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DIGITAL TWIN ENABLED CONSTRUCTION PROGRESS MONITORING

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Abstract

Digital Twin technology has revolutionised overseeing newly built structures. This study suggests employing digital twin-based automatic progress monitoring on construction sites, comparing 3D point clouds with their Building Information Modelling to track progress and predict completion. It highlights integrating semi-continuous monitoring with a building's digital twin for efficient construction management. Leveraging precise data enhances understanding and identifies schedule deviations, enabling timely actions. Demonstrated through real-world construction data, visualised Gantt charts showcase its efficacy, offering insights into task status, schedule deviations, and projected completion dates. This underscores digital twin technology's potential to transform construction oversight.

Introduction

Scan-to-BIM provides a comprehensive assessment of the as-built state in the context of performance improvement (Bosché et al., 2015; Drobnyi et al., 2023b, 2024). Despite its impact, laser scanning is somewhat limited to surface recognition, lacking depth in reflecting built element quality (Hoiem et al., 2022). Researchers explore embedded sensing for conditional data assessment (Alizadehsalehi and Yitmen, 2016). Integrating laser scanner technologies and advanced wireless sensors offers opportunities for comprehensive project exploration, enhancing performance control and project management by merging as-planned models with data-capturing reality. Effectively managing vast and complex data for real-time progress monitoring requires an intelligent system continuously learning from various sources, including historical archive data (Boje et al., 2020). IoT technologies and related systems, combined with digital twin and cognitive computing, collect real-time data (Dawood et al., 2020). Visualizing digital data for stakeholders in different project stages is crucial, with XR technologies providing multidimensional perspectives (Alizadehsalehi et al., 2020).

As per the Project Management Body of Knowledge (PMBOK), controlling and monitoring a construction project encompasses processes to oversee progress and performance, identifying areas requiring plan adjustments, and initiating corresponding changes (Guide, 2001). These processes entail measuring progress through inspections (as-built) and comparing it with the project plan (as-planned) to validate predicted performance. The overarching goal of monitoring is to ensure effectively managed results and outputs by measuring and assessing project performance (Lin and Golparvar-Fard, 2020). Measuring work in progress on construction sites is crucial for project management, impacting various aspects such as time, cost, quality, and safety. This task is particularly challenging due to the complexity and interdependency of activities (Arif and Khan, 2021).

Traditional progress tracking practice depends on visual inspections and daily or weekly reports created based on those inspections to ensure that work meets contract specifications and schedule (Golparvar-Fard et al., 2009). These traditional practices are often slow and rely heavily on the inspectors' personal judgment, observational skills, and weekly expert follow-ups with a high probability of complete and accurate reports. Effective monitoring is crucial for project success; however, even the most robust monitoring systems are insufficient if the project is poorly designed or built on flawed assumptions. Building Information Modelling is a digital representation of a building, capturing 3D geometry and semantic descriptions of components (Kim et al., 2020b). The AEC industry-accepted BIM provides a suitable basis for automated construction progress monitoring. It serves three essential purposes: providing as-planned data, as-built data, and enabling their comparison (Machado and Vilela, 2020). As the baseline for construction progress monitoring, BIM binds AEC contract information, facilitates access to geometric data, allows for special visualization of schedules, and manages progress-related information. Recognized as a rich data source, BIM is pivotal for automated project progress monitoring (Kim et al., 2020a). A well-designed BIM model analyses operations in construction, aiding site management, enhancing communication, coordinating contractors, and planning logistics (Kopsida and Brilakis, 2020). While traditional Building Information Modelling (BIM) and construction schedules effectively capture the as-designed and as-planned phases, they inherently lack timely updation of the as-built and as-performed states during construction progression. This deficiency arises due to the static nature of BIM and schedules, which do not dynamically update as construction activities unfold. Construction sites' inherent heterogeneity and temporal dynamics present formidable challenges to accurate progress monitoring.

This paper proposes using DT to monitor the progress of large-scale construction sites. The major contribution is the tight integration of progress monitoring to DT, facilitating timely progress monitoring of a real construction site. The pipeline of the DT-based progress monitoring is as follows: The workers capture laser scans at the site and are passed to the DT platform. Then, the detection

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model in the platform automatically detects as-built elements and pushes the information generated from raw data to the graph. This will trigger the progress monitor and traverse the graph to get the progress information at the activity level. Here, an activity refers to a grouping of tasks, where each task represents a specific job tied to a particular element on the construction site. We calculate the current status of the progress (on schedule, ahead of schedule, and behind schedule) of each activity and estimate the finished date if the progress is behind schedule. We visualize these results in a Gantt table via a dashboard, which managers can quickly investigate.

Background

In response to these challenges, Digital Twins Construction (DTC) is emerging as a focal point of attention, offering a reliable information source for continuous production planning and adaptive product design throughout the construction lifecycle. However, the successful integration of DTC faces challenges – industry-wide adoption, technical intricacies ensuring the precision and accessibility of data (Sacks et al., 2020). Crucially, DTC should not be perceived merely as an extension of existing tools like BIM but as a transformative approach to construction production management, emphasizing a closed control loop (Sacks et al., 2020). The concept of DTC, coupled with automated data acquisition, establishes a framework for automatic progress monitoring, obviating the limitations of conventional techniques. This study directs readers to a comprehensive exploration of digital twins in construction through a recent review paper authored by (Opoku et al., 2021), providing invaluable insights into the evolving landscape of construction technology and methodologies.

To streamline and enhance the efficiency of progress monitoring processes, the initial step involves identifying newly constructed objects since the last data acquisition. This task is inherently challenging during the construction cycle due to noise, missing data, and local disparities in the position of as-built elements compared to their as-designed counterparts. The proposed solution involves locating instances of the as-designed model within LiDAR data acquired on construction sites. Current state-of-the-art approaches for object detection fall into two primary categories: traditional and deep learning (Chu et al., 2023; Lan et al., 2024). Traditional computer vision algorithms for object detection rely on deterministic procedures involving primitive shape fitting and statistical analysis (Drobnyi et al., 2023a). The most established methods within this category include RANSAC, Hough transform, and region growing. For instance, the efficacy of the Hough transform in detecting pipes within noisy 3D point clouds was demonstrated by (Ahmed et al., 2014). RANSAC-based methods have gained popularity due to their robustness in automatically segmenting building object instances represented by basic shapes such as cuboids and cylinders, enabling the detection of slabs and pipes. (Anagnostopoulos et al., 2016) applied RANSAC to detect wall surfaces, facilitating the reconstruction of rooms from 3D point cloud data (Anagnostopoulos et al., 2016). The second category employs deep learning techniques, with deep neural networks emerging as the predominant method for object detection. Notably, the PointNet architecture, a deep neural network specifically designed for point clouds, was introduced by (Qi et al., 2017). PointNet predicts the class label for each object segment, receiving a cluster of points as input and outputting a category prediction among 13 classes (Chen et al., 2019).

(Hu and Brilakis, 2024) proposed an automatic clustering method to segment the points corresponding to the as-designed instance. The workflow contains (1) Instance descriptor generation, (2) PROSAC (Progressive Sample Consensus) based shape detection, and (3) DBSCAN (Density-Based Spatial Clustering of Applications with Noise) based cluster optimization. The method matches design-intent planar, curved, and linear structural instances in complex scenarios, including (1) the as-built point cloud is noisy with high occlusions and clutter; (2) deviations between as-built instances and as-designed models in terms of position, orientation, and scale; (3) both Manhattan-World and non-Manhattan-World instances.

Methodology

In this work, we develop our progress monitoring method based on a holistic cloud-based Digital Twin Platform (DTP). This platform operates on a structured ontology, facilitating storing both the as-designed and as-built information for every element within a construction site. This platform intricately captures and retains the element-level status of each component present on the construction site. The status information is derived through various DT services, which meticulously process raw 3D point clouds from routine construction site surveys with laser devices. We use a BIM-assisted 3D object detection algorithm to ascertain the presence of each element within the as-built data. Such information is transmitted and systematically stored in the DT platform as element-level status, forming a comprehensive repository of the construction site's dynamic and evolving conditions. By retrieving and processing the information in the DTP, we calculate the activity-level progress status and estimate the finish date of the activity.

Ontology

The pertinent partial ontology for this study is illustrated in Figure 1; the complete ontology can be found in (Schlenger et al., 2022). Construction information is organized within a graph-based database, aligning with the structure defined by the ontology. The ontology bifurcates into as-planned and as-performed segments, encompassing `Work package`, `Activity`, `Task`, and as-designed elements under the as-planned side. In contrast, the as-performed side includes `Construction`, `Operation`, `Action`, and as-built elements. These nodes adhere to a hierarchical

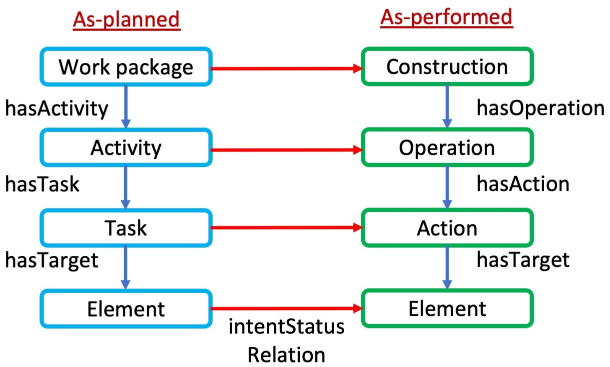

Figure 1: Visualization of a segment of the Digital Twin ontology employed in the progress monitoring pipeline.

order and establish connections through various relationships. Notably, the work package node, functioning as an aggregation of activities, is linked to respective activity nodes through the `hasActivity` relationship. The as-planned and as-performed sides of nodes are connected with `intentStatusRelation`. Recognizing that construction plans often operate at the activity level, the as-planned schedule is stored within the `Activity` node, capturing start and end dates. The schedule reflecting the as-performed activities is archived within the `Operation` node, mirroring the data in the `Activity` node. In instances where no prior surveys have been conducted for the target building, the operation's start date is presumed to align with the as-planned start date. Alternatively, if previous surveys have been undertaken, the operation's start date is designated as the most recent scan date. The conclusion of the operation is determined by extracting the latest update date at the element level. The as-built element node retains the progress at the element level, computed using the BIM-assisted 3D object detection algorithm (Hu and Brilakis, 2024).

Object detection

Automating progress monitoring necessitates the initial step of detecting constructed objects on construction sites, a task burdened with challenges, as outlined in the preceding background section. Streamlining this process requires a global registration between the BIM model and 3D point cloud data. We utilize a global registration method to align the coordinates of the BIM model and LiDAR data (Monasse et al., 2023). This efficient algorithm optimizes global robust energy between two line segments extracted from the BIM and LiDAR data. Once registered, the Region-Of-Interest can be confined to the upscaled bounding box of the query as-designed element, provided the BIM model and LiDAR data share the same coordinate system. This region of interest will be an input to a filtering step to remove clutter, if they exist. Given the geometric richness of the construction environment, we propose a novel solution based on geometric features, with a specific focus on planar polygons as a robust data abstraction. Our method involves detecting and clustering planar polygons in each dataset, followed by a matching step to compare planar polygons within associated clusters. This comparison allows us to identify local discrepancies in position, if they exist, ultimately eliminating false detection. We not only determine if there is a local discrepancy but also calculate the corresponding geometric transformation. This can avoid false positive detection when facing significant local discrepancy.

Integration with DTP

Specific Application Programming Interfaces (APIs) have been developed to facilitate seamless communication with the DTP[1]. These APIs enable the retrieval, creation, and updating of nodes within the DTP. The comprehensive progress monitoring pipeline is visualized in Figure 4. Given the assumption that the DTP is current with both as-built element progress and operation start and end dates, an initial fetch request is initiated to retrieve all `activity` nodes from the DTP. Subsequently, each activity's as-planned start and end dates are extracted from the corresponding `activity` nodes. Following the hierarchical structure, all as-designed element nodes linked to each `activity` node through relationships like `hasTask` and `hasTarget` are retrieved from the DTP. Leveraging the intent-status relation, with `intentStatusRelation` corresponding to the as-built node for each as-designed node is fetched. The element-level as-built progress is then aggregated from the as-built element nodes. Employing reverse relationships with `hasTarget` and `hasAction`, `operation` nodes are fetched, and the associated as-performed schedules are compiled. Once the as-planned schedule, as-performed schedule, and element-level as-built progress are at our disposal, the groundwork is laid for the computation of progress at the activity level.

Progress calculation

The determination of activity status in relation to the schedule is outlined in Table 1. An activity is marked as ahead of schedule if the element-level progress exceeds zero and the end date of the operation precedes the corresponding activity end date. The cumulative assessment considers an activity as ahead of schedule if a majority of its elements exhibit this characteristic. Simultaneously, the percentage of completed tasks within an activity is computed. In the case of an activity falling behind schedule, the maximum delayed task determines the extent of the delay. To further enhance understanding, the calculated percentage of tasks completed, and the determined delay duration are employed to estimate the revised end date using a projection function. Presently, the projection utilizes an S-shaped function, closely resembling actual construction progress (San Cristóbal, 2017).

Results & Discussion

The experimentation encompassed utilising both as-designed data and 3D point cloud data obtained from a

[1]`https://github.com/BIM2TWIN-Team/DTP_API`

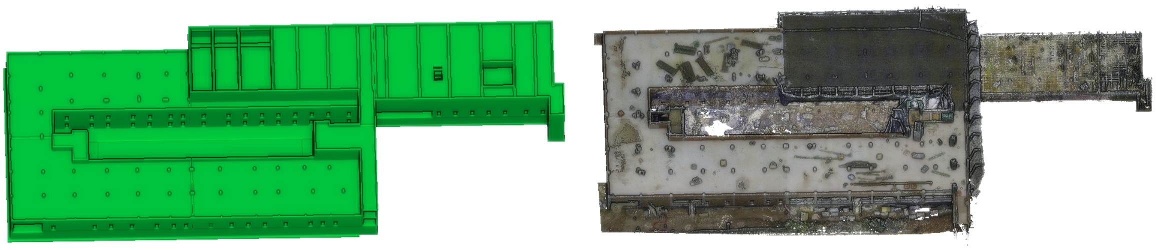

Figure 2: As-designed and point cloud data from a construction site in Spain.

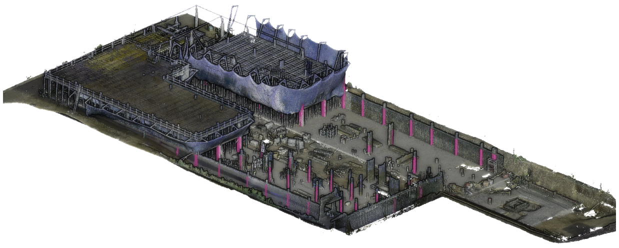

Figure 3: Visualization of columns detected on a construction site. The detected columns are marked in pink.

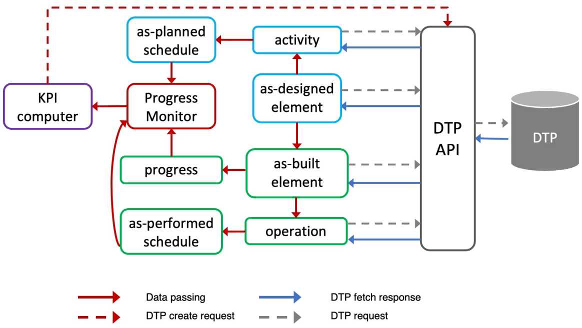

Figure 4: Visualization of the pipeline depicting the progress monitoring algorithm execution flow

Table 1: Criteria for assessing activity status concerning schedule compliance.

Condition	Decision
Element level progress > 0	
Activity end time > Operation end time	Ahead
Activity end time < Operation end time	Behind
Activity end time = Operation end time	On
Element level progress = 0	
Activity end time > Operation end time	On
Activity end time < Operation end time	Behind
Activity end time = Operation end time	On

construction site located in Spain, as shown in Figure 2. The detection results of columns in shown in Figure 3. As can be seen, our method can detect corresponding elements in the whole point cloud building. The output of the progress monitoring encompasses key metrics, including the percentage of tasks completed, progress status, the number of days ahead or behind the schedule, and the projected completion date for each activity. To enhance the interpretability for construction managers, the results are visually presented in the form of a Gantt chart, as depicted in Figure 5. Gantt charts were chosen due to their widespread usage in construction scheduling, making them a familiar and effective visualization tool for managers. Each activity is graphically represented by two horizontal bars: one reflecting the as-planned schedule and the other the as-performed schedule. The as-planned schedule is denoted by a grey bar, while the as-performed schedule is illustrated with a coloured bar. In the chart, a dark red bar signifies that the activity is complete but was delayed, whereas a dark green bar indicates that the activity is not complete but is on schedule. Light red signifies that the activity is behind schedule and has not yet been initiated, while light green indicates that the activity is on schedule and has yet to commence. The textual information overlaid on the grey bar corresponds to the name of the activity assigned by the construction company. Additionally, text overlaid on the coloured bar details the progress status, the number of days the activity is ahead or behind schedule, and the projected completion time.

Following this, the Key Performance Indicators (KPIs), including the *percentage of tasks delayed per activity* (KPI1) and the *percentage of delay in days per activity* (KPI2), are systematically computed. KPI1 is the quantitative measure obtained by dividing the number of delayed tasks for each activity by the total number of tasks scheduled for that specific activity. This ratio provides a nuanced understanding of the prevalence of task delays within individual activities, contributing valuable insights into the project's task-level performance. Simultaneously, KPI2 is calculated by determining the ratio between the number of de-

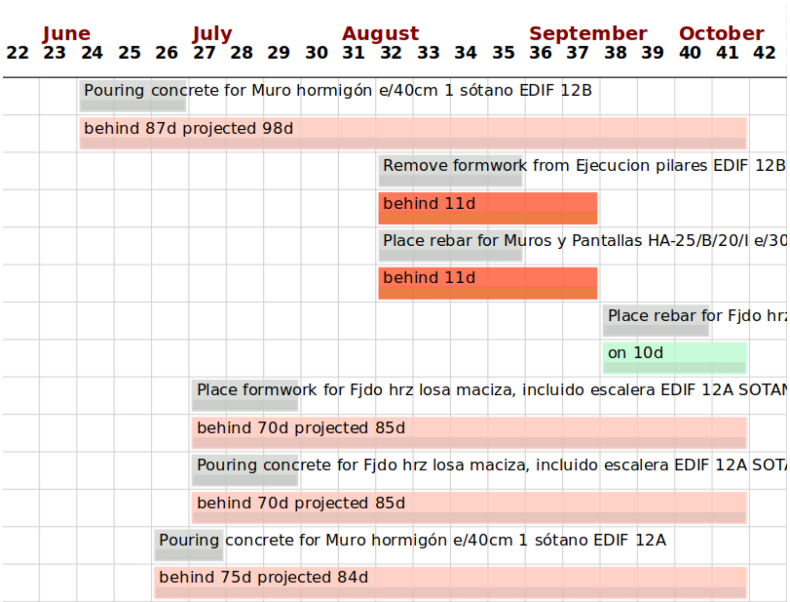

Figure 5: Graphical representation of progress monitoring algorithm output in Gantt chart format for enhanced comprehension

layed days for each activity and the planned duration (as-planned days) for that respective activity. By doing so, KPI2 offers a comprehensive overview of the temporal aspects of project performance, highlighting the extent of delays compared to the initially envisaged project timeline.

These calculated KPIs play a pivotal role in assessing the efficiency and timeliness of project activities. Once computed, the KPI values are securely stored within the DTP, forming an integral part of the platform's repository of project performance data. This centralized storage ensures that historical KPI data is readily available for analysis, comparison, and continuous improvement efforts. Furthermore, to enhance accessibility and visibility, these KPIs are dynamically displayed on the project's dashboard. This strategic placement on the dashboard gives project stakeholders timely, at-a-glance insights into key performance metrics. The dashboard becomes a central hub for monitoring and understanding project delays, fostering a proactive approach to decision-making based on the current project status. The source code for this paper is accessible on GitHub at the following URL: `https://github.com/BIM2TWIN-Team/WP3-progress-monitor`.

As highlighted in a recent comprehensive review on computer vision (CV) aided progress monitoring in construction (Sami Ur Rehman et al., 2022), the conventional progress monitoring methods are characterized by slowness, tediousness, and susceptibility to errors. However, the existing body of literature on CV-based progress monitoring is dispersed across various domains, lacking a cohesive focus on methodologies and processes throughout the entire CV-based progress monitoring workflow. This article addresses this gap by presenting a holistic approach that provides timely information and knowledge through Key Performance Indicators (KPIs). Such data availability is critical, enabling simulations of alternative execution plans that prove invaluable at different construction stages. This capability is instrumental in minimizing delays and optimizing equipment usage, as discussed by Yeung et al. (Yeung et al., 2022). By consolidating insights and methodologies, our approach aims to streamline CV-based progress monitoring into a coherent and efficient process.

Conclusion

This study emphasizes the profound impact of DT technology on monitoring and managing newly constructed buildings. The proposed DT-based method marks a substantial leap in automatic progress monitoring for real-world construction sites. Utilizing scanners to collect 3D point clouds and Digital Twin Platforms (DTP), this approach allows detailed construction status analysis and completion timeline prediction. The seamless integration of semi-continuous monitoring with the building's DT underscores the pivotal role of DT tech in efficient construction management. Leveraging precise data not only enhances project understanding but also enables timely deviation identification, empowering stakeholders to implement corrective actions and proactive strategies, enhancing project efficiency. Extensive real-world experiments validate this method's effectiveness, highlighting DT's potential to transform construction monitoring and foster adaptive project management. As DT continues evolving, its integration into construction processes will be vital for achieving optimal efficiency, accuracy, and proactive decision-making.

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