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4D POINT CLOUD (4DPC)-DRIVEN REAL-TIME MONITORING OF CONSTRUCTION MOBILE CRANES

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Abstract

Mobile cranes are essential equipment in construction sites due to their high flexibility and mobility. However, the existing sensing or monitoring methods have limitations in monitoring mobile cranes on sites. Recently, the advent of 4D point cloud (4DPC) technology with a unique spatial-temporal data structure has shown potential in addressing these issues. In this paper, we present a 4DPC monitoring approach, which includes a set of prototype devices and a rule-based object detection method. We conducted a proof-of-concept test to monitor the hoisting process of two H-beams in a footbridge construction project. The rule-based object detection method successfully detected the target beams in the collected six-hour 4DPC data. In the future, we expect more efficient and robust 4DPC sensing devices and processing methods for proactive crane motion prediction and optimization in a time-dynamic site environment.

Introduction

Cranes are critical equipment for hoisting and transporting heavy objects in the construction industry. In recent years, numerous efforts have been made to monitoring methods for crane-related activities in both academia and industry. The first reason is safety, because crane lifting is complex and risky on construction sites. Cheng and Teizer (2011) found that many crane-related safety incidents are associated with restricted visibility, e.g., sight occlusion, poor weather, or lighting conditions. Crane-related accidents usually cause casualties and significant economic losses, so extra measures must be taken. In addition, monitoring data could be visualized to help operators reduce workload and improve work efficiency, and the construction time is thus reduced. Productivity assessment may be another reason for the necessity of crane-related activities monitoring. Based on the assessment result, further optimization work could be done for the productivity improvement of the crane-related construction process.

There are two common types of cranes, i.e., mobile cranes and tower cranes. The most significant difference between them is that one is mobile, and the other one is not. Due to its fixed location and working range, monitoring or sensing devices are constantly installed on the tower crane. However, most existing monitoring methods are challenging to implement on mobile cranes. Potential reasons are the high mobility and flexibility of the mobile crane. Therefore, how to achieve practical and convenient monitoring for mobile cranes is still an unresolved issue.

With increasing focus on-site safety of the construction industry and the emerging demand of digital construction sites, developing a practical monitoring approach for mobile cranes has become increasingly necessary and urgent. In order to improve the situation, some technologies, e.g., CCTV camera (Fang, et al., 2018)s and IoT devices (Mijwil, et al., 2023), that are used in other monitoring scenarios, are tried for monitoring or tracking objects for the mobile crane during the lifting process. However, the feasibility is not high for most methods. For example, CCTV cameras, the most widely used tool to monitor activities in construction sites, always lack depth information, making it challenging to accurately capture objects' spatial position (Chen, et al., 2017). In addition, quantization errors are widely reported to be the shortcoming of conventional image-based video due to its grid-based geometric representation. Sensitivity to light conditions and the difficulty of multi-source data fusion also make it unsuitable for monitoring mobile crane in various complex environments. Second, IoT devices are other type of tools for sensing objects on sites. IoT devices are easy to locate, but various errors are widely reported. Meanwhile, IoT devices cannot achieve dynamic detail detection, such as rotation, which are significant for some tracking purposes. Extra installation procedures for each object will decrease productivity and increase risk, and using many IoT devices would increase the cost. In addition, the interaction of tracked objects and dynamic environment cannot be easily reflected. Thirdly, the Depth-RGB camera is also often reported to monitor or track objects in sites potentially, but its short detection distance restricts its application in outdoor scenarios.

Point clouds, a three-dimensional collection of data points or coordinates, provide a new data form to produce high-quality 3D reconstructions of the world (e.g. reconstructing building information model in construction site (Chen & Xue, 2023)). They provide more information than two-dimensional pictures and are insensitive to light. However, point clouds always refer to 3D point clouds and the application of 3D point clouds is limited in capturing some static objects due to only spatial information contained in the data (Mirzaei, et al., 2022). The advent of the 4D point cloud, consisting of three dimensions and time information, has expanded the application of the point cloud into a dynamic world (Silva, et al., 2022). 4D point cloud (4DPC), a form of time-series 3D point clouds, is a rich data source demonstrating how objects move against the background. 4DPC has unique advantages against other motion tracking technologies, e.g., various Internet of Things (IoT) and AI cameras (Liang & Xue, 2022):

a) Real-time environment (including objects and background) updating
b) Highly precise geometry updates
c) Higher adaptability in poor visibility environments
d) Innate localization and mapping information
e) Innate capability of multi-/many-device data fusion to eliminate visual blind spots
f) Lower cost, minimal infrastructure requirements, lower carbon footprints
g) Remote, non-destructive sensing

4DPC is a novel enabling data source that facilitates precise 4D motion tracking. In contrast to conventional camera/IoT, our methods have three characteristics:

i. High-definition 4D motion data (cm-s-level accuracy);
ii. Precise depth information in a far range (up to 500m);
iii. Simultaneous motion tracking of multiple objects; and
iv. Low cost of devices and easy operating.

Related works

Crane monitoring

In past research, numerous efforts have been put into developing computer-aided crane monitoring systems. Their primary purpose is to improve the efficiency and safety of crane operations and reduce operator workload. As listed in Table 1, this study reviews related to research, and the purpose, contribution, research focus, target crane type, methodology, and limitation are summarized. The research generally has three types of goals, i.e. crane pose estimation (Zhang, et al., 2012; Lee, et al., 2012; Zhong, et al., 2014; Yang, et al., 2014; Roberts, et al., 2017), load sway and rotation estimation (Fang, et al., 2018; Fang, et al., 2016; Chian, et al., 2022), and object detection in workspace (Li, et al., 2013; Chen, et al., 2017). Although both crane monitoring and object detection are investigated to help operators operate the crane in blind areas in the study by Price et al. (2021), the two functions are relatively separated and not well integrated into a system.

Meanwhile, two types of sensing methods, i.e., sensor-based and vision-based, are used in these studies. For the former, different sensors are serving for different sensing goals. In specific, the UWB system, consisting of several sensors and multiple tags, is used to estimate the crane pose in the study by Zhang et al. (Zhang, et al., 2012), but it is not practical due to various errors from different sources and too many sensors required for full coverage of activity range. Li et al. try to use GPS and RFID to obtain positioning data of both site workers and the crane, and using multiple tags and receivers decreases its practicality. Zhong et al. (Zhong, et al., 2014) combined a Wireless Sensor Network (WSN) and the Internet of Things (IoT) to monitor the status of tower crane groups to avoid collisions, but the interactions of tower cranes with environment are not considered. Fang et al. (2016) use a series of encoder and IMU sensors to monitor the load object and visualize in the virtual platform. Except for extensive use of sensors, another problem is the dynamic change of the environment cannot be reflected by a limited number of sensors. For the latter, CCTV cameras or UAV camera are used to estimate crane pose (Lee, et al., 2012; Yang, et al., 2014; Roberts, et al., 2017), monitor load (Fang, et al., 2018) (Chian, et al., 2022), and detect object (Chen, et al., 2017). The common limitation stems from the data, such as not containing depth information or sensitivity to lighting conditions and color. In addition to shared drawbacks, UAV's endurance, stability, and safety are also criticized.

Table 1 Summarization of related literature

Purpose and contribution	Research focus	Sensing method	Crane type	Limitation	Source
Develop a UWB-based system to track crane boom movement, and estimate crane pose near real-time for collision avoidance	crane pose estimation	UWB	Mobile crane	1) the installation space and device cost of several sensors and multiple tags would be a problem 2) the accuracy in an ideal environment (open space) is 10cm, and it may be worse in unordered sites 3) trajectory estimation is relatively rough since it is based on linear interpolation extrapolation of only two points	(Zhang, et al., 2012)
Develop a tower crane navigation system to help operators operate with blind spots	crane pose estimation	Video camera & sensors	Tower crane	1) too many kinds of sensors increase the complexity of the proposed system 2) virtual environment (BIM model) cannot BIM model cannot fully	(Lee, et al., 2012)

				represent the as-is site condition	
Identify unauthorized work or entrance of personnel within a pre-defined risk zone	object detection in the workspace	GPS & RFID	Not limited to a specific type of crane	1) too many tags, receivers, and other units are used; 2) installation complexity and high cost would hinder its practical application; 3) signal strength is also a possible issue	(Li, et al., 2013)
Develop a Safety Management System to monitor the status of tower crane groups and avoid collisions	crane pose estimation	WSN & IoT	Tower crane	1) only the main body of the crane is considered, but the site situation is usually more complex	(Zhong, et al., 2014)
Understand construction activity by tracking the pose of the tower crane	crane pose estimation	Video camera	Tower crane	1) large range view needs to be covered, and the resolution of the object will become lower, so the recognition accuracy will fluctuate due to many factors, such as light condition 2) the recognition result is general	(Yang, et al., 2014)
Develop real-time pro-active safety assistance for mobile crane lifting operations	load sway and rotation estimation	Encoder sensors & IMU sensor	Mobile crane	1) The pre-reconstructed site cannot reflect the dynamically changing site conditions 2) A large number of sensors are required to sense the movement of the crane in real time	(Fang, et al., 2016)
Detect and Classify Cranes for monitoring crane-related safety hazards	crane pose estimation	UAV	Tower crane	1) The endurance and stability of drones are obstacles to the practical application	(Roberts, et al., 2017)
Update real-time 3D crane workspace	object detection in the workspace	TLS & Video camera	Mobile crane	1) positioning accuracy (0.1-0.4m) in the ideal test environment is relatively high 2) signal synchronization of camera and LiDAR is complicated, and the error is relatively large	(Chen, et al., 2017)
Track crane load sway	load sway and rotation estimation	Video camera	Not limited to a specific type of crane	1) only the 2D location of the load could be identified 2) errors highly depend on the quality of the image	(Fang, et al., 2018)
Detect workers near the crane load	crane pose estimation & load sway and rotation estimation	Sensors, Camera, IMU, & TLS	Tower crane	1) sensor-part: positioning system has a high reliance on data from noisy encoders; large crane deflection caused by the load leads to errors 2) vision-part: positioning errors are widely reported during irregular lighting conditions and when the surrounding environment contains objects that have a similar color to the load	(Price, et al., 2021)
Develop a novel method to detect and track the crane load fall zone	load sway and rotation estimation	Video camera	Tower crane	1) the estimation accuracy heavily relies on many factors, such as the quality of training data since it is based on deep learning	(Chian, et al., 2022)

#:UWB: Ultra Wideband; GPS: Global Positioning System; RFID: Radio-Frequency Identification; WSN: Wireless Sensor Network; IoT: Internet of Things; IMU: Inertial Measurement Unit; UAV: Unmanned Aerial Vehicle; TLS: Terrestrial Laser Scanners.

In summary, existing sensor-based sensing methods in the literature showed the following drawbacks:

1) Deploying and maintaining sensors in every object onsite is complex and time-consuming, which may affect productivity of the construction process;
2) sensors are composed of many components susceptible to damage, and low reliability may hind its practice;
3) many high-precision sensors are expensive, and the use of numerous sensors on-site may increase the cost;
4) sensor technologies are sensitive to signal interference and may not adapt to the complex construction site with many existing physical obstacles (e.g., existing buildings and equipment);
5) it is difficult for sensors to capture the whole environment with dynamical change, and hence the interaction between tracking objects with the existing site environment cannot be captured;
6) Synchronization and visualization of multi-source data increase the practice complexity of sensor technologies.

Meanwhile, current vision-based sensing methods have other limitations:

1) Depth information is not contained in 2D image, and hence vertical position information cannot be precisely captured;
2) video errors caused by irregular lighting conditions and similar colors make it unreliable in daily use;
3) 3D laser scanning by TLS only captures the site geometry at the time of scanning, and hence site condition cannot be dynamically reflected in real-time;
4) Multi-angle view fusion has not been well resolved, which hinders its broad practice.

4DPC

Point clouds, a three-dimensional collection of data points or coordinates, provide more information than two-dimensional pictures and are insensitive to light (Bhople et al., 2021). Conventional static point clouds have already been widely used in many research and industrial domains, such as surveying, electricity, construction, and industry, due to their excellent ability to represent our three-dimensional world. In the construction industry, the 3D point cloud is currently used for various aims such as as-built building reconstruction and digital twin city (Wu, et al., 2021; Xue, et al., 2019; 2020). It should be noted that the applications of 3D point clouds are limited in capturing non-moving or assumingly non-moving objects.

As a window into our ever-evolving 3D environment, 4DPC are widely used in robotics and augmented reality systems. Point cloud sequences play an important role in understanding environmental changes and supporting interactions with the world that are difficult to describe with 2D images or static 3D point clouds due to their ability to record movements in physical space. In order to more accurately simulate the world, respond to changes in the environment, and interact with it, an intelligent agent must handle this kind of data with great precision.

4DPC has gained popularity for some reasons. First, the ability to comprehend a changing 3D world is essential for robotic agents and various other applications. 4DPC has enabled many innovative studies, such as how a plant grows (Li, et al., 2013) and high-definition human motions (Fan, et al., 2021), as shown in Figure 1. In addition, various identification tasks, such as calculating a moving object's acceleration or identifying human activities, benefit from temporal data sequences longer than two frames (Fan, et al., 2021). 4D point cloud has also been widely utilized in robotic SLAM, autonomous driving, and video-assisted training of athletes.

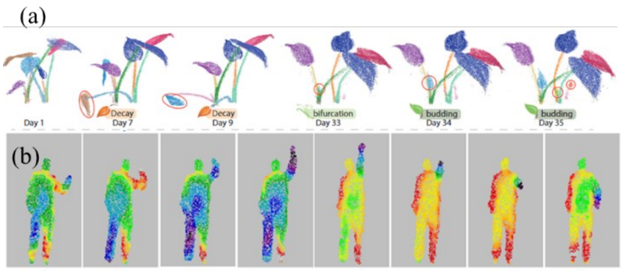


Figure 1 Example 4DPC-enabled studies. (a) how plant grows (Li, et al., 2013)—permission requesting, (b) high-definition human motions (Fan, et al., 2021)—permission requesting

In contrast to grid-based RGB video, where points regularly emerge over time, point cloud video displays irregularities and lacks order along the spatial dimension. Therefore, numerous efforts have been engaged in processing the 4DPC data. Two existing methods, i.e., voxelization-based (Choy, et al., 2019) and point-set-based, explored by many researchers to process 4DPC data.

Case study

Case description

A pilot study was conducted on an infrastructure project in Hong Kong, as shown in Figure 4. The case project was the 3rd Sassoon Road footbridge project that links a new Campus building to the student residents across Sassoon Road. Two major steel tie-beams were hoisted and installed in the mid-night of 28 June 2022, and Figure 2 shows the site condition before hoisting, the hoisting process of component 1, the completed status of the component 1 hoisting, and completed status of two components hoisting, respectively. This project uses a mobile crane since it is a temporary infrastructure project and the road is only temporarily closed for construction at night.

The case project had characteristics and requirements in hoist efficiency, collision risk, and personnel safety. First, the process needs to be completed swiftly before dawn to resume day traffic from the temporary close of the road. As the most important and challenging work in this project, hoisting efficiency will directly affect the construction time. In addition, there were already building works on both sides of the road, and the facades are expensive glass curtain walls. A collision during the hoisting process will cause economic losses. Therefore, effective measures should be taken to reduce the potential collision risk. Furthermore, the workers working on other processes on-site may have entered the risky zone where the hoisted objects may fall due to negligence of steel beam at high height during the hoisting process.

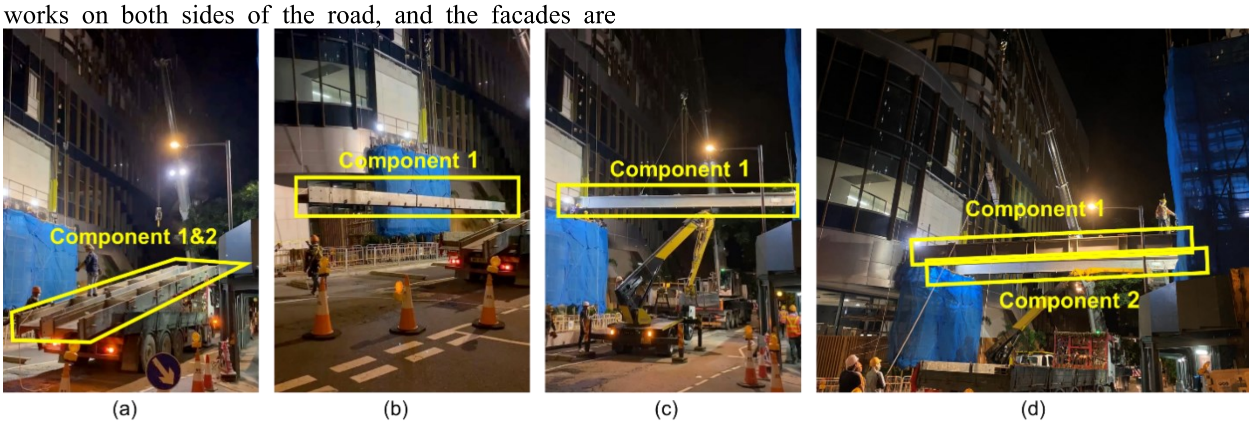


Figure 2 construction site condition of case study

4DPC devices and setup

To address the limitations mentioned in Sec. 2.1, this study proposes and validates a scheme that 4DPC technology is used to achieve the goal of monitoring all crane-related activities in real-time, including estimating crane pose, tracking load, and detecting objects on sites. To achieve that, a novel 4DPC sensing equipment for collecting high-definition 4D motion data from construction environments is developed in this study. The target spatial accuracy is cm-level, while the temporal accuracy is 0.5s-level. As shown in Figure 3(b), the device has four essential modules, i.e., (I) Livox Mid-70 sensor, (II) controller (Raspberry Pi 4), (III) LED monitor, (IV) USB drive. The Livox Mid-70 has 70.4° circular fov, 5 cm minimum detection range, and 2 cm range precision. Raspberry Pi 4 controller transmits 4DPC data to remote server via WiFi/4G/USB. The proof-to-concept test of the device is conducted in the pilot study. In order to cover the whole site, two LiDAR devices in Figure 3 (b) were installed on different locations, i.e., one is in the ground floor and the other is in the 4th floor (shown in Figure 3(a)), to collect 6 hours of 4DPC data (format: lvx; size: 80MB/min).

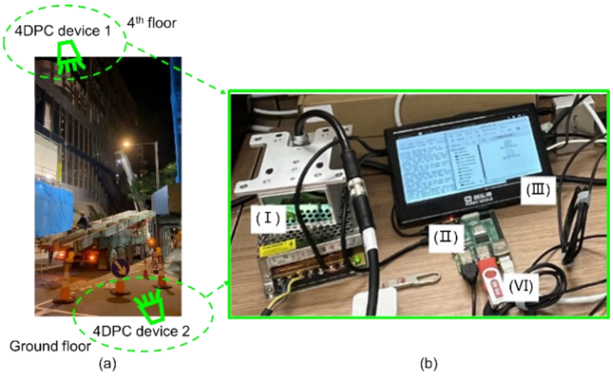


Figure 3 (a) Installation illustration of 4DPC devices on site; (b) Components of our 4DPC device: (I) Livox Mid sensor, (II) controller (Raspberry Pi 4), (III) LED monitor, (IV) USB drive

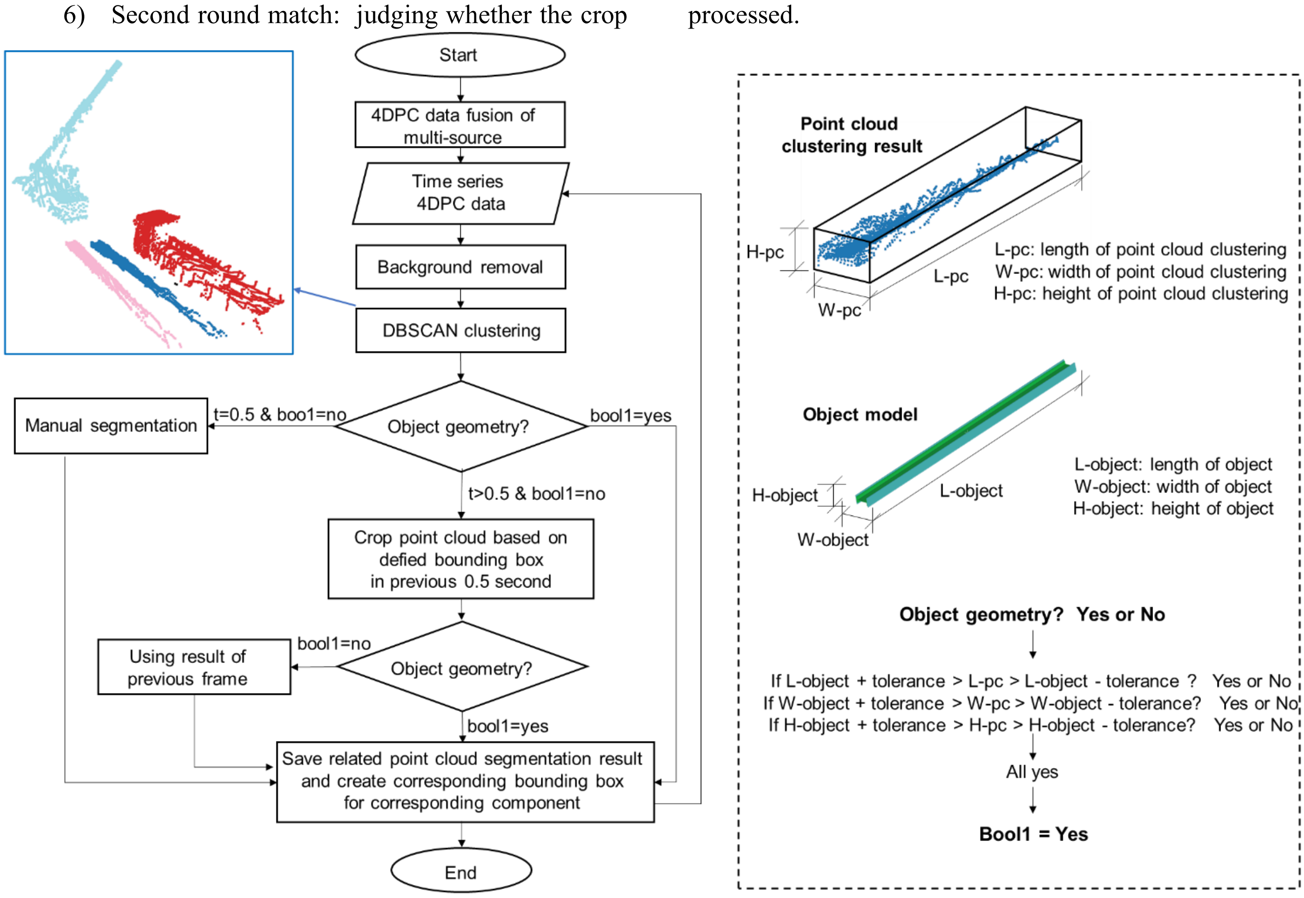
Methods

The most popular processing methods of 4DPC in existing research are based on deep learning. The impetus for this trend is mainly based on the large amount of data that can be collected. In this study, we only collected 1 construction scenario; hence, deep learning is not applicable. Therefore, a rule-based object detection method on 4DPC data is proposed to monitor target components in real time effectively. As shown in Figure 4, a cyclic processing workflow is determined:

1) 4DPC data input: Each frame of data is input in chronological order;
2) Background removal: using random sample consensus (RANSAC) algorithm (Schnabel, et al., 2007) is used to detect and delete plane of existing ground and walls
3) Clustering: using DBSCAN clustering algorithm (Ester, et al., 1996) to cluster the remaining point cloud.

4) First round match: judging whether the point cloud clustering results match the objects with known geometric dimensions. If all known components match, go to step 7. If not, continue to step 5.
5) crop point cloud: using bounding box of previous frame to crop the whole point cloud (based on the assumption that there will be no large displacement of the member in a very short time-0.5s)
6) Second round match: judging whether the crop components match, go to step 7. If not, the result of the previous frame will be assigned to the current frame (based on the assumption that there will be no large displacement of the member in a very short time-0.5s).
7) Result saving: Saving related point cloud segmentation results and creating a corresponding bounding box for the corresponding component

The program ends when all the time series data are processed.



result of point cloud match the objects with known geometric dimensions. If known

Figure 4 logic flow of rule-based detection method for time series 4DPC data

Preliminary results and discussion

As shown in Figure 5, the two steel beam components can be precisely detected in more than 95% of the time using the rule-based method described in Sect 3.3. The 4DPC data processing time per minute is within 1s.

Figure 5(a), (b), (c), and (d) illustrate the motion detection result of two beams from two views at different times, and different typical statuses of beams, i.e., remaining on the transport vehicle, being placed on the ground, hoisting in the air, are all covered, or completing hoisting. However, there are also some time frames that beams cannot be tracked. Detailed analysis suggests the ineffective capture is that the point cloud data is too sparse or no data points exist due to small sensing area of components at specific view angles, long sensing distances, or some physical obstacles. These problems can be attributed to the limited number of 4DPC devices used in this pilot study and the low point cloud density provided by Livox. Increasing the number of LiDAR devices and using advanced LiDAR devices providing higher point cloud density would improve the robustness of 4DPC data. Obtaining the spatial-temporal information of beams will help further achieve a set of proactive motion prediction and optimization applications. In addition, it could facilitate the productivity assessment of mobile cranes, and future improvement may be based on these data records.

Limitation

While this study's proposed method effectively captures targeted objects, its rule-based approach is limited to the specific scenario in which it was tested. Therefore, future research is necessary to explore its actual deployment and extended application in different conditions. Furthermore, the rule-based method can only detect known objects since rules must be set with prior knowledge of components. Also, due to the angle of the equipment installation, the object cannot be fully scanned, which limits the reflection of the true detailed geometry of the component. Detailed modeling requires additional effort. Finally, it should be noted that the 4DPC data collected from two devices was registered manually, which is a time-consuming process and hinders its application in mobile situations..

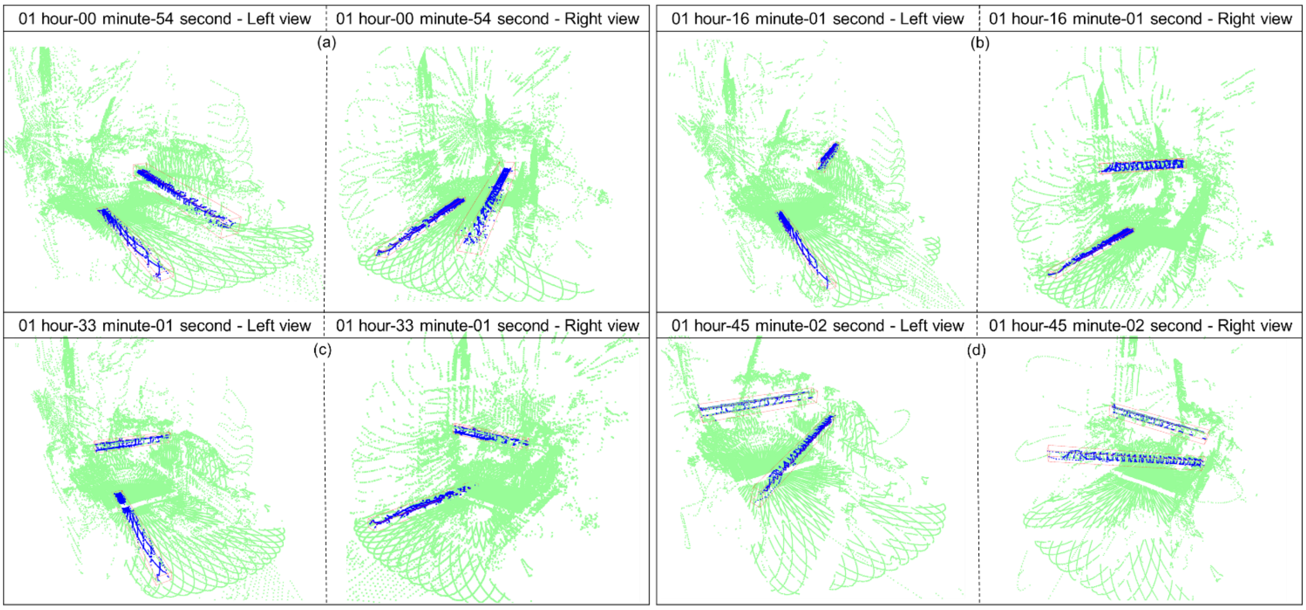


Figure 5 typical detection result of 4DPC data

Conclusion and future work

This paper evaluated the existing studies focusing on sensing or monitoring crane-related activities, including estimating crane pose, tracking load, and detecting objects in workspace. Meanwhile, the limitation of sensor-based and vision-based sensing methods are analyzed and summarized. In order to overcome shortcoming of existing methods, a state-of-art 4DPC sensing and monitoring method is proposed. A rule-based object detection method is developed with two prototype devices of 4DPC sensing, and a proof-to-concept test was conducted on a footbridge construction project. In the pilot study, two 4DPC devices covered the whole construction site for 6 hours. The promising preliminary results suggested that target beam components were precisely captured in different statuses. The spatio-temporal data series obtained from the tracking results could generally satisfy the goal of monitoring load.

There are three directions for future works. One is to develop more efficient and robust methods, such as some ML-based methods (Zhang, et al., 2019; Liang & Xue, 2023), to match or detect objects from the collected data. Another is to explore a set of proactive motions prediction and optimization applications. The last is to integrate obtained spatial-temporal information of all objects and workers to achieve dynamic site management.

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Author Contributions

Conceptualization, D.L. and F.X.; Methodology, D.L.; Software, W.Y.; Validation, Z.C., L.K. and S.C.; Formal Analysis, D.L.; Data Curation, F.X.; Writing – Original Draft Preparation, D.L.; Writing – Review & Editing, F.X.; Visualization, D.L. and F.X.; Supervision, F.X.; Funding Acquisition, F.X.

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