The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/2046-6099.htm

InDrone: a 2D-based drone flight behavior visualization platform for indoor building inspection

Ricardo Eiris
Michigan Technological University, Houghton, Michigan, USA, and
Gilles Albeaino, Masoud Gheisari, William Benda and Randi Faris
University of Florida, Gainesville, Florida, USA

Received 4 March 2021
Revised 16 March 2021
Accepted 26 March 2021

Abstract

Purpose – The purpose of this research is to explore how to visually represent human decision-making processes during the performance of indoor building inspection flight operations using drones.

Design/methodology/approach – Data from expert pilots were collected using a virtual reality drone flight simulator. The expert pilot data were studied to inform the development of an interactive 2D representation of drone flight spatial and temporal data – InDrone. Within the InDrone platform, expert pilot data were visually encoded to characterize key pilot behaviors in terms of pilots' approaches to view and difficulties encountered while detecting the inspection markers. The InDrone platform was evaluated using a user-center experimental methodology focusing on two metrics: (1) how novice pilots understood the flight approaches and difficulties contained within InDrone and (2) the perceived usability of the InDrone platform.

Findings – The results of the study indicated that novice pilots recognized inspection markers and difficult-to-inspect building areas in 63% (STD = 48%) and 75% (STD = 35%) of the time on average, respectively. Overall, the usability of InDrone presented high scores as demonstrated by the novice pilots during the flight pattern recognition tasks with a mean score of 77% (STD = 15%).

Originality/value – This research contributes to the definition of visual affordances that support the communication of human decision-making during drone indoor building inspection flight operations. The developed InDrone platform highlights the necessity of defining visual affordances to explore drone flight spatial and temporal data for indoor building inspections.

Keywords Unmanned aerial vehicles (UAVs), Drones, Construction, Flight visualization, Indoor building inspection, Human–UAV interaction

Paper type Research paper

1. Introduction

Recent developments in the aviation, robotics and engineering fields-enabled unmanned aerial vehicles (UAVs) to become reasonably priced and widely available, factors that in turn significantly improved this technology's commercial adoption. Examples of civilian drone applications include security surveillance, material and medical transport, search and rescue, soil assessment and crop health monitoring (Shakhatreh *et al.*, 2019). The Architecture, Engineering, Construction and Operations (AECO) domain in particular has witnessed an exponential growth in drone adoption over the past years (Albeaino *et al.*, 2019; Zhou and Gheisari, 2018). This wide integration stems from these devices' maneuvering capabilities and location-independency, enabling them to accomplish tasks safely, quickly and cost-efficiently, while being able to access difficult-to-reach locations (Albeaino *et al.*, 2019; Zhou and Gheisari, 2018). Drone-mediated AECO tasks include landslide mapping and monitoring, traffic monitoring, urban planning, historic preservation, in addition to other construction-

This is a substantially extended and enhanced version of the paper presented at The 20th International Conference on Construction Applications of Virtual Reality (CONVR 2020). The authors would like to acknowledge the editorial contributions of Professor Nashwan Dawood and Dr Farzad Rahimian of Teesside University in the publication of this paper.

Smart and Sustainable Built Environment

2046-6099
DOI 10.1108/SASBE-03-2021-0036

related applications expanding across the entire project lifecycle, and ranging from preconstruction (e.g. site feasibility evaluation, site surveying and site activity planning) to construction (e.g. site mapping, earthwork volume calculations, construction activities progress monitoring, safety monitoring and inspection) and postconstruction (e.g. structure inspection and maintenance, postdisaster reconnaissance and marketing) (Albeaino *et al.*, 2019; Albeaino and Gheisari, 2021; Martinez *et al.*, 2021; Martinez *et al.*, 2021). Drone technology integration in the AECO domain is expected to increase even more in the near future, especially with the growing need for enhancing project productivity and addressing skilled labor shortage through robotics and automation.

Among all AECO-related tasks, structure and infrastructure inspections emerged as the top applications in terms of UAV technology adoption (Albeaino *et al.*, 2019; Eiris *et al.*, 2020; Zhou and Gheisari, 2018). Whether intended for structural assessment, damage quantification or leak detection, inspection tasks require operators to maneuver a drone to a location of interest (e.g. a truss joint, a wall crack, a connection pad) and then independently manipulate the onboard imaging sensor [e.g. Red-Green-Blue (RGB) and thermal cameras] to visually inspect the given target. While many of these drone inspection flight operations can be performed autonomously in outdoor environments using GPS signals, similar indoor operations present challenges that limit the use of automated flight missions. For this purpose, researchers have attempted to utilize other technologies to enable autonomous flights indoors by leveraging ultra-wideband and wireless local area networks (Jang and Skibniewski, 2008), computer vision-based algorithms (Padhy *et al.*, 2018), simultaneous localization and mapping (SLAM) navigation (Zahran *et al.*, 2018) and fiducial markers (Nahangi *et al.*, 2018). Nevertheless, these approaches have been found expensive to implement, difficult to deploy or overall restrictive due to context dependencies for being applied in real-world construction sites (McCabe *et al.*, 2017; Nahangi *et al.*, 2018). Consequently, drones are still often manually operated in indoor environments for building inspection applications.

Even with manual operations, successful drone flights in GPS-denied environments are difficult to be accomplished and require extensive expertise, skills and precision from the operators and flight team members to overcome indoor challenges. Examples of indoor navigation challenges that could potentially result in drone accidents include: (1) magnetic interferences caused by the presence of several obstacles; (2) worker's distraction caused by the operation of drones in enclosed areas as well as (3) high-stress and concentration levels due to the low margin of error allowed by the pilot in indoor environments (Kruijff *et al.*, 2012; McCabe *et al.*, 2017). Extensive training is therefore needed to improve pilots' navigational capabilities and guide them in their decision-making, especially in dynamic environments such as the AECO's. In this context, recognizing the drone inflight barriers encountered during previous human-operated indoor flights and the pilots' associated behaviors is valuable for future pilot training and successful drone deployment in this setting.

Due to the importance of human-based operations in drone control systems, the understanding of bidirectional information and loop mechanisms that drive human-drone flight operations is increasingly necessary. As human operators interact with the drone technologies, the gained spatial and temporal information (e.g. position, elevation, facing direction, time) determines the subsequent operational steps within the flight maneuvers. Within the context of this research, an operational requirement refers to the decision-making process that translates into specific flight behaviors utilized by a pilot during the inspection process (e.g. pacing of flight, altitude adjustment with respect to obstacles, drone orientation within a flight path). The human understanding of spatial and temporal information requires constant updating based on the human-drone interaction cycle, allowing for the identification and adjustment of the operational requirements for a given flight in a specific location. Such human-drone interactive systems are currently investigated to improve collision avoidance algorithms (Maxey and Shamwell, 2019) and operator training strategies (Zhou *et al.*, 2019).

This exploratory study concentrates on investigating one aspect of these human-drone interactions – human interpretation of drone spatial and temporal information to determine the operational requirements in building inspection tasks. Specifically, the understanding of human-drone interactions in the AECO domain is investigated in two ways: (1) definition of visual affordances that communicate drone building inspection tasks and (2) development of a system that enables visual exploration of drone spatial and temporal data.

2. Background

Indoor building inspections using drones or UAVs entail a series of pilot behaviors (e.g. pacing of flight, altitude adjustment with respect to obstacles, drone orientation within a flight path) for maneuvering the aircraft with the physical space. Current literature on interpretable visualizations for flight spatial and temporal data of manned and unmanned aircrafts employs 3D and 2D approaches. The adoption of 3D representations to represent inherently spatial data is widely employed in the existing visualization methods (Dübel *et al.*, 2014; Zhong *et al.*, 2012). For instance, Chen *et al.* (2018) proposed the use of 3D models for drone flight path planning to capture location images. The authors demonstrated how to utilize 3D models to illustrate drone flying paths, showing the height and distance of the drone path with respect to the object being captured. It was found that with the addition of depth and camera direction to markers in the visualization, users were able to understand the spatiotemporal relationships between the drone and the environment for capturing images of complex objects. In another example, Li *et al.* (2018) employed a 3D visual comparison on various indoor flight paths obtained from the models to illustrate collision avoidance algorithms. The paper utilized different line continuity and colors, enabling the observer to locate the district paths rapidly in the 3D space. Additionally, the use of occlusion within the visualization offered the observer a sense of the locations where their vision might become obstructed by objects during that flight path.

Although 3D proposes an intuitive approach to represent real-world spatial and temporal data, challenges occur with respect to the ability of users to interpret information within these visualizations. First, distortions occur due to the view perspective of the user. This causes difficulties for the user to accurately understand relative positions, size of objects and distribution of graphical elements (Zhong *et al.*, 2012). Additionally, occlusion during the visualization introduces difficulties in the perception of the spatial location of objects, affecting the readability and measurability of object attributes (Zhong *et al.*, 2012). This effect is especially pronounced within indoor environments where the spatial distribution of buildings might introduce many fixed occluding elements (e.g. walls, staircases, installed equipment). Ultimately, the combination of these two challenges requires the introduction of complex interactions to navigate the data. The addition of another layer of complexity to the visualization challenges requires that the user must not only concentrate on observing the data for meaning but must also concentrate on manipulating the view perspectives to obtain the appropriate information.

In the construction industry, multiple researchers have recently started exploring how to enhance such operation via 2D-, 3D- and simulation-based techniques, as well as other technologies. As an example, Asadi and Han (2020) and Asadi *et al.* (2020) proposed an unmanned aerial-ground robot configuration equipped with wide-angle and stereo cameras, as well as light detection and ranging (LiDAR) devices, to improve autonomous indoor navigation, mapping and data collection. By utilizing different techniques such as SLAM navigation, semantic segmentation and fiducial markers, authors showed that their system was capable of performing autonomous tasks, with both robots collaborating interchangeably to reach predefined on-site locations (Asadi *et al.*, 2020). Building information modeling (BIM) recently emerged as a new automatic indoor path optimization and planning approach currently being studied by construction researchers. For example, despite not only being limited to drones, Hamieh *et al.* (2020) proposed a BIM-based method that consists of utilizing geometric, topological and semantic information from industry foundation classes (IFC) for the generation of navigation graphs and automatic indoor path planning. Using the open source IfcOpenShell, the authors demonstrated the system's capability in representing different scenarios and automatically finding optimal indoor paths based on given criteria. A very recent study also utilized four-dimensional (4D) BIM for the automatic, safe and optimal indoor drone flight mission planning and data collection (Hamledari *et al.*, 2021). The system, which is also based on IFC, was capable of collecting building information models, users' described objectives and inspection date as input; and in turn, automatically identifies inspection targets, timestamps the 4D BIMs and designs optimized drone-mediated inspection plans while ensuring full coverage of inspection targets.

In response to the challenges associated with representing flight spatial and temporal data in 3D, previous studies have explored 2D approaches to reduce complexity and display only key desired information that are useful for the target domain users. For example, Kang *et al.* (2018) proposed a method to simplify drone navigation and image capture by providing a novel user input modality on mobile devices. The authors demonstrated how to visually indicate drone trajectory and image capture direction simultaneously using a 2D projection of the drone path. Information is shown at certain time intervals, indicating front-facing direction of the camera and illustrating the locations where the user spent the most time for capturing the environment. The results from usability experiments showed that the filmmaking target users found the proposed approach intuitive to use and easier than traditional navigation methods (e.g. controller). In another example, Andrienko *et al.* (2019) evaluated the amount of information presented in 2D to manned aircraft pilots, reducing clutter by grouping flight data on a per-pilot and per-flight phase (take-off, cruise, landing) basis. The authors used these grouping techniques to determine how outside forces (e.g. air traffic control) influenced flight paths inequitably. Expert pilots indicated that the developed system was capable of diagnosing patterns of flight behavior as well as providing insight into the outside factors that influenced such behavior. Although existing visualization methodologies in the literature have explored some of the aspects required to understand drone flight paths, none of the studies have specifically investigated these applications within the AECO domain in general and building inspection tasks more particularly.

3. Project overview

The goal of this research is to understand human perception of drone spatial and temporal visual information for defining flight operational requirements within indoor building inspection tasks. To explore this research goal, expert pilot data were collected and studied to inform novice pilots key drone operation maneuvers inside a building location using the InDrone developed platform. To realize this research, two phases with five total steps were completed (Figure 1). In the first phase of this study, a virtual reality (VR) drone flight simulator was developed using a point cloud model of a real indoor location (Step 1). Using the drone flight simulator, a study was completed with expert pilots to identify their flight operations during an indoor inspection task (Step 2). In the second phase of this study, the data from expert pilots were used to identify the InDrone platform goals. Semi-structured interviews were performed with the expert pilots to further supplement the identified approaches to operate the drone within the indoor space for the inspection task. Based on the goals defined and the expert pilot feedback, a platform was developed to visualize the spatial and temporal components of the data (Step 3). Using InDrone, novice pilots evaluated the developed platform focusing on how to perform the inspections tasks and how useable was

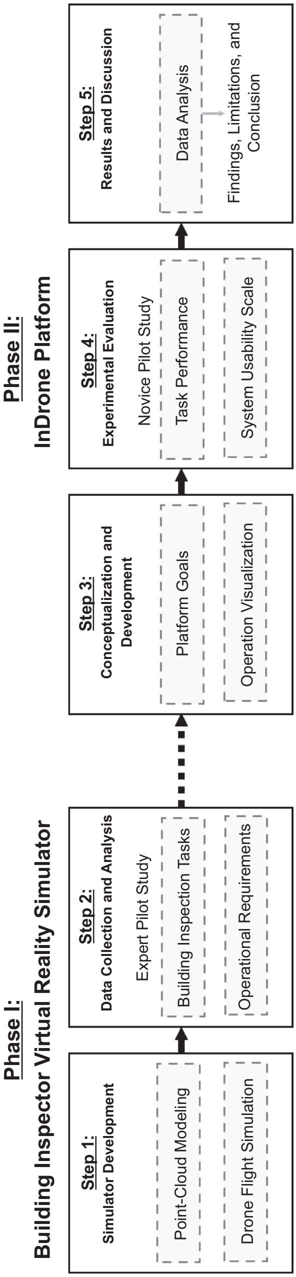

Figure 1.
Project overview

the system (Step 4). Finally, the data collected from the novice pilots were analyzed to establish the findings, limitations and conclusions of this study (Step 5).

4. Building inspector virtual reality simulator

Flight simulators are becoming a necessity for drone pilots, particularly for indoor drone-mediated building inspection types of tasks. The distinctive nature of indoor building inspections requires novice pilots to be capable of effectively interpreting drone-related spatial and temporal operational information, allowing pilots to understand different flight approaches and user behaviors made in previous indoor drone operations and recognizing commonly encountered barriers during previous flights. Ultimately, such information will allow pilots to better understand the drone operational requirements, prevent drone-related accidents from happening, train pilots and assist them in the decision-making process, and help in safely and successfully operating aerial platforms under such environments. While general real-world drone pilot training can potentially be a solution to collect such type of information, several factors including: (1) safety risks associated with operating drones in real-world GPS-denied settings; (2) liability concerns resulting from any drone-related accident that may cause injuries or even fatalities and (3) increased drone operational and potential accident-related costs, make drone flight simulators a safer, more controlled and more efficient alternative (Bu *et al.*, 2015; De la Torre *et al.*, 2016; Weldon and Kozak, 2017). For this purpose, a VR-based drone flight simulator was developed using a laser scanning-acquired point cloud with the aim of collecting actual spatial and temporal information pertaining to indoor building inspection drone flight operations performed by expert pilots.

4.1 Simulator development

The development of the building inspector VR simulator consists of a two-step process: (I) point cloud data collection and (II) simulator development. In the (I) point cloud data collection process (Plate 1), a point cloud of the inspection environment was collected to virtually generate a digitized and analogous version of a real-world building at the University of Florida (the Perry Yard in the Rinker Hall building). A FARO Focus 3D S 120 laser scanner was used to collect point cloud data at five different locations within the inspection environment. The point cloud data measured the internal surfaces of the structure and the objects in the flight environment with a precision of $\pm$ 2 mm. Initially, the .fls raw data obtained from the laser scanner was uploaded to Autodesk® Recap for stitching the five scans into a single file. The FARO Scene LT software was used subsequently for processing the generated point-cloud, removing artifacts and optimizing the number of points for efficiency. The processed point cloud file was then exported as .PTS file and imported into MeshLab to create a .OBJ mesh. Using MeshLab, the .OBJ file was converted to .PLY format, which allows data such as spatial coordinates, color, transparency, surface normal information and texture coordinates to be stored.

For the (II) simulator development, Unity3D® game engine (Version 2017.4.1f1) was used to render the processed point cloud data and to design user interactions that mimic real-world drone flights. The point cloud importer/renderer – Pcx (Keijiro, 2017) open-source library was used to incorporate the .PLY point cloud data into Unity3D®. Pcx uses a Unity3D® custom shader to render the point primitives that are adjustable in size. Using the digital setting created by the point cloud, a set of user interactions were designed to fly the drone in VR. As illustrated in Plate 1, an Oculus Rift head-mounted display (HMD) setting was used to immerse users into the VR environment. A set of game mechanisms driven by custom-built scripts allowed pilots to virtually maneuver the drone, visualize the environment and interact with the platform. A Microsoft Xbox One® Gamepad controller was used to maneuver the

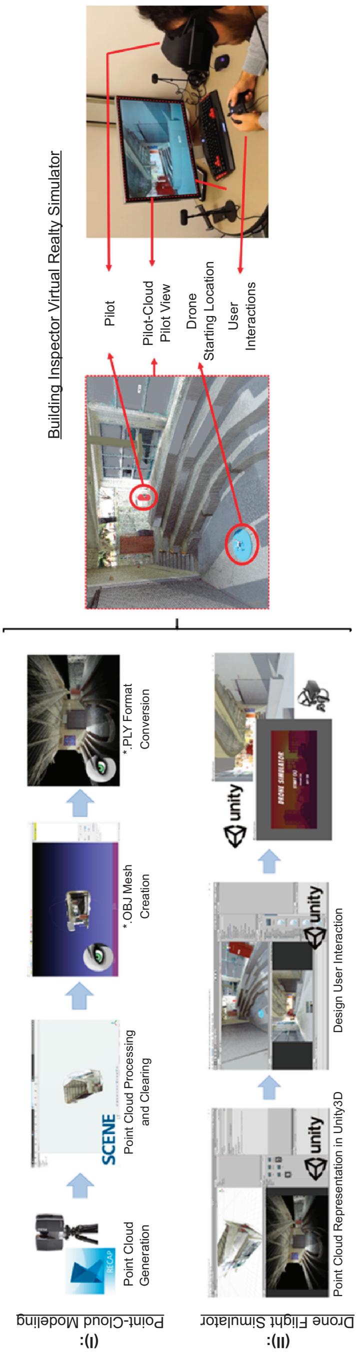

Plate 1.
Building inspector virtual reality simulator development

spatial location of the drone, and Oculus Rift HMD was used to allow the pilot to pivot their views from a static point-of-view similar to a real-world drone operation.

4.2 Data collection and analysis

To explore human interpretable drone spatial and temporal information, data were collected from four commercially certified drone pilots using the developed building inspector VR simulator. The goal of this data collection was to understand the operational steps performed by the expert drone pilots during the performance of an indoor building inspection. The data collection entailed a drone flight inspection task within the developed VR drone flight simulator. The expert pilots explored the VR environment fully immersed in the simulation using a HMD and a game controller to operate the drone. The expert pilots were tasked with examining 10 equally sized target markers placed in strategic locations on the building point cloud (Plate 2). Each marker varied in terms of elevation, position and surrounding obstacles. Spatial flight data were logged by the simulation in 1/5 second intervals. For each flight, the following data were captured: 3D (x, y, z) coordinates of the drone, rotation of the drone with respect to its center of mass (pitch, roll, yaw), drone speed (x, y, z) and the corresponding timestamp. Each of the four pilots ran through the simulation twice for a total of eight flight paths stored in eight separate data logs. For the purposes of this research, the logs were converted to .JSON format.

The data collected from the expert pilots is summarized in Table 1. The expert pilots were all male with an average age of 27 years. Two of the pilots were PhD students, one master's student and one senior undergraduate student. The construction experience of the expert pilots varied between more than two years and less than six months. All expert drone pilots reported to have a high familiarity with drones and an average familiarity with VR. The familiarity with building inspection varied from high to low across expert pilots.

The operational steps during the flight were initially analyzed using two metrics: average speed and flight duration. Table 2 displays the average speed and flight duration of each pilot during the two flights performed in the VR simulator. The highest speed recorded was during the second flight of Pilot 1 with an average of 4.49 m/s and the lowest speed recorded was during the first flight of Pilot 2 with an average of 2.03 m/s. The flight duration corresponded with the lowest average speed recorded on the first flight of Pilot 2 with 512.24 seconds, but the fastest flight duration was during the second flight of Pilot 4 with 132.56 seconds. The relationship between average speed and flight duration revealed that other factors also affected the operational requirements of each pilot, including the drone's path selection, the drone's orientation across time, changes in drone's speed and drone's relative position with respect to obstacles.

5. InDrone platform

The InDrone platform leverages a 2D interactive visual representation of spatial data to provide users with a method to identify flight patterns, facilitating the recognition of appropriate practices within the inspection tasks. The conceptualization and development of the platform followed a user-centered design based on the expert pilot data collected. To evaluate the validity of the created platform, an experimental study was performed to assess the task performance of information identification as well as the usability of the system. The details of the conceptualization and development of the InDrone platform, as well as the experimental evaluation are described in the following subsections.

5.1 Conceptualization and development

5.1.1 InDrone platform goals. The goals for the InDrone visualization platform in this study were established by iteratively exploring the collected data and interviewing commercially

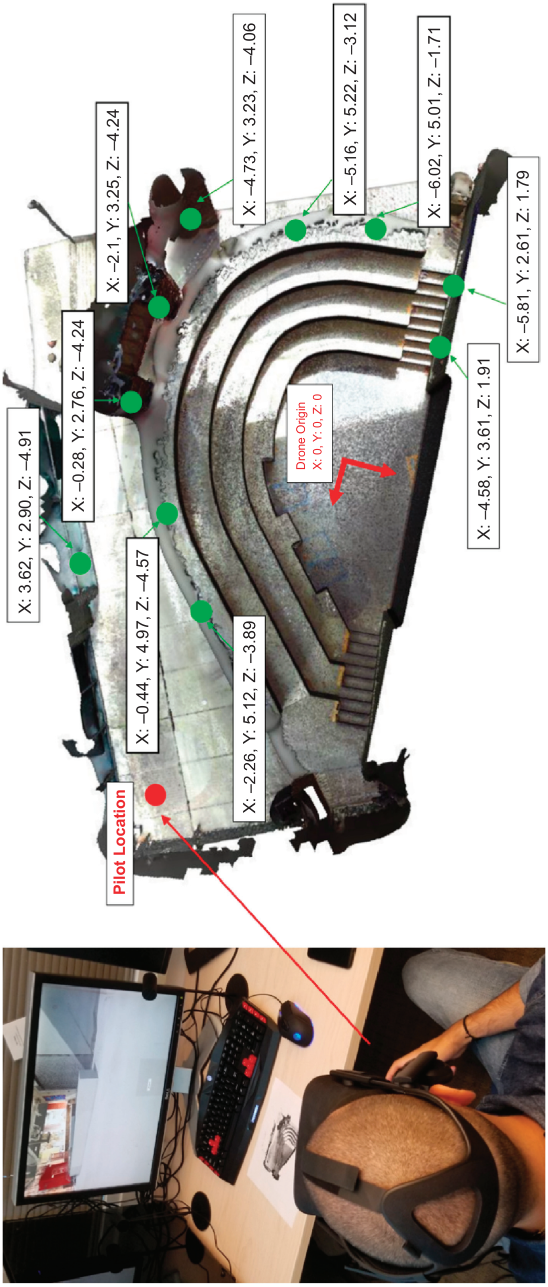

Plate 2.
Expert pilot data collection

certified drone pilots. Initially, the data from the VR flights were explored by implementing a preliminary representation of the drone spatial and temporal data that accounted for average speed and flight duration. In the existing literature, 2D and 3D approaches have been considered to represent spatial and temporal data similar to the data collected from the expert users' drone flights. This first implementation focused on displaying the spatial distribution of the drones across time. For this study, a 2D representation was selected due to the advantages of allowing the viewer to see the entire flight paths at once. In a 3D visualization, some of the paths would be occluded by parts of the building, potentially resulting in the exploration of interactivity methods to reduce spatial complexity. Additionally, within the AECO domain, users are accustomed to analyzed information utilizing isometric projections of 3D real-world objects. By maintaining 2D-based visualization, the perception expectations of domain professionals allow the proposed design to provide simple-to-interpret representations of building inspection tasks and locations.

Following, a set of semi-structured interviews were conducted with the same four expert pilots that previously participated in the VR simulation. The expert pilots observed the preliminary 2D representation of all the collected spatial and temporal data. During the interviews, information was collected regarding pattern recognition within the data and determination of flight strategies from the visual representation. From the analysis of the interviews, two main themes were identified in terms of pilot drone flight behaviors: (1) approaches to view the inspection markers and (2) difficult areas that require longer times to maneuver. These two themes translated into the design goals of this project as:

G1. Demonstration of the pilots' approaches to view the inspections markers. The visual representation of these approaches should reflect the drone spatial positions across time and drone orientation with respect to the marker locations.

G2. Detection of areas in the flight path where it was difficult to observe the inspection markers. The visual representation should reveal the inspection markers that require longer time to be explored while performing the drone flight building inspection.

Table 1. Expert pilot demographic information

Pilot	Age	Gender	Education	Experience in construction	Familiarity with Drones	Familiarity with Virtual reality	Familiarity with Building inspection
1	27	Male	PhD	More than 2 years	High	Average	High
2	24	Male	Masters	1–2 years	High	Average	Average
3	36	Male	PhD	More than 2 years	High	Average	High
4	22	Male	Senior	Less than 6 months	High	Average	Low

Table 2. Expert pilot operational requirements exploration

Pilot	Flight number	Average speed (m/s)	Flight duration (seconds)
1	1	3.20	404.42
1	2	4.49	291.02
2	1	2.03	512.24
2	2	3.22	445.01
3	1	2.12	292.10
3	2	2.36	269.33
4	1	2.54	165.30
4	2	2.59	132.56

5.1.2 Visualizing drone critical operations during inspection tasks. To accomplish the InDrone platform goals of this investigation, data were encoded following Cleveland and McGill (1986) principles for visual design. In this study's platform design, the relationship between the inspection location and the spatial data is critical for the understanding of drone operations. A web-based 2D platform was developed utilizing JavaScript and D3 Version 5 (Bostock, 2019). Within the web-based platform, a cartesian plane with real-world dimensions (in meters) hosted a background contour image of the building's point map to demonstrate the context of the flight operations (Plate 2).

Within that background, the important spatial data were encoded in the visualization using inspection markers, flight paths and drone orientations. These encodings corresponded with G1 by enabling users to determine the pilot's approaches to perform the flight tasks (Figure 2). In the visualization, the inspection markers were represented by bright red markers. These target inspection markers corresponded with spatial coordinates in the simulated flight operation. Preattentive processing enabled users to quickly recognize the targets in the spatial configurations of the projected building. For each pilot, flight paths were plotted using the x and z spatial coordinates – y coordinates were encoded separately as altitude. Each pilot's flight path was encoded with a unique color, with the second run varying in shades of the same color. This allowed the users to associate position with each pilot's paths displayed in the inspection location. Because the flight paths varied in length and contained a lot of overlapping points (the drone may not be moving every 1/5 of a second), the data was resampled using the initial steps of the $1 algorithm (Wobbrock *et al.*, 2007), reducing the number of points per line while maintaining the overall length of the path. Additionally, the start (blue) and end (yellow) points were explicitly shown to indicate the direction of the flight paths. Moreover, the drone's yaw was represented by triangular markers that scaled according to the y coordinate altitudes along the drone path (i.e. larger triangles being at higher altitudes and smaller triangles lower altitudes). These triangular markers were additionally encoded using the yaw rotation angle of the triangle to demonstrate the forward point direction at a given time. The triangular marker encoding in conjunction with the x, y and z coordinates, represent the drone flight path in a way that keeps unmanned aerial vehicle parallel to the ground. Finally, a slider was provided to the user to increase the granularity of triangles displayed and account for the potential loss of information introduced by the resampling method applied to the data (see Figure 3).

To demonstrate the areas of difficulty as described in G2, Fuchsia circles were used to represent locations with low drone speed (Figure 2). During the inspection task, areas of low speed indicate that the pilot requires maneuvering with exceptional care. The speed data for each drone pilot were ranked from low to high, and the top 2% of low speeds were employed to demonstrate the difficulty areas. A slider was provided to change this threshold varying from 1% to 10%. It is important to highlight that the Fuchsia circles were partially transparent, enabling the user to observe color intensity variations on areas with dense overlaps.

With the objective of supporting all the encodings and the user navigation of the spatial data, an interface was created following Shneiderman's mantra (Shneiderman, 1996) for information seeking. Iterative development was utilized to refine these interactions. A pilot test was performed with two users to understand the usefulness of the proposed encodings and interactions for the visualization. Improvements were done considering their feedback as well as the challenges faced during their interaction with the system. The resulting implementation from the iteration is shown in Plate 1. Initially, an overview of the data was provided by enabling the user to observe the start/end points for the first drone flight of each pilot. To provide a zoom and filter of the data, a *Drone Flight Path* menu section was provided to enable users to toggle on/off different paths using a check box interface. Using the *Drone Markers* menu section, users were able to activate or deactivate the triangles that denoted

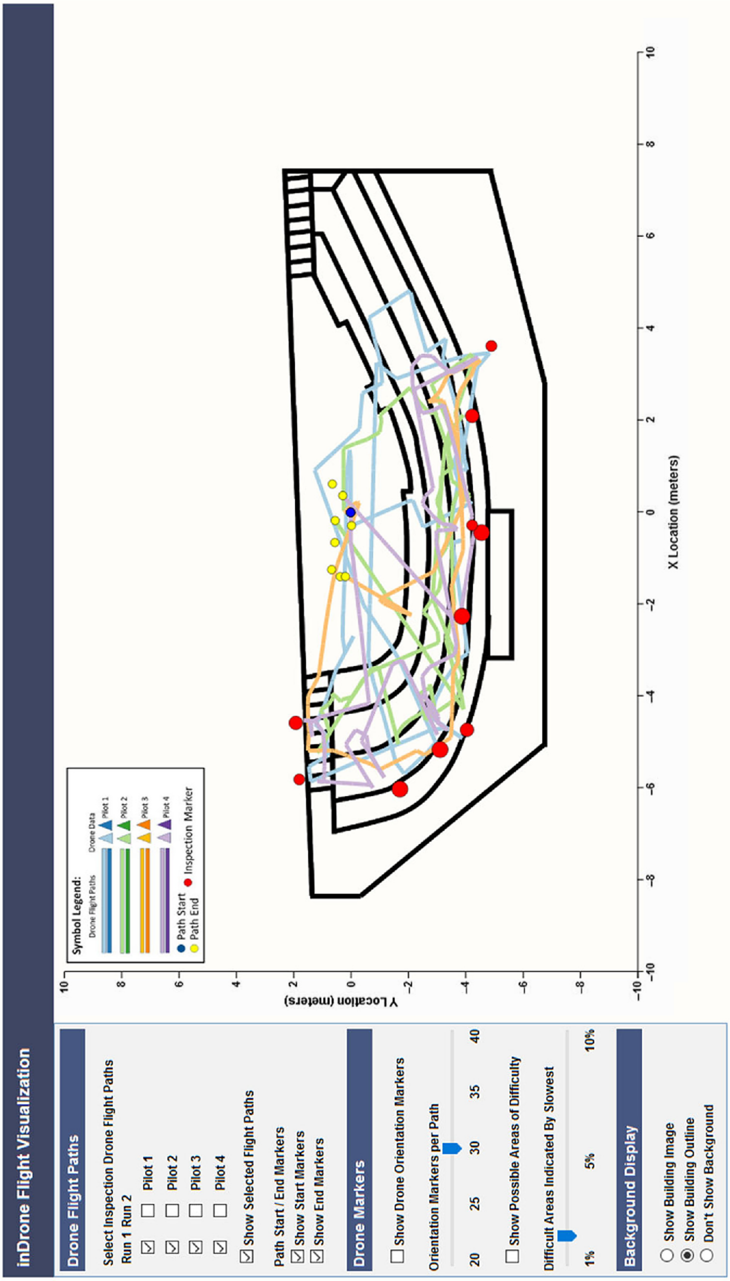

Figure 2.
Multiple drone flight paths visualization

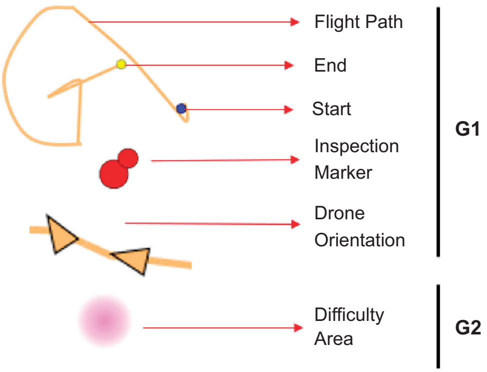

Figure 3.
Visual encodings to accomplish platform goals

orientation of the drone within the flight paths. Similarly, a *Difficult Areas* checkbox allowed users to display the Fuchsia circles that denote reduced speed areas. The *Background Display* menu permitted users to modify the background using radial buttons. Details-on-demand could be obtained from any of the markers (inspection, start, end, triangles) by hovering over them to reveal a tooltip with the raw data. Finally, the control of the parameters aligned with G1 and G2 was exposed to the users to provide them with further details that they might require.

5.2 Experimental evaluation

This project utilized a user-centered experimental evaluation to assess two different metrics: task performance and usability rating. First, task performance focused on studying how users retrieve important information from the visualization in terms of G1 – *Approaches* (pilots' approaches to view the inspections markers) and G2 – *Difficulties* (difficulties detection around inspection markers). This measurement is intended to identify the advantages and challenges of the proposed design for the users to understand drone operations during inspection tasks. A set of 10 questions was developed to assess user task performance using high- and low-level cognition analysis, as displayed in Table 3. For the G1 – *Approaches*, four questions aimed to determine how users perceived the drone navigation patterns in the inspection location as well as pilots' behaviors while exploring the

Approaches – G1	Difficulties – G2	Usability
(1) Which drone pilot performed the building inspection task the fastest?	(1) Which building inspection target was the most difficult to observe across all drone pilots?	(1) How many drone pilots are present in the data showed to you?
(2) Do drone pilots have a preference target exploration direction (i.e. clockwise, counterclockwise)	(2) Which building inspection target was the easiest to observe across all drone pilots?	(2) How many flights per pilot are shown in the visualization?
(3) Does the drone camera for Pilot 2 face every target at some point in the flight path?		(3) What general area do drone pilots start and end their flights?
(4) Did any of the drone pilots inspect a target more than once?		(4) What is the elevation of the highest building inspection target?

Table 3.
Task performance question

target markers (high-level cognition). For the G2 – *Difficulties*, two questions aimed to establish how users determined challenges to observe target markers by the drone pilots (high-level cognition). Finally, four questions were asked about usability to provide a practical understanding of how users employed different encodings to explore the visualization (low-level cognition).

Second, the System Usability Scale (SUS) survey (Brooke, 1996) was used to assess the usability rating assigned to the visualization. This survey provided a metric for the visualization in terms of ease of use, satisfaction, effectiveness and design efficiency (Brooke, 2013). The survey used a 5-point Likert scale that contained 10 questions scaled from 1: strongly disagree to 5: strongly agree. The usability score was computed by inverting the score of negative statement questions, summing all the scores, multiplying the resulting score by 2.5 and normalizing the scores (ranging from 0 to 100) as established by Brooke (1996). SUS usability benchmarks have shown that the average score of a system approximates 68% in the scale (Sauro, 2011). To further support the user responses in this survey, an open-ended comment section was provided.

Participants were recruited from the University of Florida. The participants interacted with the visualization while a researcher asked the questions defined in this document. A think-aloud protocol was employed to obtain as much qualitative data as possible from the users' interactions during the task performance activities. These conversations were recorded for later analysis. After completing the task performance questions, the SUS survey instrument was administered to the participants using an online Qualtrics questionnaire (Qualtrics, 2019). Posteriorly, the responses from the task performance questions were graded to determine the number of successfully or unsuccessfully answered questions. Furthermore, the SUS survey instrument was scored using the analysis previously described. Prior to the task performance and usability data collection, users completed a consent form (IRB201902372) and a demographics survey describing their age, gender, education and experiences with drones and building inspection tasks.

5.3 Results and discussion

A total of 10 participants evaluated the proposed design. Participants had an average age of 28 years (STD = 5 years) and were mostly males (90%). A large proportion of the participants were PhD students (60%), but the sample also contained master's (20%) and undergraduate (20%) students. None of the participants reported to have a commercial license to fly drones but presented varying degrees of familiarity with drone technologies (Low = 30%; Average = 70%; High = 0%) and building inspection tasks (Low = 40%; Average = 60%; High = 0%). While none of the participants were certified drone pilots, the goal of the InDrone platform is to enable future pilots learn flight strategies; thus, these participants were deemed to be suitable for the analysis of the InDrone platform. Participants completed the task performance and usability questions in approximately 14 min (Average = 14 min, STD = 4 min).

The results of the task performance questions were analyzed using descriptive statistics as shown in Table 4. The average score for the G1 – *Approaches* was 63% (STD = 48%). This score indicates that participants had challenges understanding some of the critical operations

Table 4.
Task performance descriptive statistics

Task performance		Approaches	Difficulties	Usability
	Average	63%	75%	95%
	STD	48%	35%	6%

during inspection tasks. While questions 1 and 2 were easily answered by the participants, questions 3 and 4 were more difficult. On average, participants scored 100% for questions 1 and 2 but had an average success rate of 50% for question 3 and 0% for question 4. Participants were unable to properly identify the drone facing direction across time due to potential issues with clutter, height identification and temporal relationships in visualization. For instance, one of the participants indicated that *"the triangles overlap in this marker, but I'm not sure if that means that the pilot is looking at the target just once or multiple times"*.

The average score for G2 – *Difficulties* was 75% (STD = 35%). This score indicates that most participants were able to detect difficult-to-maneuver areas in the inspection locations. While question 1 had a 100% success rate, question 2 had a success rate of 50%. The lower average success rate of question 2 was potentially caused by the lack of identifiers of high-speed areas. In the visualization, only low-speed areas were highlighted, and it was assumed that the target markers with a lesser number of Fuchsia circles implied lower difficulty. Finally, the average score for usability questions was 95% (STD = 6%). These consistently high scores indicate that the visualization was easy to navigate for low-level type of cognitive tasks such as the ones asked in this category.

The results of SUS survey were analyzed using the strategy outlined in Brooke (1996) and descriptive statistics were reported as shown in Table 5. For the SUS scores, the average score was 77% (STD = 15%). This average score in this investigation is above the 68% average that was found in a meta-analysis for usability studies (Sauro, 2011). Moreover, this average score is higher that prior studies that evaluated the creation of platforms to visualize human-drone maneuvering behaviors within photography applications (Kang *et al.*, 2018; Alcántara *et al.*, 2020). Differently from prior studies (Kang *et al.*, 2018; Alcántara *et al.*, 2020), the InDrone platform provides interactive method to visualize data after pilots have performed drone maneuvers. By offering such interactive method, new pilots can easily understand the manipulation of the drone on the indoor space to successfully perform future operations. The positive usability rating as reported by participants indicates that the system designed in this research was adequate for new pilots. Furthermore, these results are consistent with the scores reported for the task performance questions. Participants' comments in general were positive about the usability of the system. One participant indicated that "*[the] system was not too complicated overall after using it for a couple of tasks*" and another one suggested that "*the system can easily provide a lot of information about the paths of the pilots*".

5.4 Practical implications

The findings of this study provide insights for designers and practitioners of indoor drone data visualization platforms in terms of effective visual encodings that demonstrate human behaviors. The observed results for the designed affordances within InDrone platform indicate that trainees were able to successfully identify drone inspection speeds and flight path directions. The proposed flight paths, drone orientation and inspection marker affordances allowed trainees to detect the approaches prior pilots took to inspect the location represented within the InDrone platform. Additionally, trainees were able to identify the level of difficulty required to inspect certain markers within the location. The difficulty area maker affordance assisted the rapid detection of difficult-to-maneuver areas in the displayed locations. Ultimately, the high usability findings further support the use of these visually

SUS (Brooke, 1996)	Average	STD	Max	Min
	77%	15%	98%	55%

Table 5. SUS descriptive statistics

encoded affordances for drone inspection tasks. Other platforms that use similar affordances as the ones developed for InDrone can be easy to learn and navigate, as well as simple to get accustomed to.

6. Limitations

This study exhibited limitations in two main areas: (1) sample size and (2) data representation. First, due to the exploratory nature of the research, the sample size of the collected data was small. This eliminates the possibility to provide statistical generalizations over the whole study population in terms of G1 and G2. However, this sample size seems appropriate for usability studies, as research has revealed that 10 participants can identify up to 95% of the problems in software tools (Faulkner, 2003). Second, the 2D representation selected for this study limits the data representation flexibility. Some of the height encodings that are inherently 3D were difficult for users to understand and interpret in a 2D representation. However, constraining the visualization to 2D simplifies interaction and reduces the requirement for larger exploration times often required in 3D representations.

7. Conclusion and future work

This exploratory research investigated the design requirements and considerations necessary to understand drone pilots' behaviors while performing building inspection tasks. Design goals were established through iterative exploration of drone spatial data and interviews with commercially certified drone pilots. As a result, the two defined goals for this study were: G1 – identifying pilots' approaches to view the inspections markers and G2 – demonstrating difficulty detection around the inspection markers. A user-centered experimental evaluation was performed to assess the users' task performance and usability rating while utilizing a developed visualization system. Results showed that users identified pilots' approaches to view the inspections markers on average 63% (STD = 48%) of the time. This was caused by challenges with clutter, height identification and temporal relationships. On the other hand, it was found that on average, most users were able to identify difficult-to-inspect building areas with a success rate of 75% (STD = 35%). Finally, users reported high scores for usability of the system during both, task performance activities and the SUS survey. The survey average score was 77% (STD = 15%), indicating a good usability rating.

Future work in this research area should explore summarization of flight paths to represent commonalities across multiple drone pilots. By condensing common paths into a single representation, visualization clutter can be reduced, potentially avoiding some of the user challenges reported in this research. Moreover, an in-depth evaluation of the accurate perception of the height encoding needs to be performed to better understand the impact relative sizes have on the users' responses. Comparative analyses should also be conducted between the 2D visualization design proposed in this study and a 3D design to assess the advantages and disadvantages of each approach for drone building inspection applications. While this study focuses on the development of a UAV-mediated data visualization platform – InDrone, additional investigations are warranted to validate the effectiveness of this design in reducing the pilots' stress and concentration levels, as well as improving their navigational skills and decision-making to successfully accomplish indoor building inspection tasks.

References

Albeaino, G. and Gheisari, M. (2021), "Trends, benefits, and barriers of unmanned aerial systems in the construction industry: a survey study in the United States", *Journal of Information Technology in Construction (ITcon)*, Vol. 26, pp. 84-111, doi: 10.36680/j.itcon.2021.006.

Albeaino, G., Gheisari, M. and Franz, B.W. (2019), "A systematic review of unmanned aerial vehicle application areas and technologies in the AEC domain", *Journal of Information Technology in Construction (ITcon)*, Vol. 24, pp. 381-405.

Alcántara, A., Capitán, J., Torres-González, A., Cunha, R. and Ollero, A. (2020), "Autonomous execution of cinematographic shots with multiple drones", *IEEE Access*, Vol. 8, pp. 201300-201316.

Andrienko, N., Andrienko, G., Garcia, J.M.C. and Scarlatti, D. (2019), "Analysis of flight variability: a systematic approach", *IEEE Transactions on Visualization and Computer Graphics, Presented at the IEEE Transactions on Visualization and Computer Graphics*, Vol. 25 No. 1, pp. 54-64.

Asadi, K. and Han, K. (2020), "An integrated aerial and ground vehicle (UAV-UGV) system for automated data collection for indoor construction sites", *Construction Research Congress*, Vol. 2020, pp. 846-855.

Asadi, K., Kalkunte Suresh, A., Ender, A., Gotad, S., Maniyar, S., Anand, S., Noghabaei, M., Han, K., Lobaton, E. and Wu, T. (2020), "An integrated UGV-UAV system for construction site data collection", *Automation in Construction*, Vol. 112, p. 103068.

Bostock, M. (2019), "D3: data-driven documents", available at: https://github.com/d3/d3 (accessed 4 March 2021).

Brooke, J. (1996), "SUS-A quick and dirty usability scale", *Usability Evaluation in Industry*, London–, Vol. 189 No. 194, pp. 4-7.

Brooke, J. (2013), "SUS: a retrospective", *Journal of Usability Studies*, Usability Professionals' Association Bloomingdale, IL, Vol. 8 No. 2, pp. 29-40.

Bu, Q., Wan, F., Xie, Z., Ren, Q., Zhang, J. and Liu, S. (2015), "General simulation platform for vision based UAV testing", *2015 IEEE International Conference on Information and Automation, Presented at the 2015 IEEE International Conference on Information and Automation*, pp. 2512-2516.

Chen, Y.-A., Wu, T.-Y., Chang, T., Liu, J.Y., Hsieh, Y.-C., Hsu, L.Y., Hsu, M.-W., Taele, P., Yu, N.-H. and Chen, M.Y. (2018), "ARPilot: designing and investigating AR shooting interfaces on mobile devices for drone videography", *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services*, Barcelona, Spain, Association for Computing Machinery, pp. 1-8.

Cleveland, W.S. and McGill, R. (1986), "An experiment in graphical perception", *International Journal of Man-Machine Studies*, Vol. 25 No. 5, pp. 491-500.

De la Torre, G.G., Ramallo, M.A. and Cervantes, E. (2016), "Workload perception in drone flight training simulators", *Computers in Human Behavior*, Vol. 64, pp. 449-454.

Dübel, S., Röhlig, M., Schumann, H. and Trapp, M. (2014), "2D and 3D presentation of spatial data: a systematic review", *2014 IEEE VIS International Workshop on 3DVis (3DVis), Presented at the 2014 IEEE VIS International Workshop on 3DVis (3DVis)*, pp. 11-18.

Eiris, R., Albeaino, G., Gheisari, M., Benda, B. and Faris, R. (2020), "Indrone: visualizing drone flight patterns for indoor building inspection tasks", *Proceedings of the 20th International Conference on Construction Applications of Virtual Reality*, Middlesbrough, UK, Teesside University Press, pp. 273-282.

Faulkner, L. (2003), "Beyond the five-user assumption: benefits of increased sample sizes in usability testing", *Behavior Research Methods, Instruments and Computers*, Vol. 35 No. 3, pp. 379-383.

Hamieh, A., Ben Makhlouf, A., Louhichi, B. and Deneux, D. (2020), "A BIM-based method to plan indoor paths", *Automation in Construction*, Vol. 113, p. 103120.

Hamledari, H., Sajedi, S., McCabe, B. and Fischer, M. (2021), "Automation of inspection mission planning using 4D BIMs and in support of unmanned aerial vehicle–based data collection", *Journal of Construction Engineering and Management*, Vol. 147 No. 3, p. 04020179.

Jang, W.-S. and Skibniewski, M.J. (2008), "A wireless network system for automated tracking of construction materials on project sites", *Journal of Civil Engineering and Management*, Vol. 14 No. 1, pp. 11-19.

Kang, H., Li, H., Zhang, J., Lu, X. and Benes, B. (2018), "FlyCam: multitouch gesture controlled drone gimbal photography", *IEEE Robotics and Automation Letters*, *Presented at the IEEE Robotics and Automation Letters*, Vol. 3 No. 4, pp. 3717-3724.

Keijiro, T. (2017), "Keijiro/pcx - point cloud importer and renderer for unity", available at: https://github.com/keijiro/Pcx (accessed 4 March 2021).

Kruijff, G.-J.M., Pirri, F., Gianni, M., Papadakis, P., Pizzoli, M., Sinha, A., Tretyakov, V., Linder, T., Pianese, E., Corrao, S., Priori, F., Febrini, S. and Angeletti, S. (2012), "Rescue robots at earthquake-hit Mirandola, Italy: a field report", *2012 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, IEEE, pp. 1-8.

Li, F., Zlatanova, S., Koopman, M., Bai, X. and Diakité, A. (2018), "Universal path planning for an indoor drone", *Automation in Construction*, Vol. 95, pp. 275-283.

Martinez, J.G., Albeaino, G., Gheisari, M., Issa, R.R.A. and Alarcón, L.F. (2021), "iSafeUAS: an unmanned aerial system for construction safety inspection", *Automation in Construction*, Vol. 125, p. 103595.

Martinez, J.G., Albeaino, G., Gheisari, M., Volkmann, W. and Alarcón, L.F. (2021), "UAS point cloud accuracy assessment using structure from motion–based photogrammetry and PPK georeferencing technique for building surveying applications", *Journal of Computing in Civil Engineering*, American Society of Civil Engineers, Vol. 35 No. 1, p. 05020004.

Maxey, C.J. and Shamwell, E.J. (2019), "Navigation and collision avoidance with human augmented supervisory training and fine tuning via reinforcement learning", *Micro- and Nanotechnology Sensors, Systems, and Applications XI*, *Presented at the Micro- and Nanotechnology Sensors, Systems, and Applications XI*, International Society for Optics and Photonics, Vol. 10982, p. 1098228.

McCabe, B.Y., Hamledari, H., Shahi, A., Zangeneh, P. and Azar, E.R. (2017), "Roles, benefits, and challenges of using UAVs for indoor smart construction applications", *Computing in Civil Engineering*, Vol. 2017, pp. 349-357.

Nahangi, M., Heins, A., McCabe, B. and Schoellig, A. (2018), "Automated localization of UAVs in GPS-denied indoor construction environments using fiducial markers", *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction; Waterloo*, Waterloo, Canada, Waterloo, Vol. 35, IAARC Publications, pp. 1-7.

Padhy, R.P., Verma, S., Ahmad, S., Choudhury, S.K. and Sa, P.K. (2018), "Deep neural network for autonomous UAV navigation in indoor corridor environments", *Procedia Computer Science*, Vol. 133, pp. 643-650.

Qualtrics (2019), Qualtrics, Provo, Utah.

Sauro, J. (2011), "MeasuringU: measuring usability with the system usability scale (SUS)", available at: https://measuringu.com/sus/ (accessed 9 June 2020).

Shakhatreh, H., Sawalmeh, A.H., Al-Fuqaha, A., Dou, Z., Almaita, E., Khalil, I., Othman, N.S., Khreishah, A. and Guizani, M. (2019), "Unmanned aerial vehicles (UAVs): a survey on civil applications and key research challenges", *IEEE Access*, *Presented at the IEEE Access*, Vol. 7, pp. 48572-48634.

Shneiderman, B. (1996), "The eyes have it: a task by data type taxonomy for information visualizations", *Proceedings 1996 IEEE Symposium on Visual Languages*, *Presented at the Proceedings 1996 IEEE Symposium on Visual Languages*, pp. 336-343.

Weldon, W. and Kozak, D. (2017), "Effects of simulator training for unmanned aerial systems in undergraduate education", *Presented at the 19th International Symposium on Aviation Psychology*, p. 190.

Wobbrock, J.O., Wilson, A.D. and Li, Y. (2007), "Gestures without libraries, toolkits or training: a $1 recognizer for user interface prototypes", *Proceedings of the 20th Annual ACM Symposium on*

User Interface Software and Technology, USA, Association for Computing Machinery, Newport, Rhode Island, pp. 159-168.

Zahran, S., Moussa, A., Sesay, A. and El-Sheimy, N. (2018), "Enhancement of real-time scan matching for uav indoor navigation using vehicle model", *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. IV No. 1, pp. 171-178.

Zhong, C., Wang, T., Zeng, W. and Müller Arisona, S. (2012), "Spatiotemporal visualisation: a survey and outlook", *Digital Urban Modeling and Simulation*, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 299-317.

Zhou, S. and Gheisari, M. (2018), "Unmanned aerial system applications in construction: a systematic review", *Construction Innovation*, Vol. 18 No. 4, pp. 453-468, doi: 10.1108/CI-02-2018-0010.

Zhou, J., Zhu, H., Kim, M. and Cummings, M.L. (2019), "The impact of different levels of autonomy and training on operators' drone control strategies", *ACM Transactions on Human-Robot Interaction*, Vol. 8 No. 4, pp. 22:1-22:15.

Corresponding author
Ricardo Eiris can be contacted at: reiris@mtu.edu