INDRONE: VISUALIZING DRONE FLIGHT PATTERNS FOR INDOOR BUILDING INSPECTION TASKS

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ABSTRACT: *The use of drones or unmanned aerial vehicles for indoor building inspection tasks requires users to understand flight patterns (e.g., flight routes, camera focus points, target approach strategies) for maneuvering the aircraft. This study focuses on exploring the visual representation of human behaviors performing indoor building inspection flight operations using drones. An interactive 2D representation of drone flight spatial data – InDrone – was developed to characterize flight patterns during the inspection of indoor markers that were already defined in the inspection area and visualize potential maneuvering difficulties around those markers. This study evaluated InDrone via a user-centered assessment methodology that measured performance and usability ratings. Using visual flight patterns, users identified inspection markers and difficult-to-inspect building areas in 63% (STD = 48%) and 75% (STD = 35%) of the time on average, respectively. Overall, users reported high scores for the usability of InDrone during the flight pattern recognition tasks with a mean score of 77% (STD = 15%). This study contributes to the definition of visual affordances that support the communication of flight patterns for drone indoor building inspection tasks. The InDrone pilot system demonstrates the usefulness of visual affordances to explore drone flight spatial data for indoor building inspections.*

KEYWORDS: *Unmanned Aerial Vehicles (UAVs), Drones, Construction, Flight Visualization, Indoor Building Inspection*

1. INTRODUCTION

Drones or Unmanned aerial vehicles (UAVs) have been increasingly adopted in the architecture, engineering, and construction (AEC) industry for inspecting building structures (Albeaino et al., 2019). Building 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 camera on the drone 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 limits the use of automated operations. Researchers have attempted to utilize other technologies to enable autonomous flights indoors by leveraging ultra-wideband (UWB) and wireless local area networks (WLAN) (Jang and Skibniewski, 2008), computer vision-based algorithms (Padhy et al., 2018), SLAM navigation (Zahran et al., 2018), and fiducial markers (Nahangi et al., 2018). However, 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 the pilots' navigational capabilities and guide them in their decision making, especially in dynamic environments such as the AEC'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 information (e.g., position, elevation, facing direction) determines the subsequent operational steps within the flight maneuvers. This human understanding of spatial information requires constant updating based on the interaction cycle. 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 information to determine the operational requirements in building inspection tasks. Specifically, the understanding of human-drone interactions in the AEC 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 data.

2. BACKGROUND

Current literature on interpretable visualizations for flight spatial 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 offers 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 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 response to the challenges associated with representing flight spatial data in 3D, previous studies have explored 2D approaches to reduce complexity and display only key desired information that is 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 demonstrate 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 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 AEC domain in general and building inspection tasks more particularly.

3. METHODOLOGY

To explore human interpretable drone spatial information representations, data was collected from four commercially certified drone pilots within a virtual reality (VR) simulation to create a visualization of building inspection operations. Using the experts' data, this investigation explored the visual design elements necessary to demonstrate human behaviors during building inspection tasks in terms of approaches to view the inspection targets and detection of areas with potential difficulty. The created InDrone platform leverages a 2D interactive visual representation of spatial data to provide users a method to identify flight patterns, facilitating the recognition of appropriate practices within the inspection tasks. To evaluate the produced design, a user-centered study was performed to assess the task performance of information identification as well as the usability of the system. Interviews with expert pilots were conducted to define a set of tasks and evaluate the proposed design, employing a think-aloud methodology and a post-assessment survey. Detail explanation of each of platform design rationale are provided in the following subsections.

3.1 InDrone Platform

The goal of this paper's visualization is to convey the operational steps from expert drone pilots during the performance of an indoor building inspection. These operational steps can be visualized through flight behaviors using elements such as path patterns, drone direction, and target approach strategies. Data was collected from four commercially certified drone pilots to understand these operational steps for building inspection tasks. These expert pilots were asked to perform a drone flight inspection of the Perry Yard in the Rinker Hall building at the University of Florida campus within a VR simulation. The VR environment used an Oculus Rift head-mounted display and an Xbox game controller to operate the drone (Figure 1). The Perry Yard simulation was created within the Unity Game Engine, employing a point cloud obtained from the FARO Focus 3D S 120 laser scanner. The expert pilots were tasked with examining 10 target markers placed in strategic locations on the point cloud of the building. Spatial flight data was logged by the simulation in 1/5 second intervals. For each flight, the following data was 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 a timestamp. Each of the four pilots ran through the simulation twice for a total of 8 flight paths stored in 8 separate data logs. For the purposes of this research, the logs were converted to JSON format. A series of 2D web-based implementations were produced utilizing JavaScript and D3 Version 5 (Bostock et al., 2011).

Fig. 1: Virtual Reality Data Collection from Expert Pilots (Real -left- site duplicated as a Virtual -right- site).

3.1.1 InDrone Platform Goals

The goals for the InDrone visualization platform in this study were established by iteratively exploring the collected data and interviewing commercially certified drone pilots. Initially, the data from the VR flights was explored by implementing a preliminary representation of the drone spatial data. In the existing literature, 2D and 3D approaches have been considered to represent spatial 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 the inspection space. 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 which would have resulted in the exploration of interactivity methods to reduce spatial complexity. Additionally, within the AEC domain, users are accustomed to analyzed information utilizing isometric projections of 3D real-world objects. By maintaining 2D 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 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 inspection markers. The visual representation should reveal the inspection markers that require a longer time to be explored while performing the drone flight building inspection.

3.1.2 Visualizing Drone Critical Operations During Inspection Tasks

To accomplish the InDrone platform goals of this investigation, data was encoded following Cleveland and McGill (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 the drone operations. 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 (Figure 2).

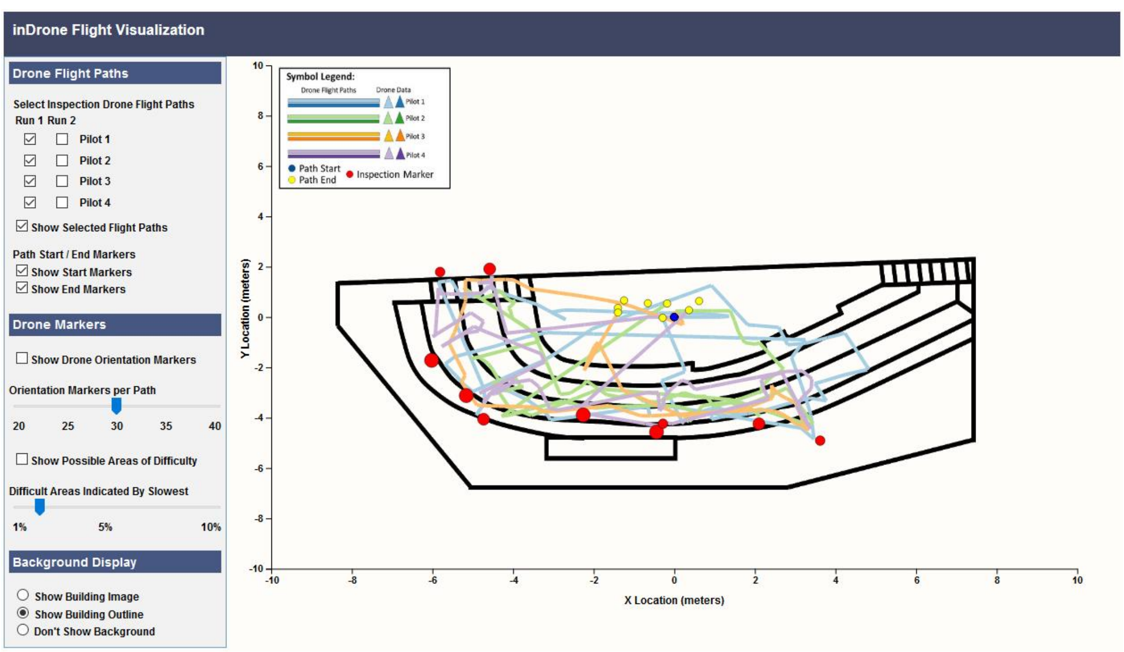

Fig. 2: Multiple Drone Flight Paths Visualization

Within that background, the important spatial data was 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 3). 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. Pre-attentive 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 path. Moreover, the drone's yaw was represented by triangular markers that scaled according to the y coordinate altitudes along the drone path (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, represents the drone fly path in a way that keeps unmanned vehicle parallel to the ground. Finally, a slider was provided to the user to increase the granularity of triangles displayed to account for the potential loss of information introduced by the resampling method applied to the data.

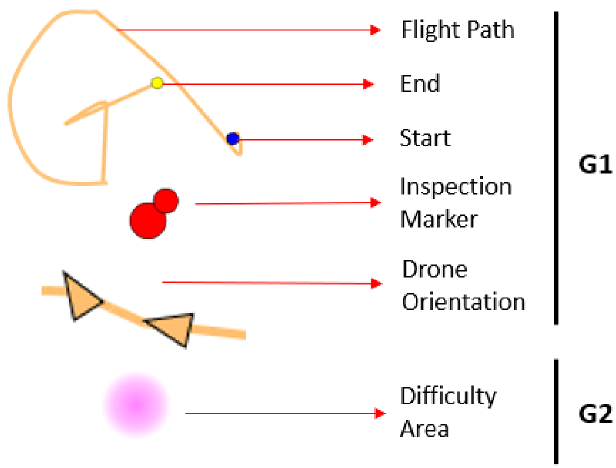

Fig. 3: Visual encodings to accomplish platform goals

To demonstrate the areas of difficulty as described in **G2**, fuchsia circles were used to represent locations with low drone speed (Figure 3). During the inspection task, areas of low speed indicate that the pilot requires maneuvering with exceptional care. The speed data for each drone pilot was 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, and the challenges faced during the interaction with the system. The resulting implementation from the iteration is shown as Figure 2. 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 orientation of the drone within the 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.

3.2 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 1. 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 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 ten questions scaled from strongly disagree to 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.

Table 1: Task Performance Question

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?

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.

4. 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 minutes (Average = 14 minutes, STD = 4 minutes).

The results of the task performance questions were analyzed using descriptive statistics as shown in Table 2. The average score for the **G1 – Approaches** was 63% (STD = 48%). This score indicates that participants had challenges understanding some of the critical operations during inspection tasks. While questions 1 and 2 were easily answered by the participants, questions 3 and 4 were very 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.

Table 2: Task Performance Descriptive Statistics

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

The results of SUS survey were analyzed using the strategy outlined in Brooke (1996) and descriptive statistics were reported as shown in Table 3. 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). This result indicates that the system design in this research presents a good usability rating as reported by participants. Moreover, 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*".

Table 3: SUS Descriptive Statistics

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

Overall, the observed results for the designed affordances within InDrone platform indicate that trainees were able to successfully identify drone inspection speed and flight path direction. Additionally, trainees were able to identify the level of difficulty required to inspect certain markers within the location. The high usability findings further support the use of these visually encoded affordances for drone inspection tasks. Ultimately, 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.

5. 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 are 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.

6. 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** – identify pilots' approaches to view the inspections markers and **G2** – demonstrate difficulty detection around 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, which could avoid some of the 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.

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