A Framework and Cyber-Physical System Architecture for Cloud-Based Construction Monitoring with Autonomous Quadrupeds

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Abstract –

Construction progress monitoring is a crucial aspect of project management, ensuring project completion on time, within budget, and meeting quality standards. Current data collection and processing methods are time-consuming and labor-intensive, and modern technologies, including robots and computer vision, offer a potential solution to this challenge. While past research has improved data collection and processing independently, a significant manual effort is still required to classify and transform collected data for processing. This research introduces the foundation of a novel framework to bridge this gap, leveraging an autonomous four-legged robot using the Software Development Kit (SDK) and the Robot Operation System (ROS). Additionally, Simultaneous Localization and Mapping (SLAM) for navigating, and cloud computing platforms for data processing, are employed to establish a repository for raw data from images captured by the robot, facilitating simultaneous processing stages. The research proposes a cloud-based machine-learning service that hosts a deep-learning algorithm for material identification and quantification. The objective of the proposed framework and system architecture is to capture images of the indoor environment of construction projects, classify and process data to create quantified material lists, and compare them to the full material list on the cloud, construction schedules can potentially be updated in real-time.

Keywords –

Computer Vision; Cloud-Based Construction Monitoring; Autonomous Quadruped; Framework; Cyber-Physical System Architecture

1 Introduction

The construction industry faces challenges in adopting novel technologies, rendering it unproductive and inefficient [1, 2]. Despite the improvement rates observed in other sectors, such as manufacturing and information technology, over the past decades, the construction industry's productivity remains stagnant [3, 4]. Technology-driven systematic approaches, such as construction automation and robotics, have been introduced to enhance efficiency, constructability, planning, and overall productivity [5].

Limited real-time data and analysis from construction environments result in a gap between ongoing project stages and decisions made by top managers [6, 7]. While traditional methods such as human interactions and paper-based task recording have long been relied upon for many project monitoring tasks, there is a growing trend among project participants to adopt technology and modern tools [8, 9]. Considering the industry's current status, efficiency in the data-collecting process is crucial to support managers in making decisions grounded in accurate data and up-to-date information [10, 11].

Effective and regular inspections, along with quantifying completed and ongoing construction tasks, are essential and require innovative strategies. Technology-driven systematic approaches, such as construction automation and robotics, have been introduced to enhance efficiency, constructability, planning, and overall productivity [5]. Optimizing the data-collecting process is crucial to assist managers in making decisions based on accurate and updated information [10], and data-collection automation can facilitate construction monitoring [12].

To evaluate the effectiveness of the proposed application of robots, specifically utilizing quadrupeds for live data collection and updating construction schedules, a survey was conducted among academic researchers and professionals in the construction industry as part of another research study [13]. There is data available to verify the benefits of the proposed utilization of the robot and its ability to perform required tasks (Figure 1). Current applications of quadrupeds in this domain mostly require manual navigation for tasks such as collecting data or remote inspection. However, the scope of this paper, as a prerequisite for a larger research project, is to present the foundation and hypotheses for the autonomous operation of the robot.

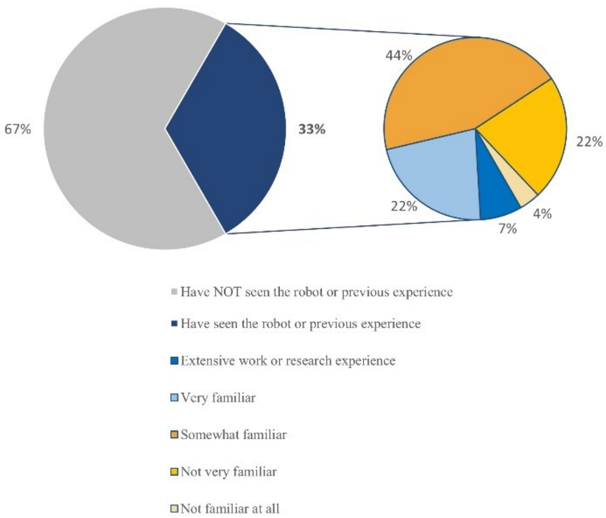

Figure 1. Survey results on utilizing the robot for the assigned task

While several studies have explored the use of collected data from the construction environment for construction monitoring, a gap still persists between data collection and the processing and updating of construction schedules by an autonomous robot. This paper contributes to the existing body of knowledge by proposing a framework and a cyber-physical system architecture to leverage Spot, a four-legged autonomous robot, for real-time construction schedule updates. A preliminary workflow was introduced in a prior study [4], and this paper presents the required developed framework along with the necessary system architecture.

2 Research Significance

The primary objective of this research is to propose the fundamental components of an automated method for collecting, classifying, and processing data to update construction schedules in real-time. The system is designed to automatically update construction schedules, with a specific emphasis on enhancing efficiency and accuracy within indoor construction environments and eliminating the lag between 'actual' and 'reported' progress.

Despite advancements in data collection and processing within indoor construction environments, a notable gap persists, requiring substantial manual effort to classify and prepare collected data for further processing. This research contributes to the existing body of knowledge by proposing the initial steps of addressing this critical gap, creating the foundation of a platform for streamlining the process, and facilitating real-time updates to construction schedules and well-detailed information, preventing possible delays and cost overruns as the final goal of future studies [10].

3 Methodology

A comprehensive review of existing literature, involving the search, selection, and analysis of relevant sources, was conducted to understand the functionality of the robot. Since the implementation of the idea of using a quadruped for regular inspection and real-time updating of construction schedules is complex, a meticulous selection of system components and architecture is necessary. Part of the selection process was based on the authors' experience in other research, while the remaining parts were informed by literature review.

Additionally, as the study focuses on a specific type of autonomous robot for construction monitoring and planning, technical specifications, manuals, and manufacturer's websites were consulted. The application of autonomous robots as the selected model was thoroughly investigated, taking into account both challenges and benefits.

To establish a feasible goal for the study, the previously proposed workflow [4] underwent updates through further research and optimization. Furthermore, aligned with the required system performance and anticipated outcomes, a cyber-physical system architecture was designed to provide a platform for the next step of the research, which involves developing a Construction Material Library (CML) using Convolutional Neural Networks (CNNs).

4 Literature Review

The use of modern technologies and the improvement in data collection methods have enabled project managers to reduce the gap between ongoing project stages and crucial decisions [14]. Given the inefficiency, labor-intensive, and error potential of traditional data collection methods [15], innovative solutions, along with regular and effective inspections, play a pivotal role in identifying schedule deviations [10]. This approach facilitates resource allocation to prevent delays and cost overruns in construction projects [1, 11, 12].

Computer vision has emerged as a promising alternative solution in recent years, providing automated and continuous monitoring capabilities through image and video capture. This approach offers rich insights into project entities, behaviors, and site conditions, facilitating a more comprehensive understanding of complex construction tasks [16]. Machine learning algorithms have streamlined the progress monitoring process, employing the analysis of as-built images for accurate calculations [17].

Fard & Peña-Mora [18] utilized captured images from construction environments for camera matching and material detection to assess and identify physical progress in projects. While this approach simplifies procedures, reducing both time and costs, it necessitates the use of handheld cameras and personnel for image classification and alignment with planned models. Recognizing the limitations of this manual process, there is an emerging need to incorporate advanced equipment to minimize human intervention throughout the entire process [19-21].

In another research, Golparvar-Fard et al. [10] used captured images to create an as-built 4D BIM model and proposed to compare as-planned and as-is models to recognize construction progress. Vähä et al. [22] emphasized that the integration of cutting-edge tools, such as easy-to-use robots in construction automation, would deliver benefits in terms of value, safety, quality, productivity, and overall performance.

Petersen et al. [23] explored various categories of construction robots, classifying them based on equipment, performance, and outcomes. Moreover, Asadi et al. [14, 24] demonstrated how a mobile wheel-enabled robot can identify obstacles, deliver real-time vision-based data in particular conditions, and be integrated with other tools like unmanned aerial vehicles in hard-to-reach areas. A system architecture for a Multi-Agent Robotic System is proposed for path planning in indoor environments [25]. It demonstrated its capabilities by assisting in automated path planning and navigation for collecting 2D image and 3D point cloud data.

An autonomous mobile robot equipped with a navigation and drift correction algorithm was employed to collect data from an indoor environment and incorporate it into the decision-making process [26]. While ground mobile wheel-enabled robots exhibit proficiency in collecting data from indoor environments and elements situated on the same building story, the primary challenge lies in autonomous travel between levels without human intervention [23, 27]. Taking into account mobility and diverse capabilities, legged robots offer advantages compared to wheeled or other ground mobile robot types. Multi-legged systems play a crucial role in attaining superior mobility performance, energy efficiency, speed [27, 28], and obstacle negotiation capabilities [29].

This research proposes a workflow and a cyber-physical system architecture to leverage Spot, an autonomous quadruped robot, for collecting and processing data to update real-time construction schedules in real-time. The robot has been employed in construction-related research, demonstrating its potential and capabilities in indoor environments [30-32].

5 Framework

Nearly half of the construction cost is associated with building materials, and effective material monitoring can facilitate the accomplishment of project goals [32, 33]. This research proposes a framework that employs Spot as the central component of a system designed to recognize materials, assess physical progress by comparing the implemented materials list with the full materials list, and update construction schedules in real-time. The robot's task is to autonomously navigate across different stories, inspect designated areas on each floor, and collect data for real-time processing. Given the system's complexity with various subsystems and components, this paper focuses on the foundational aspects of the system, particularly recognizing components and their interactions to achieve the required performance.

Figure 2. Boston Dynamic's SPOT with 360° camera and a LiDAR payload.

The robot can navigate diverse terrains while simultaneously sensing and analyzing its environment [34]. Equipped with sensor modules on its front, rear, and sides, including stereo cameras, a wide-angle camera, and a texture projector, the robot utilizes these sensors to facilitate SLAM navigation and wayfinding, enabling autonomous movement across various building stories and areas [35]. As an autonomous quadruped, Spot is equipped with ten cameras, comprising five optical cameras for operator view and five depth cameras for robot perception and obstacle avoidance (Figure 3).

Figure 3. Front, side, and rear sensors and wide-angle cameras

This configuration provides Spot with a comprehensive optical Field of View (FoV) and a depth camera range of approximately 2 meters [35]. However, since the robot's cameras do not offer sufficient quality for the purposes of this research, and considering issues with lighting and shadows in captured images [36, 37], a powerful inspection tool such as the Spot CAM+ is required. Featuring a payload 360° spherical camera, it ensures accurate and high-resolution images (Figure 4), facilitating the material recognition process [38].

Figure 4. Spot CAM+ payload, and spot Core I/O and Velodyne VLP-16 LiDAR

Utilizing LiDAR as additional sensing detectors (Figure 4), the robot can create 3D point clouds of environments, which are beneficial for obstacle detection and avoidance, as well as secure and efficient pathfinding [37, 39]. While research has explored using dynamic point cloud scans, the high level of noise and the extensive computational processes required for the robots [40] make this method inefficient for our goal, which is to update construction schedules in real-time during progress monitoring. Due to data size and computational limitations, LiDAR can only serve as a navigation tool. Instead, semantic data extracted from 360° camera RGB images, along with their locations, can identify implemented materials in specified locations and compare them with the total amount to calculate overall progress.

The current study represents the initial phase of a larger project aimed at collecting data from indoor construction environments, identifying physical progress, and updating construction schedules in real-time. The proposed method involves directing the robot along predefined paths to regularly visit designated locations, capturing images and collecting data. The framework utilizes cloud services and CNNs to process the data and update the construction schedule promptly (Figure 5).

Autonomous quadrupeds, exemplified by Boston Dynamics Spot, have demonstrated their capabilities in construction environments [41, 42]. In our approach, Spot is considered to perform two parallel sets of actions: data collection and data processing. During data collection, the quadruped utilizes SLAM and the robot's camera, Spot CAM+, to navigate specified areas, capture images, and upload them to the cloud.

Amazon SageMaker, as a cloud-based platform hosting the CNN, is utilized for material identification and quantification through a CML. The quadruped is tasked with regularly visiting specified areas to compare the used materials with the comprehensive material list, thereby identifying physical progress and updating construction schedules in real-time.

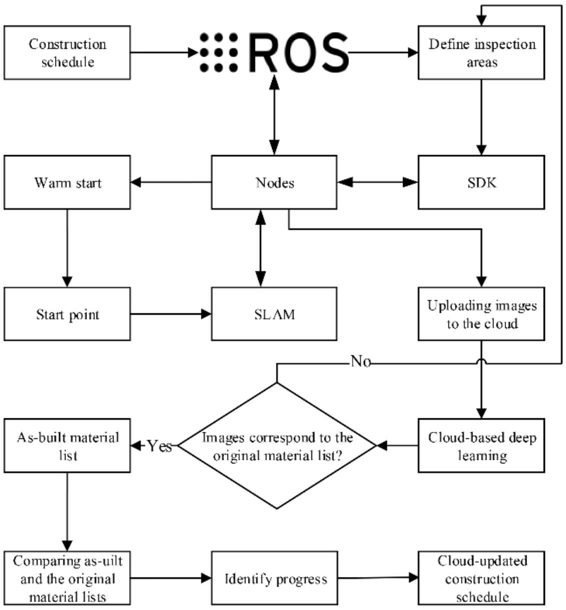

Figure 5. Spot's Real-Time Construction Schedule Updates Workflow

In the proposed framework, ROS Noetic, running on Ubuntu 20.04, serves as the primary framework for the robot, facilitating communication among various components. It ensures coordination of nodes, such as sensing cameras and LiDAR [43], for traveling between locations and collecting accurate information from specified areas or uploading captured data to a cloud computing platform like Amazon Web Services (AWS). Users have the capability to program and interface with the robot using the SPOT SDK [37, 43].

Autonomous robots can navigate indoor environments using either a pre-built map or live sensor data. During the warm start, the quadruped employs SLAM in the initial step and navigates through the designated area, either manually or autonomously, to construct an offline map that includes all physical components in the environment, such as obstacles and available paths [44]. Spot uses Velodyne VLP-16 LiDAR for localization [37], allowing the robot to determine its position and employ grid-based path planning to create a path. Subsequently, the robot utilizes live sensor data and an autonomous navigation and mapping library, such as

RTABMap, for further localization and navigation through specified requested areas [45, 46].

The robot can visit requested areas, capture images, leverage a cloud computing platform such as AWS, and upload the collected images to the cloud [47]. This framework relies on computer vision to extract semantic data or utilize filters to cluster images based on their physical features, enabling material classification through a CNN [48]. The algorithm hosted by SageMaker can be trained for material classification, enabling the robot to recognize and quantify materials based on their locations [49]. This facilitates the subsequent step of comparing implemented material lists with full material lists, considering start and finish dates, locations, and recognizing construction progress [48].

The proposed cyber-physical system architecture for this research implements the designed framework and integrates the required sensors' performance of Spot into ROS (Figure 6). It establishes a closed loop for acquiring data from nodes, which include the VLP-16 LiDAR for wayfinding and message transmission in ROSCORE, and the CAM+ 360° camera for capturing RGB images.

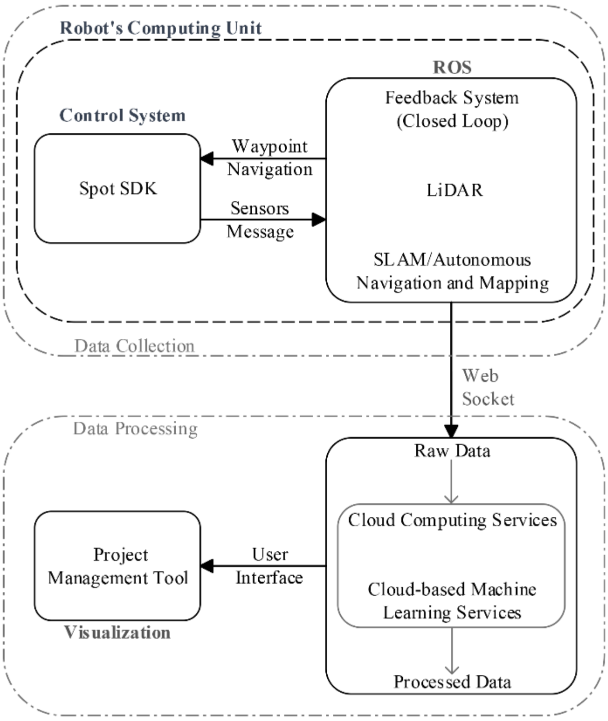

Figure 6. Spot's Cyber-Physical Systems Architecture for Real-Time Construction Schedule Updates

In terms of autonomous wayfinding, SLAM libraries like RTAB-Map enable Spot to map and navigate its environment effectively. Given that LiDAR is designated for wayfinding in this framework, the RTAB-Map library processes 3D scans generated by the VLP-16 [50].

During the initialization phase, ROS undergoes registration, and publishers are instantiated. As the process unfolds, the program enters a loop dedicated to SDK calls for data acquisition. The collected data undergoes processing, is packaged into ROSCore messages, and subsequently published [37]. Since the proposed CNN for the next phase of this research should consider a wide range of Hue-Saturation-Value (HSV) color values for construction materials due to different types of shadows and lighting conditions, a large dataset is needed [48]. AWS and SageMaker provide an appropriate platform for our cloud-based model training for the future step of the study [49].

The system architecture comprises nodes responsible for uploading captured images to the cloud and utilizes a cloud-based machine learning service like SageMaker for image organization. A deep learning algorithm hosted on the cloud is employed to train the dataset, classify, and quantify materials within images captured in construction environments [51]. With data collected and processed in the cloud, outputs such as implemented material lists can be generated. This enables the updating of construction schedules across various interfaces, such as Primavera or MS Project.

6 Discussion and Limitation

In recent years, novel technologies and equipment have been employed for data collection in construction environments. Despite this, a substantial portion of the necessary data for construction monitoring and progress assessment still relies on personnel. Through routine inspections and comparisons between actual progress and planned objectives, construction schedules can be updated, guided by inspection sequences and the availability of construction workers [10]. However, the collected data must be organized and classified for various applications, including construction monitoring. The manual nature of these processes highlights the need for innovative solutions to minimize human intervention during both the data collection and processing stages [19].

Regular inspections and schedule updates can identify schedule deviations early, enabling managers to allocate resources effectively, enhance overall performance, and prevent potential delays and cost overruns [10]. Computer vision has emerged as an innovative and successful solution for updating construction schedules, offering automation in regular construction monitoring through the use of captured images and videos from construction environments for further processing [16].

Utilizing autonomous robots for data collection and processing captured images to identify construction progress improves project efficiency by enabling appropriate workforce allocation [12, 22]. Automated data collection and processing have the potential to enhance construction labor productivity and add value to project performance [52]. Additionally, automated construction monitoring eliminates the gap between task completion, reporting, and approval. It has the potential to streamline financial transactions for invoices and bridge gaps [53].

The primary focus of this study centered on an in-depth review of existing literature and the authors' knowledge regarding the integration of autonomous robots in construction monitoring, including their experience with similar experiments. However, due to the limited body of research available, the efficacy of the suggested framework requires further investigation through upcoming experiments within construction projects. Additionally, the successful deployment of quadruped robots in indoor settings necessitates careful consideration of existing limitations, technology acquisition costs, operational challenges, ambient environmental factors, and safety considerations associated with human-robot collaboration.

Evaluating the long-term sustainability of benefits in adopting a quadruped robot necessitates project stakeholders to comprehensively assess cost factors, covering initial investment, operational expenses, and maintenance costs over its entire lifespan, rather than merely throughout a specific project [54]. In addition, by ensuring ambient lighting in the construction environment [35, 36, 42, 55], the robot can be utilized during sparsely populated night hours [56], improving safety and efficiency and adding value to the project's daily performance and outputs.

During the construction phase, the application of quadrupeds may encounter operational limitations in tasks involving elevated heights, such as inspecting steel framing, building facades, and false ceilings [35, 41]. Optimal lighting conditions are crucial for the robot's effective operation, as it may struggle to detect obstacles in shadowy areas and transparent elements like glass doors and windows [35, 36, 55, 56]. Consideration of these factors ensures safe and optimal performance in diverse environments and enables the construction industry to explore new technological advancements to improve construction monitoring processes.

7 Conclusion and Future Research

Construction robotics has experienced remarkable progress, marked by notable advancements. Despite this progress, persistent technical challenges include functional integration, localization, planning, guiding algorithms, sensor technology, and robot intelligence [57]. Nevertheless, the construction industry's unstructured, complex, and dynamic nature is being effectively addressed by recent advances in artificial intelligence, incorporating machine learning and deep learning methods [58]. This research has proposed the initial step to bridge the gap between collecting data and processing and updating construction schedules, eliminating the lag between actual and reported progress in construction environments.

Additional steps are required to Implementing the proposed framework and system architecture for a robot in construction settings. Moreover, customizing the robot for a specific construction site would aid in assessing its functionality and operational efficiency for project monitoring and scheduling. Furthermore, investigating the integration of diverse unmanned vehicles alongside the robot, such as ground vehicles, drones, and swarm systems, either individually or in conjunction, can help overcome the limitations of quadrupeds.

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