2025 European Conference on Computing in Construction
CIB W78 Conference on IT in Construction
Porto, Portugal
July 14-17, 2025

AUTOMATED HAZARD IDENTIFICATION IN TOWER CRANE LIFTING OPERATION USING RTK-GNSS POSITIONING AND TRACKING

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Abstract

Tower cranes play an essential role in lifting heavy building elements, often posing significant hazards to workers. However, automated methods for crane monitoring remain underdeveloped. This paper introduces a data-driven method to track crane trolley trajectories and identify associated hazards. The method utilizes the Real-Time Kinematic Global Navigation Satellite System (RTK-GNSS) to capture the spatial movements of the trolley. The high-precision tracking provided by RTK-GNSS enables the detection of tiny jib deflection during lifting loads. By analyzing changes in height and speed, a lifting operation can be divided into distinct stages. Integrating the trajectory of the workers and trolley with the site model and schedule allows for incident detection. The proposed method offers a cost-effective and implementable alternative for crane safety monitoring.

Introduction

Tower cranes play an essential role in construction sites for their capability to lift and transport heavy loads efficiently. However, the operational complexity also makes them a significant source of workplace fatalities and injuries. Between 2020 and 2024, 339 crane-related accidents were recorded in the United States (OSHA, 2024). Among various crane types, tower cranes accounted for 22% of accidents, with 8% occurring in the European Union (Milazzo et al., 2016). The primary causes of these accidents include crane collapses, load drops, equipment failures, and operator errors. Milazzo et al. (2016) identified that 16% of crane-related accidents were attributed to workers being struck by falling loads from crane booms, while 2% were linked to mishandling heavy loads. Despite these risks, effective and automated tower crane monitoring methods to ensure worker safety remain underdeveloped. Traditional safety measures rely on the experience and observation of operators and workers, underscoring the need for more automated and robust approaches.

Smart sensing technologies have been widely adopted to automate tower crane monitoring (Ali et al., 2024). Various sensors, including location- and vision-based systems, have been implemented to enhance the safety and productivity of tower cranes. These sensors measure parameters such as hook location, slewing angle, and load weight to monitor lifting operations (Danel et al., 2024; Nishizawa & Mishima, 2024; Sacks et al., 2005). However, existing monitoring systems are often integrated into crane operation systems for safety and maintenance, making it challenging to retrieve data for further analysis. Additionally, methods that involve external sensors frequently depend on multiple devices to achieve robust activity and hazard identification in lifting operations (Hu et al., 2024).

Hence, a research gap is identified in developing simple yet robust methods for monitoring trolley movement and load status, enabling the classification and identification of distinct stages in lifting operations. This study addresses this gap by proposing a method that employs Real-Time Kinematic Global Navigation Satellite System (RTK-GNSS) technology to track the spatial movement of the crane trolley, including small displacements caused by the lifted load and horizontal movements within the context of the construction site layout. Compared to other methods, it reduces reliance on multiple devices by leveraging the correlation between load status and location data. In addition, it contributes to the application of centimeter-accurate RTK-GNSS tracking technology to understand the dynamics of the crane trolley during lifting operations. Thus, this method enables more targeted and effective tower crane monitoring strategies, forming a foundation for advanced hazard monitoring and analysis during lifting operations.

The paper starts with a brief review of related work in tower crane monitoring methods and RTK-GNSS technology applications. It then elaborates on the method and presents implementation results on a construction site.

Related work

This section presents overarching sensing technologies and methods for tower crane monitoring, followed by a narrowed-down focus on localization sensors and activity identification.

Methods and applications of tower crane monitoring

The tower crane monitoring has been extensively studied using various sensing technologies, such as localization and vision-based methods. The applications address various on-site challenges, such as operator visibility, worker safety, and productivity tracking. For instance, Yang et al. (2014) presented a vision-based crane tracking system for tracking crane jib trajectories to understand tower crane activity. Limited operator visibility is also a challenge in crane operations. Therefore, Cheng and Teizer (2014) developed a model to evaluate tower crane operator visibility, emphasizing the potential of remote sensing technologies, such as ultra-wideband (UWB), to ensure worker safety by tracking pedestrian movement in hazardous zones. The challenges of resource tracking in harsh construction environments were also addressed by Cheng et al. (2011), who evaluated the performance of UWB technology for resource location tracking. Their work included a mobile crane use case and highlighted fall-from-above hazards, demonstrating the feasibility of UWB for improving safety in demanding site conditions.

In addition to tracking technologies, incident detection and analysis have been studied to improve pedestrian worker safety. Teizer et al. (2013) explored the use of location tracking and data visualization technologies to improve training in safety and productivity. The detection and recording of incidents also play a crucial role in mitigating construction site risks. Teizer and Cheng (2015) introduced a proximity hazard indicator for capturing and mapping near-miss locations, focusing on worker-equipment interactions.

Localization sensors in tower crane monitoring

Localization and kinematics sensors have been widely implemented in tower crane monitoring (Ali et al., 2024). For example, Hwang (2012) presented a method of mounting UWB tags on crane booms to detect the proximity of different crane booms for collision prevention. Fang & Cho (2015) implemented an inertial measurement unit (IMU) module to measure load orientation and track load position and sway during daily lifting activities.

Enhanced from traditional GPS capabilities, RTK-GNSS is a centimeter-level accurate outdoor positioning method. It achieves this high accuracy by receiving signals from additional satellites and corrections from static sensors, which calibrate errors in stand-alone systems (Wielgocka et al., 2021). This precision makes RTK-GNSS suitable for monitoring small deformations and displacements in both static structures and moving equipment. For example, Xiong & Niu (2019) utilized RTK-GNSS to monitor the dynamic behavior of high-rise structures, while Nishizawa & Mishima (2024) mounted an RTK-GNSS receiver and camera on a crane hook to identify lifting work stages and recognize lifted elements. Although their approach achieved high accuracy in work cycle identification, misclassifications occurred due to a lack of information about the load status on the hook. Additionally, the centimeter-level accuracy of RTK-GNSS was underutilized, as the height changes of the hook were measured at a meter scale.

Activity Identification in Lifting Operations

Activity identification in lifting operations has been studied using diverse types of operational data, such as lifted weight, hook height, and slewing angle. Identification methods can broadly be categorized as either rule-based or machine learning approaches. Rule-based methods differentiate stages using preset criteria, such as identifying periods where motion or weight exceeds a defined threshold. For instance, Sacks et al. (2005) proposed a concept of using hook location and weight to isolate crane working cycles by identifying points in the data with sharp changes in motion or load. Danel et al. (2024) collected data on load weight and hook height from built-in anti-collision systems to track concrete pouring progress, offering insights into productivity improvements. Similarly, Nishizawa & Mishima (2024) divided a lifting operation into four stages based on hook height changes.

Machine learning methods, on the other hand, classify activities using models trained on labeled data. For example, Jiang & Ding (2024) applied transfer learning to detect different hazardous hoisting scenarios using data from strain sensors mounted on crane towers. Rashid and Louis (2020) used data from IMU sensors installed on excavator components to identify activity patterns during earthmoving operations. Compared to vision-based methods, rule-based methods are advantageous when less data is available for training and can be easily adapted for different tower cranes.

This study aims to propose a rule-based method for tower crane activity identification using only RTK-GNSS data. The method detects displacements of the crane trolley in both vertical and horizontal directions, which reflect the weight of the load attached at the hook location.

Methods

The methods begin with the collection of tower crane data from a construction site, followed by preprocessing to prepare the data for analysis. The analysis focuses on classifying and evaluating the distinct stages of lifting operations and identifying the associated hazards. Based on these insights, a rule-based algorithm was developed to automatically identify lifting activities and associated hazards. For validation, the algorithm was implemented on a real construction site. The results of the lifting operation and stages of identification and incident detection were compared with video data captured on the site.

Data collection and processing

A case study was conducted at a residential building construction site in Helsinki, Finland, where a seven-story high-rise residential building was constructed using prefabricated elements.

The construction site layout is illustrated in Figure 1(a), showing designated zones for material storage, concrete pumps, truck unloading, and driveway. At the time of system implementation, the project was in the early stages, as shown in Figure 1(b), with the ground floor structure under assembly. As the site layout models, in the format of Industry Foundation Classes (IFC), lacked site layout information, the surroundings were approximated as flat planes with manually modeled designated zones.

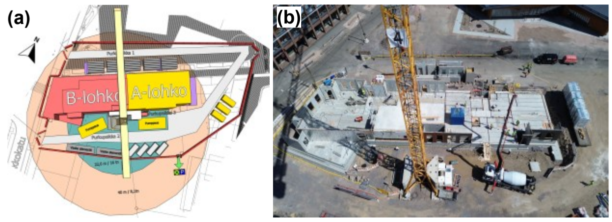

Figure 1: (a) Construction site layout for a residential building in Helsinki, Finland (b) Construction site overview at the time of the system implementation

A tower crane was installed to lift these prefabricated components from the storage area to assembly places. The tower crane had a height of approximately 50 meters from the ground, with a main boom radius of 40 meters and an auxiliary boom radius of 22.6 meters. Additionally, two surveillance cameras were installed—one on the trolley and another in the cabin—providing a visual understanding of the lifting operations and site conditions.

RTK-GNSS installation

An RTK-GNSS system was installed on-site to track the movements of five workers and the tower crane. For the tower crane, the sensor was mounted on the trolley instead of directly on the crane hook to ensure operational stability and facilitate charging. The location data was batched and periodically streamed to the cloud for analysis and storage. Data collection spanned three days to study the interactions between the crane and the workers, while tower crane data was automatically collected and stored on the cloud platform for one and a half months.

A static precision test of the RTK-GNSS system was conducted to evaluate its accuracy in both horizontal and vertical directions by calculating the median radius of a 3-hour location distribution collected from a statically placed RTK-GNSS sensor. The accuracy of location data at certain spots was affected by signal obstructions, which were addressed during the preliminary analysis by removing the compromised data.

Data preprocessing

The raw data from RTK-GNSS sensors, recorded in latitude, longitude, and altitude format, was not aligned with the Cartesian coordinate system used in the IFC model. Furthermore, the IFC model was not georeferenced, necessitating post-georeferencing to enable the integration of RTK-GNSS data into the model.

To achieve this, two surveyed positions at the building's corners, with known locations in the building model, were used as reference points. Simultaneously, the RTK-GNSS data was converted from the WGS84 format (i.e., latitude and longitude) to the UTM format (i.e., easting and northing), allowing Euclidean distances between points to be measured in the model. Following the translation and rotation method in a previous study (Hong & Teizer, 2024), the RTK-GNSS data and the building model were successfully merged to provide contextual insights into the crane trolley and worker trajectories.

The trolley's movement can be decomposed into bidirectional components: Axial movement along the boom and angular movement with the boom. As illustrated in Figure 2, the position of the trolley is defined by the horizontal distance (x) between the turntable and the trolley. The weight of the load deforms the crane boom, resulting in a vertical displacement of the trolley. The vertical displacement (δ_h) of the boom caused by the same load varies depending on the trolley's position along with the crane boom.

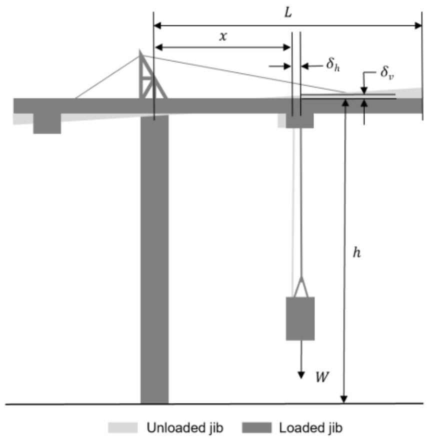

Figure 2: Model of a tower crane hoisting weight.

Due to the structural design of the boom, there is a tilt angle between the boom and the horizontal plane when it is unloaded. To determine vertical displacement, it is crucial to account for the slope of the boom. When the crane is unloaded, the height of each location on the crane boom can be linearly modeled as follows:

$$h\,(x) = kx + b \tag{1}$$

where k denotes the slope of the crane boom while b denotes the height of the turntable.

The height drop of the trolley was calculated as the height difference between its unloaded and loaded states. The velocity of the trolley on the horizontal plane was numerically determined by dividing its displacement by the sampling interval. A simple moving average filter was applied to collected data to smooth out high variations in the signals caused by activities that are not related to lifting operations, such as wind. This method is efficient in computation time and simplicity as it does not require a priori knowledge.

Rule-based stage classification

Figure 3 illustrates an example of a lifting operation. The crane's lifting operations were broadly categorized into three main stages: (a) hoisting, (b) transportation, and (c) lowering. Additionally, two supplementary stages are included: one preceding and one following the crane movement, during which riggers assist with the attachment (rigging) and detachment (derigging) of the load. Differentiating these stages is critical for effectively monitoring and assessing associated hazards.

Based on the RTK-GNSS data, we were able to recognize the different stages involved in the lifting operation. The movement patterns were identified from the crane trolley's trajectory. The change in height and speed during one lifting operation is shown in Figure 4. The distinct stages of height and speed change can be observed. The diagram shows clear patterns of change in the crane trolley's height and speed.

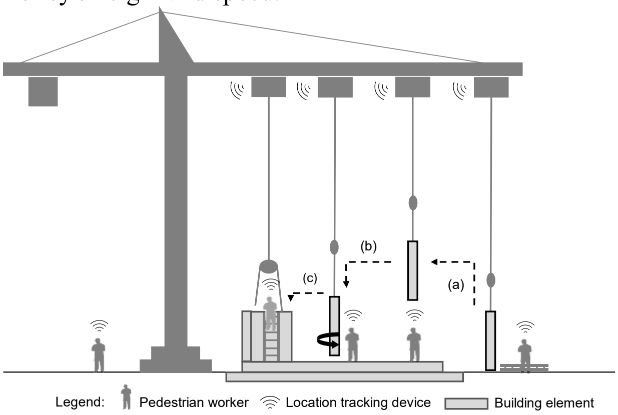

Figure 3: Stages in a lifting operation: (a) rigging and hoisting, (b) transportation, and (c) lowering and derigging

Several critical time points are defined, marking transitions between loading and moving status. Zero height drop indicates that no load is attached to the crane hook, while zero trolley speed indicates that the crane is stationary. Using these two indicators, the stages can be differentiated based on intervals between critical time points as follows:

- T1: The trolley moves to the pickup location without a load, marking the start of the lifting cycle.
- T2: The trolley begins to hoist the load as its height drops due to boom deformation.
- T3: The pickup process is completed, and the trolley starts moving toward the assembly location, marked by a stable height and increasing speed.
- T4: The lowering process begins as the trolley arrives at the assembly location.
- T5: The lowering process ends when the weight is completely transferred from the hook to the supporting structure.
- T6: The lifting cycle concludes as the trolley leaves the lowering location.

Table 1 summarizes the classified stages identified between timestamps, along with the associated hazards involved in the lifting operations.

Table 1: Classification criteria and involved hazard types of crane lifting stages

Stage	Description	Involved hazards	Criteria
I Rigging	Riggers attach loads to the hook before lifting.	Fall hazards due to climbing up	$\delta_V \cong 0$ $v \cong 0$
II Hoisting	Crane operator begins lifting loads to operational height	Struck-by hazards due to jib deflection and crash to nearby objects	$\delta_V < 0$ $v \cong 0$
III Transportation	Lifted loads travel above workers positioned underneath the lifted weight.	Struck-by hazards due to load falling	$\delta_V < 0$ $v > 0$
IV Lowering	Riggers guide the operator to lower the load to the assembly location.	Struck-by hazards due to load flipping	$\delta_V < 0$ $v \cong 0$

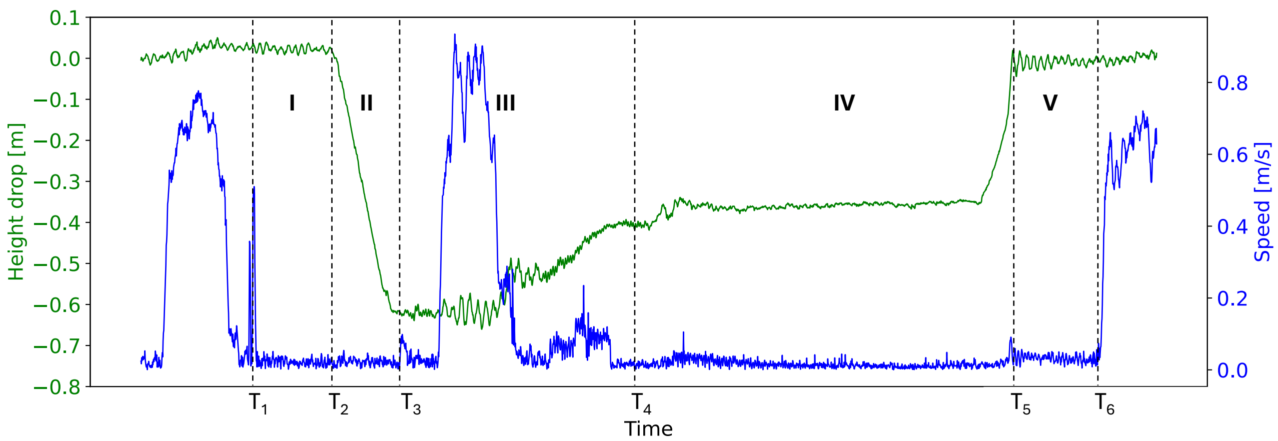

Figure 1: Height and speed change of a complete lifting cycle and identified critical points and stage

V derigging	Riggers detach loads from the hook.	Struck-by hazards due to load flipping	$\delta_V \cong 0$ $v \cong 0$

When hoisting a heavy element, crane booms tend to deflect, causing an increase in the radius of the crane hook. This jib deflection results in the horizontal displacement of the lifted elements, posing a struck-by hazard to riggers or nearby objects.

During the transportation of loads from the material storage area to the assembly place, the crane may traverse active working areas and individual workers, increasing the risk of struck-by hazards from above. Additionally, riggers often climb up and down prefabricated elements, such as walls, to attach and detach the hook, which poses fall hazards or risks of being struck by flipping prefabricated elements.

Hazard zones due to lifted loads are highly related to the geometry of the object, while the energy potential of the hazard correlates to its weight, which requires additional information, such as element model or vision-based object segmentation (Chian et al., 2022), to determine the exact shape and size of the hazard zones. Given the scope of this study is to identify different activities and hazards related to lifting operations, we adopted a simplified cone-shape hazard envelope to detect incidents where workers entered these hazard envelopes, as in a previous study (Johansen et al., 2024).

Results

This section presents the results of the RTK-GNSS precision test and stage classification in lifting operations.

RTK-GNSS precision test

A commercially available RTK-GNSS sensor was used to collect trolley location data. According to the specification provided by the manufacturer (Emlid, 2024), its positioning can reach an accuracy of below 1 cm. The accuracy of static positioning was tested for validation during data collection. One rover was placed statically in an open space on the site to collect its location for three hours. The precision of the location data was determined by measuring the deviation of collected data from the mean value.

A total of 10,800 location points were recorded. On the horizontal plane, the 50th percentile precision was 0.8 cm, and the precision at the 95th percentile reached 1.9 cm. In the vertical direction, the 50th percentile precision was 0.7 cm, and the precision at the 95th percentile reached 2.0 cm. Figure 5 illustrates that the RTK system achieved centimeter-level precision under static conditions in both horizontal and vertical directions. Therefore, RTK-GNSS data can be used to indicate the height change of the tower crane trolley caused by lifting payloads.

Static and kinematic model of crane trolley

As a result of this preprocessing, an example of tower crane data is presented in Table 2.

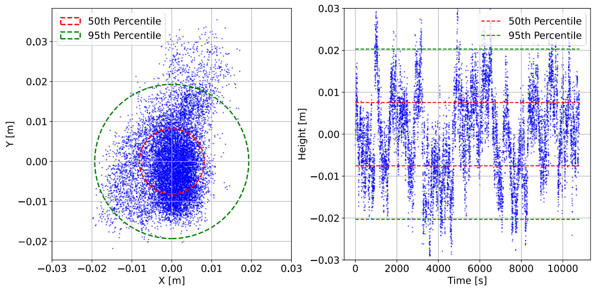

Figure 5: 3-hour precision test results: horizontal plane (left image) and vertical direction (right image).

Given that the RTK-GNSS technique can reach centimeter precision, the precision of the data was kept to the mm level. The height data represents the height from the sea level.

Table 2: Tower crane data after processing

Datetime	x [m]	y [m]	Height [m]
2023-05-31 08:22:00	27.119	24.903	93.346
2023-05-31 08:55:20	42.293	-1.959	94.154
2023-05-31 09:28:41	30.406	0.185	94.014
2023-05-31 10:35:21	42.852	30.302	93.603

The RTK-GNSS data and the building model were merged to provide contextual insights into crane and worker trajectories, as illustrated in Figure 6.

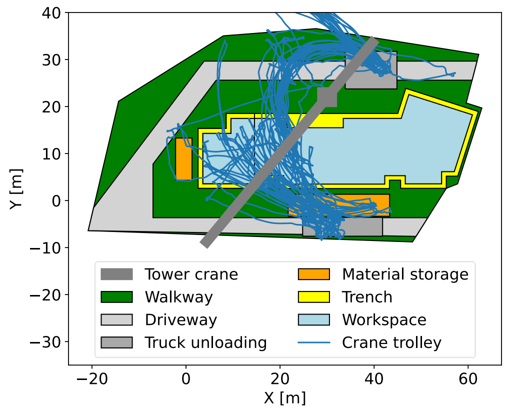

Figure 6: Site layout with crane trolley trajectory

The tower crane boom height was measured while the trolley moved along the crane boom without a load, which is $h(x) = 0.0315x + 93.28$. The velocity (v) and height drop (δ_V) was calculated. A simple moving average filter is applied to the data, with the size of the moving window set as 1s, i.e., every five data points.

Stage identification in lifting operations

The algorithm was applied to identify lifting operations and the various stages within each operation. To avoid the disturbance caused by external factors, the height drop threshold was set as 5 cm, and the speed threshold was set as 0.1 m/s for rule-based stage identification. The hazards were observed in Figure 7, which corresponds to the hazards identified in Table 1.

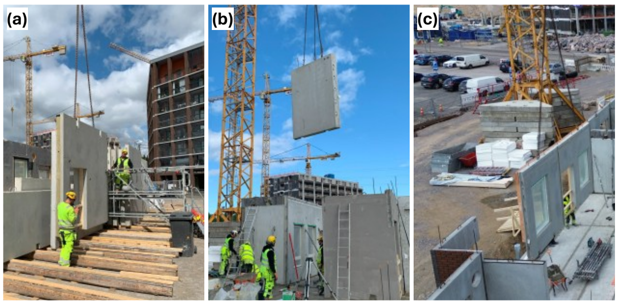

Figure 7: Struck-by hazards observed during site inspection due to (a) jib deflection, (b) load falling, and (c) load flipping

A 30-minute example of the identification results is presented in Figure 8, where seven lifting operations were detected. Comparisons with video data confirmed the identified lifting operations. However, one crane movement between 14:20 and 14:30 was not detected. Reviewing the crane video, it was observed that this occurred because the lifted barrel wheel was too light and moved too quickly to produce a noticeable height change in the trolley.

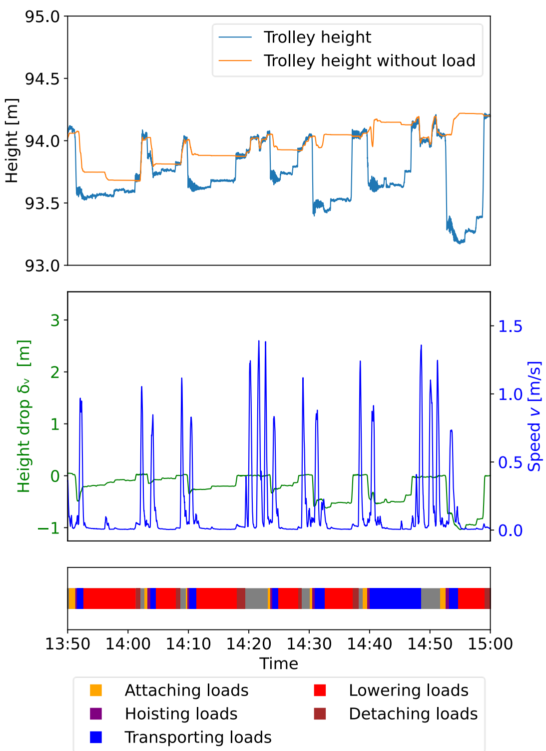

Figure 8: Identified stages in four identified lifting operations

Throughout the day, 36 lifting operations of prefabricated elements were correctly identified. The identification provides insights into the average duration of lifting operations and the various stages involved on the day, as shown in Figure 9. One lifting operation takes an average of 6 min18 seconds on that day. The results revealed that the lowering stage took significantly longer than other stages, thereby posing a higher struck-by hazard from falling loads to workers.

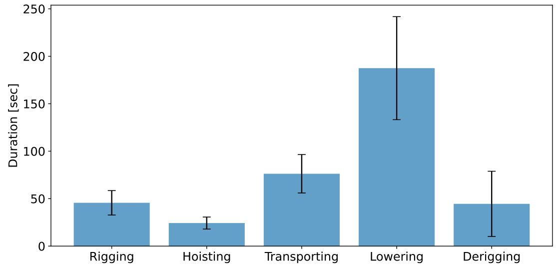

Figure 9: Duration of different stages in lifting operations

Incident detection during lifting operations

A hazard zone was defined as a cone with the crane hook at the center and a radius of 3 meters. Identifying lifting operations and their distinct stages effectively enhanced incident detection by ruling out cases where the crane trolley traveled over workers without a load attached, which could otherwise lead to false alarms. The results of one day's incident detection, presented in Figure 10, indicate that most incidents occurred in the assembly areas.

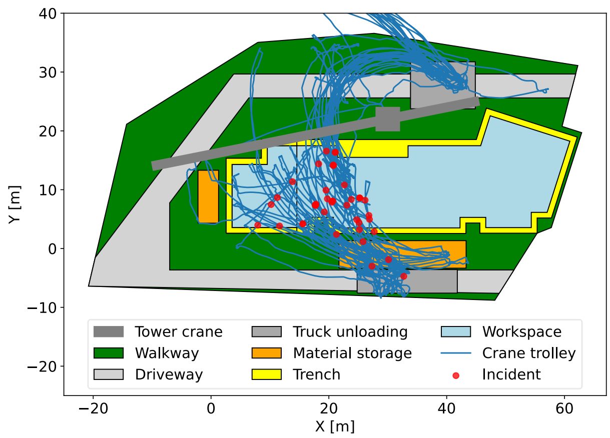

Figure 10: Incident detection result

The results facilitate a better understanding of when and who are exposed to specific hazards. As shown in Figure 11, incidents detected when no load was attached to the hook accounted for 50% of the total, significantly exaggerating the number of incidents compared to detection methods that incorporate the identification of lifting operations and their stages. Figure 12 highlights that Worker 02, a rigger, was the most exposed to struck-by hazards. However, the precision of incident detection remains limited in terms of the hazard zone size, as it does not account for the geometry of the lifted elements.

Incident detection can provide safety managers and crane operators with an overview of the tower crane's operational safety situation. Additionally, it enables further automated mitigative methods, such as lifting path planning and work task scheduling, to reduce the risk of incidents.

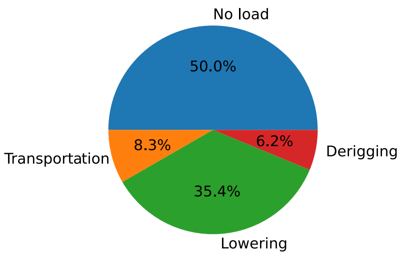

Figure 11: Incident counts by activities in lifting operations

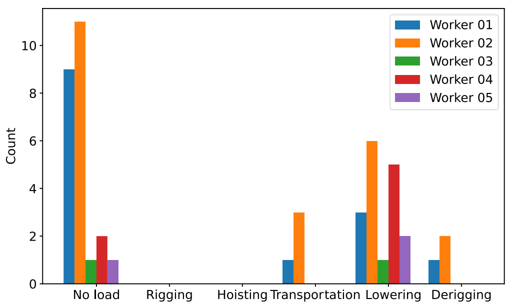

Figure 12: Incident counts by individual workers

Discussion

The study utilized height data tracked by RTK-GNSS techniques to monitor the load status of the trolley, marking the first use of location-tracking sensors to investigate changes in load. Compared with other methods using sophisticated systems of multiple sensors, our method uses only one RTK-GNSS receiver installed on the tower crane trolley. The results demonstrated that the method effectively detects lifting operations and classifies the different stages within these operations. This lays a foundation for identifying and assessing hazards associated with various operations.

However, some limitations were observed. When the lifted weight is too small, lifting operations and their stages may not be effectively recognized through height changes, although speed variations may still indicate tower crane activities. Currently, the minimum detectable height drop is predefined as 0.05 cm. Moreover, the study considered height changes only in a static context, without accounting for the dynamics of vertical trolley movement. Since the RTK-GNSS sensors were installed on the trolley, the height of the lifted load was not directly available and could only be estimated through lifting times or alternative methods, such as computer vision. Additionally, the installation of multiple RTK-GNSS receivers on the tower crane can help understand the dynamics of the tower crane in a more detailed manner.

During the study, a correlation between the value of height drops and lifted weight was observed, suggesting that future research could explore this relationship further. Currently, the hazard envelope used for incident detection in this study was approximated as a simplified cone shape. Inferring the weight of lifted elements from height drops could enable better integration with IFC models, facilitating the identification of prefabricated elements and their geometries. This would allow for a more precise determination of hazard zones around lifted elements.

By combining height, weight, and dimensions, it would be possible to better quantify and assess the hazards involved in lifting operations, for example, using high-energy control assessments. Furthermore, integrating this approach with Virtual Reality (VR) could enhance hazard zone identification and assessment for tower crane operations. VR-based simulations could help quantify worker exposure to hazards, as suggested by (Cheng & Teizer, 2013; Speiser et al., 2024), providing an innovative tool for improving safety management on construction sites. As an outlook, it can be incorporated into a digital twin as a critical component for real-time monitoring and safety analysis (Teizer et al., 2024).

Conclusions

This paper presents a rule-based method for tracking tower crane lifting operations and identifying the associated hazards. The proposed method leverages accurate RTK-GNSS data to detect small displacements of the crane trolley in the vertical direction, enabling the determination of load status on the hook and the identification of distinct stages in lifting operations. The method was tested on a construction site, with results demonstrating accurate identification of the various stages involved in lifting operations over the course of a day. Further work should explore the correlation between height drop and lifted weight, with a focus on assessing and quantifying the hazards identified at different stages of the lifting operations.

Acknowledgments

The research presented in this paper was funded by the EU Horizon 2020 research and innovation program under grant agreement no. 101058548 (BEEYONDERS). The authors thank Fira Oy and SiteDrive Oy for providing access to their construction site in Helsinki, Finland.

References

Ali, A. H., Zayed, T., Wang, R. D., & Kit, M. Y. S. (2024) Tower crane safety technologies: A synthesis of academic research and industry insights. Automation in Construction, 163, 105429. https://doi.org/10.1016/j.autcon.2024.105429

Teizer, J., & Cheng, T. (2015) Proximity hazard indicator for near miss location recording and mapping of workers-on-foot interactions with construction equipment and geo-referenced hazard areas. Automation in Construction, 60, 58-73. https://doi.org/10.1016/j.autcon.2015.09.003

Cheng, T., & Teizer, J. (2013) Real-time resource location data collection and visualization technology for construction safety and activity monitoring applications. Automation in Construction, 34, 3–15. https://doi.org/10.1016/j.autcon.2012.10.017

Cheng, T., & Teizer, J. (2014) Modeling Tower Crane Operator Visibility to Minimize the Risk of Limited Situational Awareness. Journal of Computing in Civil Engineering, ASCE, 28(3), 04014004. http://ascelibrary.org/doi/abs/10.1061/(ASCE)CP.1943-5487.0000282

Chian, YET., Goh, YM., Tian, J., & Guo, BHW. (2022) Dynamic identification of crane load fall zone: a computer vision approach. Safety Science, 156(6): 105904. https://doi.org/10.1016/j.ssci.2022.105904

Danel, T., Lafhaj, Z., Puppala, A., BuHamdan, S., Lienard, S., & Richard, P. (2024) Identifying tower crane activities with data: The case of the concrete pouring. Engineering, Construction and Architectural Management, 31(2), 939–956. https://doi.org/10.1108/ECAM-10-2021-0936

Emlid. (2024) Reach M2 RTK GNSS Receiver & GPS Module. Emlid. https://emlid.com/reach/

Fang, Y., & Cho, Y. K. (2015) Crane Load Positioning and Sway Monitoring Using an Inertial Measurement Unit. Computing in Civil Engineering 2015, 700–707. https://doi.org/10.1061/9780784479247.087

Hong, K., & Teizer, J. (2024) Automated Construction Site Safety Monitoring Using Preidentified Static and Dynamic Hazard Zones: 41st International Symposium on Automation and Robotics in Construction. Proceedings of the 41st International Symposium on Automation and Robotics in Construction (ISARC 2024), 388–395. https://doi.org/10.22260/ISARC2024/0051

Hu, S., Wang, J., & Fang, Y. (2024) Semantic Web–assisted progress monitoring of crane operations in construction projects. Proceedings of the Institution of Civil Engineers - Smart Infrastructure and Construction, 1–10. https://doi.org/10.1680/jsmic.24.00011

Hwang, S. (2012) Ultra-wide band technology experiments for real-time prevention of tower crane collisions. Automation in Construction, 22, 545–553. https://doi.org/10.1016/j.autcon.2011.11.015

Jiang, W., & Ding, L. (2024) Unsafe hoisting behavior recognition for tower crane based on transfer learning. Automation in Construction, 160, 105299. https://doi.org/10.1016/j.autcon.2024.105299

Johansen, K.W., Hong, K., Schultz, C., & Teizer, J. (2024) Automated Quantification of Construction Workers' Exposure to Struck-by Hazards. Management, Procurement and Law, 1-16. https://doi.org/10.1680/jmapl.23.00103

Milazzo, M. F., Ancione, G., Brkic, V. S., & Vališ, D. (2016) Investigation of crane operation safety by analysing main accident causes. Risk, Reliability and Safety: Innovating Theory and Practice, 74–80. https://doi.org/10.1201/9781315374987

Nishizawa, Y., & Mishima, M. (2024) Acquisition of Tower Crane Operational Performance Using Hook Mounted RTK Positioning and Image Recognition. Proceedings of the Creative Construction Conference 2024. https://doi.org/10.3311/CCC2024-030

OSHA. (2024) Accident Search Results. https://www.osha.gov/ords/imis/AccidentSearch

Sacks, R., Navon, R., Brodetskaia, I., & Shapira, A. (2005) Feasibility of Automated Monitoring of Lifting Equipment in Support of Project Control. Journal of Construction Engineering and Management, 131(5), 604–614. https://doi.org/10.1061/(ASCE)0733-9364(2005)131:5(604)

Speiser, K., Teizer, J., & Ali, G.M. (2024) Smart signalperson for safe tower crane operations on a future digital construction site. In: CIBW099W123, Kumasi, Ghana, October 8-11, 2024, 353-365. ISBN: 9789988391386

Teizer, J., Cheng, T., & Fang, Y. (2013) Location Tracking and Data Visualization Technology to Advance Construction Ironworkers' Education and Training in Safety and Productivity. Automation in Construction, 35, 53-68. http://dx.doi.org/10.1016/j.autcon.2013.03.004

Teizer, J., & Cheng, T. (2015) Proximity hazard indicator for near miss location recording and mapping of workers-on-foot interactions with construction equipment and geo-referenced hazard areas. Automation in Construction, 60, 58-73. https://doi.org/10.1016/j.autcon.2015.09.003

Teizer, J., Johansen, K.W., Schultz, C.L., Speiser, K., Hong, K., & Golovina, O. (2024) A Digital Twin Model for Advancing Construction Safety. J. Fottner et al.: CLEaR 2023, Lecture Notes in Civil Engineering (LNCE 390), ISBN: 978-3-031-44020-5, pp. 201–212. https://doi.org/10.1007/978-3-031-44021-2_22

Wielgocka, N., Hadas, T., Kaczmarek, A., & Marut, G. (2021) Feasibility of Using Low-Cost Dual-Frequency GNSS Receivers for Land Surveying. Sensors, 21(6), 1956. https://doi.org/10.3390/s21061956

Xiong, C., & Niu, Y. (2019) Investigation of the Dynamic Behavior of a Super High-rise Structure using RTK-GNSS Technique. KSCE Journal of Civil Engineering, 23(2), 654–665. https://doi.org/10.1007/s12205-018-0238-9

Yang, J., Vela, P.A., Teizer, J., & Shi, Z.K. (2014) Vision-Based Crane Tracking for Understanding Construction Activity. Journal of Computing in Civil Engineering, ASCE, 28(1), 103-112. http://dx.doi.org/10.1061/(ASCE)CP.1943-5487.0000242