Autonomous Safety Barrier Inspection in Construction: An Approach Using Unmanned Aerial Vehicles and SafeBIM

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Abstract -

Construction sites are dynamic, and the environment is changing fast, which means the collective safety equipment, such as fall protection barriers, should also be changed to keep it compliant with the construction codes. However, any safety equipment can become non-compliant for several reasons, e.g., temporal removal in combination with incorrect or omitted re-installation or changes in the building process. Thus, there is a demand for frequent inspection of the equipment, which is time- and labor-intensive as this is currently done through manual examination by safety experts. In this work, we utilize an unmanned aerial vehicle (UAV) to detect the presence, absence, and defects of safety equipment in construction work-site environments. Furthermore, the UAV continuously inspects and provides safety object location information that human collaborators can use to improve safety within the environment. We utilize an 3D occupancy grid representation to map the environment and compact point pair feature representations for efficient and robust object recognition and pose estimation. To assess the applicability and accuracy of our methods for model-based pose estimation of Building Information Model (BIM) structures, we created a realistic, simulated construction environment. Our experiment demonstrates the applicability and precision of drone-aided localization and inspection of safety equipment in the construction industries.

Keywords -

Automation; inspection; safety; point clouds; unmanned aerial systems; object detection and pose estimation; augmented Reality (AR); human robot collaboration (HRI).

1 Introduction

Construction is considered one of the most dangerous industries due to the continuous change in the environment [1]. Construction safety design and planning is, therefore, a vital part of the construction business. Thus, comprehensive regulations and guidelines have been developed to keep construction workers safe while construction work is undertaken. Despite the labor-intensiveness of the creation of a safe construction plan, it is paramount. As this is the case, time and effort are allocated to facilitate and ensure health and well-being for the workers and prevent fatalities, severe injuries, minor injuries, and close call accidents (also referred to as prevention through design (PtD)). A statistical analysis of industries and their hazard types has been compiled into [2] in the US. The report

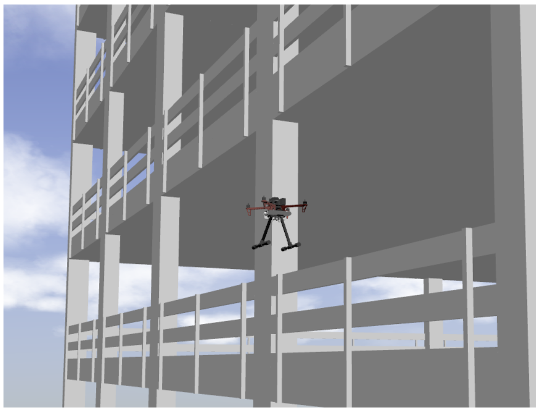


Figure 1. Simulation mission of an autonomous construction site inspection task using a multi-stereo camera UAV.

from 2019 shows that fatalities in the private construction industry correspond to 21.6% of fatalities (4907). Furthermore, the report shows that fatalities exclusively as a result of falls correspond to 33.5%. This is the reason that our work is focusing on fall hazards and more concretely protective barriers. We base the safe design on a software system called SafeCon [3], which automatically identifies the hazard fall-spaces in the BIM according to the regulation described in BG Bau 100 [4]. The system enhances the model with the safety equipment necessary to adhere to the [4] regulation. Another indispensable aspect of safety in construction operations is inspecting and localizing missing or deficient safety equipment (e.g., guardrails). Inspecting collective safety equipment is also a labor-intensive task as construction sites are very dynamic; thus, the inspection must happen with high frequency. Often, the installation of the measure differs from the intended quality designed in digital models. Using data from an UAV provides a real-time object location to centralized or distributed systems. As-planned vs. as-performed comparisons can extract deviations that have to be followed up and addressed.

The proposed method identifies critical incidents and points these out to the responsible personnel in a construction site's centralized safety operations center or individual workers through augmented reality (AR) glasses. A solution for autonomous barrier detection and pose estimation in construction environments is made by mapping the environment using stereo camera systems and utilizes 3D point cloud information to detect the type and location of barriers in the environment. We base our work on the method presented in [5] representing objects using a hash table of shape features, which efficiently allows matching features that vote for object pose hypotheses. An experiment in a realistic gazebo environment demonstrate the applicability of our method for localization and pose estimation of barrier structures in construction site environments.

2 Related Work

In order to create a safe construction design and plan, one must include both the rules that apply to the country and region where the construction is undertaken. The rules describe clearly what, for example, a guard rail has to comply with to be correctly installed. A safeBIM can be modeled manually, where the as-designed baseline plan is enhanced with safety equipment by safety experts according to the safety rules, which is the typical approach nowadays [6]. Another approach of turning the empty BIM into a safeBIM is utilizing an automated framework, like SafeCon [3]. In this work, the safety regulation is modeled into a logic-based domain model, consisting of spatial artifacts that can be used to analyze and enhance the incoming BIM. The process flags the presence of fall hazard paces, which need mitigation by collective protective equipment (e.g., guardrails). The output is a safeBIM (as-designed) plan that can be used to compare the actual state (as-built) of a construction site captured in, e.g., point cloud data.

In terms of automated safety inspection in construction, two main branches of research exist: (1) is based on sensors placed on UAV. Therefore, the acquisition of the as-built-state is included in the research, and (2) where the focus is more on the training and comparing different computer vision methods/approaches and less on the data acquisition. In the first branch, different research methods have been carried out. [7] presents a well-defined process (using IDEF0-modeling) to apply drones on a construction site and integrate UAV and BIM. [8] also presents a workflow that is more dedicated to detecting and locating guardrails and openings on surfaces. The analysis is based on point cloud data that is generated from RGB images and video feeds. A pilot study was carried out in a mock-up setting, where the UAV records a guardrail and an opening in the testbed. The study in [9] is another example where a UAV is applied for guardrail inspection. The objective is to analyze the guardrails' level of compliance with safety regulations. The inspection is performed based on visual, physical markers placed on the guardrail boards and a distance calculation. The distance between makers facilitates the compliance checking of the guardrail. [10, 11] develop a UAV platform that can be used in the construction industry and analyze the accuracy and barriers in UAV application in this industry. Finally, [12, 13] utilizes the UAV as help to reach inaccessible, hard-to-reach, and unsafe areas for safety assessment. The analysis is mainly based on manual inspection of the video/image feed.

The other branch of fall hazard prevention equipment inspection concentrates more on computer vision than image acquisition. [14] applies an R-CNN to detect workers in the scene and, afterward, a CNN to detect if a worker uses a safety harness [15]. Investigates safety rule compliance of guardrails on scaffolds using 3d point cloud data. They first find the working platforms by slicing the point cloud and locating the guardrails in the close vicinity. Subsequently, the guardrails are conformance checked. [16] applies transfer learning in their process of detecting guardrails.

Object recognition and pose estimation play a role of significant importance in robotics applications. In the following, we review the related work on this topic in regards to 3D point cloud data. There are two main approaches to this problem that depend on the availability of 3D object models: 3D model-based and learning-based. If one has a description of the 3D shape of the object, either given by a parametric surface representation or by a CAD mesh representation, the 3D model-based methods are often used for simultaneous object recognition, and 3D pose estimation [17]. On the other hand, if such representations are not available, the dominant approaches rely on machine learning techniques that learn an internal model representation given a set of image samples of the object, acquired by the robot sensors [18].

One of the most successful approaches for model-based 3D object recognition using point clouds are based on [19],[20] where a global descriptor for a given object shape model is created, using point pair features. The CAD model of the object is used to create an extensive database of features. At run-time, the matching process is done locally using an efficient and robust voting scheme similar to the Generalized Hough Transform [21]. Each point pair detected in the environment casts a vote for a particular object from a database of known objects, and a 3D pose [22],[5].

In this work, we study the suitability of the latter methods for object detection in construction environments, since we assume that geometric models (i.e., 3D CAD) representing known objects in the environment are provided.

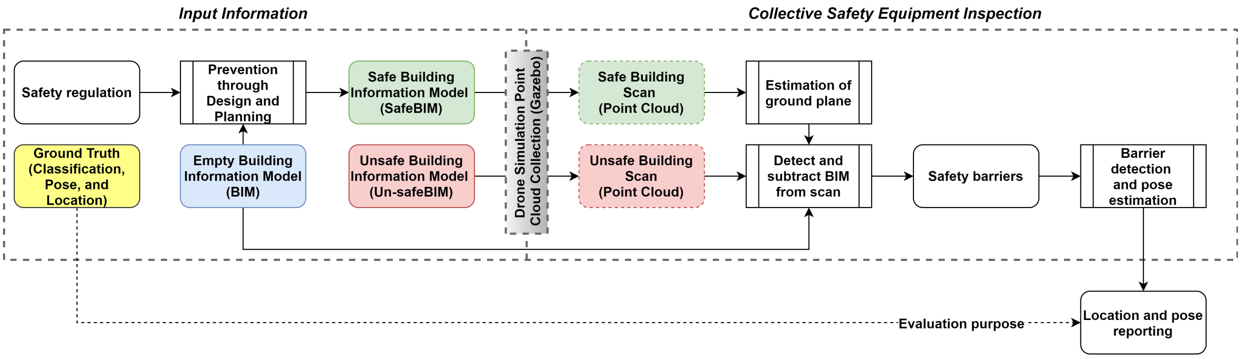


Figure 2. Overview of steps included in automated collective construction safety equipment inspection.

3 Methodology

In this work, we follow the overall approach illustrated in Figure 2, which include three inputs: (1) the empty BIM, that is assumed to be available for most construction projects, (2) A safeBIM containing the demanded safety barriers accordingly to safety regulation [4], and is relying on the SafeCon-application developed in [3], and (3) database of safe and unsafe objects created based on same safety regulation [4].

To perceive and capture the environment, we utilize point cloud data acquired from RGB-D cameras. These point clouds are used for recognition and estimation of the pose of safety barrier objects in construction sites (safe and unsafe) simultaneously. As shown in Figure 2 we use the point cloud data collected by the UAV to (I) Extract the ground plane, (II) Detect and subtract empty BIM from the point cloud data, and (III) perform barrier detection, location, and pose estimation. The first step of the framework is performed by detecting the predominant plane in the scene using a RANSAC plane fitting approach. Then, the second step is utilizing a combination of Point Pair Feature (PPF) and Generalized Hough Transform (GHT) detect the empty building using a pre-existing CAD model. Finally, the same method is employed iteratively to detect barrier structures.

We rely on the method of [23] that extracts point-pair features (PPF) from 3D point clouds with associated normals [20] as local descriptors and employs a GHT to simultaneously estimate the pose and object type, using a clever voting scheme.

In an offline phase, we build a database of known objects from existing CAD models. Then, we extract a point cloud with associated normals for each model and build a hash table containing all model PPFs.

Let $\mathbf{s}_r = (\mathbf{p}_r, \mathbf{n}_r)$ and $\mathbf{s}_i = (\mathbf{p}_i, \mathbf{n}_i)$ represent two surflets (i.e. point and associated normal). For each surflet pair (see Figure 3) belonging to the model point cloud, we store them in a hashtable using the following hash function:

$$\mathrm{PPF}(\mathbf{s}_r, \mathbf{s}_l) = (||d||, \angle(\mathbf{n}_r, \mathbf{d}), \angle(\mathbf{n}_i, \mathbf{d}), (\mathbf{n}_r, \mathbf{n}_i)) \quad (1)$$

We extract PPFs from the captured point clouds during the online recognition phase and match them against the hash table, and compute the pose that align PPF matches. Then, the candidate poses with the highest number of votes in the Hough accumulator are retrieved. This step is performed for each model in the database of known objects. The model and pose with the highest score are selected. Finally, since the Hough voting space is discrete, we employ an iterative closest point (ICP) algorithm [24] to fine-tune the estimated pose of the object. The ICP algorithm iteratively searches for the transformation that minimizes the distance between points belonging to the scene, and the ones belonging to the most voted CAD model one. In each iteration, the points from the scene will be matched to the closest points in the model from the database. Subsequently, the transformation that minimizes the sum of the error between corresponding points is estimated, using a gradient descent optimization method. Finally, the transformation is performed to the point cloud, and the process starts over until it converges, i.e., no reassignment of the points is performed. We initialize the ICP method with the discretized pose determined with the GHT method, to speed-up convergence speed.

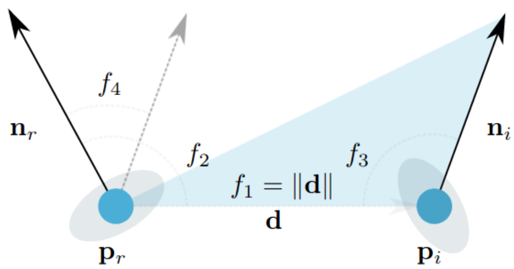
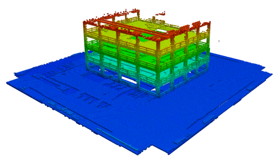
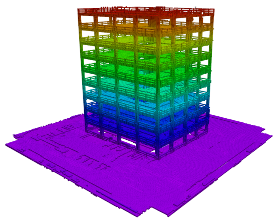


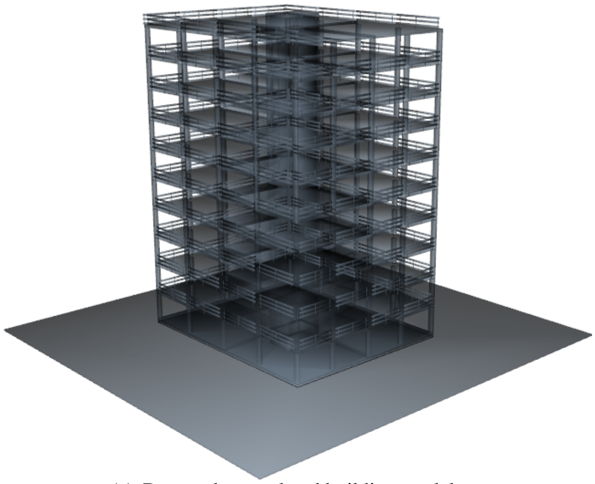
Figure 3. Point pair feature.



(a) 3D reconstruction (initial).



(b) 3D reconstruction (last).



(c) Detected ground and building models.

Figure 4. Environment 3D reconstruction from point cloud data collected by a UAV and estimated locations of known objects (i.e., CAD models).

4 Experiment

In our experiment, we let the UAV fly around the construction site and build a 3D map of the environment. In an offline phase, we train our detector with different types of barriers, building a hash-table of point pair feature descriptors for each barrier type. In the online phase, we apply the detector to point cloud mapping data, to find instances of barriers.

4.1 Experimental Setup

We perform the experiment in a simulated construction site (see Figure 4), and introduced an infrared noise with Gaussian distribution of fixed mean value of $0mm$, and a standard deviation of $1mm$ in the collected point cloud data. The colors in the 3D occupancy grid (see Figure 4) representing the environment reconstructed with point cloud data represent relative height. Figure 4(c) shows the super-imposed building CAD model after estimation and detected ground plane and building location, that is performed after completion of point cloud data acquisition. In order to evaluate location and pose estimation error performance, we developed two different experimental scenarios, in a realistic gazebo simulation environment [25].

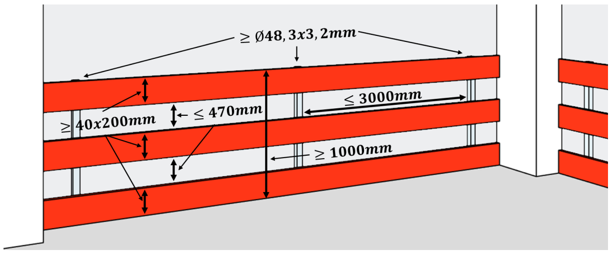


Figure 5. Safety code BG Bau 100 [4] illustration using horizontal boards with a thickness of $4mm$ and height of $200mm$.

The experimental study is based on the BG Bau 100 safety code [4], which is illustrated in Figure 5. This building code describes installing compliant and safety barriers in a construction site, such as high-rise buildings. The safety code describes how to comply using different board dimensions, but the one used and illustrated in this work utilizing $40x200mm$ boards. Besides the safe version of the BIM, we have created an unsafe version, where non-compliant and hazardous scenarios are introduced on purpose (see Figure 8, third row).

We modeled the faulty and hazardous scenarios to create unsafe BIM, introducing different safety code violations. An overview of the violations is shown in Figure 6, where we introduce issues regarding six different violations:

1. Absence of horizontal boards
2. Absence of vertical poles
3. Combination of absence of horizontal and vertical boards
4. Part of guardrail is absent or guardrail completely absent
5. Horizontal board is diagonal
6. Horizontal board placed to close to bottom or top, and the vertical pole placed too far to the left

The placement of the faulty object are represented graphically in Figure 7, which is an overview of the south and north facing facade, where hazardous situations are introduced in the unsafe BIM. Therefore, the east and west face are not altered in the unsafe model (also visible in Figure 8). Furthermore, we provide an overview of the introduced scenarios in Table 1, where the number of occurrences of each variation has been counted for later ground truth comparison, which also contains translation and rotation from the BIM origin to each of the guardrails.

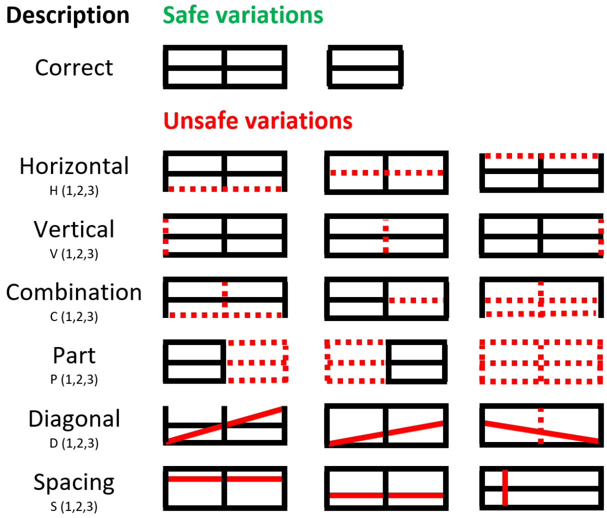


Figure 6. Object overview: safe variations are compliant with regulation, and unsafe objects violating with regulation [4].

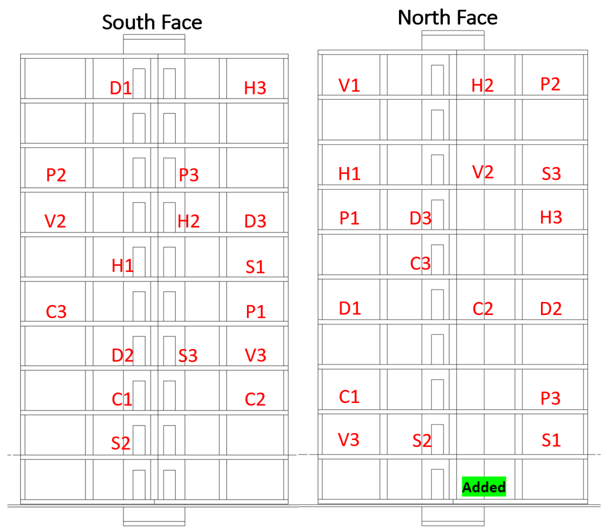


Figure 7. Overview of the placement of the different faulty scenarios shown in Figure 6. Non-labeled squares are not altered and are therefore safe and compliant with the safety code.

4.2 Evaluation Metrics

In order to assess the performance of our 6D pose estimation approach, we consider the error of the estimated pose $\hat{\mathbf{P}} = (\hat{\mathbf{R}}, \hat{\mathbf{t}})$, with respect to the ground truth pose $\mathbf{P} = (\mathbf{R}, \mathbf{t})$, according to

$$e_{\text{trans}} = \|\mathbf{t} - \hat{\mathbf{t}}\| \tag{2}$$

$$e_{\text{rot}} = \|\mathbf{R} - \hat{\mathbf{R}}\| \tag{3}$$

Table 1. Number of different correct and anomalous (incl. variation) in Figure 6, placed in the safe and unsafe BIM (Figure 7)

Guardrail scenario	**Safe Model [No.]**	**Unsafe [No. (Var1,2,3)]**
Correct	194	139
Anomalous	0	36
Horizontal	0	6(2,2,2)
Vertical	0	6(2,2,2)
Combination	0	6(2,2,2)
Part	0	6(2,2,2)
Diagonal	0	6(2,2,2)
Spacing	0	6(2,2,2)

where $\mathbf{R}$ and $\mathbf{t}$ represent rotation and translation, and e_{trans}, and e_{rot} the translation and rotational errors, respectively.

From Table 2 we observe that the performance of the proposed method is relatively good as the average translation and rotation errors are low in comparison to the sizes of the models. The environment we operate has the dimensions of approximately $43x41x33m$ $(WxDxH)$, where a deviation of $0.54m$ corresponds to 1.64%. We calculate this by averaging the dimension corresponding to $39m$. This is reasonable as the error in Table 2 is also based on the average along all three axes (translational error). Furthermore, the rotational error of $0.88°$ corresponds to a deviation of 0.99%, which is also impressively low.

Table 2. Resulting average translation and rotation error of 6D pose estimation performing PPF in combination with ICP

Method	**Average e_{trans} $[m]$**	**Average e_{rot} $[°]$**
PPF+ICP	0.540652	0.880321

5 Discussion

Our framework for automatic safety barrier detection and inspection in construction sites using vision-based UAVs and a database of CAD models, which can be extended to contain other types of safety railing. The obtained results in a realistic simulation environment demonstrate our method's potential applicability in real construction sites. Furthermore, our results show that we could estimate the location of BIM structures accurately with sub-meter and sub-degree precision, corresponding to $1,63\%$ and 0.99% in terms of translation and rotation, respectively. Based on these results and experience with correspondence between reality and the realistic simulation environment, we intend to employ this method in an actual construction setting and confirm its applicability. A system like the one we are proposing would assist the safety expert in pointing out issues that are not discovered

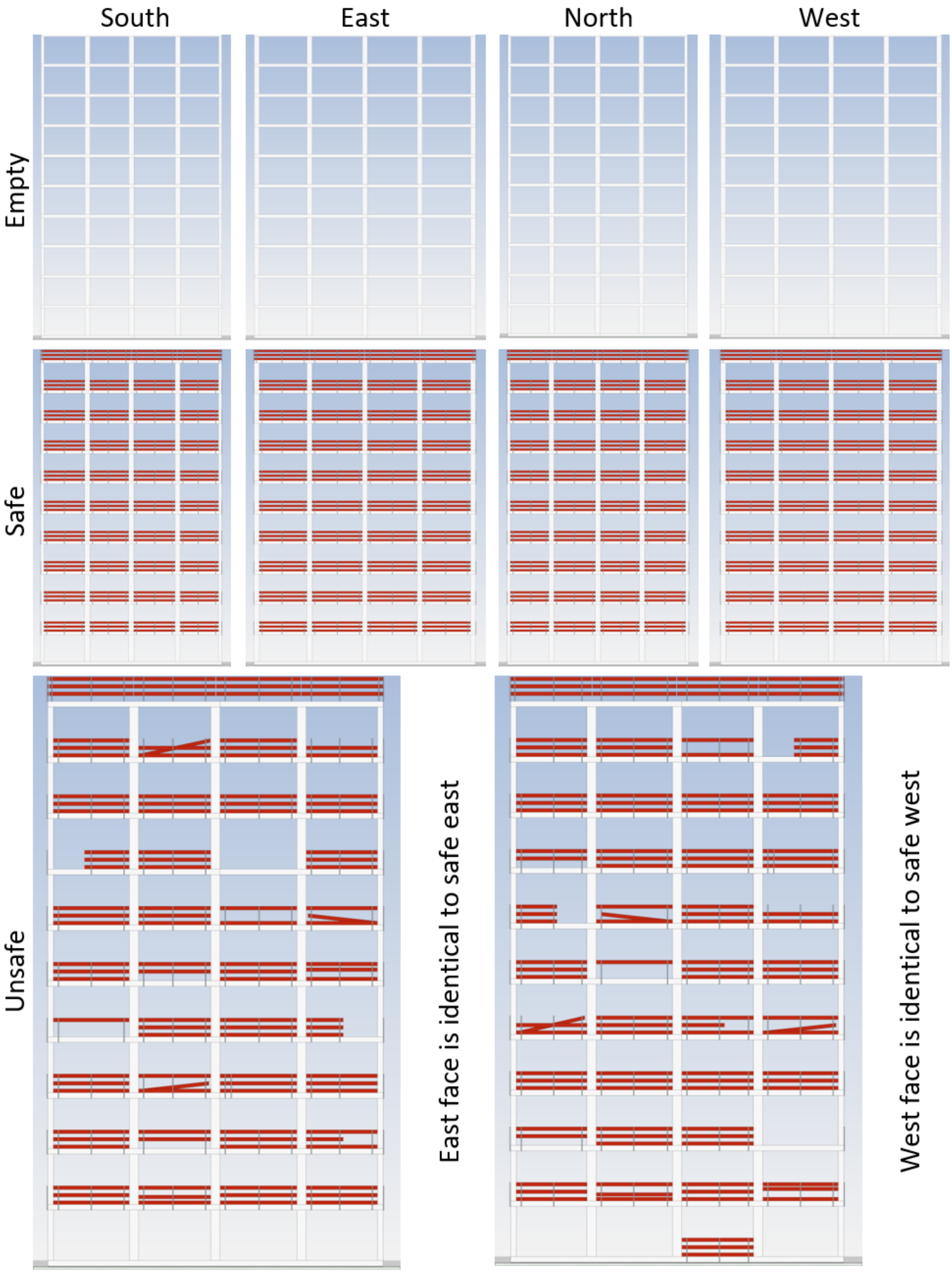


Figure 8. Overview of all four faces (south, west, north, and west, column 1 to 4 respectively) of the three utilized models (empty, safe, and unsafe, row 1 to 3 respectively).

manually and improve the safety at the construction site. As the system improves, it could very well also fully automate the inspection of some objects. However, this should still be a collaboration where the safety expert can solve issues instead of wasting time looking at correctly installed barriers. Furthermore, we will study ways to classify the detected barriers to separate the hazards and even propose mitigations in future work. Furthermore, automating the launch of the UAV and improving the autonomous exploration of the construction would be beneficial for the applicability and a promising future research direction.

6 Conclusion

This paper proposes a system utilizing UAVs to handle the labor-intensive tasks of collective safety equipment inspection. Much effort is put into inspection of the construction site, and some of these tasks should be automated to get a higher temporal resolution. The proposed system is initially analyzed in a simulation tool with the objective of determining feasibility and applicability. Our experiments demonstrate that automation of the inspection is possible with high precision, which can eventually lead to the actual replacement of current practices.

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References

[1] A. Pinto, I. L. Nunes, and R. A. Ribeiro. Occupational risk assessment in construction industry – overview and reflection. *Safety Science*, 49(5):616–624, 2011. ISSN 0925-7535. doi:10.1016/j.ssci.2011.01.003.

[2] Bureau of labor statistics. National census of fatal occupational injuries in 2019. On-line: `https://www.bls.gov/news.release/pdf/cfoi.pdf`, Accessed: 10/06/2021.

[3] B. Li, C. Schultz, J. Melzner, O. Golovina, and J. Teizer. Safe and lean location-based construction scheduling. In *Proceedings of the 37th International Symposium on Automation and Robotics in Construction (ISARC)*, pages 1409–1416. International Association for Automation and Robotics in Construction (IAARC), 10 2020. ISBN 978-952-94-3634-7. doi:10.22260/ISARC2020/0195.

[4] Berufsgenossenschaft der Bauwirtschaft. Absturzsicherungen auf baustellen. On-line: `https://www.bgbau-medien.de/handlungshilfen_gb/daten/bausteine/b_100/b_100.htm`, Accessed: 10/06/2021.

[5] R. P. de Figueiredo, P. Moreno, A. Bernardino, and J. Santos-Victor. Multi-object detection and pose estimation in 3d point clouds: A fast grid-based bayesian filter. In *2013 IEEE International Conference on Robotics and Automation*, pages 4250–4255. IEEE, 2013.

[6] T. M. Toole and J. Gambatese. The trajectories of prevention through design in construction. *Journal of Safety Research*, 39(2):225–230, 2008. ISSN 0022-4375. doi:10.1016/j.jsr.2008.02.026.

[7] S. Alizadehsalehi, T. Yitmen, I.and Celik, and D. Arditi. The effectiveness of an integrated bim/uav model in managing safety on construction sites. *International journal of occupational safety and ergonomics: JOSE*, 09 2018. doi:10.1080/10803548.2018.1504487.

[8] M. Gheisari, A. Rashidi, and B. Esmaeili. Using unmanned aerial systems for automated fall hazard monitoring. In *Construction Research Congress 2018*, 04 2018. doi:10.1061/9780784481288.007.

[9] C. M. Mendes, B. F. Silveira, D. B. Costa, and R. R. Santos de Melo. Evaluating uas-image pattern recognition system application for safety guardrails inspection. In *Proceedings of the Joint CIB W099 and TG59 Conference*, 7 2018.

[10] J. Martinez, G. Albeaino, M. Gheisari, R. Issa, and L. Alarcon. isafeuas: An unmanned aerial system for construction safety inspection. *Automation in Construction*, 02 2021. doi:10.1016/j.autcon.2021.103595.

[11] W. Li, H. Li, Q. Wu, X. Chen, and K. Ngan. Simultaneously detecting and counting dense vehicles from drone images. *IEEE Transactions on Industrial Electronics*, PP, 02 2019. doi:10.1109/TIE.2019.2899548.

[12] R. Melo, D. Costa, J. Álvares, and J. Irizarry. Applicability of unmanned aerial system (uas) for safety inspection on construction sites. *Safety Science*, 98, 10 2017. doi:10.1016/j.ssci.2017.06.008.

[13] J. Martinez, M. Gheisari, and L. Alarcon. Uav integration in current construction safety planning and monitoring processes: Case study of a high-rise building construction project in chile. *Journal of Management in Engineering*, 36:1–15, 03 2020. doi:10.1061/(ASCE)ME.1943-5479.0000761.

[14] F. Weili, L. Ding, and H. Luo. Falls from heights: A computer vision-based approach for safety harness detection. *Automation in Construction*, 91:53–61, 02 2018. doi:10.1016/j.autcon.2018.02.018.

[15] Q. Wang. Automatic checks from 3d point cloud data for safety regulation compliance for scaffold work platforms. *Automation in Construction*, 104:38–51, 08 2019. doi:10.1016/j.autcon.2019.04.008.

[16] Z. Kolar, H. Chen, and X. Luo. Transfer learning and deep convolutional neural networks for safety guardrail detection in 2d images. *Automation in Construction*, 89:58–70, 2018. ISSN 0926-5805. doi:10.1016/j.autcon.2018.01.003.

[17] Y. Guo, M. Bennamoun, F. Sohel, M. Lu, and J. Wan. 3d object recognition in cluttered scenes with local surface features: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 36(11):2270–2287, 2014. doi:10.1109/TPAMI.2014.2316828.

[18] C. R. Qi, H. Su, K. Mo, and L. J. Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[19] R. B. Rusu, G. Bradski, R. Thibaux, and J. Hsu. Fast 3d recognition and pose using the viewpoint feature histogram. In *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2155–2162, 2010. doi:10.1109/IROS.2010.5651280.

[20] T. Birdal and S. Ilic. Point pair features based object detection and pose estimation revisited. In *2015 International Conference on 3D Vision*, pages 527–535, 2015. doi:10.1109/3DV.2015.65.

[21] P. V. C. Hough. Method and means for recognizing complex patterns, December 18 1962. US Patent 3,069,654.

[22] T. Birdal and S. Ilic. Point pair features based object detection and pose estimation revisited. In *2015 International Conference on 3D Vision*, pages 527–535, 2015. doi:10.1109/3DV.2015.65.

[23] B. Drost, M. Ulrich, N. Navab, and S. Ilic. Model globally, match locally: Efficient and robust 3d object recognition. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 998–1005, 2010. doi:10.1109/CVPR.2010.5540108.

[24] P. J. Besl and N. D. McKay. A method for registration of 3-d shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 14(2):239–256, 1992. doi:10.1109/34.121791.

[25] N. Koenig and A. Howard. Design and use paradigms for gazebo, an open-source multi-robot simulator. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2149–2154, Sendai, Japan, Sep 2004.