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Using Unmanned Aerial Systems for Automated Fall Hazard Monitoring in High-rise Construction Projects

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Using Unmanned Aerial Systems for Automated Fall Hazard Monitoring in High-rise Construction Projects

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Final Report

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ABSTRACT

Unmanned Aerial Systems (UASs), a.k.a. drones, are flying agents that operate under remote control without a pilot on board. One emerging technique for using UASs in the construction industry is applying photogrammetry methods to visual data acquired by the UAS. Within the last decade, researchers have heavily focused on developing computer vision techniques for automating various operations, including detecting job site hazards and safety-related issues and conducting automated and semi-automated safety inspections. These techniques are based on processing either images or videos, and civil infrastructure computer vision has been a well-established and well-studied area among the construction research community. The goal of this project was to use UASs as a data collection platform, combining the data with novel computer vision techniques to create an automated fall hazard detection and monitoring system. The specific objective was to investigate the practical implementation of UASs for monitoring guardrails near unprotected edges and openings. To achieve this objective, a real-time video feed of the construction site was collected using an UAS, and then an image-processing algorithm was developed and tested for guardrails detection from true-color images. This project adopted a case study approach to investigate the technical development of the hazard identification system and then its implementation and testing in a high-rise construction project. The outcomes of the research illustrated that the proposed automated fall hazard recognition system could facilitate recognition of guardrails in high-rise construction projects.

KEY RESEARCH FACTORS AND FINDINGS

- This project proposed an image-processing algorithm for guardrails detection from images captured by an Unmanned Aerial System (UAS).
- A three-step machine-learning pipeline was developed to detect guardrails from the UAS-captured images: (A) guardrail detection, (B) floor detection, and (C) space estimation.
- Integrating the second step (floor detection) in the image-processing algorithm significantly enhanced its guardrail detection precision.
- Including a cascade classifier (i.e. a machine-learning object detection algorithm used to identify objects in an image or video based on a binary pattern) with floor detection and guardrail spacing estimation achieved the best performance in terms of precision and recall metrics for guardrail identification.

INTRODUCTION

Falls remain the leading cause of fatalities in the construction industry (Gillen et al. 1997; Hinze et al. 2005, CPWR 2013, NSC 2015, OSHA 2017, Kang et al. 2017). In 2016, 384 out of 991 total deaths in construction (38.7%) were attributed to fall (OSHA 2017). The fatality rate from falls to a lower level in construction is eight times higher than the average fatality rate from falls in all industries; in particular, falls to a lower level account for 49% of all occupational fatalities (NSC 2015). In addition to their frequency, falls usually lead to severe injuries (Lipscomb et al. 2004) and require longer periods of recovery that result in significant medical costs (Janicak 1998). Therefore, falls have become a key area for intervention and prevention in construction (Rivara and Thompson 2000).

By examining various dimensions of 9,141 fall accidents that occurred in the United States between 1997 and 2012, Kang et al. (2017) found that the percentage of fall accidents has increased substantially and residential housing projects experienced a higher portion of fall accidents. Kang et al. (2017) showed that more than 80% of fall accidents occurred from a height of less than 9.1 m (30 ft), and only 11% of fall accident victims were properly equipped with fall protection.

The risk of fatality due to fall accidents increases with the height of a building. Although the previous literature has emphasized the importance of safety controls, such as guardrails and personal protective measures (Tarrants 1980; Hinze 1997, Kang et al. 2017) or considering safety during the design of the facility (Gambatese et al. 2005), the backbone of any safety program is detecting and mitigating hazardous situations. Therefore, developing new means and methods to perform frequent and automated site inspection is necessary to reduce the number of fall-to-a-lower-level accidents. Recent developments in Unmanned Aerial Systems (UASs) equipped with video cameras make it possible to identify hazards during construction operations, and project managers can take proper actions to mitigate safety risks, or workers exposed to unseen hazards can then receive warnings that facilitate their safety.

Although frequency and quality of inspecting the conditions and safety behavior of workers on the site can be used as an indicator of safety performance (Jaselskis et al. 1995; Laitinen et al. 1999; Reese, 2001; Abudayyeh et al., 2006), several factors make it hard for safety managers to increase the number of safety inspections in high-rise buildings. First, the number of safety managers in each company is limited, and, they may be located hundreds of miles away from construction sites. Second, the large square footage of high-rise buildings also makes frequent inspections difficult. Therefore, finding ways to increase frequency of safety inspection and also to observe hard-to-reach areas would have a great impact in improving safety performance.

This research project used UASs as the data collection platform, together with novel computer vision techniques, to create an automated fall hazard detection and monitoring system. The objective was to collect the video feed of the construction site using a UAS and then developing and testing an image processing/computer vison algorithm to identify fall hazards. In this study, we specifically explored an automated approach for guardrail detection from an RGB (red-green-blue) image. RGB images were used due to their true-color values that could make it possible to extract colors from the images using machine learning algorithms and then filter those images (or specific regions of the images) based on RGB values to identify a targeted object. This project first investigated the technical development of this system and then implemented and tested it in a high-rise construction project.

RESEARCH BACKGROUND

Unmanned Aerial Systems

Unmanned Aerial Systems, a.k.a. drones, are flying agents that operate under remote control without a pilot onboard. UASs have already been applied in a wide range of construction engineering and management applications, including monitoring of structures (Rathinam et al., 2008), surveying (Siebert and Teizer, 2014), bridge inspection (Ellenberg et al. 2016), material tracking (Hubbard et al. 2015), site monitoring (Wen and Kang, 2014), progress monitoring (Lin et al. 2015), and safety inspection (Irizarry et al., 2012, Gheisari & Esmaeili 2016 and de Melo et al. 2017).

UASs have the potential to improve safety performance and can be used as a vehicle for a variety of other technologies. UASs can move faster than humans to inaccessible or unsafe areas of job sites. They can be equipped with various devices such as video cameras, sensors, radar, or communication hardware to transfer real-time data to safety managers (Gheisari & Esmaeili 2016, Gheisari & Esmaeili 2019). They can also perform tasks similar to those done by manned vehicles but more quickly, more safely, and at a lower cost (Gheisari and Irizarry, 2015). Irizarry et al. (2012) and Gheisari et al. (2014) conducted the earliest studies on using UASs for safety applications: a usability study and a heuristic evaluation of a small-scale quadcopter equipped with a camera as a safety inspection tool on construction sites. The study ultimately proposed that UASs could be an ideal safety inspection assistant, providing a safety manager with real-time access to videos or images from a range of predefined paths and locations around the job site, as well as voice interaction with construction workers. Gheisari and Esmaeili (2019) have also conducted a recent survey study with safety managers about using UASs in various safety-related operations and the importance of using UASs to improve safety monitoring and control practices on site. That study (Gheisari & Esmaeili 2019) showed that safety managers considered work near an unprotected edge/opening one of the most important hazardous activities that UASs have great potential to improve (See Table 1). These unprotected edges and openings were the focus of this research, and we would study the use of UASs and novel computer vision techniques to identify guardrails protecting openings and edges. One emerging technique of using UASs is applying photogrammetry (explained below) methods to the visual data acquired by the UAS.

Table 1. Top 10 application areas of UASs to improve onsite safety monitoring and control practices (Adapted from Gheisari & Esmaeili 2019)

	Hazardous Situation or Safety-Related Activity	Effectiveness		Frequency		Importance Factor*
		Median	Average Rating	Median	Average Rating	
1.	Using boom vehicles/cranes in the proximity of overhead power lines	5	4.30	4	3.80	16.31
2.	Working in the proximity of boom vehicles/cranes	4	4.06	3	3.51	14.27
3.	Working near unprotected edges/openings	5	4.02	3	3.44	13.85
4.	Conducting post-accident investigations	4	3.77	4	3.64	13.69
5.	Inspecting for the proper use of fall-protection systems	4	4.13	3	3.24	13.39
6.	Inspecting house keeping	4	3.87	3	3.43	13.29
7.	Working in the blind spots of heavy equipment	4	3.72	3	3.44	12.83
8.	Inspecting at-risk rigging operations	4	3.77	3	3.36	12.67
9.	Inspecting the requirements for ladders/scaffolds	3	3.47	2	3.00	10.40
10.	Working in an unprotected trench	4	3.45	3	2.95	10.18

* *Importance factor = Effectiveness × Frequency*

Photo/Videogrammetry

Within the last decade, emerging digital imaging techniques as well as advances in computational capacities of computers and other processing units have enabled practitioners and researchers to capture high-resolution digital images and videos of objects of interest and extract useful information by processing those visual datasets. Photogrammetry and videogrammetry (science of automatically processing photo/videos and extracting information regarding the scene) are now two well-established areas of practice and research. Due to recent advances in computer vision techniques, it is possible to take several pictures or videotape an object (or a larger scene) and automatically generate a virtual 3D model. This process is known as "3D Reconstruction" and the output will be in the form of thousands or millions of 3D points in the space, also known as "Point Cloud Data" or PCD. A sample of PCD for a building is presented in Figure 1. PCD contains 3D coordinates of points as well as color values for each point. These geometrical and color features can be used for extracting information from PCD such as automatically detecting objects of interest with certain geometric and color values, such as a cylindrical column. 3D points within the PCD that form a concrete column are clustered in the form of vertical cylinder (geometrical constraints) and possess certain gray color (color value).

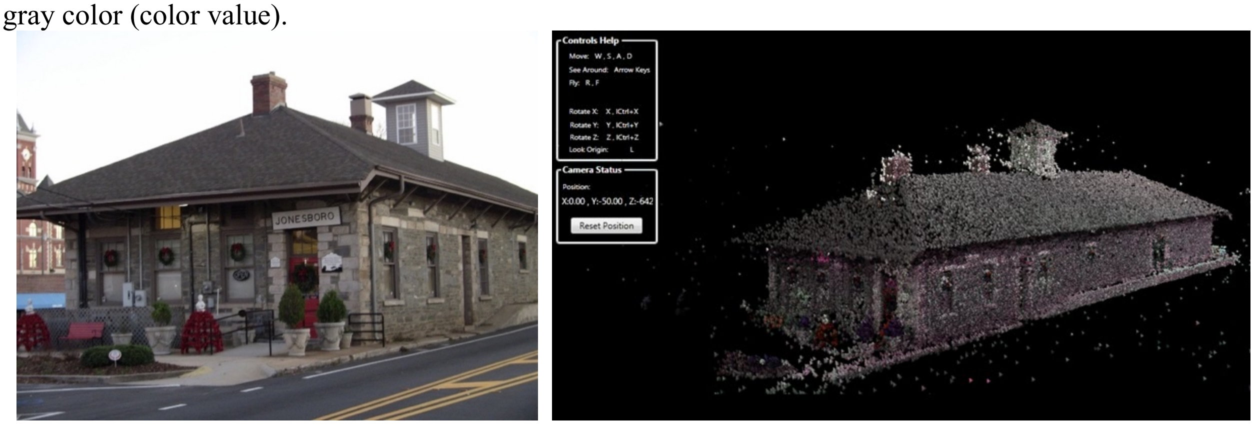

Figure 1: Sample of a generated PCD for a building (Rashidi et al. 2013)

In this project, existing algorithms for processing videos captured by UASs were improved to detect objects of interests (e.g., guardrails). Implementing and developing image processing/computer vison algorithms to solve a challenging problem in the area of construction safety (e.g., auto-detection of guardrails) is an innovative approach to handle a safety-related task on dynamic construction workplaces. In this study, we specifically used an automatic approach for guardrails detection from an RGB image. Figure 2 shows an example of a picture taken by a UAS of an under-construction high-rise building. The detected guardrails were annotated with red bounding boxes to denote their location. We developed a high "recall" rate process where ideally all the guardrails can be detected with a high precision. Such fully automated guardrail detection could be used as a valuable tool within the current fall assessment procedures.

Figure 2: Visualization of the labeled bounding box of guardrails

Safety Scope: Fall Protection and Guardrails

A large number of studies have focused on introducing new injury prevention practices with emphasis on falls. Singh (2000) evaluated some innovative protection measures for fall accidents on low-rise roofs. He found that falls cannot be prevented by a single, global practice and continuous monitoring of potential fall hazards is of great importance. Since it is not feasible for safety managers to continuously monitor construction sites, safety researchers are highly interested in developing automated methods to inspect sites. In one important study, Navon and Kolton (2006, 2007) developed an algorithm to identify hazardous activities in a project schedule that may lead to fall accidents and to automatically monitor installation of guardrails. Although this method improved the ability of safety personnel to monitor fall hazards, having an as-built location-based measurement system of guardrails could be laborious. One recent technology applied in construction engineering applicable for detecting potential fall hazards is the use of UASs equipped with video cameras. However, no study has developed an algorithm to identify fall hazards drawing on UASs because of technical complexities in detecting hazards in a video. This study aimed to address this knowledge gap and complemented current practices by providing an active fall hazard identification technique.

Related Preliminary Study

In order to verify the applicability and determine the level of success of using UASs-based automated process for fall hazard identification, a pilot study was conducted by research team (Gheisari et al. 2018). Perry Yard construction training site at the Rinker School of Construction Management at the University of Florida campus was used as the test location of this experiment, and a full-size mock-up platform was built to test an algorithm developed by the research team (Figure 3-a). To evaluate the feasibility of the proposed fall hazard detection method, a quadcopter UAS platform was used to capture a three-and-a-half-minute MP4 video of the built platform from various angles and orientations (Figure 3-b). The UAS was a

Phantom 2 Vision+, an electronic battery-powered quadcopter manufactured by DJI. This quadcopter carried a high-quality camera that shoots full HD videos at 1080p/30fps and photos at 14 megapixels.

(a) Built test platform (b) The quadcopter UAS captures a video of the built platform

Figure 3: The full-size mock-up test platform with guardrails and an opening

As the next step, the proposed algorithm processed the collected videos, and the existing objects (e.g. guardrails) were detected (Figure 4). The algorithm developed in the pilot study was limited to the platform created in the lab, and further development was conducted to enhance its reliability in real construction environments. In this proposal, the research team worked on detecting guardrails in a real-world construction jobsite.

Figure 4: Snapshots of the generated PCD

RESEARCH OBJECTIVES

This project investigated the practical implementation of UASs for monitoring fall hazards near unprotected edges and openings. Using UASs, the research team developed and implemented an automated fall hazard recognition system that facilitated safety engineers' task of identifying guardrails in high-rise construction projects. There were two specific research objectives in this study: (1) Develop a UAS-based hazard identification algorithm with focus on guardrails and (2) implement and test the UAS-based guardrail recognition system in a real-world high-rise construction project.

By focusing on mitigating risk of fall hazards, the results of the study directly supported NIOSH's National Occupational Research Agenda (NORA) construction strategic *Goal 1.0*: Reduce Construction Worker fatalities and serious injuries caused by falls to a lower level. By using the outcomes of this study, practitioners could expand their awareness of existing fall prevention and protection solutions by constantly monitoring their effectiveness. This outcome specifically addressed Research Goal 1.1.2: Develop and evaluate engineering interventions and guidelines to address the three fall protection gaps (e.g. unsafe guardrail systems).

METHODS

This study was a collaborative effort between the University of Florida, University of Utah, and George Mason University. A UAS-based fall hazard identification system was developed and evaluated to establish a benchmark for the use of unmanned aerial systems in identifying fall hazards in high-rise construction projects.

Step I: Data Collection Using a UAS

The automated process for fall hazard identification began with traversing the scene using the UAS and capturing a comprehensive video. The video process took place from various directions, orientations and angles to minimize occlusions and record as much detail as possible. A quadcopter recorded a series of videos of the guardrails of an under-construction high-rise building project (See Figure 5) using a combination of manual and semi-autonomous flight features (e.g. course lock, waypoints, and point-of-interest). Under the FAA's Small UAS Rule (14 CFR part 107), UASs should not fly directly over people (U.S. Department of Transportation 2016). The research team had several UAS platforms and certified pilots to fly and record the required videos for the implementation phase of this project. The specific UAS platform that the research team used for this project was their DJI Phantom 4 PRO Quadcopter, an electronic battery-powered quadcopter manufactured by DJI (Figure 6). This quadcopter carries a high-quality camera that shoots 4K videos at 60fps and photos at 20 megapixels.

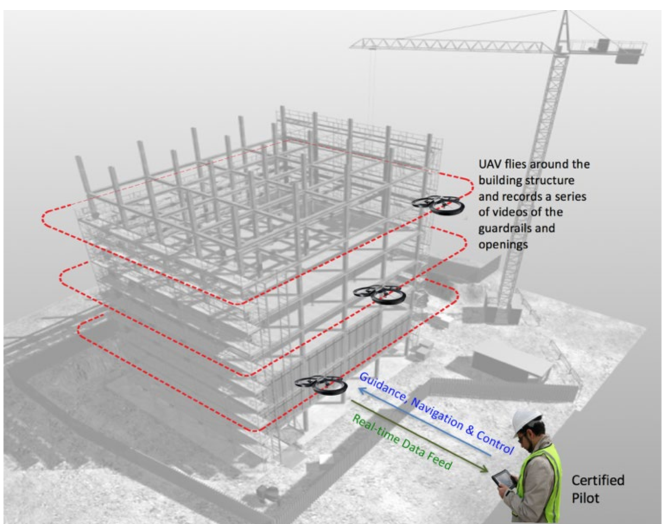

Figure 5: A conceptual illustration of capturing videos of a high-rise construction projects using a quadcopter

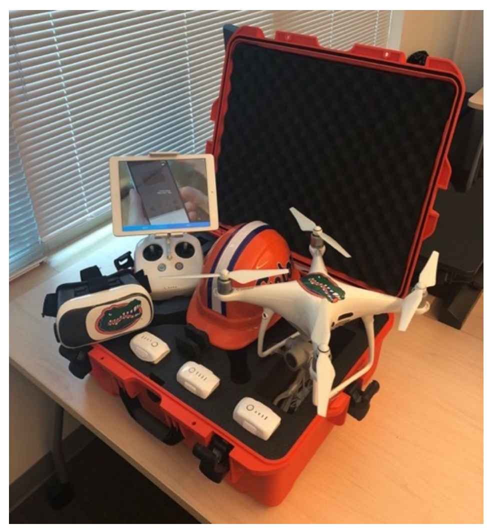

Figure 6: Phantom 4 PRO Quadcopter UAS

Step II: Guardrail Detection Algorithm Development

A three-step pipeline was developed to detect guardrails from the captured images. In the first step, a guardrail detection algorithm was trained to localize the candidate locations of poles supporting the guardrails. As images taken from the real world were used in this process, the detector was expected to generate a significant amount of false detections. So, additional constraints were introduced to filter out the false detections. Considering that the guardrails are located at different floors, a horizontal line detector was applied to the image to locate general floors and remove the detections that were not in close proximity of the detected floors. Since the guardrails are installed by humans and there is an approximate normal distribution between neighboring guardrail poles, the space between them was estimated and used to find the most likely combination of their locations.

<u>*1: Guardrail Detection*</u>

The classic sliding-window approach was adopted in this phase. First, starting from the upper left window of the image, a window was slid through the whole image to collect candidate locations that are likely to contain a guardrail. Note that multi-scale windows were not used here due to significant amount of scale variation observed in building images. This made the sliding window approach more efficient. From each window, a histogram of oriented gradients (HOG) feature was extracted, which is one of the most efficient human-designed features for object detection problems and has already been demonstrated on pedestrian detection applications (Dalal et al. 2005). A trained classifier in the algorithm was used to decide if the window contains a guardrail. For each window, the classifier took its HOG feature, processed it and predicted a score. If the score was above a threshold, then this window was decided as a positive detection. Two specific classifiers were used in this phase: (a) cascade classifier and (b) linear SVM (support-vector machine) classifier. Finally, the NMS (non-maximum suppression) algorithm (Forsyth et al. 2002) was adopted to reduce the number of overlapping detections. Positive detections from the classifiers were collected, and the ones with the highest classification score were selected from a group of detections with overlapping area. The overlapping area was measured by an IOU (intersection over union) metric. IOU is the ratio of the overlap between areas A and B of the ground truth bounding box A and predicted bounding box B and their union. (Forsyth et al. 2002).

(a) Cascade Classifier: a cascade classifier was trained specifically for guardrail detection. Previously, this classifier has been used for efficient face detection (Viola et al. 2001). During the training stage, guardrail labels were prepared for the training of the captured data. This classifier was trained to use a cascade of classifiers to efficiently process image regions for the presence of a target guardrail. Each stage in the cascade applied increasingly more complex binary classifiers, which allowed the algorithm to rapidly reject regions that did not contain the target. If the desired object was not found at any stage in the cascade, the detector rejected the region and processing was terminated. An off-the-shelf CascadeObjectDetector from MATLAB (Matlab 2019) was adopted for training purposes.

(b) Linear SVM Classifier: a linear SVM was trained to classify the candidate windows into guardrail and background. The SVM model learned a binary boundary in the HOG feature space to do the classification. The research team learned that to find the best set of hyper parameters, parameter selection and cross validation should also be adopted. A grid search algorithm was applied for selecting the parameters. A 2D grid was built containing all the possible combinations of the values of parameters C and γ, which were the weight of the constraint term and kernel parameter described in Chang et al. 2011. The block in the grid corresponded to one pair of parameter values. In practice, an exhaustive search was conducted on the whole parameter space. A linear SVM model was trained for each block of parameter values to evaluate its performance on the validation set. The SVM model with the best performance was selected as the final one. The libsvm library (Chang et al. 2011), a Library for Support Vector Machines, was used for training the SVM classifier.

<u>*2: Floor Detection*</u>

First, horizontal segments of the floor system were detected by identifying the vanishing points and the corresponding parallel lines. Because building images were used, there are many parallel horizontal lines in the image. First, the horizontal segments were identified using the vanishing point with the largest group of parallel lines (See Figure 7). Next, the floors were localized in a large number of detected line segments. Since images from a real-world project were used in this phase, the segments were not usually consistent, which led to having disconnected segments belong to the same horizontal lines. Instead of dealing with all the small line segments directly, the small segments were clustered into long ones by merging segments with similar intercept. Then the coverage of each clustered line segments was assessed on the x-axis and the maximum ones were considered as the detected floor. In practice, for an image of three floors of a building, the top 10 lines were picked as the detected floors. These detected floors were then used to filter out false positive detections. The number of false detections was reduced using a threshold that considered the distance of the bottom of a detected bounding box to the closest detected. A threshold of 10 pixels distance in an image was implemented for this assessment. This threshold was a function of image resolution but reflected the fact that detections more then 10 pixels above the detected floor were eliminated from the false positive count.

Figure 7: Visualization of the detected horizontal line segments

<u>3: Space estimation</u>

First, a Gaussian Mixture Model (GMM) was used to estimate the space between neighboring guardrails in the training set (Duda et al. 2012). The space was computed as the center distance between neighboring bounding box annotations. Guardrails without neighbors were ignored in this process. Because images were taken from different viewpoints, the spaces were normalized through dividing them by the mean of the length of the detected floors before the distribution was estimated. The normalized distance was then summarized in a histogram. An expectation-maximization (EM) algorithm (Duda et al. 2012) was used to fit a Gaussian Mixture Model (GMM) of the histogram. At the expectation step of the EM algorithm, posterior probabilities of component memberships were computed. Then these posterior probabilities were used as weights to estimate the component means, covariance matrices, and mixing proportions by applying maximum likelihood. This was the maximization-step of the EM algorithm. In practice, the number of components is estimated to be three, meaning three normal distributions were found. Figure 8 shows the estimated distribution. Finally, a “space-ubiquity” table was built so that by providing a space value, the table could predict the corresponding of the space value across the whole training set.

During the testing stage, given the group of bounding box detections, the goal was to find the combination of them with the maximum ubiquity. This goal was achieved by first computing the ubiquity value between every pair of detections through the space-ubiquity table. And then, dynamic programming was used to find the maximum combination. Note that in practice, the ubiquity value was reduced at each space by a certain threshold which made it negative for some spaces.

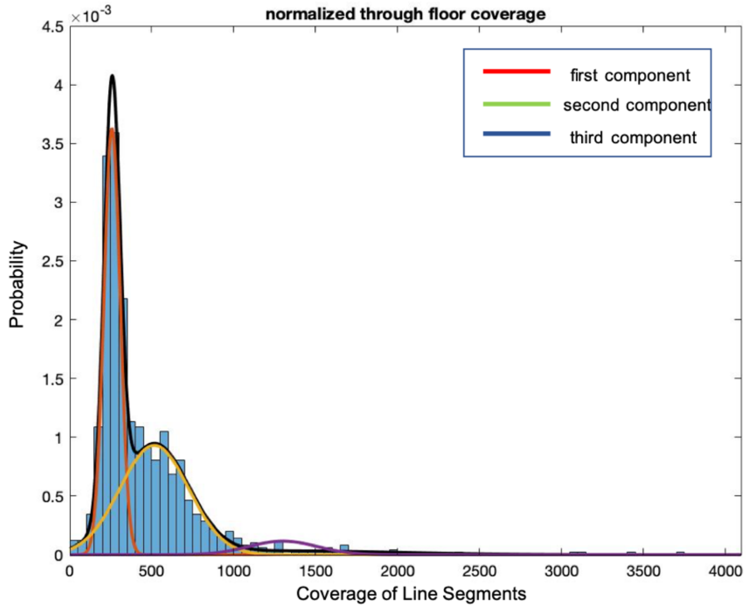

Figure 8: Visualization of the space distribution among the training data. The colorful bell curves are the approximations for the 3 components.

Step III: Guardrail Detection Algorithm Evaluation in a Real-world Project

The research team conducted a visit to a state-of-the-art, 16-floor tower that will serve as a patient care facility (Figure 9). They conducted multiple flights on site and captured over 55 gigabytes worth of aerial data (videos and images) using a DJI Phantom 4 Pro and 4K resolution to ensure the best possible results for image processing and fall hazard identification (Figure 10).

Figure 9: Data Collection on site: Construction Jobsite (left); Researchers conducting the flights (right)

Multiple flights characterized by variations in flight conditions and settings (e.g., image percentage overlap, manual and autonomous navigation, variations in speed, proximity to buildings) were performed on the jobsite, covering almost all the facades of the facility. Although the flights captured the whole building, the research team focused on the upper part of the tower, where vital visual information regarding guardrails and openings were acquired for analysis.

Figure 10: UAS-captured 4K resolution images of the building façade

Sixty-eight high-resolution RGB images were captured from the UAS collected videos. The sampling rate was about 100 frames per second to reduce the similarity between extracted images. The images were split into training and testing data following a 50:18 ratio. All the sampled images were labeled manually. Overall, 1158 guardrails were labeled in the training data and 416 ones were labeled in the testing data.

A: Evaluating Guardrail Detection

The previously discussed cascade classifier and a linear SVM were trained using the training data and their performance was then evaluated on the testing data using "Precision" and "Recall" metrics. Precision is the fraction of relevant instances among the retrieved instances, while recall is the fraction of the total amount of relevant instances that were actually retrieved (Forsyth et al. 2002). It is worth noting that the linear SVM (Figure 11) achieved a 10 percent advantage over the cascade classifier (Figure 12) on recall, which showed that it detected the majority the guardrails in the image (Table 1). However, its precision is also significantly lower. Comparatively, the cascade classifier achieved a balance between precision and recall.

Table 1: Evaluation results of trained guardrail detectors

Approach / Metric	Cascade Classifier	Linear SVM
Precision	0.1510	0.0438
Recall	0.7077	0.8062

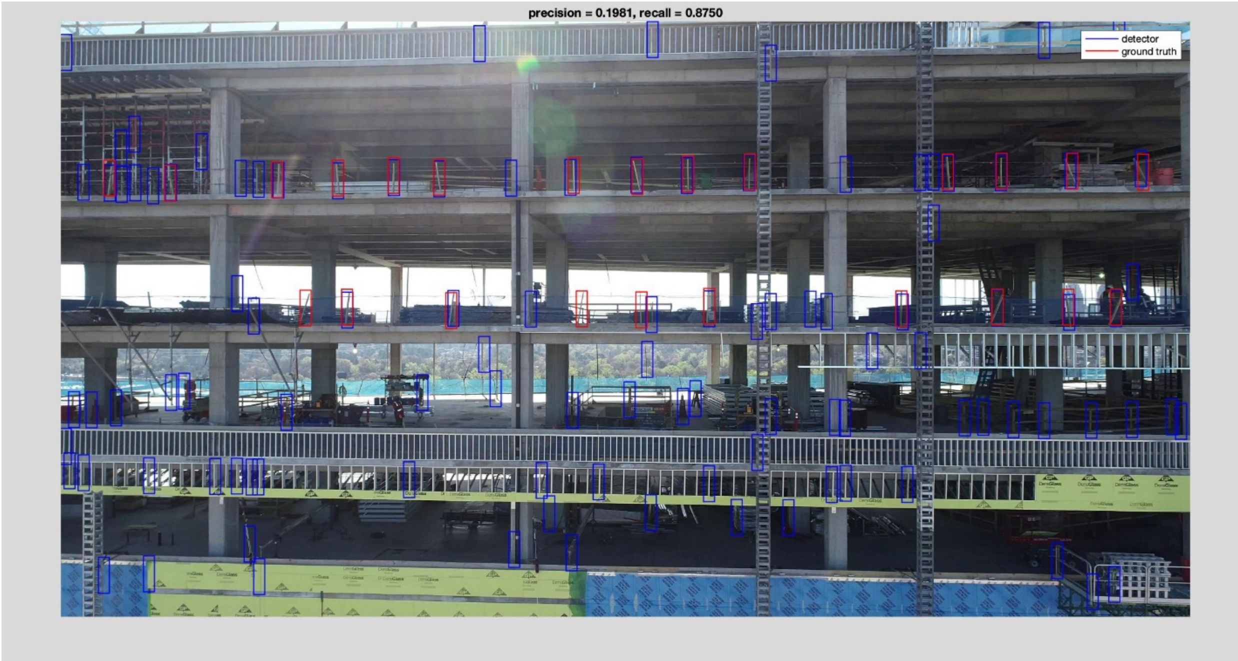

Figure 11: Visualizations of the guardrail detections using linear SVM

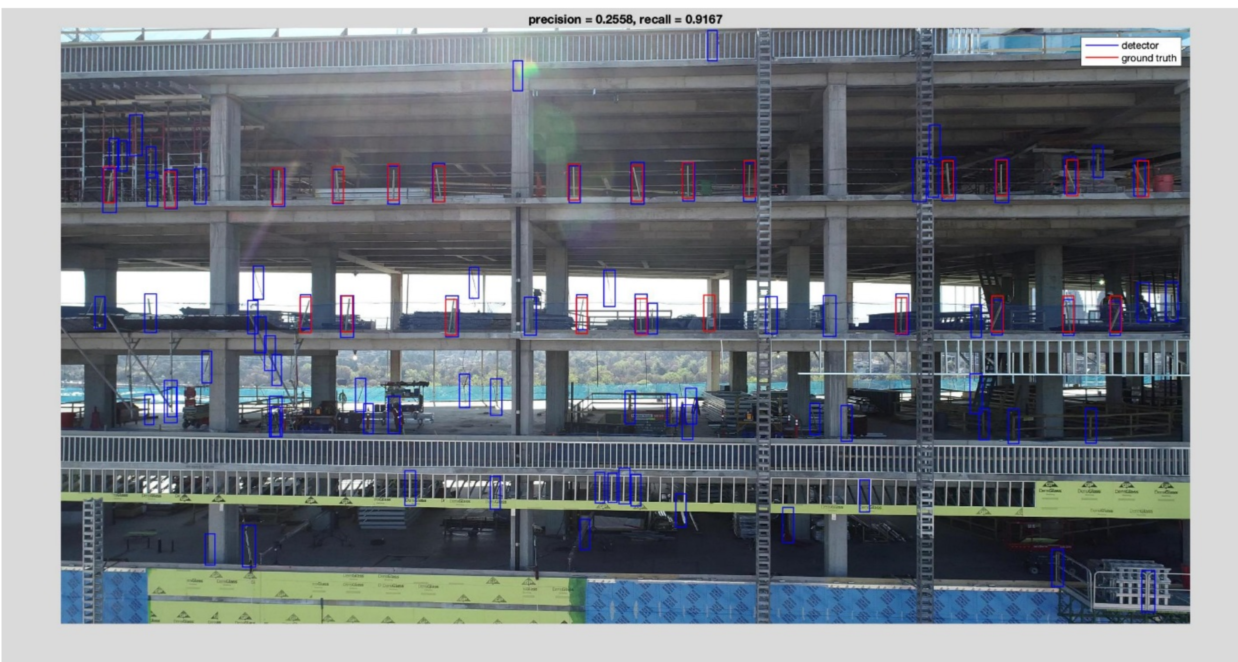

Figure 12: Visualizations of the guardrail detections using the cascade classifier.

B: Evaluating the Guardrail Detection + Floor Detection

As previously discussed, the floors were detected on the test images and then the floor detection filtering was applied to the detected windows. It is worth noting that many false positive detections were removed after integrating the floor detection, and the precision of both the cascade classifier and linear SVM approaches almost doubled as a result. Figure 13 illustrates the effectiveness of the floor detection filtering on the linear SVM detection result.

Table 2: Evaluation results after applying the floor detection

Metric \ Approach	Cascade Classifier + Floor Detection	Linear SVM + Floor Detection
Precision	0.2531	0.0974
Recall	0.7015	0.7908

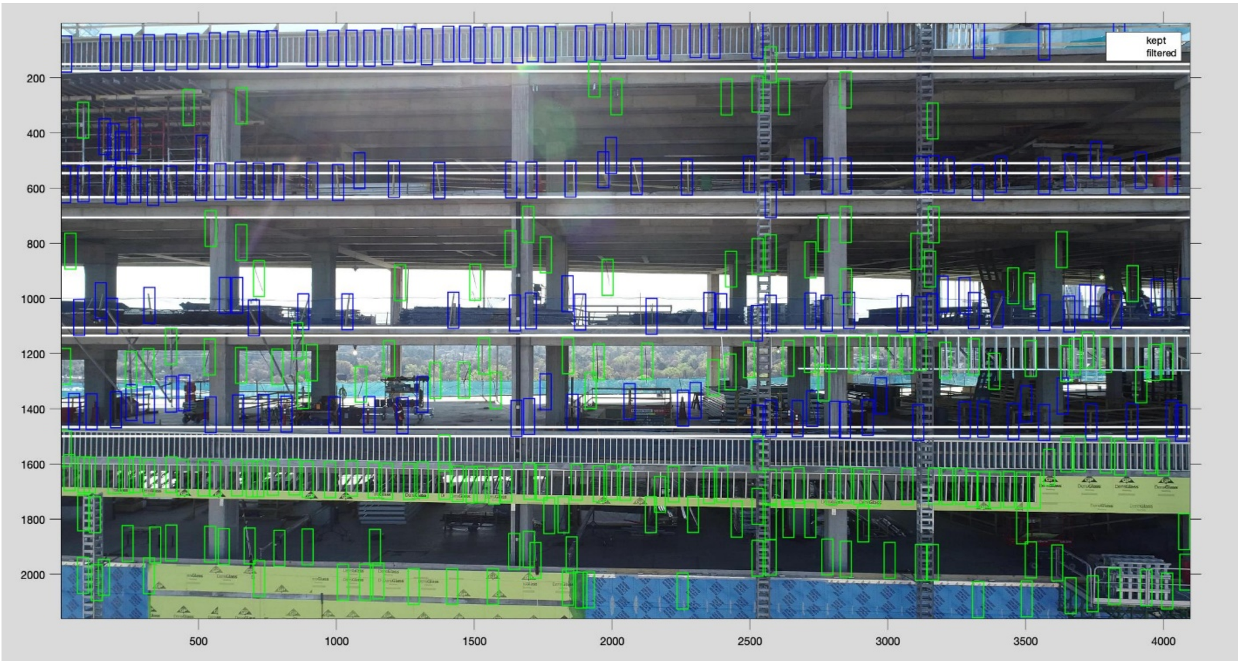

Figure 13: Visualization of the filtered false positive windows (denoted as green bounding boxes). White lines are the detected floors.

<u>*C: Evaluating the Guardrail Detection + Floor Detection + Space Estimation*</u>

Finally, space estimation, the last post-processing technique, was applied to achieve the best combination of guardrail detections. Table 3 demonstrates the result. Using the cascade classifier, the overall recall was around 62percent, and the precision was over 35 percent. If linear SVM detection were used, the precision was reduced 10 percent, but recall increased around two percent. It should be noted that the performance was not very good on a small set of testing images. In fact, after using cascade classifier on some of the testing images, there were over 80 percent recall and 50 percent precision. Figure 14 is the illustration of the final results on two images.

Table 3: Evaluation results after applying space estimation

Metric \ Approach	Cascade Classifier + Floor Detection + Space Estimation	Linear SVM + Floor Detection + Space Estimation
Precision	0.3666	0.2680
Recall	0.6215	0.6400

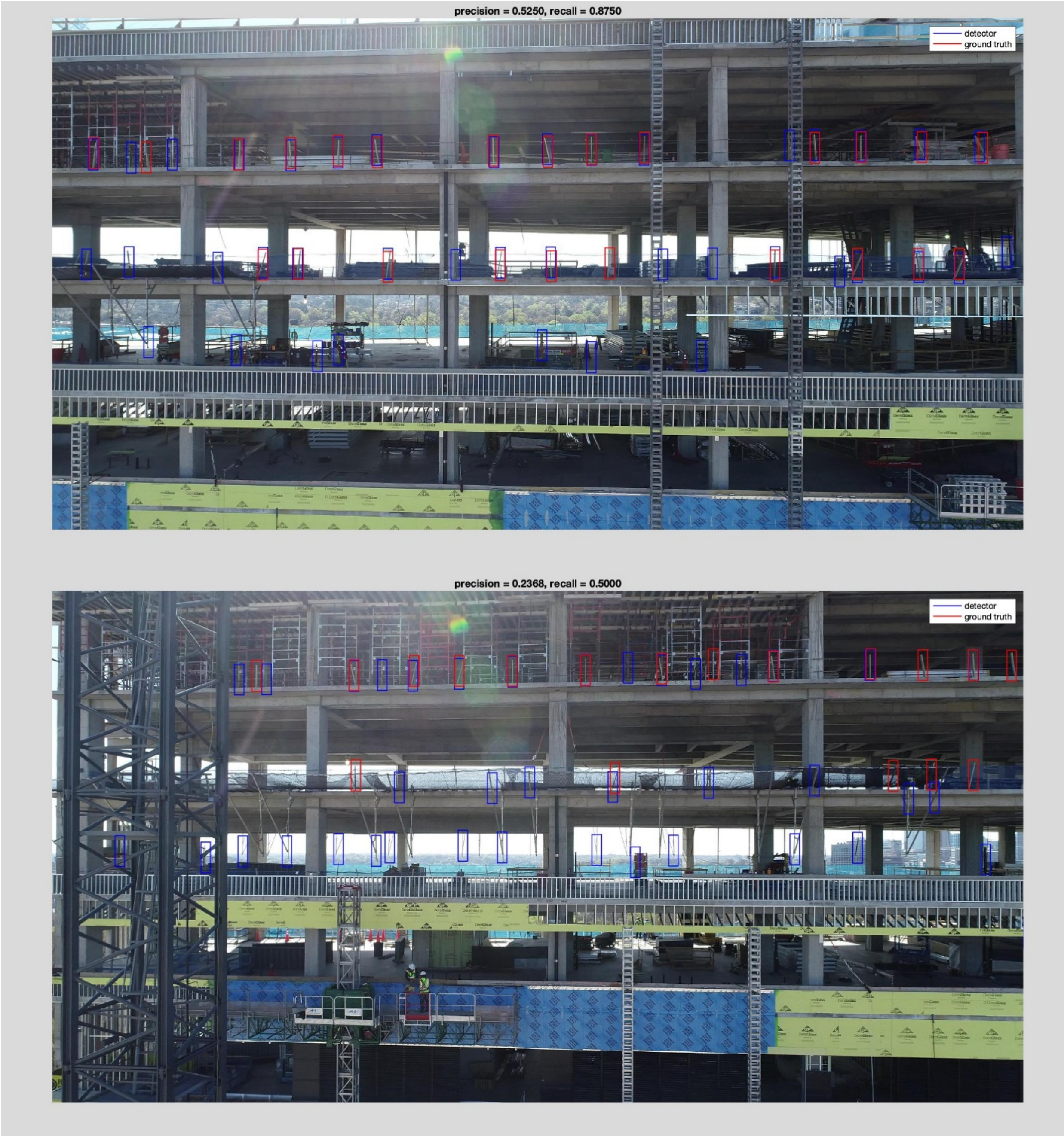

Figure 14: Final Detection Results on Two Images. The blue bounding boxes are the detected windows and the red ones are the ground truth labels.

FINAL REMARKS

In this study, a UAS-based image processing algorithm for guardrails detection from an RGB image was developed and tested in a real-world high-rise construction project. A three-step image processing pipeline of guardrail detection, floor detection, and space estimation was developed. In the guardrail detection step of the pipeline, two methods of cascade classifier and linear SVM classifier were used for guardrail detection purposes. Various combinations of the developed approaches were used to assess guardrail recognition in the captured images from a high-rise construction site (See Table 4). Considering the

'Precision' and then the 'Recall' metrics, the cascade classifier, with floor detection and guardrail spacing estimation achieved the best performance, as indicated in the Precision column.

Table 4: Summary of evaluation results for all approaches

Approach \ Metric	Precision	Recall
Cascade Classifier	0.1510	0.7077
Linear SVM	0.0438	0.8062
Cascade Classifier + Floor Detection	0.2531	0.7015
Linear SVM + Floor Detection	0.0974	0.7908
Cascade Classifier + Floor Detection + Space Estimation	0.3666	0.6215
Linear SVM + Floor Detection + Space Estimation	0.2680	0.6400

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