A REVIEW OF COMPUTER VISION-BASED PROGRESS MONITORING FOR EFFECTIVE DECISION MAKING

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ABSTRACT: *Construction Progress Monitoring (CPM) is a significant aspect of project management aimed to align planned design with the actual construction on site, the process ensures that the project is well within the control of the stakeholders involved and ensures the project is completed complying with the construction documents, on time, and within budget. Despite how central progress monitoring is to attaining project success and advances in technology, the progress monitoring is majorly implemented manually, which requires manual retrieving and processing of site data to compare with the planned design. This manual process is both time-consuming and prone to errors. Automating the task of progress monitoring involving real-time data acquisition and timely information retrieval can assist the project managers for effective decision making to the successful delivery of the project. Thus, the objective of this research was to assess the impact of computer vision (CV) – based progress monitoring as a driver for effective decision-making in project management. A qualitative methodology was implemented for this research using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to review and analyze studies on the application of computer vision (CV). The study reviews studies of CV based CPM process, highlighting its benefits against the traditional method of progress and the limitation to its adoption. Research findings from this paper provide an increased understanding and have a broader scope on the application of computer vision-based progress monitoring.*

KEYWORDS: Computer Vision, Construction progress monitoring, Decision-making, Project management

1. INTRODUCTION

Progress monitoring involves the processes required in tracking, evaluating and organizing the performance of a project, and identifying areas where modification needs to be implemented (PMOK, 2017). In the development phase of construction projects, site activities are tracked by the project manager using progress monitoring methods (Qureshi et al., 2022). Progress monitoring of a construction project is essential to the successful delivery of the project, this is because it entails recognizing the disparities between the planned design and the ongoing construction. As most tasks are interdependent, frequent inspections assist managers to detect anomalies early, avoid potential delays, and decide when to take remedial action (Reja et al., 2022). The progress monitoring phase is regarded as a complex task, it requires efficiency as it provides the essential inputs to the managers on site for prompt and informed decisions. This process, when done effectively helps to prevent cost and schedule overruns and improve the retrieval, management and processing of site data (Kopsida et al., 2015). According to Hanet et al. (2016), the limitations in manual and other conventional data acquisition procedures in progress monitoring cause more than 53% of construction projects to fall behind schedule and more than 66% of them to fall short financially.

The traditional method of progress monitoring of construction projects involves manual retrieving of data, information processing, documentation, and reporting on the project status. However, this method is time-consuming, information obtained are prone to human errors, and often report obsolete information which impedes effective decision-making from stakeholders (Rehman et al., 2022). To improve this, the process can be made effective through automation. Technologies exist for the automation of progress monitoring; with focus on retrieving data from the site, some of which include unmanned aerial vehicle (UAV), geographic information system (GIS), virtual reality (VR), augmented reality (AR), radio frequency identification (RFID), and global positioning systems (GPS). However, computer vision technology can be consolidated with these technologies to be implemented for progress monitoring. Computer vision (CV) is similar to the human vision, but utilizes machine learning algorithms or deep learning models in analyzing, predicting and making useful interpretation from data inputs which could be images or videos (Paneru & Jeelani, 2021).

For the automation of construction progress monitoring, a noticeable amount of research has been carried out. An overview study conducted by Ekanayake et al., (2021) on the application of computer vision-based interior construction progress monitoring. The study categorized the challenges that hinder the successful implementation of CV based interior construction project monitoring (CPM) into indoor objects, lighting condition and movements of the camera used. However, the study mostly focused on challenges for interior use. McCabe et al., (2017) also

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investigated on indoor CV-based CPM, their study identified the challenges encountered using UAV's. for automated data retrieval. A related study by Kopsida et al., (2015) categorized the different stages involved in the automation process in terms of technology used and assessed, time efficiency, accuracy, cost and mobility. Most of the studies highlighted the need to overcome challenges for the successful implementation of a CV-based CPM. The objective of this study is to assess the impact of CV– based CPM as a driver for effective decision-making in project management. Investigating how this technology can improve decision making, by revealing its current level of adoption identifying the benefits, and the limitation involved to its application.

2. METHODOLOGY/APPROACH

For this study, a systematic review was conducted. This type of review involves identifying all relevant literature that is pertinent to the review question, critically evaluating identified literature and summarizing the findings (Gough et al,.2012). It helps to answer an important question or identify areas of importance relevant to the research question (Harris et al., 2014). The review begins by posing a research question, identifying relevant studies, critically evaluation of the studies, data collection, analyzing and structuring of the data, summarizing the evidence and reporting findings from the study (Khan et al., 2003). While the systematic review approach has been predominately used to conduct research in the medical field (Munn et al., 2018). It has been used several times in the field of construction management; for a review of sustainable construction management (Araújo et al., 2020), a review of the concept of buildability as it relates to construction management (Osuizugbo et al., 2022), and a review of the inter-relationship building information modeling (BIM) and safety in construction (Martínez-Aires et al., 2018). This is because the output from this type of review is usually comprehensive and exhaustive requiring an explicit methodology and helps present output in a structured sequence (Shamseer et al., 2015)

This systematic review was conducted using the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) which include four stages: Identification, Screening, Eligibility, and Includes (as shown in Figure 1). The databases sources used were Scopus, Web of Science (WOS) and Civil Engineering Database from the American Society of Civil Engineering (ASCE). Google Scholar was also used for the search of relevant studies. Keywords used in the databases for search include, "Computer vision" and "construction progress monitoring," as well as "Computer vision-based construction progress monitoring." For relevant extant literature, the search range was from the year 2005 upward. Duplicate files, and records having a different language from English that could not be translated were also excluded. Also, some papers had a methodological approach that did not align with the objective of this study, such papers were screened out. After screening and eligibility criteria the total number of papers evaluated and appraised for this study were 47.

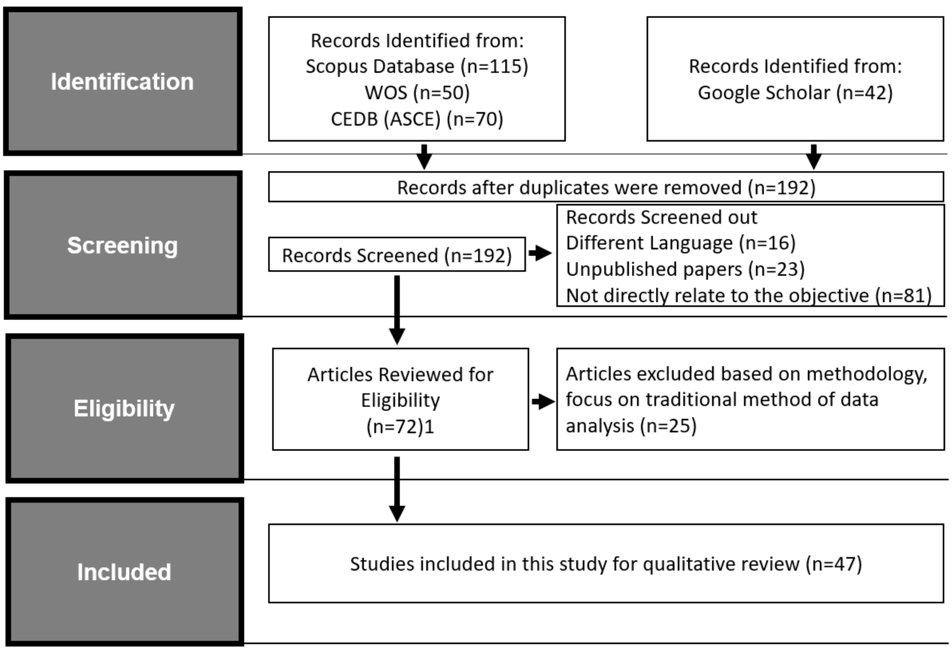

Fig. 1: Flowchart showing the systematic review process using PRISMA.

3. ANALYSIS AND RESULTS

3.1 Description of subprocesses of CV-based CPM process

In recent times, the application of CV-based CPM in project management has gained traction as the advantages it possesses has been observed to aid stakeholders for an effective decision-making process in the lifetime of a project (Braun et al., 2020). Different studies categorized the sub processes involved in CV-based CPM. The categories include, data acquisition, information retrieval, progress estimation, and output visualization (Kopsida & Vela, 2015; Rehman et al., 2022). Data acquisition and 3D reconstruction, as-planned & as-built modelling and progress monitoring (Reja et al., 2022). This review categorizes the process into three data acquisition, information retrieval and progress monitoring and visualization as shown in Figure 2. Each of the subprocess is summarized based on review of extant literature. The sequence is such that the data obtained automatically is analyzed to retrieve germane information such that there can be a systematic comparison between the as-planned and the as-built structure, and the disparities are made known in a comprehensible pattern. This section reviews the subprocesses associated with CV-based CPM.

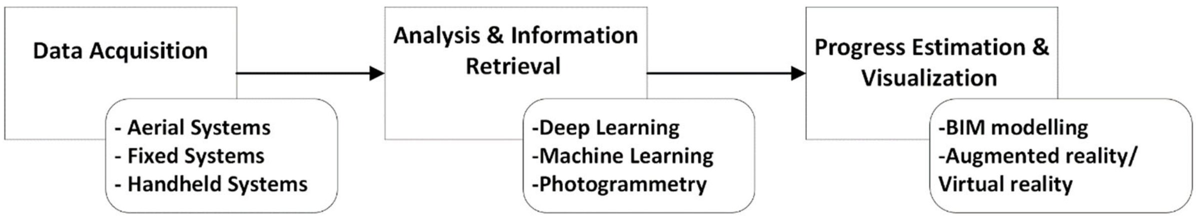

Fig. 2: Subprocesses of the CV based CPM.

3.2 Data Acquisition

Data format for automated progress monitoring include but not limited to two-dimensional (2D) or three-dimensional (3D) images, from cameras and depth cameras respectively (Omar & Nehdi, 2016). Videos obtained from videos cameras which could be fixed or mobile with the aid of technologies such as unmanned aerial vehicles (UAV), or unmanned ground vehicle (UGV). Also, a point cloud which involves tiny points which could be plotted for relevance in a 3D space or surface that can be sourced from 3D laser scanners like light detection and ranging (LIDAR) (Paneru & Jeelani, 2021a).

The construction site is known to be very dynamic in nature, consisting of various activities occurring most times intermittently (Ibrahim et al., 2009). Thus, the need to have a comprehensive overview that can be augmented by using digital images and videos in monitoring construction progress requiring little expertise because of the simplicity in its application. Table 1. Shows a summary of the data acquisition subprocess indicating the method of acquisition, devices utilized in this method, the benefits and the limitations to its use.

Table 1: Computer Vision Data Acquisition

Acquisition method	Devices	Benefits	Limits	Ref.
Aerial systems	UAV's integrated with sensors	- Provides a detailed coverage of site - Maneuvers complex areas which are difficult to manually navigate. - Can be integrated with sensors like cameras and laser scanners	- Requires expertise and certification to operate - It could be expensive depending on the specification - Precision when use is required	(D. Kim et al., 2019; McCabe et al., 2017)
Fixed Sytems	Surveillance cameras	- Provides stability for more clarity in data input obtained - Adequate for sustained period of data acquisition	- Restricted to one angle of view. - Not efficient for comprehensive coverage	(Benyeogor et al., 2020)

Handeld systems	Mobile cameras, tablets, smartphones	- Portable and handy making it comfortable for use - Provides flexibility in use, no restriction in getting elevations and angles - Best for use in getting up-close data for clarity	- Requires multiple takes to cover the entirety of construction space - Data obtained is subject to the users bias and accessibility.	(Jeon et al., 2006; Mahami, Nasirzadeh, Ahmadabadian, et al., 2019)

3.3 Information Retrieval & Analysis

The data retrieved in form of images and videos needs to be analyzed in order to obtain useful information, which will be vital for progress estimation (next sub-process). Some of the commonly used methods includes traditional machine learning technique which includes support vector machines, Hough transform, artificial neural network and deep learning techniques using deep convolution neural networks (CNN). Zhu et al., (2010) proposed a novel technique using Hough Transform Technique to analyze 373 images of large-scale concrete columns for inspection of surfaces to detect defects, the technique when evaluated performed well with a high precision of 89.7% and recall of 84.3%. Kim et al., (2013) presented a method for measuring construction progress based on information included in 4D building information modelling (BIM) and 3D data, the data was classified using support vector machines (SVM) classifier, the SVM model was trained using a labelled 3D data. Because the initial as-built statuses of some components may be inaccurate as a result of an incomplete 3D data set, a two-stage revision was performed. The first stage was based on the sequence of activity execution and the second stage was based on the connectivity between components. Both the sequence of activity execution and the connectivity between components were stored in the BIM. The final as-built statuses produced by this process may be used to determine actual finish dates and to measure actual construction progress. The accuracy of the proposed method was validated using an incomplete set of 3D data acquired on an actual construction site achieving 99% precision rate on the second revision. Additionally, Wang et al., (2021) proposed a vision-based framework for monitoring precast walls during construction, using convolution neural networks (CNN) based computer vision method including Mask R-CNN and DeepSORT to realize object detection, instance segmentation and multiple objects tracking on the dataset obtained from surveillance cameras. The output from the study confirmed the detection rates of CNNs are fast compared to other techniques, this agrees with studies from (Paneru & Jeelani, 2021b; Sultana et al., 2018). Other relevant analytical methods include, Simultaneous Localization and Mapping (SLAM) (Kim et al., 2018), Structure From Motion (SFM) (Mahami et al., 2019),) Histogram Oriented Gradients (HOG) (Memarzadeh et al., 2012 ,and Laplacian of Gaussian (LoG) (Hui & Brilakis, 2013). Table 2. Shows a summary of the information retrieval and analysis subprocess indicating the analytical method, models utilized in the method, the benefits and the limitations to its use.

Table 2: Information Retrieval & Analysis.

Analytical method	Model	Benefits	Limitations	Ref
Traditional Machine Learning	HOG, LoG, SURF, Hough transform, SVM	- Can handle large data - Reliable and high accuracy when trained with balanced dataset.	- Requires large dataset - Requires preprocessing and feature extraction of data	(Zhu et al., 2010)
Deep learning	Mask R-CNN, DeepSORT	- Models can learn patterns from data in high speed - Models trained usually have accuracy - Requires no manual feature extraction or engineering	- Requires high end hardware for processing. - Requires large dataset fir better analysis,	(Z. Wang et al., 2021)
Photogrammetry	SFM, SLAM	- Usually cost effective in comparison with laser scanners - Flexibility of use on construction sites	- Long processing time - Requires hardware with	(Kim et al., 2018)

3.4 Progress Estimation & Visualization

This subprocess makes use of the information retrieved by analyzing the information retrieved. This process is usually a comparison between the as-planned model and the as-built model. The comparison is also known as registration as identified from various literature (Kopsida & Vela, 2015; Rehman et al., 2022). The output is significant for project controls as it gives an update on the project schedule; if the project is on schedule or behind schedule by showing the extent of construction which has been put in place on site (Reja et al., 2022). The result of this comparison is necessary in identifying the successive steps which the stakeholders can take in order to meet the project's objective. The concept of building information modelling (BIM) is very prominent in this subprocess, as the format of the as-planned model can be presented in the four-dimensions 4D BIM model for comparison. After the comparison process, a matching process to see the disparity between the observed and the planned is conducted. The use of voxels, object matching, and probabilistic model have been used to detect progress. This progress is visualized using technologies which enable immersion such as Augmented reality and virtual reality (Ahmed, 2019). Several studies have identified the use of AR and VR as better visualization tools for progress monitoring (Omar & Nehdi, 2016; Rohani et al., 2014). In a case study, Meža et al., (2015) conducted a survey comparing AR with traditional visualization techniques like Gantt charts, AR ranked highest in "understandability of project documentation in monitoring of construction" and "usability of project documentation in monitoring of construction". Wang et al., (2013) proposed a framework for integrating BIM with AR; the platform which is able to couple BIM and AR so that information about 'as-built and as-planned progress' as well as 'current and future progress' can be obtained and presented visually. Comprehensively, consolidated studies have identified AR and VR technologies to be ideal visualization techniques in progress monitoring, as they have shown to facilitate understanding of construction progress estimation.

3.5 Cost and Time-factor of Traditional and Computer Vision-based Progress Monitoring

In project management, cost and time are very significant factors that are used in defining the success of the project, and mangers are constantly seeking ways to optimize cost, be on schedule and to meet standard requirements of a construction project (Chan et al., 2004; Luong et al., 2021). They are also very important criteria which managers and stakeholders consider during decision-making in construction. Hence, it is imperative to include these parameters for the comparison of CV-based CPM and traditional progress monitoring. The cost of setting up a CV based CPM is relative depending on the devices used in each subprocess. In comparison to the traditional method which requires no automation or negligible technology, is perceived as an expensive process. Expenses including purchase of equipment, software, maintenance cost, technical support personnel and the training of users (Omar & Nehdi, 2016). Additionally, numerous researches have shown that CV based CPM is a time-saving and efficient process (Golparvar-Fard et al., 2009; C. Kim et al., 2013). In a case study conducted by Braun et al., (2020), using deep learning technique with sfm-based data consisting of categorized images of formwork, scaffolding and columns, a real time comparison between the as-planned and as-built, to detect progress of site activities was achieved in real time. When evaluated, the method produced a high precision of 90% in detection rate, enormously saving time in the process.

3.6 Comparison between Traditional progress monitoring and CV based CPM

In this section, the CV-based CPM was compared with the traditional progress monitoring using relevant indices which can assist stakeholders when making decision on both methods. Table 4 shows summary was obtained from the systematic review of literature on the application of both methods.

Table 4. Summary of the comparison between CV-based CPM and Traditional progress monitoring

Evaluation Criteria	CV-based CPM	Traditional Progress Monitoring
Data Acquisition	Reliable and timely	Depends on the sense of judgement of the personnel executing the task
Information retrieval & Analysis	Requires expertise from the personnel performing the analysis, mistakes can be spotted and quickly	Requires more of human input, personnel involved in the process needs to be properly trained to avoid errors, which will lead to impact on the project.
Progress monitoring & visualization	The use of BIM/virtual reality/augmented reality gives a sense of realism and immersive and provides sturdy detail of the project.	Doesn't provide the realism and immersion that CV based CPM provides. Output might be difficult to interpret.
Cost	Process can be expensive, especially cost of hardware, software and training	Cost relatively cheaper when compared to CV based CPM

Time	Generally, saves time, notable for efficiency in site management.	Time consuming process

3.7 Limitations to the application of CV-based CPM

Despite the benefits which CV based CPM process offers to stakeholders to enable effective decision making, there still exist some barriers which leads to the hesitation to its adoption. Some of these limitation include; lack of technical expertise on software and hardware, adverse weather conditions, occlusions, specifications of data acquisition device. These limitations were grouped into three which include, environmental factors, technical factors and human factors.

Environmental factors are the barriers within the site location which prevent successful application of CV-based CPM. This includes, the impact of weather, for automating the data acquisition subprocess. The impact of the weather isn't negligible as adverse weather condition distorts the quality of the image which inadvertently leads to poor analysis of the input (Omar & Nehdi, 2016). Poor lightning condition is also significant in the processing of input data. Hamledari et al., (2017) proposed a framework that automatically detects components of an interior partitions using 2D images, their study inferred on the significance and impact of good lightning in order to achieve good results on the detection of site objects. Other environmental factors include, air quality, site condition, due to varying activities, certain sites may be too clustered leading to data acquisition device hindered view of the entirety of work site space.

Technical factors include the factors related to the technology implemented in each of the subprocess. Some are, the specification of data acquisition devices, image and video capturing devices, knowledge on the appropriate devices for the type of data required. Also, for the information retrieval, knowing the proper analysis on the data can be challenging, certain techniques require a lot of data to be trained in order to give a desired output (Moragane et al., 2022). Aerial systems like the UAVs require certifications, and a level of technical knowledge to operate, this can be challenging especially if it's a small-scale project involved.

Human factors are largely critical to the successful implementation of CV-based CPM. Barriers such as privacy issues, and reduced creativity from workers due to the displeasure caused by the feeling of being monitored (Ibrahim et al., 2009; Moragane et al., 2022). Despite this method being an automated process, certain subprocesses require the input of personnel in order to operate. For example, at the information retrieval subprocess, the technical know-how of the personnel executing the task is significant and as such requires requisite training (Paneru & Jeelani, 2021a).

3.8 Intellectual Merit / Broader Impact

The intellectual merit of this work is how it reviews CV based CPM, highlighting on the process involved, developing an evaluation criterion to compare CV-based CPM with the traditional monitoring process, also identifying limitation to its application in project management. The broad impact of this work is will yield an increase understanding of CV based CPM by as an alternative to the traditional monitoring process, as its current level of adoption is still at its nascent stage. A simple holistic understanding of the process by stakeholders can assist in a more informed decision towards project monitoring in project management.

3.9 Conclusion

In project management, construction progress monitoring is a very significant process in achieving a successful project delivery. However, most projects still undergo the traditional manual progress monitoring process. The process has been identified to be time consuming, error prone and subject to the bias and technical know-how of the personnel involved in the process, and this concern leads to the need to automate the process. The objective of the paper was to assess the impact of CV based CPM as an effective decision making tool by highlighting key subprocesses involved in the process, including listing an evaluation criteria for comparing the CV based CPM with the traditional manual monitoring process, and to identify barriers to its adoption as a project monitoring tool in project management. A systematic review was conducted, to evaluate literature relating to the topic. Databases from Scopus, WOS, ASCE and Google scholar were sources of data for the review, PRISMA analysis was used in screening all the papers in order to ascertain relevant literature for this study.

The outcome of this study gave a concise description of subprocesses associated with CV based CPM process. Images and videos are currently the most utilized data in this process and this is most common because of its ease of accessibility and availability of processing systems. Aerial systems which include the use of drones and augmented reality googles show great potential as an effective data acquisition device. Deep learning technique using CNN due to its speed in detection can be integrated with aerial systems for an effective monitoring system with real time output. Lastly, the study highlighted limitations for the applications of CV based CPM and categorized these as human environmental and technical factors, and the review identified technical factors to be a significant factor among others. In short, this study is important because it provides a simple holistic understanding of the process thus aiding stakeholders with accurate knowledge for decision-making towards CV based CPM in construction project management.

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