Semantic web-assisted progress monitoring of crane operations in construction projects

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Abstract. The rising importance of cranes in modern construction has led to the need for more efficient crane monitoring and operational management. Previous studies have focused on acquiring crane monitoring data through Internet of Things (IoT) devices. However, they offer limited data reasoning capacity and only understand a few particular construction activities that have distinct patterns. This restricts the applicability and generalisability of crane monitoring systems in real-world projects. Thus, this study proposes a semantic web-based method to enhance the reasoning of crane monitoring data by correlating as-is and as-planned information of crane operations from different IoT devices and information systems. The proposed method was validated through laboratory experiments, substantiating the potential for monitoring construction progress and enhancing crane utilisation.

Introduction

Cranes are essential machinery in most construction projects, responsible for handling a diverse assortment of heavy materials and equipment. With the rise in popularity of prefabricated construction methods, cranes have become even more indispensable (Goh, Hu and Fang, 2019). They are tasked to hoist prefabricated building modules frequently, making the on-site logistics process more susceptible to potential disruptions caused by limited crane availability (Soman, Molina-Solana and Whyte, 2020). Thus, in current practice, site managers must vigilantly monitor the operating status of cranes, track completed lift tasks, and update pre-determined lift schedules to enable flexible adjustment of lifting resources (e.g., the crane, personnel, and rigging accessories). As construction sites expand in scale and the need for crane operations increases, manual methods in such situations prove to be laborious, leading to cumbersome communication and misunderstanding of the construction progress (Hu, Fang and Guo, 2021).

As Internet of Things (IoT) technologies continue to evolve, researchers are exploring automated methods for tracking crane operations. Various IoT sensors were employed, including Computer Vision (CV) (Teizer, Cheng and Fang, 2013), real-time locating systems (RTLS) (Zhang, Hammad and Rodriguez, 2012), laser scanners (Chen, Fang and Cho, 2017) to monitor the movements of cranes and their interactions with the surrounding environment. These methods are particularly effective in identifying real-time safety hazards by analysing the spatial-temporal relationship between cranes and building structures or workers (Hu, Fang and Moehler, 2023). However, their capacity to retrieve productivity-related information is limited, which poses challenges for site managers in minimising waste and avoiding bottlenecks in material flow on-site. Specifically, progress tracking, which is crucial for measuring productivity performance (e.g., cycle time, downtime, utilization rate), needs to be automatically derived from the sensor-captured data.

Yet, automating progress tracking is challenging due to the need to synthesise data from multiple IoT devices, recognise crane operations from raw data, and correlate recognised operations with lift schedules. One promising technology that facilitates data integration and reasoning processes is the Semantic Web, which enables computers to understand the meaning and context of data and perform more accurate and efficient analysis (Tavakolan, Mohammadi and Zahraie, 2021). It has been widely applied to construction projects, representing domain knowledge, integrating information from different sources, and providing data-driven insights to support decisions (Zheng, Törmä and Seppänen, 2021). With the aid of Semantic Web technologies, this study aims to develop an automated method to recognise lift operations by combing IoT data and human inputs from lift scheduling systems. As a result, the proposed method is expected to track crane poses, geometric features of lifted loads, and weight on the crane hook, and correlate them with lift schedules using rules formalised in a generic ontological model. A lab test has been conducted to evaluate the effectiveness of the proposed approach.

The following sections provide an overview of recent advancements in crane monitoring and scheduling, and data reasoning in construction activities using Semantic Web technology. The methodology and detailed lab test results are presented, followed by in-depth discussions and conclusions of the study.

Literature Review

Crane Operation Monitoring

The emergence of the Internet of Things (IoT) proliferates crane monitoring systems. During the early stages, crane monitoring systems primarily focused on recognising crane poses (Zhang, Hammad and Rodriguez, 2012) and its excessive displacements (Lalik *et al.*, 2017). RTLS such as Ultra-Wideband (UWB) tags (Zhang, Hammad and Rodriguez, 2012), accelerometer/gyroscopes (Li and Liu, 2012) and cameras (Gutierrez, Magallon and Hernandez, 2021) were strategically deployed to track the spatial-temporal information of crane parts and mechanical properties of the crane and lifted loads. The information was then used to detect potential hazards such as crane mast collapse (Jiang, Ding and Zhou, 2022), failure of lifting gears (Liu *et al.*, 2022), excessive load sway (Fang and Cho, 2015), crane load fall zones (Chian *et al.*, 2022) and crane collision with personnel (Li, Chan and Skitmore, 2013), machinery (Hwang, 2012; Zhong *et al.*, 2014) or other moving objects (Chen, Fang and Cho, 2017). The majority of market-ready products exhibit a common emphasis on equipment health monitoring and construction safety, exemplified by TMEIC (2023) and Alatas (2023) crane management systems with a wider range of information overseen, such as wind speed, the status of twist locks, and water tank temperature of the crane.

While ensuring safety is a critical aspect of managing crane operations, optimizing productivity is also a significant objective that has received continuous attention. Multiple research studies attempt to track the progress of construction activities based on crane tracking data. For example, Yang et al. (2014) embedded specific domain heuristics of crane behaviour (e.g., hook's location, moving status, presence of concrete bucket) into CV to identify crane activities in concrete pouring, such as loading concrete and moving an empty bucket. Similarly, Wang et al. (2022) captured the footage of the concrete pouring process for dams and calculated the completed volume and corresponding cycle time automatically. RTLSs were also investigated, which relies on the metadata gleaned from RTLS tags to provide information on the crane's lifted items. Niu et al. (2016) installed Bluetooth tags on prefabricated modules and the crane hook to communicate the geometric and semantic information (e.g., connection type). Guven and Ergen (2021) deployed RFID tags on pallets, crane hooks, and construction lifts to explore the on-site logistics of masonry materials.

However, relying on a single source of information, such as footage and RTLS signals, may result in inaccuracy and uncertainty due to camera occlusion and signal obstruction. Meanwhile, these methods have a limitation in their robustness and generality on construction sites where a mix of loads are being lifted. Thus, to obtain productivity insights into crane operations consistently and robustly in a real-world setting, it is essential to integrate multiple data sources and contextual information (e.g., lift schedules).

Crane Lift Scheduling

Lift scheduling is a common construction management task that coordinates the use of cranes and other lifting resources to satisfy the on-site demands of material logistics. Multiple cloud-based applications have been developed to allow crane users (e.g., subcontractors) to submit lifting demands, pending site managers' approval and crane operators' execution, including HammerTech (2023), DataScope (2023), Veyor (2023), and CraneTime (2023). These solutions are designed for efficient management of crane booking, scheduling, and asset management. They offer features such as drag-and-drop lift scheduling, crane maintenance tracking, customisable checklists for operators' eligibility, and asset utilisation management. Some of these solutions provide a manual tracking feature for sub-contractors to report the degree of schedule fulfilment. However, this feature has been misused, leading to outdated data on crane availability and unreported idle times.

Having that said, using these lift scheduling systems is expected to generate a wealth of contextual information that can be used to enhance the interpretation of crane monitoring data. For instance, these systems store the identities of crane users, load specifications (weight and dimensions), and details of lifting tasks (destination and time of lifting). Such information can be used to map the semantic similarity between as-planned and as-is crane operations, correlate crane actual crane behaviour with lift orders, and automatically update completed tasks. To realise this, a knowledge base that incorporates domain-specific expertise in crane operation management is required.

Semantic Web-assisted Data Reasoning in Construction

Semantic Web technology combines ontology and rules to enable automated data reasoning. Ontology is a formal representation of domain-specific knowledge, which organises concepts, properties, and relationships using ontology languages like OWL and tools such as Protégé (Viljamaa and Peltomaa, 2014). Rules, on the other hand, are written in formal languages such as SWRL and used to validate data, derive new information, and guide automated reasoning (Soman, Molina-Solana and Whyte, 2020). By representing knowledge in a machine-readable format using ontology and applying rules to manipulate and reason about that knowledge, the semantic web supports a wide range of applications in enhancing construction productivity. For example, Koo et al. (2007) created a constraint ontology to standardise the temporal dependencies and priority rules among construction activities, to assist planers in understanding alternative sequences of construction activities. Zheng, Törmä and Seppänen (2021) proposed a digital construction ontology (DiCon) to integrate heterogeneous construction workflow information, such as construction activities' sequence, equipment demands, material consumption, and locations, to create an explicit specification of a shared conceptualisation. While these works focus on standardising domain knowledge, Li et al. (2022) strived to incorporate knowledge in modular construction ontologies (e.g., products, topology, and tasks) to automatically cluster and map physical building components and work packages with higher accuracy and less planning time.

As cranes become increasingly dominating resources in on-site logistics, operational parameters of cranes have been featured as important construction resources for construction activities, requiring meticulous planning to avoid bottlenecks. The studies by Tavakolan et al. (2021) and Soman et al. (2020) utilised an ontological model to program crane specifications such as maximum load capacity, inventory, and location. Their studies focused on examining crane specification against constraints related to the Safe Working Load (SWL) and crane reach in resource planning and look-ahead scheduling, assisting planners in recognising and addressing the resource shortage before they impact project schedules. However, the studies only considered peak demands and did not account for the changing crane availability. This gap in the literature highlights the need for further research to analyse crane operations in greater detail, scrutinising the formation, execution and updating of day-to-day lift schedules to avoid resource bottlenecks and disruption.

Methodology

While much research has focused on automating crane monitoring and lift scheduling, the practicality of such techniques is limited to certain construction activities and the interaction between monitoring and scheduling is often ignored. To advance the body of knowledge on automated crane monitoring and maximise the value proposition, this study proposes a Semantic Web-assisted method for automatically monitoring and updating the progress of crane operations in construction projects. The architecture of the proposed method, depicted in **Fig. 1**, consists of two main components: Data Acquisition Module and a Data Reasoning Engine.

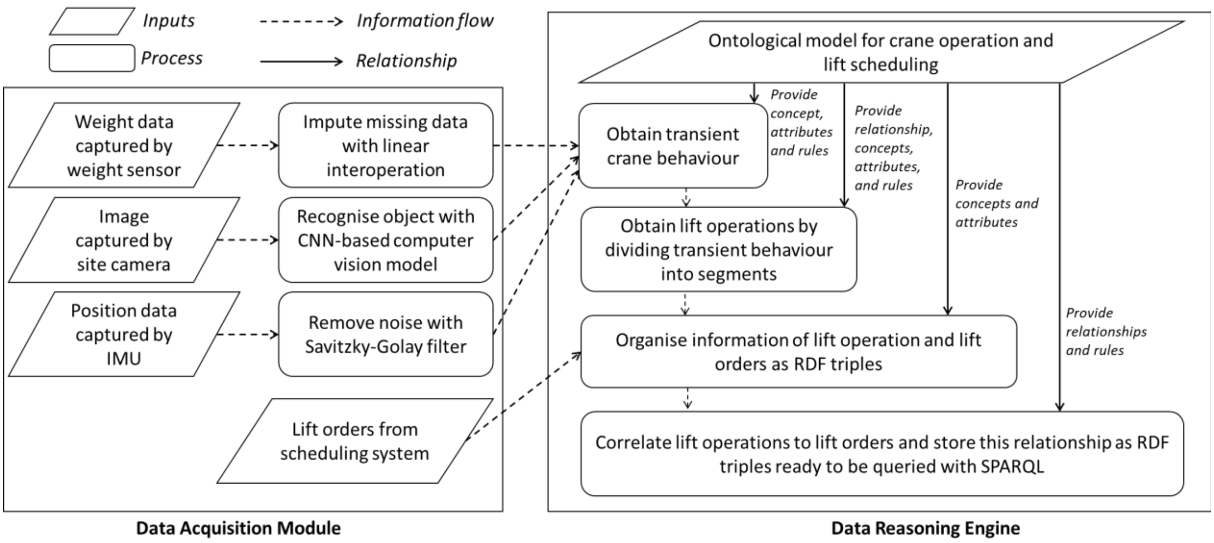

Fig. 1 Architecture of the proposed method

Designed to monitor pressures on crane hooks, identify objects on-site, and track crane poses, the Data Acquisition Module consists of three types of sensors: weight sensors, cameras, and Inertia Measurement Unit (IMU) sensors. These sensors are typical IoT devices on construction sites that measure a variety of signals, including pressure, visual, and electronic signals. To begin with, raw data from each sensor is pre-processed separately through data smoothing and cleaning techniques. To be specific, the weight data, which is non-periodically measured and reported due to in-built stabilising algorithms, is linearly interpolated to estimate missing values. The crane lifting operation is recorded by a camera and the images are then processed using a CNN-based object-detection model to identify the presence and locations of building components (i.e., columns, beams, and slabs) and the crane hook. The IMU data is filtered using a Savitzky-Golay filter to eliminate noise. After pre-processing the raw data, Boxcar averaging is applied to down-sample the frequency of data from different sources. Finally, all sensor data is synchronised using the lowest sampling frequency of all sensor data (1Hz).

The Data Reasoning Engine tracks the progress of crane operations using ontological models built upon domain knowledge and data from IoT devices and lift scheduling systems. The ontological model is comprised of three overarching entities: transient crane behaviour, lift operations, and lifting orders (see **Fig. 2**). Firstly, by examining the pre-processed data from the three IoT devices, the transient behaviours of the crane can be deduced from following data reasoning rules. The crane's transient behaviours can take on five different forms, which include loading, transporting a load, unloading, moving without a load, and being idle. The relationships between pre-processed data and the transient behaviours of the crane, as well as the dependencies among those behaviours, are specified by rules created using Apache Jena, an open-source Java framework for building Semantic Web, to flag and correct any data points that fall outside of expected ranges or values during data fusion. The Jena Generic Rule codes are comparable to SWRL in providing a basic rule syntax for ontology expansion, but they offer greater capacity for expressing complex logic.

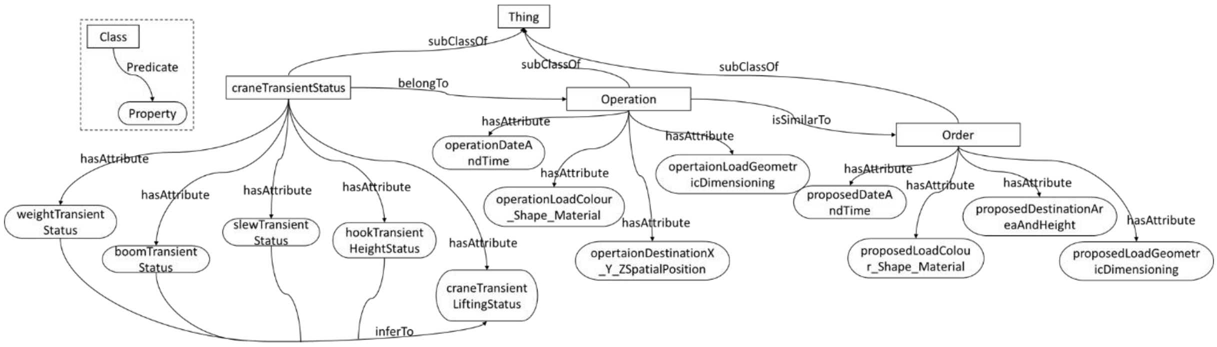

Fig. 2 The ontological model (class, attributes, relationship)

After obtaining the transient behaviours of the crane, they are segmented to recognise lift operations. To be considered a lift operation, the crane's behaviours status must follow a precise pattern, where the crane executes loading, transporting the load, unloading, and then being idle or moving without a load in sequence. To ensure data reliability, rules have been established based on two assumptions: (1) the lifted load cannot change during a single lift operation, and (2) each lifting status must last for at least three seconds to allow manual material handling. Unreliable data that conflicts with these two assumptions is removed. In the meantime, the information from lift scheduling systems is also organised into the ontological model. To collect the lift schedule data, a user interface (UI) is created as a simplified version of web-based lift scheduling systems but requests the same information from users. The collected information consists of attributes of the concept “lifting orders” with each set of inputs forming an instance of that concept.

The Data Reasoning Engine is concluded by correlating actual lift operations with lift orders. This correlation is achieved by calculating the semantic similarities between instances of those two concepts using the Jaccard similarity measure, which determines the ratio of the intersection size to the union size between two data sets. Nine attributes shared by both "lift operations" and "lifting orders" are used to calculate the Jaccard similarity, including load weight, load colour, load material, load shape, load length, load width, and unloading destination X-axis, Y-axis, and Z-axis coordinate values. To account for uncertainties stemming from sensors and human errors, buffers are added to the as-planned attributes (e.g., lifting destinations) when matching actual crane behaviours (e.g., unloading poses). After mapping a lift operation with a lifting order, the ontological model is updated to reflect the results and is ready to be queried by the SPARQL language.

Implementation

Experiment Design

Timber structures have gained popularity due to their sustainability, efficiency, and aesthetic appeal. This study uses a scaled model of timber structure as part of a testbed for the lab test. The model comprises prefabricated columns, interconnected beam systems, and slabs. In addition to the structure, the testbed includes a mobile crane model and a simulated construction site with cured concrete footing, as shown in **Fig. 3a**. An Intel RealSense D435i, a Yost Labs' 3-Space™ sensor, and an Adam DU CKT48 digital scale were used in the lab test. The Intel RealSense D435i is a depth-sensing camera designed to capture high-quality 3D images and video. The Yost Labs 3-Space Sensor is a miniature, high-precision IMU sensor for accurate tracking of the crane's rotational movements. The Adam DU CKT48 digital scale with a 50-gram accuracy is used to measure the weight of the crane-load system.

The lift orders were programmed into the lift scheduling system in advance, following a level-by-level installation sequence. During the actual installation, the crane operator was assigned to install timber structures section by section, dividing the structure into separate sections and constructing the columns, beams and slabs in each independently before integrating them into the final structure. It is worth noting that an additional crane operation has been programmed into the actual installation. This operation involves picking up a load, which is then intentionally unloaded back to the loading area to simulate double handling. **Fig. 3b** illustrates both the planned and actual lift sequences, with the double handling activity (i.e., DH0) highlighted in red. During the test, the crane operator manually attached the load from a fixed location (i.e., loading zone) and transported it to designated locations on the concrete slab footing, during which the operator had full freedom to choose the lift path as they would in real lifts. Once the load reached its destination, another participant (i.e., installer) carefully detached the load to minimise errors introduced to the scale readings. A total of six components (i.e., four columns, one beam system, and one slab) were installed, and sensors continuously captured data throughout the entire process (4 minutes) without interruption or human intervention.

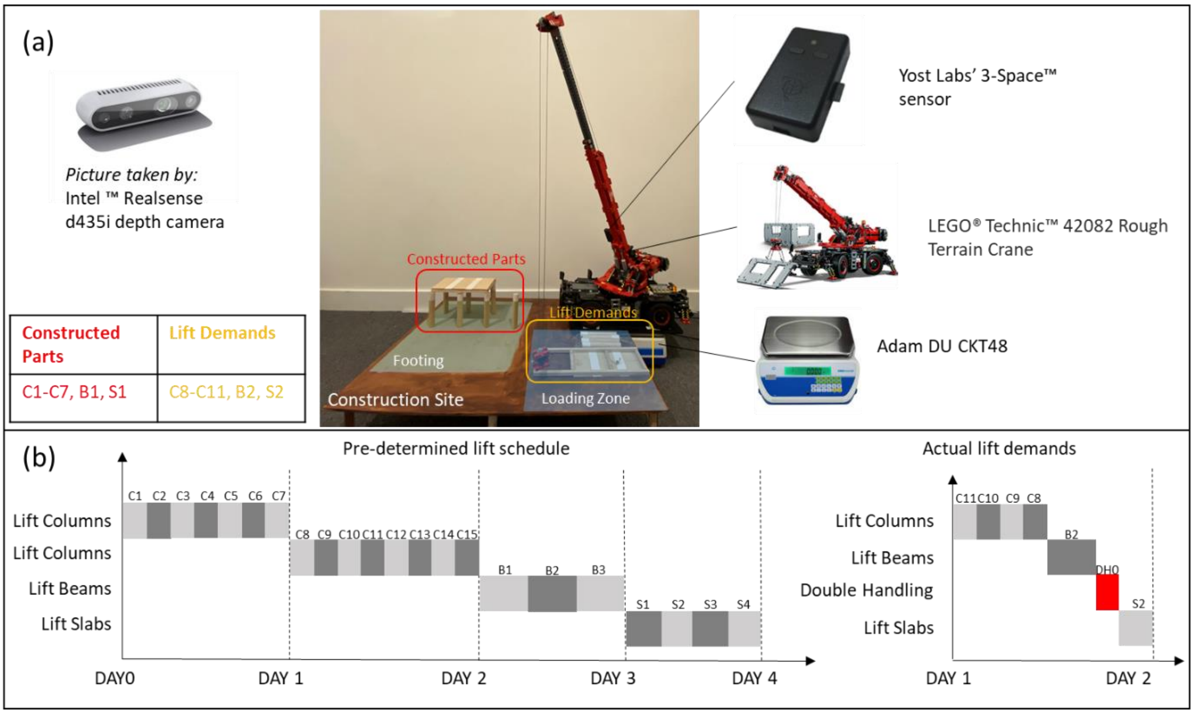

Fig. 3 (a) Test bed setup and (b) Pre-determined lifting schedule vs. actual demands conveyed to the crane operator

Test results

The outcomes of the pre-processing are illustrated in **Fig. 4a**, depicting the change of weight, crane rotational movements, recognised objects, and crane hook height, respectively. These processed data are then transformed into transient crane behaviours, where each instance represents one sample time point, obtained via the rules embedded in the ontological model (**Fig. 4b**). Then, the proposed method segmented transient crane behaviour into seven individual lift operations and accurately correlated six of these operations (C8-C11, B2, and S2) with their corresponding lift orders, while successfully disregarded the double handling activity (**Fig. 5**). Queries were programmed using SPARQL to extract details about lift operations (such as the duration of each status and actual unloading location) and corresponding lift orders (such as scheduled lift time). Such information can provide valuable insights for site managers, such as the amount of delay in scheduled lifts and the utilization rates of the crane within a specific timeframe, with detailed implications discussed in the next section.

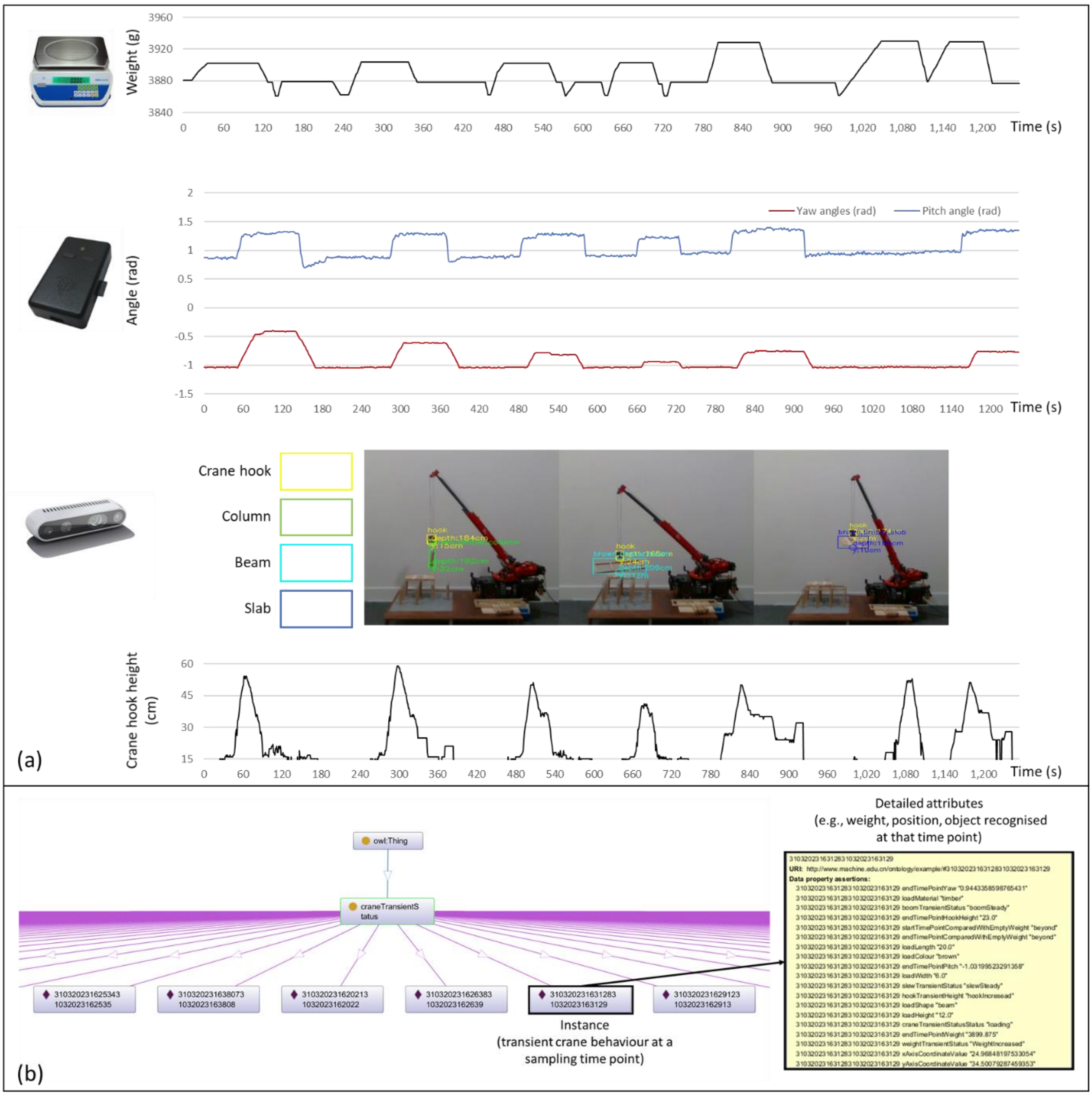

Fig. 4 (a) Results of pre-processing of data: weight, crane rotational movements, recognised objects, and crane hook height (b) Instanced transient crane behaviour

Fig. 5 Mapping results visualised in Protégé

Discussion

Fig. 6 provides a concise illustration of SPARQL queries that retrieve information for a specific lift order (Order A) and its semantic similarity with all lift operations. The query outcomes show similarities ranging from 0% to 88%, which allows for mapping lift orders to the corresponding operations even when some of the mapping criteria are not met. This exemplifies how the semantic web-based approach can effectively handle errors or missing data from particular IoT devices, rendering it more resilient than a reasoning process relying solely on a single piece of information. Although this laboratory test achieved 100% accuracy, in cases where errors may occur, querying the data can help site managers comprehend the underlying causes of the error and adjust the rules or sensors accordingly. This, in turn, enhances the interpretability of the results significantly.

OrderA:

sub	pre
<http://www.machine.edu.cn/ontology/example/#operation_6>	<http://www.machine.edu.cn/ontology/example/#Similarity0.0>
<http://www.machine.edu.cn/ontology/example/#operation_4>	<http://www.machine.edu.cn/ontology/example/#Similarity0.8888888888888888>
<http://www.machine.edu.cn/ontology/example/#operation_1>	<http://www.machine.edu.cn/ontology/example/#Similarity0.7777777777777778>
<http://www.machine.edu.cn/ontology/example/#operation_7>	<http://www.machine.edu.cn/ontology/example/#Similarity0.4444444444444444>
<http://www.machine.edu.cn/ontology/example/#operation_5>	<http://www.machine.edu.cn/ontology/example/#Similarity0.4444444444444444>
<http://www.machine.edu.cn/ontology/example/#operation_3>	<http://www.machine.edu.cn/ontology/example/#Similarity0.7777777777777778>
<http://www.machine.edu.cn/ontology/example/#operation_2>	<http://www.machine.edu.cn/ontology/example/#Similarity0.7777777777777778>

pre	obj
<http://www.machine.edu.cn/ontology/example/#proposedLoadMaterial>	"timber"
rdf:type	<http://www.machine.edu.cn/ontology/example/#Order>
<http://www.machine.edu.cn/ontology/example/#proposedDestinationLoadLiftingHeight>	"LevelG"
<http://www.machine.edu.cn/ontology/example/#proposedDestinationArea>	"A0"
<http://www.machine.edu.cn/ontology/example/#proposedLoadColor>	"brown"
<http://www.machine.edu.cn/ontology/example/#proposedLoadWeight>	"3904"
<http://www.machine.edu.cn/ontology/example/#proposedLoadShape>	"column"
<http://www.machine.edu.cn/ontology/example/#proposedLoadWidth>	"12"
<http://www.machine.edu.cn/ontology/example/#proposedDateAndTime>	"31/03/2023 09:00-31/03/2023 11:00"
<http://www.machine.edu.cn/ontology/example/#proposedLoadLength>	"2"

Fig. 6 SPARQL query for a specific lift order

Moreover, the proposed method was able to accurately record crane behaviour. During the experiment, a benchmark was established by observing video footage and manually noting the start and end times of each type of transient crane behaviour for a specific lift operation. The automatically generated experiment results were then compared to the benchmark, as shown in **Fig. 7**. The variances were plotted in a box plot, revealing an average error of 0.32 seconds, with a range from 0 to 0.8 seconds over the 242.7-second operation.

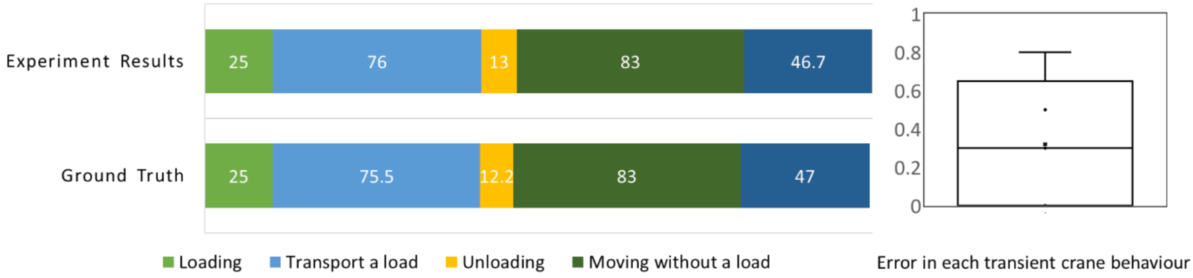

Fig. 7 Periods of various types of transient crane behaviours and error analysis (measured in seconds)

Conclusion

Previous research efforts have attempted to track crane behaviour in order to understand construction progress. However, these methods have encountered significant challenges with regard to their robustness and generalisability. In contrast, human site managers are able to synthesise data from multiple sources for making informed judgments under various circumstances. In this study, Semantic Web technologies were utilised to enable IoT devices with a similar cognitive capacity. The results demonstrate the effectiveness of this method in recognising lift orders for a scaled timber structure in the lab setting. Additionally, it highlights the ability to record detailed data for crane operations, which is fundamental for making informed decisions but often labour-intensive to record manually in daily practice. Future studies include integrating Natural Language Processing (NLP) to interpret lift schedules and adjusting semantic similarity based on lift order descriptions. As such, robustness could be improved by parameterizing buffering parameters in mapping rules according to sensor specifications, environmental factors, and building topology. Field tests with live construction data are planned to quantify the method's adaptability, accuracy and potential time-saving benefits compared to manual/other automated progress tracking methods in actual projects.

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