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DroneSim: a VR-based flight training simulator for drone-mediated building inspections

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Abstract

Purpose – This study aims to explore DroneSim, a virtual reality (VR)-based flight training simulator, as an alternative for real-world drone-mediated building inspection training.

Design/methodology/approach – Construction, engineering and management students were asked to pilot drones in the VR-based DroneSim space and perform common flight operations and inspection tasks within the spatiotemporal context of a building construction project. Another student group was also recruited and asked to perform a similar building inspection task in real world. The National Aeronautics and Space Administration (NASA)–Task Load Index (TLX) survey was used to assess students' inflight workload demand under both Real and DroneSim conditions. Post-assessment questionnaires were also used to analyze students' feedback regarding the usability and presence of DroneSim for drone building inspection training.

Findings – None of the NASA–TLX task load levels under Real and DroneSim conditions were highly rated by students, and both groups experienced comparable drone-building inspection training. Students perceived DroneSim positively and found the VR experience stimulating.

Originality/value – This study's contribution is twofold: to better understand the development stages involved in the design of a VR-based drone flight training simulator, specifically for building inspection tasks; and to improve construction students' drone operational and flight training skills by offering them the opportunity to enhance their drone navigation skills in a risk-free, repeatable yet realistic environment. Such contributions ultimately pave the way for better integration of drone-mediated building inspection training in construction education while meeting industry needs.

Keywords Drones, Unmanned aerial vehicles (UAVs), Virtual reality and visualisation, Construction building inspection, Unmanned aerial systems (UASs), VR-based drone flight simulator

Paper type Research paper

1. Introduction

Building inspection is one of the most explored drone applications in construction (Albeaino *et al.*, 2019; Zhou and Gheisari, 2018). Drone technology has proven efficient in accomplishing

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building inspection tasks, capable of improving maneuverability and safety while decreasing associated costs and time compared to traditional techniques (Albeaino *et al.*, 2019; Zhou and Gheisari, 2018). Drone-mediated building inspection typically consists of equipping aerial platforms with various sensors to collect visual or thermal data, used to evaluate building conditions. Specifically, drone-acquired visuals and models are used for building damage quantification, structural integrity assessment or thermal leak detection (Albeaino *et al.*, 2019; Kang and Cha, 2018; Mutis and Romero, 2019). Despite the increased interest and adoption of drones in construction, this technology is currently hindered by pilots' limited level of skills and high training requirements to navigate aerial platforms in a dynamic and complex jobsite environment (Albeaino *et al.*, 2019; Alizadehsalehi *et al.*, 2018; Eiris *et al.*, 2020; Gheisari and Esmaeili, 2019; Martinez *et al.*, 2021). These factors encouraged researchers to explore other techniques (e.g. ultrasonic beacons, computer vision, simultaneous localization and mapping) to ultimately automate and simplify drone operation, particularly in indoor or global positioning system-denied environments (Kang and Cha, 2018; Padhy *et al.*, 2018; Zahran *et al.*, 2018). Nevertheless, human intervention to perform manual drone flights remains among the least expensive and restrictive adopted navigation approaches (Eiris *et al.*, 2020).

To better equip construction, engineering and management (CEM) students for the increasing demand for drone-based jobsite inspection skills, academics have been attempting to integrate drone inspection training into CEM education curriculums. Researchers have been exploring general drone flight training (O'Keeffe *et al.*, 2017; Qi *et al.*, 2018; Smolyanskiy and Gonzalez-Franco, 2017; Ware, 2017; Wlodyka and Dulat, 2015); however, challenges such as high costs, liability concerns and safety risks hinder the adaptation of such training in CEM education programs (Bu *et al.*, 2015; De la Torre *et al.*, 2016; Weldon and Kozak, 2017). These factors paved the way to introduce virtual reality (VR)-based simulators as safe, advantageous and efficient training alternatives (Balakirsky and Kootbally, 2012; Bu *et al.*, 2015; De la Torre *et al.*, 2016; Meyer *et al.*, 2012; Sakib *et al.*, 2020, 2021; Wang *et al.*, 2017; Weldon and Kozak, 2017). Although drone building inspection flights and general flights seem to require similar piloting skills, there are distinctive flight operation characteristics pertaining to the construction domain. Within inspection tasks, drones need to be flown in proximity to targets and hover steadily while collecting data. In addition, the nature of the operations requires pilots to better understand building construction and be capable of evaluating building conditions (e.g. thermal leakage assessment, damage and corrosion identification and quantification) based on drone-retrieved feedbacks. Therefore, to evaluate VR simulators as drone building inspection training solutions, it is necessary to establish a building construction project setting that allows students and trainees to complete specific inspection tasks within the spatial and temporal contexts of a construction project.

The following study establishes a virtual construction setting to specifically evaluate VR-based drone simulators as alternatives for real-world drone-mediated building inspection training. Among all reviewed studies, none has yet evaluated the use of drone simulators to train construction professionals in building inspection and explored the corresponding advantages and challenges. In addition, none has used digitized versions of real inspection environments such as laser scanning-acquired point clouds in the training scenes, and only a few have offered settings for performing inspection tasks. The current investigation addresses the knowledge gap of developing a drone simulator specifically for building inspection training while offering a real-world flight environment using a laser scanner-captured point cloud of a building. The contribution of this research centers on two areas of knowledge within the construction discipline: recognizing the key elements to develop a VR-based drone simulator for building inspection training; and understanding the use of such VR-based training systems for training CEM students to perform drone-mediated building inspection tasks. In addition, the study provides CEM students with the opportunity to practice challenging and construction-specific drone flight operation and inspection requirements in a repeatable, realistic and risk-free virtual building environment. It also allows students to become better prepared academically while meeting the growing industry needs for drone-mediated jobsite inspection skills. Such academic contributions would ultimately improve the integration of drones in the CEM curriculum.

2. Background

The construction industry is increasingly adopting drones in current building inspection tasks (Albeaino *et al.*, 2019; Zhou and Gheisari, 2018). Through comparative analyses between building facade point clouds generated using a camera-equipped drone and traditional terrestrial laser scanning, Roca *et al.* (2013) showed that the drone-mediated technique is an efficient building inspection alternative and advocated its usage in this setting. To perform autonomous building inspections and overcome drone-associated indoor navigation problems, Kang and Cha (2018) relied upon geotagging, deep learning and ultrasonic beacon systems and were successfully able to accurately localize and detect concrete damages. Mutis and Romero (2019) equipped a drone with an infrared thermography sensor to identify and quantify building thermal bridges. After comparing the obtained thermal values with baseline standards, they demonstrated the usability of their system in evaluating the thermal performance of building curtain walls and proposing retrofitting actions. A very recent study successfully equipped an aerial platform with a custom-built payload system, capable of operating indoors and separately from the drone's navigation system (González-deSantos *et al.*, 2020). After testing their system in indoor and outdoor conditions, the authors showed that their drone-payload was capable of performing stable and semi-autonomous contact-based inspections. Among all inspection studies, many required human pilots to operate aerial platforms close to buildings to efficiently perform data collection and energy audits. For example, Roca *et al.* (2013) operated the drone around three to four meters away from the building facade due to the limited range of the Microsoft® Kinect sensor. Gillins *et al.* (2016) recommended two to three meters as a safe stand-off distance between the drone and the target elements for bridge inspection applications. A recent literature review summarizing drone-mediated building inspection procedures showed that drone inspections were performed at different drone-target surface distances, ranging from 25 meters to less than 1 meter in the case of small-scale masonry damage identification (Rakha and Gorodetsky, 2018). This indicates that the optimal distance drones must maintain from the targeted inspection surface varies based on each industry's specific needs and has neither been identified yet nor agreed upon (Rakha and Gorodetsky, 2018). Such limiting factors necessitate highly skilled and well-trained pilots to manually operate drones safely and assertively in dynamic and complex construction environments (Albeaino *et al.*, 2019; Gheisari and Esmaeili, 2019; Zhou and Gheisari, 2018).

Many scholars have studied how to perform general drone training over the years. For example, Qi *et al.* (2018) analyzed the qualification requirements for drone pilots and discussed the content and methods of drone training. Smolyanskiy and Gonzalez-Franco (2017) conducted an experiment where students operated drones to take off, fly and land wearing VR headsets. O'Keeffe *et al.* (2017) integrated the Oculus® Rift VR headset with a low-cost aerial platform for easier drone training. In particular, several academic institutions have conducted research studies exploring the effectiveness of integrating drone training in education programs. Eiris *et al.* (2018) integrated drone technology as an undergraduate construction management course module to better introduce students to drone regulations, operations and integration with photogrammetry and building information modeling (BIM). Williamson III and Gage (2019) developed a drone-mediated construction surveying activity to expose undergraduate students to the overall drone surveying process, ranging from flight planning and data collection to post-processing. Ware (2017) incorporated drones into an existing geospatial information science program at the United States Military Academy. Wlodyka and Dulat (2015) provided students with drones to conduct field investigations in an engineering design course. Molina *et al.* (2014) invited an interdisciplinary team of undergraduate engineering students to collaborate and provide solutions to the drones' range and endurance issues. Very recently, Camarillo *et al.* (2020) integrated drones and photogrammetry in a civil engineering course in order to improve the students' technology exposure and competency. Despite these attempts, real-world drone training remains a difficult task. Specifically, researchers indicated that real-world drone training is associated with the risk of inflight drone crash, especially since mistakes are always part of the learning process (Weldon and Kozak, 2017). For example, Camarillo *et al.* (2020) indicated that students were not involved in the drone flight mission and only observed the data collection workflow, correlating the successfulness of their real-world drone flight with the experience of the drone pilot. In addition, others stated that the risk of inexperienced pilots causing serious accidents in actual drone flights is significant (De la Torre *et al.*, 2016), not to mention the potential monetary damage and struck-by risks associated with drone training over people (Bu *et al.*, 2015).

To overcome these limitations, researchers have been exploring the effectiveness of drone simulators as an alternative to real-world drone training over the past ten years. For example, Bu *et al.* (2015) and Meyer *et al.* (2012) built simulation platforms based on Gazebo and Robot Operating System (ROS), two standard tools in the area of robotics that are contributed by multiple worldwide researchers. De la Torre *et al.* (2016) recruited eleven volunteers and tested their workload demands during a virtual drone flight training. Crespo *et al.* (2016) built a VR drone simulator based on arm gestures with the aim of improving the health and quality of the elderly population. Durlach *et al.* (2010) developed a prototype training procedure that not only teaches piloting skills but also demonstrates employment tactics, mission planning and coordination. Nguyen *et al.* (2019) proposed a Web-based VR drone simulator based on real-world map data to assist operators in avoiding drone-associated building crashes and ensure safe drone landing. Stated advantages of using such simulators include the ability to train pilots for an unlimited time, in real-time, at reduced training costs and in different conditions and environments that are typically not available in non-virtual or real-world training (Balakirsky and Kootbally, 2012; De la Torre *et al.*, 2016; Wang *et al.*, 2017). These factors, in turn, reduce the risks of drone-associated real-world accidents and casualties caused by inexperienced pilots and increase the overall training efficiency (De la Torre *et al.*, 2016; Wang *et al.*, 2017). Simulators also allow for a more straightforward evaluation of future pilots and enhanced opportunities to study different parameters that could otherwise be risky or difficult to evaluate in non-virtual or real-world flights (De la Torre *et al.*, 2016). Recently, Sakib *et al.* (2020) analyzed pilots' performance, mental workload and stress during VR-based and non-virtual drone training conditions. Based on physiological data collected by wearable devices, results showed that VR-mediated drone training is an efficient real-world training alternative. Using the same VR-based and real-world drone training environments, a more recent analysis demonstrated the reliability of physiological metrics and self-assessments in accurately evaluating pilots' performance, mental workload and stress while operating drones (Sakib *et al.*, 2021).

Two types of drone simulators are currently available on the market: racing simulators and commercial simulators. Drone racing simulators such as DRL Drone Racing Simulator

("The Drone Racing League", 2021), Velocidrone ("VelociDrone FPV Racing Simulator", 2021) and Liftoff ("Liftoff | Drone simulations", 2021) are designated for first-person-view (FPV) drone race training. Racing simulators often feature various courses with gates and obstacles to simulate competitive drone racing sessions, which refine users' drone handling skills and improve their maneuvering speed in challenging flight environments. On the other hand, commercial drone simulators are designed to train users for commercial applications. Many commercial simulators on the market offer a variety of virtual environments for different drone applications. As an example, Simlat ("Simlat | UAS Simulation", 2021) provides scenarios including search and rescue, mining, maritime exploration, power line inspection, wind turbine inspection, railroad inspection, pipeline inspection, infrastructure security, among others. DroneSimPro ("droneSim Pro | Drone Simulator for UAS Pilots", 2021) offers flight environments that pertain to public safety, utilities and cinematography. QUANTUM3D ("Quantum3D", 2021) is a fixed-wing platform simulator designed for pilots, mission commanders and image interpreters training for various mission profiles. Among all the reviewed simulators, none has yet explored using drone simulators to train CEM students and professionals in building inspection, and only a few have provided settings for general inspection tasks. In addition, though many of the reviewed simulators offer high-fidelity modeled virtual flight environments, none had used captured visual data of real-world inspection environments such as laser scanning-based point cloud models in training scenes. This study thereby aims to address this gap by designing a VR-based drone simulator specifically intended for building inspection training while offering a true-to-life flight environment using laser scanner-captured point cloud data. The adopted research methodology is discussed in the following section.

3. Methods

This paper aims to evaluate DroneSim as an alternative for real-world drone-mediated building inspection training. To achieve this goal, this study was completed in two phases: DroneSim development and DroneSim evaluation (Figure 1). In Phase (1), a virtual drone simulator, DroneSim, was developed using the Unity® game engine and a laser scanner-generated point cloud. In Phase (2), an experimental between-subject study design was implemented to evaluate DroneSim as an effective training platform for building inspection applications. Using the drone training method as the study's independent variable, a baseline group of students that performed a real-world drone flight (i.e. Real training group) was compared to the DroneSim treatment group that utilized a VR-based drone flight (i.e.

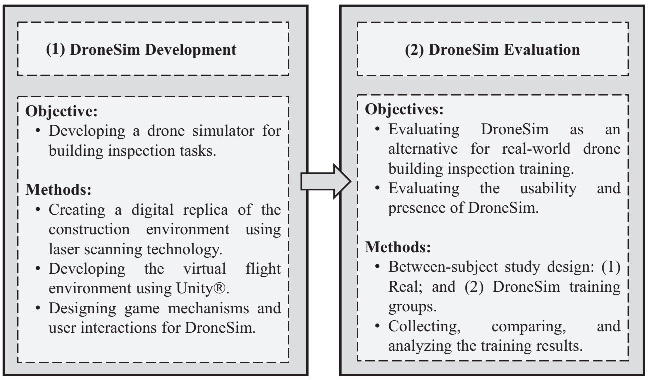

Figure 1.
Adopted research methodology

DroneSim training group). The dependent variable – workload demands associated with the drone flight – was collected from the participating students under both conditions using post-experiment survey instruments. Additionally, the student group using DroneSim was asked to complete post-experiment questionnaires specifically designed to collect their feedback regarding the usability and presence of the VR platform. Demographic information was also collected prior to accomplishing both training modules to understand participants' background information.

3.1 DroneSim development

DroneSim was developed using a two-step process: point cloud modeling; and simulator development (Figure 2). For the first step, data was collected from a real-world location at the University of Florida to create a digital representation using point cloud laser scanning technology. Virtual environments generated based on laser scanner-acquired point clouds resemble reality more closely compared to 3D models created using modeling software

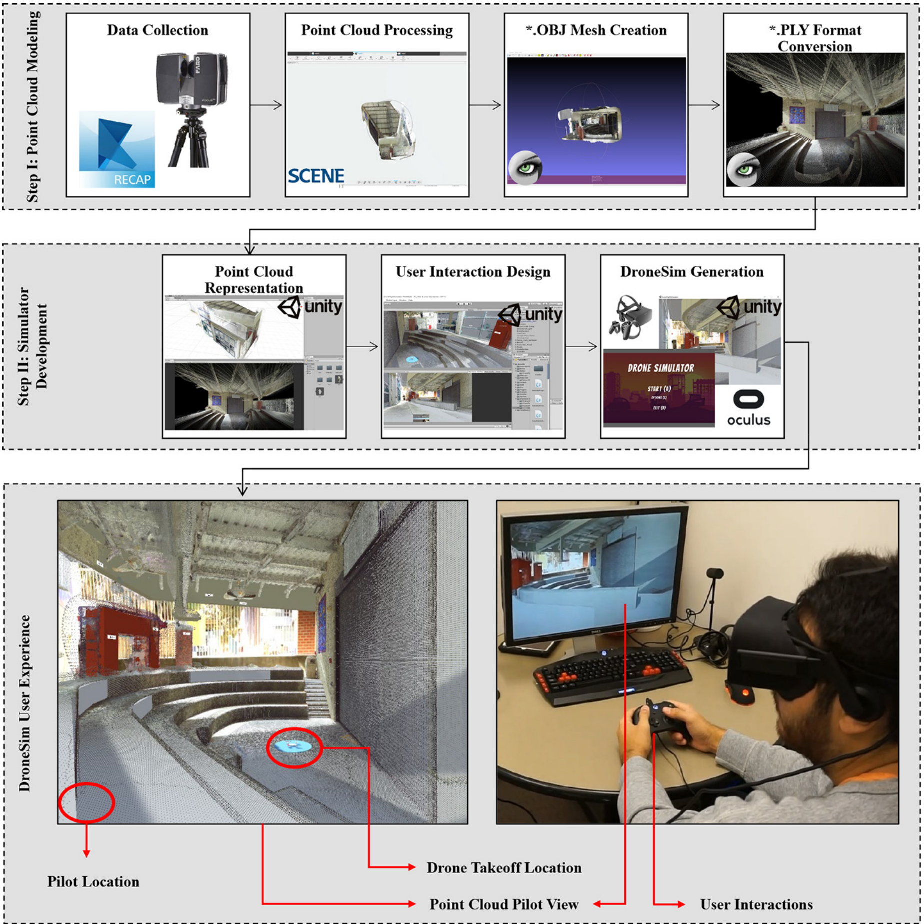

Figure 2.
DroneSim development workflow

packages. The use of laser scanning point clouds expedited the development process of DroneSim, as creating comparable 3D models would necessitate a significant amount of additional time. For this study, a FARO® Focus 3D S 120 laser scanner (precision of ± 2mm) was employed during the point cloud data collection. The data collection was performed at five different locations within the inspection environment to obtain a comprehensive representation of the interior surfaces and objects within the building. A set of five .fls scan files were obtained from this process after using Autodesk® Recap for processing the point cloud data. Subsequently, the five .fls files were loaded into the FARO Scene LT® software to clean, filter and correct artifacts in the generated point cloud and federate the independent files into a single point cloud. The processed point cloud was then exported as .PTS file and imported into the MeshLab® open-source software to create a .OBJ mesh of the point cloud data (Figure 2). Additionally, the MeshLab® software was also used to transform the .OBJ mesh file into to .PLY format. The .PLY data format contains information required in later steps of the development process, such as spatial coordinates, color, transparency, surface normal and texture coordinates.

For the second step, the DroneSIM development used the Unity® game engine (Version 2017.4.1f1). This game engine enables the rendering of the point cloud data and the creation of user interactions for flying the drone similarly to a real-world setting. To import the point cloud data into Unity®, the open-source library called Pcx (Keijiro, 2017) was used. This library facilitates the incorporation of point cloud data using .PLY files into the Unity® game engine. Pcx employs a Unity® custom rendering method to display the point primitives as a geometry shader. The created point cloud virtual environment was the basis for developing the corresponding user interactions for the drone flight. As shown in Figure 2, the Oculus Rift® head-mounted display was used to immersively display the virtual environment to the users. The user interactions were driven by custom-built scripts that allowed users to maneuver the drone, visualize the environment and interact with the DroneSim platform. The drone piloting simulation was achieved using a Microsoft® Xbox One gamepad controller, replicating similar user input as real-world drone flight operation requirements from pilots (i.e. roll was assigned to right stick left/right inputs; pitch was assigned to right stick up/down inputs; ascending and descending were assigned to left stick up/down inputs; yaw was assigned to left stick left/right inputs).

3.2 DroneSim evaluation

The objective was to assess students' perspectives on DroneSim as an alternative for real-world drone-mediated building inspection tasks. A between-subject experimental study was selected to reduce the learning and transfer effects across experimental conditions. Within this experimental design, each student participated in only one of the flight training conditions, taking part either in the Real training group that undertook the non-virtual drone flight module or in the DroneSim training group that completed the virtual-based drone flight module. The two groups of students were recruited from the BIM technology class offered at the Rinker School of Construction Management at the University of Florida. Participants were randomly assigned to one of the experimental groups (i.e. Real or DroneSim) to perform the training independently. During the training, students were accompanied by a visual observer.

To evaluate drone-mediated building inspection tasks, an inspection activity was designed, aiming at replicating real-world requirements in a laboratory environment. The goal of the inspection task adopted in this study was to simulate typical building inspections such as crack detection or damage assessment that require drone pilots to report or record their observations transmitted from their drone's onboard camera (Albeaino *et al.*, 2019; Rakha and Gorodetsky, 2018; Kang and Cha, 2018). Based on this goal, a simplified inspection training task was created, requiring students to inspect ten locations in a building that contained ten different codes (1 code per location), each consisting of six random characters. These inspection codes were fixed at the same locations in both Real and DroneSim flight environments and were placed in a way that required users to specifically rely on the drone's onboard camera to identify them (Figure 3). To accomplish the inspection task, students were required to: be positioned at a location from which the identification of the codes is not feasible without relying on the drone's provided visual feedback; operate the drone near the target codes and use the aerial platform's visual feedback to identify and report each code; and operate the aerial platform in proximity to a structure, which is common in any drone-mediated building inspection. The drone flight environments were fully controlled under both experimental conditions. In the real-world condition, students completed the flights using a DJI® Spark drone in a laboratory space at the Perry Yard, a covered hands-on training facility at the Rinker School of Construction Management at the University of Florida. In the DroneSim virtual simulator, a 3D digital replica of the Perry Yard was created in Unity® using laser scanner-captured point cloud data and a functional replica of the DJI® Spark drone was designed (Figure 3). Under both Real and DroneSim training modules, students were required, within a total duration of ten minutes (code identification rate: 1 code per minute), to operate a drone by performing ascend, descend, roll and pitch movements and maintaining altitude and proximity, then adjusting the camera angle to identify and report these codes.

In a pre-study demographic survey, information pertaining to the student's age, gender, academic year, eyesight, knowledge of radio-controlled (R/C) vehicles, drones, drone applications in construction and drone-related Federal Aviation Administration (FAA) regulations were collected from both training groups. Four-point Likert-scale format questions were provided to assess the student's eyesight, understanding of drone applications in construction and the FAA regulations pertaining to drone operations. Upon experience completion, students from the DroneSim group were asked to complete three questionnaires: National Aeronautics and Space Administration (NASA) Task Load Index (NASA-TLX) survey; Questionnaire for User Interface Satisfaction (QUIS); and Slater-Usoh-Steed (SUS) Presence Questionnaire, whereas students from the Real training group were only required to fill out the NASA–TLX survey.

NASA-TLX survey was used to collect and assess students' workload demands under both drone building inspection training conditions: Real and DroneSim (Hart and Staveland, 1988). NASA-TLX is a multi-dimensional scale that estimates workload from one or more

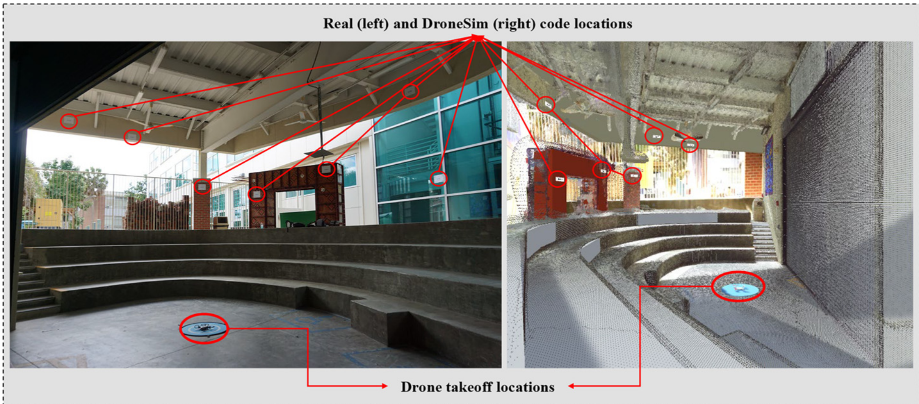

Figure 3.
Real (left) and DroneSim (right) code locations

operators during or immediately after a task (Hart, 2006). The survey uses 20-point Likert scales to assess six independent variables: mental, physical and temporal demands, in addition to frustration, effort and performance (Table 1). The scale emerged as the most cited workload measurement survey over the past decades, being: demonstrated for validity and reliability; and broadly applied across different disciplines and areas, including VR-based simulated environments for robot and unmanned system operation and control (Grier, 2015). The importance of NASA-TLX is that it has been proven to be reliably sensitive to experimentally important manipulations (Grier, 2015; Hart, 2006), justifying its usage in the current study. It should be noted that the study was first approved by the University of Florida Institutional Review Board (UFIRB #201802922) prior to recruiting any CEM student. Demographic and Likert-scale post-experiment questionnaires were analyzed descriptively. In addition, independent samples *t*-test was performed to compare the means of NASA-TLX workload demands of both Real and DroneSim training groups, since the data was proved to follow a normal distribution, as determined by the Shapiro–Wilk normality test (both, $p \geq 0.215$).

For the DroneSim condition, the subjects also filled out the QUIS Usability and SUS Presence questionnaires. The overall experience and interface quality were adapted from the University of Maryland's QUIS (Chin *et al.*, 1988). QUIS (version 7.0) is a validated survey that accurately evaluates the ease-of-use and level of user satisfaction for computer software. It has been previously adapted to evaluate the usability of VR-based safety training platforms (Eiris *et al.*, 2018). All questions are nine-point Likert-scale (Table 2), with endpoints representing the extremes of the subjective dimensions (e.g. Terrible: 1 – Wonderful: 9). Likert-scale type of questions allows authors to collect students' user feedback on the platform (Eiris *et al.*, 2018).

The SUS presence questionnaire was developed by Slater *et al.* (1994) and Usoh *et al.* (2000). Slater (1999) defines presence as "the subjective experience of being in one place or environment, even when one is physically situated in another". The measurement of presence is well established, consisting of three indicators: user self-assessment questions that use indicators to evaluate users' sense of presence; the extent of the virtual environment to represent reality; and the thought of visiting a place rather than observing images (Slater *et al.*, 1994). The validated nine-point Likert-scale questionnaire has been used to evaluate the presence of virtual environments in many different contexts (Higuera-Trujillo *et al.*, 2017). Particularly for this study, it was necessary to measure and ensure high levels of user presence in the VR-based DroneSim environment to replicate real-world drone inspection situations. A summary of the questions asked in the QUIS and SUS questionnaires to evaluate both realism and

Question	Scale
Q1. How mentally demanding was the task?	(1) Very Low — (20) Very High
Q2. How physically demanding was the task?	(1) Very Low — (20) Very High
Q3. How hurried or rushed was the pace of the task?	(1) Very Low — (20) Very High
Q4. How successful were you in accomplishing what you were asked to do?	(1) Perfect — (20) Failure
Q5. How hard did you have to work to accomplish your level of performance?	(1) Very Low — (20) Very High
Q6. How insecure, discouraged, irritated, stressed, and annoyed were you?	(1) Very Low — (20) Very High

Source: Adapted from (Hart, 2006; Hart and Staveland, 1988)

Table 1. Summary of NASA–TLX survey

presence is shown in Table 2. At the end of the post-experiment questionnaire, a text-entry box was provided for open-ended comments.

4. Results and discussion

4.1 Demographics

A total of 36 CEM students participated in the Real (N = 18) and DroneSim (N = 18) training modules. Table 3 summarizes the demographics pertaining to both CEM student groups. The study population had an overall average age of 24, with an average age of 22 for the Real training group and 25 for the DroneSim.

For the Real training group, 4 (22%) participants were graduate students, 13 (72%) were junior undergraduate students, and only 1 (6%) was a senior undergraduate student (Table 3). More than half (61%) of the participants had less than one year of construction experience, 6 (33%) had between 1 and 5 years, and only 1 (6%) had between 6 and 10 years of related experience. The majority (78%) of the subjects were males. None (0%) of the students self-identified their vision as weak, 4 (22%) indicated that their vision is fair, 9 (50%) as good and 5 (28%) as excellent. Eleven (61%) participants had prior experience with R/C vehicles. Fourteen (78%) students had never used drones either at home or work, with the remaining 4 (22%) having used aerial platforms before. Three students (17%) stated that they had no understanding of drones in the construction industry, 12 (67%) indicated that they had some knowledge, 3 (17%) stated that they had a fair understanding, and none (0%) of them indicated having a competent understanding. Ten (56%) subjects mentioned that they had no understanding of FAA regulations for drones, 5 (28%) stated that they had some knowledge, 3 (17%) indicated that they had a fair understanding, and none (0%) reported having a competent understanding.

As for the DroneSim training group, 11 (61%) participants were graduate students, 6 (33%) were junior undergraduate students, and only 1 (6%) was a senior undergraduate student. The majority of the students (95%) had less than five years of construction

Table 2.
Summary of QUIS and SUS presence questionnaires

Question	Scale
Q1. Overall experience with the platform:	(1) Terrible — (9) Wonderful (1) Frustrating — (9) Satisfying (1) Dull — (9) Stimulating (1) Difficult — (9) Easy (1) Rigid — (9) Flexible
Q2. Quality of the virtual scenes in DroneSim:	(1) Fuzzy — (9) Sharp
Q3. Readability of the codes in the Perry Yard:	(1) Hard to read — (9) Easy to read
Q4. Amount of time to identify the codes during the test:	(1) Inadequate — (9) Adequate
Q5. Your sense of being in the space:	(1) Not at all . . . (9) Very much
Q6. To what extent were there times during the experience when the Perry Yard was the reality for you?	(1) At no time . . . (9) Almost all the time
Q7. When you think back about your experience, do you think of the Perry Yard space more as images that you saw, or more as somewhere that you visited?	(1) Images that I saw . . . (9) Somewhere that I visited
Q8. During the time of the experience, which was strongest overall, your sense of being in the Perry Yard, or of being elsewhere?	(1) Being elsewhere . . . (9) Being on the jobsite
Q9. During the time of the experience, did you often think to yourself that you were in the Perry Yard?	(1) Not very often . . . (9) Very much so

Sources: QUIS questionnaire [adapted from (Chin *et al.*, 1988)] and SUS presence questionnaire [adapted from (Higuera-Trujillo *et al.*, 2017; Slater *et al.*, 1994; Usoh *et al.*, 2000)] experience, with only 1 (6%) student having between six and ten years of industry-related experience. Only 2 (11%) students were females in this group. One (6%) student self-identified their vision as weak, 2 (11%) fair, 8 (44%) good and 6 (33%) excellent. More than half of the participants (67%) had no prior experience with R/C vehicles. Fifteen (83%) students had never used a drone either at home or work, with the remaining 3 (17%) having used it previously. None (0%) of the subjects in the DroneSim group had a competent understanding of drones in the construction industry, with the majority (95%) stating that they either had some knowledge (67%) or a fair understanding (28%) of drone technology in the domain. Ten (56%) students indicated that they had no understanding of the FAA regulations for drones, 5 (28%) had some knowledge, 2 (11%) had a fair understanding and only 1 (6%) had a competent understanding (Table 3).

Parameter	Real Training Group N (%)	DroneSim Training Group N (%)
Year in school		
Freshman	0 (0%)	0 (0%)
Sophomore	0 (0%)	0 (0%)
Junior	13 (72%)	6 (33%)
Senior	1 (6%)	1 (6%)
Graduate	4 (22%)	11 (61%)
Construction experience		
Less than 1 year	11 (61%)	5 (28%)
Between 1 and 5 years	6 (33%)	12 (67%)
Between 6 and 10 years	1 (6%)	1 (6%)
More than 10 years	0 (0%)	0 (0%)
Gender		
Male	14 (78%)	16 (89%)
Female	4 (22%)	2 (11%)
Eyesight		
Weak	0 (0%)	1 (6%)
Fair	4 (22%)	2 (11%)
Good	9 (50%)	8 (44%)
Excellent	5 (28%)	6 (33%)
Experience with R/C vehicles		
No	11 (61%)	12 (67%)
Yes	7 (39%)	6 (33%)
Previous Drone Usage at Home/Work		
No	14 (78%)	15 (83%)
Yes	4 (22%)	3 (17%)
Level of understanding regarding drone applications in construction		
None	3 (17%)	1 (6%)
Some knowledge of	12 (67%)	12 (67%)
Fair	3 (17%)	5 (28%)
Competent	0 (0%)	0 (0%)
Level of understanding regarding FAA regulations for drones		
None	10 (56%)	10 (56%)
Some knowledge of	5 (28%)	5 (28%)
Fair	3 (17%)	2 (11%)
Competent	0 (0%)	1 (6%)

Table 3. Respondent demographics

4.2 Comparative Task load assessment

None of the task load levels (i.e. mental, physical, temporal, performance, effort and frustration) in both the Real and DroneSim groups were rated high by the participating CEM students (Figure 4). Specifically, students from both groups indicated that the inspection task demands moderate mental workload (Real: 11.7 ± 5.3; DroneSim: 11.9 ± 4.8) and effort (Real: 11.6 ± 4.3; DroneSim: 10.9 ± 5.3) levels. These moderate levels could be associated with the nature of the building inspection task, which regardless of the environment (i.e. Real or DroneSim), requires students' full concentration to be able to operate the drone safely and crash-free while successfully identifying the target codes within the given time period. Participants also indicated that the inspection task required low physical (Real: 4.2 ± 3.1; DroneSim: 4.1 ± 2.9) and temporal workload (Real: 6.2 ± 3.9; DroneSim: 9.1 ± 4.6) levels. The only physical effort required by students was to control the drone using either the remote controller (Real condition) or the Microsoft Xbox One® gamepad controller (DroneSim condition), factors that could potentially contribute to the low physical workload levels. In addition, despite allocating a code identification rate of 1 code per minute (on average, for a total of ten minutes) during the inspection task, the low temporal workload rating shows that CEM students neither felt high pressure while completing the task, nor consider the code identification rate to be challenging to achieve. CEM students from both groups have also experienced low frustration (Real: 5.0 ± 4.5; DroneSim: 6.3 ± 4.6) and achieved high performance (Real: 4.4 ± 4.7; DroneSim: 7.1 ± 5.9) levels, while accomplishing the inspection training task. This indicates that the experience was neither stressful nor annoying for most participants, and that participants perceived their overall performance positively, achieving high levels of success in the training modules.

Regardless of the group they were assigned to, the CEM students experienced comparable drone building inspection training. Indeed, students in the Real training group scored an average of 43.1 ± 18.1 compared to an average score of 49.4 ± 17.5 for participants in the DroneSim group (Table 4, $p = 0.285$).

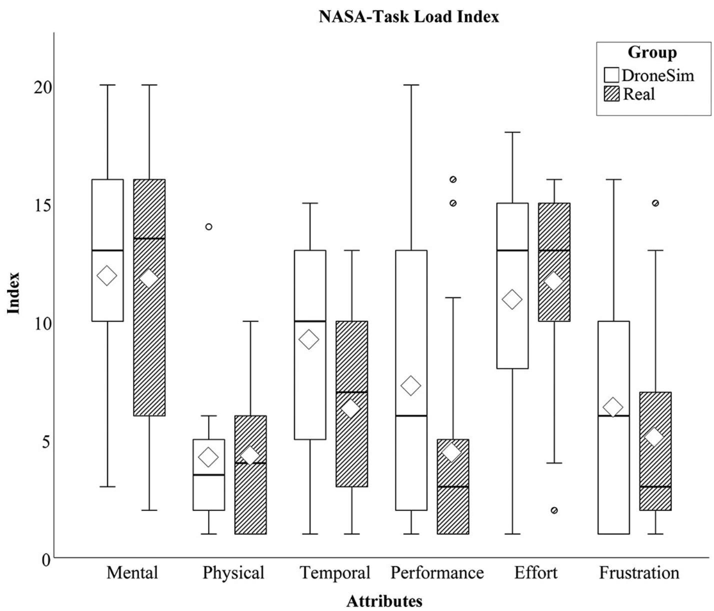

Figure 4.
NASA–TLX participant ratings for both groups (diamonds illustrate mean values)

Broken down into attributes, and aside from the temporal demand ($p \leq 0.050$), no statistically significant differences in the mental demand, physical demand, performance, effort and level of frustration were detected between both Real and DroneSim groups (Table 4; all, $p > 0.050$). The obtained results compare well with those of a meta-analysis aiming at providing practitioners with benchmark datasets of published NASA–TLX scores to improve this test's interpretability (Grier, 2015). Specifically, Grier (2015) showed that for the robot operation type of task, defined as the simulated or real control of an unmanned system, NASA–TLX workload scores were characterized by a minimum of 9.6, 25th percentile of 41.0, a median of 56.0, 75th percentile of 63.0 and a maximum of 80.0 (Table 5). The implication of our analysis is therefore twofold. First, no differences or differentiating characteristics were identified between this study's population (for both, the Real and DroneSim training groups) and the one analyzed in the meta-analysis (Grier, 2015). These population similarities add confidentiality to our findings. In addition, these results show that the virtual training group, represented by DroneSim, is an efficient drone-mediated building inspection training alternative compared to real-world inspection training.

The advantages of using DroneSim as a drone building inspection training include drone pilots' ability to operate drones in a repeatable, risk-free and controllable environment. In addition, effective real-world building inspection training requires pilots to operate their aerial platforms in a challenging and hazardous jobsite environment, potentially exposing construction workers to additional drone presence-associated onsite safety hazards. Such challenge can actually be eliminated using DroneSim, which emerged as a reliable virtual training environment conforming to real-world environmental conditions through the use of laser scanner-generated point cloud. Such advantages would ultimately improve the integration of drone-mediated building inspection training in the CEM curriculum while offering students the opportunity to meet current construction industry needs.

4.3 DroneSim usability and presence assessment

The feedback provided by the DroneSim student group (N = 18) in the QUIS and SUS post-experiment questionnaires was analyzed descriptively. The mean and standard deviation pertaining to each of the Likert-Scale responses are summarized in Table 6. The results indicate that the CEM students perceived the overall experience with DroneSim positively (8.1 ± 0.9) and found the platform stimulating (8.1 ± 1.1). The CEM students seem to consider DroneSim moderately satisfying (6.6 ± 2.2) and flexible (6.5 ± 1.6). The average rating of the test difficulty (5.9 ± 1.7) seems low compared with other measurements. This lower rating could be caused by the quick acceleration of the virtual drone in the vertical direction, as indicated in the comments of three students highlighting that the control is sensitive. The average rating of the virtual scenes' quality in DroneSim (5.9 ± 1.9) also appears low

Attributes	Scale	Real group mean (STD)	DroneSim group mean (STD)	*P*-value
Mental	1 – very low, 20 – very high	11.7 (5.3)	11.9 (4.8)	0.871
Physical	1 – very low, 20 – very high	4.2 (3.1)	4.1 (2.9)	0.955
Temporal	1 – very low, 20 – very high	6.2 (3.9)	9.1 (4.6)	0.050
Performance	1 – perfect, 20 – failure	4.4 (4.7)	7.1 (5.9)	0.144
Effort	1 – very low, 20 – very high	11.6 (4.3)	10.9 (5.3)	0.682
Frustration	1 – very low, 20 – very high	5.0 (4.5)	6.3 (4.6)	0.382
Total	0 – 100	43.1 (18.1)	49.4 (17.5)	0.285

Table 4. Descriptive statistics and p-values of NASA–TLX results

compared with other measurements. This could be attributed to the noise in the point cloud-generated virtual environment, as highlighted by two students who indicated that certain geometries in the simulator were not visible enough, causing drone collisions. Participants seem to consider the codes in DroneSim to be moderately easy to read (6.4 ± 1.9) and the amount of time (i.e. 10 minutes) allocated for the test to be adequate (8.0 ± 1.4).

The results also suggest that the students consider the platform overall immersive, as the scores in the sense of being in the space (7.4 ± 0.8), the extent to which the Perry Yard feels like the reality during the experience (6.4 ± 1.8), the extent to which the students think of the Perry Yard space more as somewhere they visited instead of images they saw (6.5 ± 1.9), the students' sense of being in the Perry Yard instead of being elsewhere (7.4 ± 1.5), and the extent to which students think that they are in the Perry Yard (7.0 ± 1.3) were all well above the neutral score of 5.0.

Overall, CEM students were satisfied with the usability and presence of DroneSim based on the feedback provided in the post-experiment questionnaires, with mean score values ranging from above average to high on all nine questions (See Table 6). Nevertheless, the importance of these questionnaires was to highlight potential areas for improvement while using DroneSim. Such areas include: (1) improving the sensitivity of the Microsoft® Xbox One Controller by optimizing the software (i.e. control sensitivity) and hardware (i.e. controller) components to

Table 5. NASA–TLX workload scores

NASA-TLX	Minimum	First quartile	Median	Third quartile	Maximum
Real	11.0	31.0	45.0	55.8	76.0
DroneSim	15.0	39.8	51.5	61.5	78.0
Benchmark (Grier, 2015)	9.6	41.0	56.0	63.0	80.0

Table 6. Results of QUIS and SUS presence questionnaires

Questions	Scale	Mean (SD)
Q1. Overall experience with the platform:	(1) Terrible — (9) Wonderful	8.1 (0.9)
	(1) Frustrating — (9) Satisfying	6.6 (2.2)
	(1) Dull — (9) Stimulating	8.1 (1.1)
	(1) Difficult — (9) Easy	5.9 (1.7)
	(1) Rigid — (9) Flexible	6.5 (1.6)
Q2. Quality of the virtual scenes in DroneSim:	(1) Fuzzy — (9) Sharp	5.9 (1.9)
Q3. Readability of the codes in the Perry Yard:	(1) Hard to read — (9) Easy to read	6.4 (1.9)
Q4. Amount of time to identify the codes during the test:	(1) Inadequate — (9) Adequate	8.0 (1.4)
Q5. Your sense of being in the space:	(1) Not at all . . . (9) Very much	7.4 (0.8)
Q6. To what extent were there times during the experience when the Perry Yard was the reality for you?	(1) At no time . . . (9) Almost all the time	6.4 (1.8)
Q7. When you think back about your experience, do you think of the Perry Yard space more as images that you saw, or more as somewhere that you visited?	(1) Images that I saw . . . (9) Somewhere that I visited	6.5 (1.9)
Q8. During the time of the experience, which was strongest overall, your sense of being in the Perry Yard, or of being elsewhere?	(1) Being elsewhere . . . (9) Being on the jobsite	7.4 (1.5)
Q9. During the time of the experience, did you often think to yourself that you were in the Perry Yard?	(1) Not very often . . . (9) Very much so	7.0 (1.3)

prevent rapid and abrupt drone movement and render the VR-based training simulation more reliable; and (2) improving the quality of the generated point clouds by reducing noise in the generated models, as well as optimizing data collection and data processing procedures, ultimately ensuring highly-accurate and complete virtual environments.

5. Conclusion, limitations and future study

To evaluate drone simulators as real-world building inspection training alternatives, a virtual drone building inspection platform – DroneSim – was designed and tested among CEM students from the Rinker School of Construction Management at the University of Florida. The virtual inspection environment developed in DroneSim was based on point cloud data of a real environment captured using laser scanning technology, and the drone control mechanisms and platform interface were developed in Unity®. A simplified building inspection training task was designed in DroneSim, in which CEM students were required, through a between-subject experiment, to observe, identify and report a set of codes placed at different locations within both Real and DroneSim environments. Students' workload demands (i.e. NASA-TLX) were collected from both groups upon experience completion. Post-experiment questionnaires, including the QUIS and the SUS validated evaluation surveys, were also adopted in this study to collect students' feedback regarding the usability and presence of DroneSim for drone-mediated building inspection tasks. NASA–TLX comparative analysis showed that, except for the temporal demand ($p \leq 0.050$), no statistically significant differences in all other NASA-TLX attributes were detected between Real and DroneSim groups. NASA–TLX results were well comparable with others found in the literature, demonstrating the efficiency of DroneSim as a drone-mediated building inspection training alternative. In addition, questionnaire results revealed that, on average, students perceived their overall experience with DroneSim positively and found the platform stimulating.

The limitations of this study are twofold: sample size; and software and hardware limitations. First, it should be noted that generalizing the findings of this study might be restricted by its sample size, a factor that warrants further research to validate the accuracy of the obtained results. Nonetheless, this experimental investigation has offered insight into utilizing drone simulators in building inspection training. It included a sample size that is comparable and even higher than the number of participants recruited in other studies exploring drone flight training in both real and virtual environments (De la Torre *et al.*, 2016; Eiris Pereira *et al.*, 2018; Sakib *et al.*, 2020, 2021; Smolyanskiy and Gonzalez-Franco, 2017). In addition, the right joystick on the Microsoft® Xbox One Controller affected the vertical movement of the drone. This has been noticed by three students who noted that drone control in DroneSim is "sensitive", with an acceleration exceeding that of a real drone. Further optimizations in the software (i.e. drone control sensitivity) and hardware (i.e. controller joystick) components of DroneSim are required to better simulate real-world drone flight training conditions and ensure an even more reliable assessment. Similar to manned aircrafts, future research must also focus on exploring the physical and psychological differences and conducting comparative analyses between the training results obtained under both Real (i.e. real-world training) and DroneSim (i.e. virtual training) flight environments. This would ultimately enhance the effectiveness of DroneSim as a virtual drone flight training simulator for building inspection applications.

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