A Review of Computer Vision-Based Techniques for Construction Progress Monitoring

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Abstract –
Monitoring the progress of construction operations on site is crucial to keep an up-to-date schedule. In the past, manual methods were used for that purpose, which lead to errors and delays in generating up-to-date schedules. Current practices and research lines have been studying different methodologies to reach a fully automated progress-monitored construction.

Automated progress monitoring and tracking are important to avoid delays and cost overruns resulting from a lack of timely management decisions. Manual reporting and human intervention on site are error-prone, time-consuming, and can negatively impact productivity. Recently, computer vision techniques are proving to be cost and time efficient for monitoring and progress reporting of construction operations.

This paper investigates the required steps and technologies used to have an automated tool for progress monitoring. The paper also provides a review of the common methodologies used, previous practices, limitations, and future directions for the evolution of automated construction progress monitoring.
Keywords –
Progress Monitoring; Automation in Construction; Sensing Technology; Computer Vision; Data Acquisition

1 Introduction

Construction progress monitoring is crucial aspect of construction projects, as it plays a key role in ensuring process control and the success of the project [1, 2]. Failure to monitor construction progress accurately has been found to result in cost overruns in more than 66% of the projects and schedule delays in more than 53% of the projects[2]. The pressure of monitoring the budget and adhering to the schedule can also have an impact on the quality of work during the progress of the project [1]. Therefore, it is essential to select an efficient data acquisition tool that can measure construction progress in an accurate and efficient manner. Various studies have investigated different technologies commonly used on construction sites for daily monitoring, reviewed data acquisition methodologies, and evaluated methods of storing, and reviewing data [2, 3].

Computer vision (CV) is an artificial intelligence branch that leverages images to obtain visual data that resembles human visualization. In the recent times, CV has attracted significant interest from researchers due to its impressive capabilities of automation in construction. CV can be applied in different fields, such as quality control, progress monitoring, and quality management [4–6]. Several CV technologies, including Laser scanning, photogrammetry, and videogrammetry, have been studied for data acquisition. Additionally, several startups, such as OpenSpace, Smartvid.io, and HoloBuilder have emerged in recent years.

Laser scanning is widely regarded as the most accurate method of data acquisition. However, this method is also known to be very expensive and requires a long data-acquisition time [7]. In contrast, taking daily images using cameras has gained popularity due to their cost-effectiveness and ease of accessibility. This development has led to extensive research on data acquisition and construction site monitoring using various forms of media [8].

The objective of this study is to provide a systematic review of recent developments and necessary steps to reach automated progress monitoring using computer vision-based technologies, recent studies, challenges, and future directions.

2 Research Methodology

In this research, a systematic literature review methodology was used to gather most research on the use of computer vision-based technologies in construction progress monitoring. The literature was collected through the following databases and search engines; google scholar, Web of Science, and Scopus. The keywords that were used in this study include: “automated project monitoring”, “construction project updating”, “construction progress tracking”, “construction progress detection”, “construction progress recognition”, “progress monitoring”, “progress tracking”, “computer vision”, “image processing”, “3D scene reconstruction”, “building information modelling”, “deep learning”, and “as built 3d reconstruction”. The papers were scanned and filtered to include only the related papers from review papers, peer-reviewed conference proceedings and journal papers. Another further filtration was processed to include only papers in English and papers that were published from 2013 to 2022. After the screening and filtration, a total of 156 papers were selected and reviewed. The papers were then configured according to the year of publication and were categorized into “Journal Technical papers”, “Review papers”, and “Conference Technical Papers” as shown in Figure 1 and further details about technologies used, mounting method, whether indoor or outdoor and they key focus of these studies shown in Table 1.

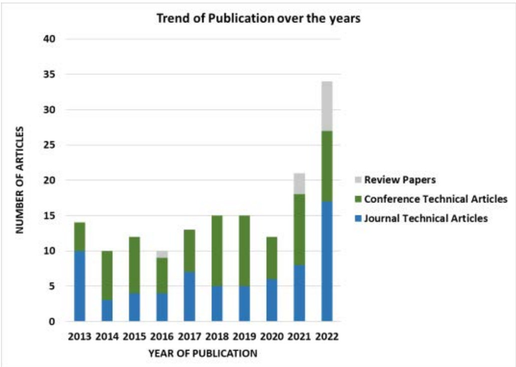

Figure 1. Papers Distribution and categorization

3 Overview of vision-based monitoring of construction progress

Based on literature review, the process of monitoring construction progress using computer vision in any construction site can be divided into three main steps. These steps are illustrated in Figure 2 and provide an overview of the framework for computer vision-based construction progress monitoring (CV-CPM).

In the following sections, each of these steps will be discussed in detail. Specifically, Section 3.1, will cover the data acquisition technologies and the various methodologies used for mounting cameras or other data acquisition devices. Section 3.2 will describe the 3D reconstruction process, including the methods and algorithms used to generate a three-dimensional model of the construction site. Finally, 3.3 will address the last step in the process, which involves generating an as-built model from the 3D reconstruction and comparing it with the as-planned model.

By following these steps, construction project managers and stakeholders can use computer vision-based monitoring to track and manage construction progress more efficiently and accurately. This approach can provide valuable insights into the construction process, facilitate decision-making, and help identify potential issues or delays.

3.1 Data Acquisition

Data acquisition is the first and most important step in the CV-CPM process. The method used will determine how well the construction site can be monitored and how subsequent steps can be developed. To successfully manage a construction site, the acquired data must be accurate and reliable, covering all aspects of the site and updated regularly to reflect changes in the schedule and to generate an as-built model [9].

The Architecture, Engineering, and Construction (AEC) industry leverages various imaging devices to acquire data, such as monocular/binocular cameras, Unmanned Aerial Vehicles (UAVs) with cameras or video cameras, video cameras, laser scanners, depth cameras, and others. The key performance indices of these devices are presented in Table 2 [10]. For competent project management and control, the team must acquire an accurate data collection methodology in order to be able to compare it later with the as-planned data and stay up-to-date with the actual progress to deliver a time and cost-efficient project [11] . There are different types of technologies used for data acquisition,

Table 1 Review of papers used vision-based progress monitoring.

Paper	Technology	Mounting Method	Indoor/Outdoor	Key Focus
[12]	Camera	Fixed	Outdoor	Bridge
[13]	Laser Scanner	Manual	Outdoor	4 story building
[14]	Digital Camera + Laser Scanner	Fixed / Manual	Outdoor	Structural work for a residential building
[15]	Lidar	Manual	Outdoor	Bridge
[1]	Camera	UAV	Outdoor	Columns

[16]	Camera	Manual	Indoor	Plastering
[17]	Camera	UAV	Outdoor	Building structure
[18]	Depth Camera	Manual	Indoor	Building Elements
[19]	Camera	Manual	Both	Walls
[20]	Laser Scanner	Manual	Both	Rectangular Columns

but the types of technologies used for data acquisition, but the type of data extracted from them doesn't only depend on the type of technology but also on the method of mounting these technologies.[21]

Table 2. Device performance comparison

Technology	Mounting Method	Data Type	Cost	Technical Threshold	Resolution
Camera	Fixed	Photos	Low	Low	High
	UAV/UGV	Photos	Medium	Medium	High
Video Camera	Fixed	Video	Low	Low	Low
	UAV/UGV	Video	Medium	Medium	Low
Laser Scanner	N/A	Point Cloud	High	High	High
Depth Camera	N/A	Point Cloud	Medium	Low	High

The data generated by these instruments can be categorized into two types: image and point cloud. The laser scanner, which produces point cloud data, exhibits feature such as high equipment costs and technical requirements, rendering it unviable for most construction companies. Consequently, images, including photographs and videos, are employed as a feasible substitute. Multiple devices can be used to obtain images, with most of them being low-cost, possessing low technical demands, portable, and high-resolution. As a result, image-based 3D reconstruction is a critical technology for automated progress monitoring [10].

Various studies have investigated the use of different acquisition technologies and their combinations for vision data acquisition. Digital cameras [12, 14], video camera [22], laser scanner [23], and range imaging (RGB-D camera)[24, 25] are commonly used technologies. These technologies can be mounted in different ways, such as being fixed in a location with minimal movement, handheld, or mounted on unmanned ground or aerial vehicles, including drones equipped with optical sensors or digital cameras [26] .

Unmanned aerial vehicles (UAVs) have gained popularity in the construction industry due to their low cost, speed, and ability to collect data in areas that may be difficult to reach for humans or ground-based vehicles [11]. However, operating UAVs requires expertise and careful planning of flight paths with various data capturing angles. Modern UAVs now allow pre-planned flight paths to be programmed [11, 27, 28].

Handheld devices such as mobile phones, small digital cameras, or video cameras are also widely used on construction sites to collect daily photologs and record construction updates due to ease of access and availability. [26, 29]. The visual data captured by these devices can be used to create 3D as-built models in various studies.

Other studies have explored the benefits of mounting digital cameras on fixed cranes, camera mounts [25] and using surveillance cameras for progress monitoring and reporting instead of installing an additional video cameras [30]. Additionally, sensors can be mounted on unmanned ground vehicle (UGV) using robotic systems or unmanned aerial vehicles (UAV) [22, 31, 32]

3.2 3D Reconstruction

Three-dimensional (3D) reconstruction techniques have been increasingly used in construction engineering to obtain the 3D representations of objects, such as point cloud models, mesh models and geometric models. Among these, point cloud models are the most commonly used [3]. 3D models can be generated from 2D and 3D visual data, and this step involves generating 3D models (mesh models, geometric models and point clouds) from the output of cameras, video cameras, laser scanners, or range cameras [10]. The main objective is to transform the output of each of sensing technology into an as-built point cloud model [3, 10]. The data collected can be either monocular, stereo, RGB-depth images, or video frames.

After the data acquisition step, the next step is to process 3D reconstruction algorithms to generate the point cloud model. Laser scanner output already generates point cloud models and does not require further processing. However, digital camera images and video frames do not include any location information, accordingly, the SfM (Structure from Motion) approach is used to add depth information for sparse 3D reconstruction.

Depth images generated from depth cameras (RGB-D) contain three coordinate information (XYZ coordinates) along with color information (RGB). This information is used for mapping and executing 3D reconstruction using extrinsic and intrinsic camera factors [33].

This paper presents the basic concept of Structure from Motion (SfM) as a technique for photogrammetric 3D reconstruction from multiple image frames. SfM combines algorithms for feature extraction, feature matching, camera motion estimation, sparse 3D reconstruction, and model parameter correction [10, 34]. The quality and sequence of the image frames obtained are crucial for feature matching of image pairs. However, SfM can work with unordered image frames, making it suitable for construction sites that collect images from multiple location-aware sensors. Visual SfM and Open SfM [35] are popular implementations of SfM.

3.2.1 SfM (Structure from Motion)

Structure from Motion (SfM) is a photogrammetric technique used to reconstruct a 3D model/point clouds from 2D images of a scene or object. SfM requires at least two or more images of the same scene taken from different viewpoints to triangulate the 3D positions of points in the scene. It belongs to the quantification photogrammetric techniques, which involves collecting real-life measurements from 2D image dataset [36]. SfM automatically detects and matches features from an image dataset of varying scales, angles, and orientations, and collects feature points that reflect the primary formation of the scene. The inputs are in the form of image data with recommended 60% side overlap and 80% forward overlap between images to achieve high-quality and detailed 3D models/point clouds as outputs [37].

The technique has been applied in several studies that exploit images taken from construction sites for productivity analysis, quality control, progress monitoring, and safety. These applications allow project management teams to visualize as-built data and exercise better control over the project [1, 19].

The next step after feature point collection and camera position estimation is absolute scale recovery and dense 3D reconstruction. This is necessary because the output from the initial step is sparse.

3.2.2 Absolute Scale Recovery

After processing images and video frames captured by cameras and video cameras using SfM, the resulting outputs are typically sparse and non-scalar point clouds that require absolute scale recovery and dense 3D reconstruction. Absolute scale recovery is the process of determining the real-world size and distance of the reconstructed 3D scene. While laser scans do not require this step, determining the absolute scale of the sparse point cloud is achieved using local coordinates. This typically involves manual techniques, such as using pre-measured objects or georegistration, although the latter can be automated by sensing the camera parameters rather than relying on manual measurements and ground truth.

3.2.3 Dense 3D Reconstruction

Dense 3D reconstruction involves recovering the actual scene with all its details, which is done using various algorithms such as SGM (semi-global matching), CMVS (clustering views for multi-view stereo), MVS (multi-view stereo). This step is essential as the point clouds reconstructed from monocular or stereoscopic images or video frames are sparse. On the other hand, the reconstruction output from the depth images is dense enough and does not require dense 3D reconstruction. After generating the dense point cloud, the next step is pre-processing, which includes registration, noise filtering, down-sampling, and outlier removal [21].

3.3 Model Generation

To assess the current state of progress, determine whether it is behind schedule, ahead of schedule, or on track, and potentially take corrective action, it is necessary to compare the as-built model data obtained from the previous step with the as-planned data.

This step, illustrated in Figure 2, involves generating the as-planned model and identifying its features. By comparing the two models, it is possible to identify any discrepancies and assess the level of conformity with the original plan.

3.3.1 As-planned model

As planned models are the baseline plans for a project, typically created during the design phase. To monitor progress accurately and ensure functionality, as-planned models are essential for comparing against the as-built models. As-planned model, or 4D models, combine a3D BIM model with the project's time schedule. As-built models are then overlaid onto the 4D BIM to facilitate comparison between the two models.

3.3.2 As-built model

The creation of accurate as-built models involves several essential steps. The first step is to acquire a point cloud generated from the previous stage or obtained from laser scanners. The main step in generating as-built models is point cloud pre-processing, which involves eliminating outliers and noise points from the acquired point cloud [38]. Outliers and noise points are unnecessary points from the surroundings that can be removed using outlier removal and noise filtering processes [39]. Common algorithms used for both processes include manual point removal from the surrounding [40] and RANSAC [39]

Moreover, the process of overlapping the point cloud during registration makes the model dense and requires down sampling to avoid reducing the efficiency of the subsequent processing. A point spacing strategy algorithm, typically used for down sampling [41],

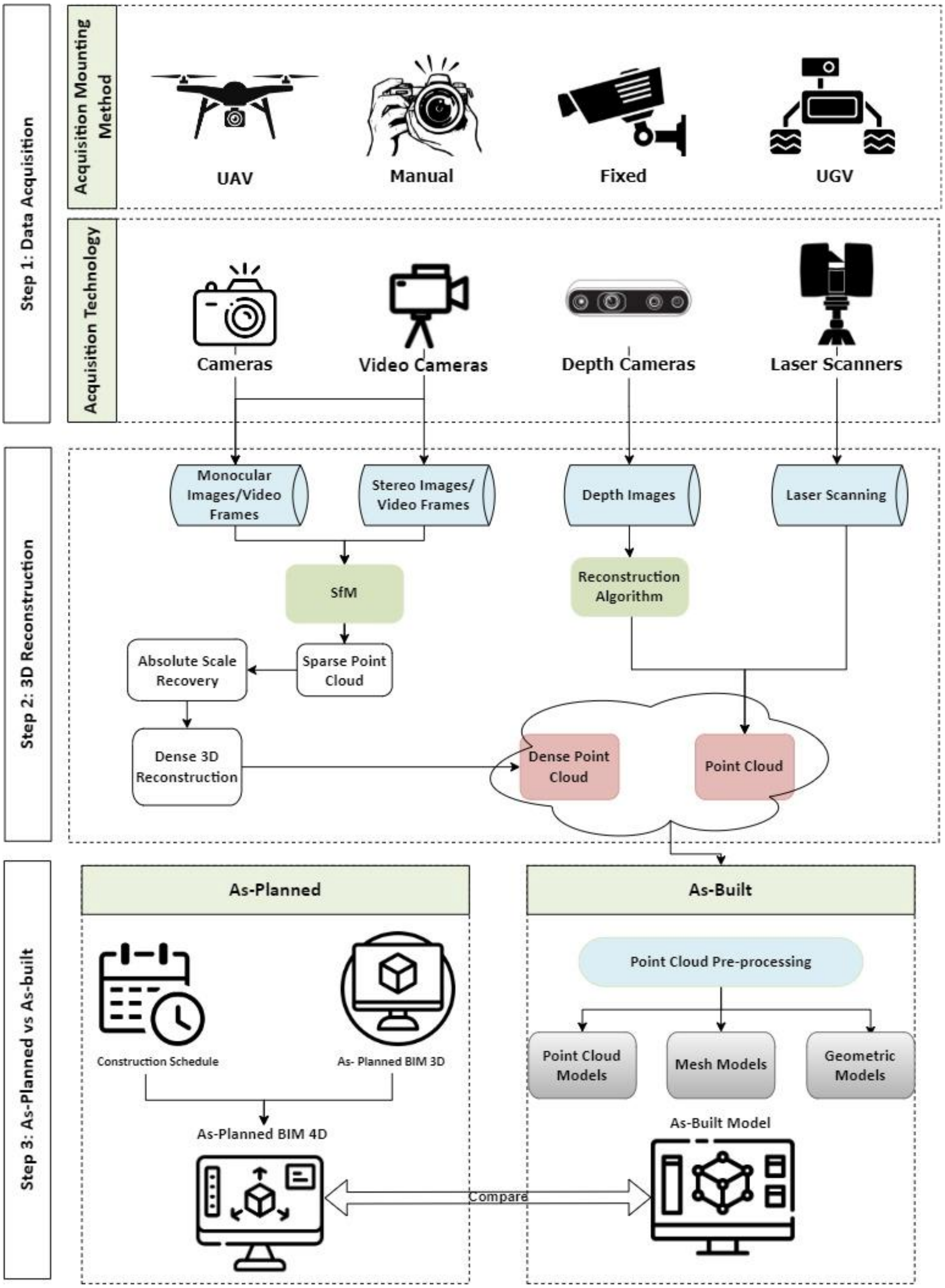

Figure 2 Framework for computer vision-based construction progress monitoring (CV-CPM)

organizes the point cloud into a 3D grid cell with equivalent portions. Points in each single 3D grid cell, including at least one point, are reduced until they meet the requirements [42].

Previous studies have identified three main types of as-built models: point cloud models, mesh models [24], and geometry models. The level of progress monitoring proposed for a project plays a vital role in deciding the type of as-built model to be generated.

3.4 Visualization & Quantification

The literature has discussed various methods of visualization, including color labels, Augmented Reality (AR) [43, 44], 3D model Viewers, Virtual Reality (VR) Environments [18] and Mixed Reality (MR) Environment [24]. Visualization plays a crucial role in enabling the continuous monitoring of construction sites and is considered a predominant method for sites implementing Computer Vision-based Construction Progress Monitoring (CV-CPM) methodology.

Quantification, on the other hand, is primarily useful for contractors, owners, and other stakeholders for reporting and tracking progress on the site. It involves quantifying the completed work tasks, which helps in understanding the overall progress of the project.

4 Discussion

The present research study addresses the crucial role of automated progress monitoring in construction projects, which can significantly improve project management and enhance project outcomes. In particular, the study aims to shed light on the potential benefits and techniques of implementing computer vision technologies for automated progress monitoring.

To achieve this aim, the study provides an overview of various computer vision technologies that can be used for automated progress monitoring. This includes a detailed exploration of the different techniques for mounting these technologies and integrating them into the construction process.

Moreover, the study explains the process for creating a 3D as-built model, which is a critical component of the automated progress monitoring system. The model is generated by following a sequence of steps that include data acquisition, registration, and integration, which are described in detail.

Finally, the study describes the algorithm used for estimating progress based on the data collected, which is the final step in the automated progress monitoring system. The algorithm considers various factors, such as the current state of the project, the expected completion time, and the rate of progress, to provide an accurate estimate of the project's status.

In summary, the present study contributes to the growing body of research on automated progress monitoring in construction projects. By providing a comprehensive understanding of the potential benefits and techniques of implementing computer vision technologies, the study can assist construction professionals in improving project management and enhancing project outcomes.

A systematic review was conducted to identify applications of digital images and computer vision techniques for construction progress monitoring and reporting, as well as integrated frameworks utilizing Building Information Modeling (BIM) and computer vision. Challenges in 3D reconstruction within the construction industry were also documented, emphasizing the need for future research to improve the accuracy and efficiency of algorithms used to produce point clouds. Furthermore, the study identified opportunities for automated integration of computer vision activities with BIM for as-built modeling. Our research aims to develop a real-time building progress monitoring framework that leverages sensor technology and enhances algorithms to further advance the field.

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