Our hardware experimental approach is as follows:

- Have subject perform in a scored test scenario.
- Repeat performance with varied hardware constraints.
- Gather data on performance variation as a function of hardware constraints.

In a similar way, different autonomous algorithms can be programmed into the robots, with the simpler algorithms representing restricted computing power. This will lead to informed tradeoffs between computational requirements and system performance.

3.3 Scaling and Scalability

Scaling a system's size may be advantageous in many scenarios. A scalable system can increase or decrease in size (i.e., the number of robots) with costs that are proportional to the change in system performance (Bondi 2000; Humann et al. 2018; Humann and Pollard 2019). For example, in a foraging system if we were accustomed to returning 10 units of a resource per robot, we would expect this ratio to hold as more robots are added to the system, with no other major costs imposed beyond the incremental costs of more robots. An example of a disproportionate cost would be a major overhaul to the communication infrastructure if too many robots are added to a network. The cost of an extra human operator, or retraining of an existing operator, could also be considered a disproportionate cost that would hinder the scalability of a system.

The economic benefits of scalability are the option to increase in size to meet increased system demands, or to decrease in size to minimize cost during periods of low demand (Humann and Pollard 2019). The research questions of human interaction with scalable systems are concerned with human tendencies and whether they help or hinder scalability. Some example questions that scalability studies could ask are the following:

- How many simultaneous data feeds can a subject accurately monitor?
- How many robotic assets can a subject simultaneously control while maintaining good performance?
- If given a suite of robotic assets, will a subject default to using every available asset, or leave some idle to maintain a comfortable workload?
- Why does system-level performance sometimes decrease when the number of available assets increases?

A scalability study would vary the number of robotic assets and look to this number for a main effect on the system-level performance of the task. An outline of scalability studies is given here:

- Place subject in control of multiple robots in a scenario that can be scored at a system level, independently from the behavior of individual robots.
- While holding all other variables equal, increase the number of assets available to the subject.
- Collect data on system-level performance as a function of the number of robots available.

Note that many causes can lead to a breakdown in scalability. Just a few from our recent review of the subject are task saturation (the task is already being completed to near-perfection, so that adding more resources cannot help), operator overload, loss of situational awareness, and loss of fine control (Humann and Pollard 2019).

3.4 Human Variability

Humans have a variety of traits and states that vary by individual and by situation. For example, the human's amount of past experience, their skill level, and the training they have had are all likely to impact how they interact with robots and swarms and how well they perform in human-autonomy tasks (Chen and Barnes 2012; Chen and Barnes 2014). Similarly, relatively stable individual dispositional traits, such as personality, are expected to affect interaction behavior and performance. A human's opinions, expectations, trust, mood, alertness/fatigue, attention levels, and other factors are also likely to play a role. Exploring the effects of these traits and states on human–swarm interaction behavior, and human–swarm performance, are promising avenues of research. Furthermore, the effects of the autonomous agents on the human are also worth investigating.

Human-variability experiments based on traits will be very similar to the other experiments listed in this section. They may even be run in parallel, as trait information can be collected via surveys before engaging in the experimental task. State studies will investigate how different swarming algorithms or task constraints affect subjects' cognitive load, motivation, feelings of trust, and physiological indicators of challenge and stress. AIRSHIP provides flexible, modifiable capabilities to examine these questions experimentally with real hardware.

A general outline of study approach might include the following:

- Select human states and/or traits of interest and identify suitable measurement tools (e.g., surveys, eye tracking, and impedance cardiography).
- Have the human interact with the multirobot/swarm scenario, or with variations of scenarios.
- Measure state responses.
- Measure performance (e.g., by time to task completion, number of errors during task, number of subtasks successfully completed).
- Examine relationships among trait, state, task variations, and/or performance variables.

4. Possible Experiment Scenarios

A main goal of the testbed is to be highly flexible and modifiable so that it can reproduce a wide range of experimental task scenarios for robot research, human performance research, and human–swarm interaction research. The customizability of the physical environment, of the robot-control software, and of the robot's payload capabilities and combinations leads to a wide variety of possible experimental scenarios that can be represented in our testbed. Several example scenarios are listed in this section.

4.1 Scenarios

4.1.1 Initial Toy Demo: Tic-Tac-Toe

One early demonstration option is to create an interactive tic-tac-toe game, where a user plays against artificial intelligence (AI), and after choosing a square, a drone with a blue LED flies to the corresponding space inside a drone cage. Then the AI sends a drone with a red LED to its chosen space. The user and AI continue to take turns until a winner or draw results. While this would not yet be human–*swarm* interaction, as the user would be sending commands to only one UAV at a time, it would still demonstrate important capabilities that are fundamental to future experiments: user interaction, autonomous flight, simultaneous flight of up to nine UAVs, close formation flying, and shared human–AI control of the UAVs.

4.1.2 Search and Rescue, Search and Disarm, Foraging

Currently, five infrared beacons and receivers (Model VS1838B) are available for use in the testbed. These beacons project IR light that is not visible to the human eye but can be detected via the receivers onboard a robotic asset. To mimic a search and rescue scenario, the IR sensors can be hidden among environment structures such as cardboard building mockups, furniture, debris, or other obstacles. If they are hidden from a human subject's line of sight, the subject would then need to rely on the robotic assets to locate them. The human would need to use the assets to conduct an efficient search pattern, react to unanticipated problems (such as simulated UAV failure), and locate the targets. Performance could be scored based on time to completion or number of targets found within a prespecified time limit.

A variant of this task could involve "rescue" of the beacons, perhaps via directing a ground robot to pick them up. Some scenarios might require a heavy-duty robot (e.g., a Jackal) to push some "debris" out of the way to allow a safe path for other assets to reach the target beacon. This simulates search and rescue operations. Another variant, foraging, is well-known in the natural world, and many foraging algorithms have been created for swarms (e.g., Ostergaard et al. 2001; Kolling et al. 2013; Humann et al. 2018). In AIRSHIP, we could test the feasibility of these algorithms, and whether they are enhanced or hindered by human interaction.

4.1.3 Construction

The UAVs have limited individual payload capacity, but the combined payload capacity of multiple UAVs is greater. In this scenario, the human is tasked with constructing a barrier, simulating the real-world mission of building a makeshift wall to protect against active fire or deploying sandbags to keep back floodwater. The UAVs, equipped with 3-D printed hooks, may have to jointly lift pieces of the barrier, fly them to the construction site, and deposit them in the proper position. With a homogeneous swarm, we could instantiate versions of ant-colony construction and stigmergy (Werfel and Nagpal 2006; Calvez and Hutzler 2007). For a heterogeneous swarm, more complex structures could be built, like a campsite, but the human user would have to understand the individual capabilities of the assets and coordinate their operation. Performance could be scored based on number or size of structures successfully placed within the time allotted.

4.1.4 Collaborative Scene Reconstruction

Groups of coordinated robots can be used to capture images, analyze them, and reconstruct 3-D scenes. Simultaneous Localization and Mapping (SLAM) solutions are commonly used for 3-D reconstruction, but are not particularly well suited for execution by distributed, autonomous agents. They typically require sensors that are in constant communication and computationally expensive optimizations. They also do not scale well with the number of agents or size of the map (Chebrolu et al. 2015; Kurazume et al. 2017).

In AIRSHIP, we could test mapping algorithms designed for distributed, scalable architectures with the aid of human intervention. For these to work, the agents must have the ability to select what they are going to reconstruct, and choose a view. Then they must plan trajectories to arrive at that view, ensuring that there are no collisions with other swarm members (Milani and Memo 2016). Finally, the 3-D reconstruction must be anchored to a globally consistent map that relates all views to the real world. This scenario would combine strengths of robots (automated planning, aerial mobility, etc.) with strengths of humans (anomaly detection, real world context, troubleshooting, etc.) in interesting ways, opening up research into how these strengths can best be combined.

4.1.5 Coordinating Swarm and Ground Users

Scenarios that require a tight formation of users and the swarm (e.g., entering a building), could be studied. These are highly relevant to the military, where in future exercises it may be necessary to maintain a precise formation of warfighters, vehicles, offensive/defensive autonomous assets, and civilians. Each member of the formation will have different motion constraints and interaction modes. Simultaneously ensuring safety, speed, and precision will be key.

These scenarios would be heavily dependent on the user interface and modes of communication between human and swarm. With the hardware in AIRSHIP, we could re-create and test recent advances in gesture control (Pourmehr et al. 2014), recognizing implicit intent (Kelley et al. 2008; Chang et al. 2018), and heterogeneous formation keeping (Phan et al. 2018).

4.1.6 Building Monitoring

An application that has many parallels in defense and law enforcement is monitoring of a building. Assume, for example, that criminals (red team) are known to be inside a tall building, and a police team (blue) is waiting for reinforcements and formulating a plan. The blue team wants to use UAVs to monitor movement inside the building and any attempts to exit the building. There are four exits, facing in the cardinal directions on different sides of the building, so no single UAV can monitor all of them simultaneously. Activity will happen in windows as well, such as movement, lookouts, and lights turning on and off

In the lab, this could be represented by a scaled wooden structure with four doors and many windows. Automated signals would simulate the activities of the red team within the building (e.g., flashing LEDs indicate movement, Quick Response codes indicate individuals). The subject could control up to 10 blue-team drones. At least four are necessary to monitor all exits. The rest can be deployed however the subject wishes to monitor the windows. The subject must constantly multitask, placing UAVs, monitoring their video feeds, monitoring battery levels, replacing UAVs with low battery levels, recording activity, and so on. This would be very taxing on the user but provide a rich set of possible experimental interventions. To score the subject's mission success, he would receive points for successfully identifying activities in windows and large penalties for allowing red team members to exit unmonitored.

4.1.7 Predator and Prey

A common multirobot research problem is the behavior of "predators and prey," (Asher et al. 2018) where the predators attempt to capture the prey (usually by surrounding and trapping it). A testbed with 10 UAVs would be ideal for predator/prey research experiments, as the user could control either prey (studying a human's perception and understanding of the swarm trying to capture him), or predators (studying human control of the swarm under dynamic and time-constrained missions). In a larger space, the human could also assume the role of prey himself to study the effects of stress and human perception when surrounded by a swarm.

4.2 Summary of Scenarios

The scenarios here represent a wide range of practical civilian and military uses. They will challenge the subjects to interact with heterogeneous swarm members, maintain situational awareness of a complex dynamic environment, and complete objectives under time constraints. All these abilities are critical for developing future resilient military systems.

5. Discussion and Conclusions

In this report, we have briefly explained our swarms project and the development of AIRSHIP, a physical testbed for swarms/multiagent systems. We discussed the hardware and software we currently have available and possible scenarios for testing concepts for human–swarm interaction as well as other swarm characteristics that could impact human interaction and the ability to conduct operations. To fully realize AIRSHIP's experimental opportunities will take considerable thought and planning by interested experimenters. Our purpose here was to lay out possibilities of what might be done with existing resources, to identify ideas for future expansion, and to discuss research questions of interest.

There is much to explore with regard to future use of swarms. There are software control elements that are required and can be improved for effective execution. Then there are human-factors questions, because the swarm will be used to perform tasks for human purposes. No matter how autonomous the technology may be, in near-term military scenarios, a human will always at least be involved in setting the task, monitoring execution, and receiving status or task completion information.

Although we have discussed possible tasks and scenarios that could be considered within the physical testbed, it will be very important to choose *military relevant tasks and scenarios* in which to work. Tasks and scenarios do not necessarily need to be exact replicas of military missions, but they must have elements that can be analogous to what service members will have to perform. In addition to the tasks, we will want to ensure that *military-relevant conditions* are explored. For example, elements of time pressure, stress, adversarial behavior, and degraded communications should be present in studies as they are in military scenarios.

While AIRSHIP was designed with human–swarm research in mind, it is not limited to these multiagent scenarios or even to human-in-the-loop studies. Research on human–single-agent teaming, fully autonomous swarming, new AI or machine-learning algorithms, or new hardware designs is possible as well. With the current expertise at ARL, we have the opportunity to use AIRSHIP to develop experiments that cross disciplinary domains, including human sciences, electrical engineering, computer science, and systems engineering. We hope that by showcasing the testbed we have developed, researchers looking to use hardware to gain meaningful insight into human–swarm interactions may be inspired to create new experiments they may not have originally envisioned. Additionally, we hope to attract researchers who may already have aspirations for moving from theory and simulation into hardware, which we could readily provide.

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List of Symbols, Abbreviations, and Acronyms

3-D	3-dimensional
AI	artificial intelligence
AIRSHIP	Arena for Indoor Research on Swarm-Human Interaction Performance
ARL	Army Research Laboratory
AURORA	Accelerated User Reasoning for Operations, Research, and Analysis
CCDC	US Army Combat Capabilities Development Command
DAC	Data & Analysis Center
DCIST	Distributed Collaborative Intelligent Systems and Technology
HRED	Human Research and Engineering Directorate
ICT	Institute for Creative Technologies
IR	infrared
LED	light-emitting diode
LPS	Loco Positioning System
MIX	Mixed Initiative Experimental
OCU	Operator Control Unit
PC	personal computer
SEDD	Sensors and Electronic Devices Directorate
SLAM	Simultaneous Localization and Mapping
SWaP	Size, Weight, and Power
TDoA	Time Difference of Arrival
TWR	Two-Way Ranging
UARC	University Affiliated Research Center
UAV	unmanned aerial vehicle
UI	user interface

UGV	unmanned ground vehicle
VR	virtual reality
VTD	Vehicle Technology Directorate

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