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Review

Computer vision-based interior construction progress monitoring: A literature review and future research directions

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ABSTRACT

Computer vision (CV)-based technologies have been used to automate construction progress monitoring. The automation attempts to maximise precision and minimise human intervention in onsite progress monitoring. Such attempts have mainly focussed on exterior construction environments while there are significantly lesser number of studies on interior construction. This imbalance impedes automation of the onsite progress monitoring as a whole. Thus, the core intent of this study is to pave the way for advancing automated indoor progress monitoring by providing a systematic survey of extant literature. Main contributions of this survey include 1) presenting a full spectrum of CV-based approaches, tools, and algorithms adopted for indoor construction progress monitoring (ICPM) 2) portraying a succinct reference to the shortcomings, technical challenges, and scope limitations of the past studies on ICPM. The study then synthesises a readily usable agenda for hybridising CV with other data-driven technologies to improve automation in ICPM.

1. Introduction

Progress monitoring in construction projects is crucial to determine progress discrepancies between as-planned and as-built status and to take corrective actions in a timely manner [1,2]. Inefficient and inaccurate progress monitoring are considered as two major factors accounting for time and cost overruns in construction projects [3]. The computer vision (CV)-based technologies have accelerated the automation in construction progress monitoring process thus, overcoming the challenges of labourious and error prone traditional manual methods [3–5]. CV-based methods involve acquiring, processing, and understanding 2D or 3D image data with the use of object recognition algorithms [6]. The adoption of CV for progress monitoring is concerned with modelling and replicating human vision using computer software and hardware and analysing the captured site images and measuring the work in progress [7]. The tendency to employ CV-based technologies for construction progress monitoring mainly stems from the competitive advantages in low cost, less time, and ease of digital image data collection [8–10]. Continuous advent of high-definition cameras and advancements in image processing algorithms have enhanced accuracy and reliability of CV [8,10,11].

Majority of CV-based progress monitoring studies have focused on the exterior construction environment and a few studies have been conducted for the indoor sites [10,12,13]. Based on the systematic review, the authors found that since 2005 until the final date of this survey, around 280 articles have been published on CV-based construction progress monitoring. From this collection, only 21 articles were found relevant to indoor construction progress monitoring (ICPM) with the rest being focused on exterior construction. The focus of these articles is on the physical progress monitoring in the indoor construction sites. They predominantly cover the aspects of image data collection, object detection, localisation, activity tracking, measurement, as-built vs as-planned comparison and visualisation. It is also noteworthy that the first publication on CV-based indoor progress monitoring dates back to 2009 [14], lagging four years behind the initial works published on outdoor construction activities. Yet, a little has been done thus far to fill this gap and advance CV-based ICPM.

There are significant physical and contextual differences between the exterior and interior construction environments. Exterior construction environment mostly consists of outer columns, beams and walls, while the interior mainly comprises of elements such as electrical, plumbing, fire protection, framing and drywalls [12,15]. The scope of ICPM is wide and spans from the as-built status of new fit-out projects to the as-is status of existing buildings subjected to refurbishments, renovations and retrofitting [13,16]. As the construction processes become more complicated when moved indoors [12,17], the studies on CV-based

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progress monitoring have been predominantly focussed on large physical components such as columns, beams, and floors that are viewable from outdoor [18,19]. On the other hand, construction is often presumed to be an outdoor activity, although major share of work is completed indoors [20]. As a result, the CV-based ICPM tends to be undervalued [12,13].

It has been found that interior works are prone to schedule delays and the average cost share of these works lies between 25% and 40% [21]. For example, according to [22], a commercial high rise building in Australia has a percentage cost per square meter share of approximately 40% for building finishes and services. Moreover, many schedule delays and cost overruns in the interior construction environment are caused by unrealistic understanding of the details and complexity associated with interior works [23]. Advancing ICPM will not only benefit to new constructions but also the existing buildings. Although the small separate contracts for parts of a refurbishment project make the economies of scale difficult to achieve [24], refurbishment projects have gained increased attention, with the growth of aged buildings [25] and necessity to maintain the functionality of buildings [26,27]. Therefore, the indoor conditions of the existing buildings need to be monitored effectively [25]. A key to monitor the progress of interior works is having access to real time, accurate and usable data from the scene. However, many factors associated with indoor environments make the object detection challengeable, leading to complications in CV-based data collection and algorithmic processing [10,15].

The automation in ICPM has resulted in reasonable cost and time savings [13] and has triggered the interest of the construction professionals besides academic researchers. However, lack of a systemic review on existing research studies in this context impedes the opportunities to identify research areas and directions for further developments, failing to fill the gap between indoor and outdoor construction research. A systematic review of extant literature on automated ICPM is therefore necessitated to present a synthesis of the status of application of CV-based technologies. The objectives of this study are (1) to present a holistic review of the main research approaches, tools, and algorithms in the context of CV-based ICPM and (2) to identify the areas where additional efforts are mostly required and discern the future directions, especially to increase the level of real time automation and accuracy in ICPM.

2. Methodology

This review is based on methodically screened articles retrieved from previous publications, which focus on CV-based ICPM. The review method was adopted from [28–30] and it comprises of three major steps: literature search, literature selection and data abstraction. These three steps were employed to search, appraise and collate the relevant studies on CV-based ICPM to ensure transparency and reproducibility. According to [31–33], transparency is expected in a systematic review to assure that the review process is made explicit. If the underpinning methodology is not clearly and adequately communicated, replicating the same research design in future studies will be impeded, thus constraining the reproducibility [31–33].

2.1. Step 1: literature search

Given the limitations of using only one search tool, two search tools were employed. The use of Scopus, the largest abstract and citation database of peer-reviewed literature along with Google Scholar, the largest web search engine for literature is effective in this regard [34]. Scopus covers a wide range of indexed documents and Google Scholar directs to both indexed and non-indexed articles [35]. A systematic search based on "article title/abstract/keyword" to retrieve journal papers, conference proceedings, research dissertations, scholarly reports, technical reports, industry reports and other miscellaneous publications in the area, "computer vision-based interior construction progress monitoring" was conducted. The keywords adopted were as follows; "interior construction environment", "indoor construction projects", "interior finishes", "refurbishment projects", "progress measurement", "progress monitoring", "progress tracking", "image capturing", "computer vision", "imaging technology". The studies related to CV-based construction progress monitoring amount to around 280 publications since 2005, and among them, 45 articles were initially retrieved as relatable to ICPM. These articles were exported to EndNote X9 [36] software to be organised for the literature selection.

2.2. Step 2: literature selection

Rayyan [37], a free online tool for organising literature was used in conjunction with EndNote X9 for screening and selecting articles. The titles and abstract were screened, and the duplicates were removed. Even though the titles and abstract were in English, the articles with the content not written in English were also excluded. For the remaining articles, the articles carrying the relevant keywords in their titles or abstracts, but irrelevant to the research topic explored in this study were excluded. A total of 21 articles spanning from year 2009 to year 2020 was retrieved for full-text screening.

2.3. Step 3: data abstraction

After selecting the final sample of articles, methods of abstracting appropriate information from each article should be employed in a standardised manner. This review paper followed the data abstraction recommended in [30], because it provides a step-by-step guidance on extracting information from articles of a small sample size. Data abstraction can be conducted in two ways. The first method summarises the facts in the form of descriptive information on title, authors, publication year, published source, affiliation of the authors, key emphasis and findings of the selected articles. The second method of data abstraction takes the form of conceptualisation of ideas from the theoretical perspective. Selecting the method of data abstraction depends on the objectives of the specific review [30]. The objectives of this study are (1) to present a holistic review of the main research approaches, tools, and algorithms in the context of CV based ICPM and (2) to identify the areas where additional efforts are mostly required and discern the future directions. In addition to that, this review does not intend to formulate a conceptual model or framework from the theoretical perspective. Therefore, abstracting appropriate information from each article was employed to organise and understand the common themes and patterns among the studies discussed in those articles using the first method of data abstraction. As per the findings of the data abstraction, the descriptive statistics on CV-based ICPM studies are initially presented on the annual publication trend, the contribution of publication sources and the distribution of publications by institution and country.

The annual trend of publication related to CV-based ICPM studies over the years from 2009 to 2020 is illustrated in Fig. 1. There was no related publication in the years 2010 and 2015 and the years 2017 and 2018 record the highest number of publications. The lesser extent of studies on CV-based ICPM is evidenced by this trend of publication, which spans little over a decade.

Table 1 presents an account of the contribution of journal articles and conference proceedings publications with the corresponding number of relevant articles during the studied period. It can be observed that two thirds of the articles have been presented at conferences, whilst Construction Research Congress conference being the prominent contributor. In terms of journals, Automation in Construction and Journal of Computing in Civil Engineering have an equal contribution of about 14% of studies related to CV-based ICPM. The contributing journals and conferences are the renowned publication sources in the field of CV-based applications in the construction industry.

The distribution of publications by the institution and the country of the lead author at the time of the research, with the number of articles

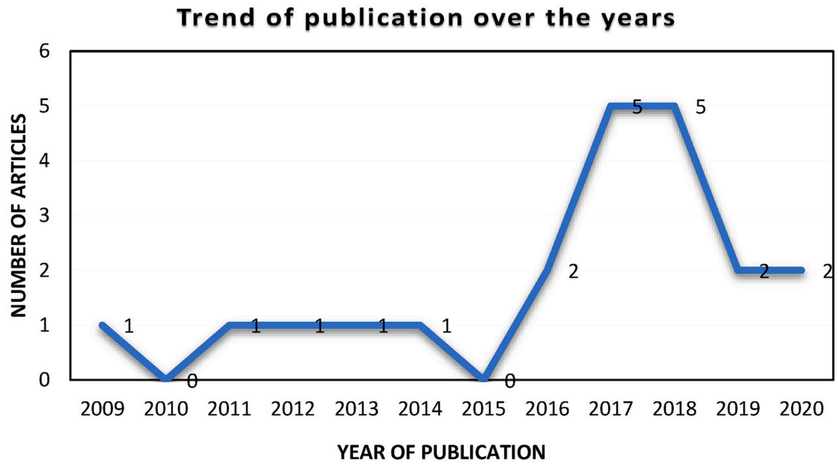

Fig. 1. Annual trend of publications.

Table 1
Contribution of publication sources.

Publication	Journal/Conference proceedings	Number of articles
Construction Research Congress	Conference Proceedings	6
Automation in Construction	Journal	3
Journal of Computing in Civil Engineering	Journal	3
International Conference on Computing in Civil and Building Engineering	Conference Proceedings	3
Journal of Construction Engineering and Management	Journal	1
International Workshop on Intelligent Computing in Engineering	Conference Proceedings	1
International Symposium on Automation and Robotics in Construction	Conference Proceedings	1
CSCE/ASCE/CRC International Construction Specialty Conference	Conference Proceedings	1
International Structural Engineering and Construction Conference	Conference Proceedings	1
ASCE International Workshop on Computing in Civil Engineering	Conference Proceedings	1
Total		21

published is illustrated in Fig. 2. The top two contributors are USA and Canada with 7 publications each. In total, the academics of North America have contributed to two thirds of CV-based ICPM studies, while Germany has a share of 5 publications and China and Hong have one publication each.

Following the descriptive statistics, the in-depth analysis on the key emphasis and findings of the CV-based ICPM studies are presented in the subsequent sections of this review paper.

3. Overview of CV-based construction progress monitoring

Prior to examining CV-based ICPM, capturing the holistic view on CV-based construction progress monitoring is pivotal. Construction progress monitoring is described as collecting, recording and reporting information of project progress [1,18]. The traditional progress monitoring methods such as daily site reports [38,39], require manual data collection from construction drawings, schedules produced by construction personnel [18]. Hence, the traditional practices are labour intensive, time-consuming, costly, visually complex and prone to errors [40,41]. To address these issues, the automation levels in progress monitoring have been improved using CV technologies. The automated progress monitoring process encompasses (a) capturing as-built/as-is scenes, (b) information retrieval from the captured data (c) progress estimation by comparison between the as-built/as-is and as-planned model (d) visualisation of the results [4,23].

Early automated progress monitoring systems employed 3D computer aided design (CAD) model as the as-planned model with 3D point clouds acquired via laser-scanning on as-built status for the exterior

Fig. 2. Distribution of publications by institution and country.

construction environment [42,43]. These systems gradually developed in to employing building information models (BIM). A BIM model loaded with schedule, the 4D BIM was integrated with 2D images, processed with machine learning (ML) algorithms to track progress deviations and update the schedule [11,44–46]. Among the recent advances in CV-based studies conducted for exterior construction progress monitoring, the use of deep learning (DL) based convolutional neural networks (CNNs) algorithms is notable. To monitor the progress of pre-cast concrete walls installation, Mask region-based CNN (Mask R-CNN) for instance segmentation and tracking by detection using Deep simple online and real time tracking (DeepSORT) have been employed by [47]. The detection and tracking information are used to timestamp the progress of pre-cast wall installation in the BIM. In another study, further improvements to construction elements have been achieved through image-based point clouds generated through Structure-from-Motion (SFM), compared against BIM representing position and dependencies of elements [48]. Despite such advances in the exterior construction progress monitoring, very few CV-based studies have been conducted for the ICPM [10,13,49], due to the complexities in comparison to exterior environment [12,17].

4. Challenges related to CV-based indoor progress monitoring

Interior construction environment is challenging for both CV-based and non CV-based data capturing devices [10]. Unlike the exterior construction site, the indoor construction environment poses challenges for capturing positioning data [50]. The global navigation satellite system (GNSS) based platforms usually fail in navigating indoors because of the blockage of satellite signals [51]. The concrete and steel enveloped indoor environments interrupt global positioning systems (GPS) readings and ultra-wide band (UWB) are similarly affected as signals are blocked by building materials [9]. The radio frequency identification (RFID) can determine the presence of objects through walls and can be deployed indoors, but are limited in localisation [13]. Moreover, they require constant installation, scanning, and maintenance [49,50].

Although laser scanners are accurate and efficient in collecting volumetric data, they are expensive and require expert operators to define scanning configurations [52]. Laser scanners generate less accurate point clouds for reflective materials such as metal studs and pipes in the interior construction environment [1,53] and registration followed by post-processing of scans is time consuming [51]. The incomplete point clouds due to obscured indoor building elements [54] and challenges related to detecting transparent indoor elements like glazed doors and windows, which do not reflect laser beams [55], impede the use of laser scanning for ICPM. The CV-based progressing methods that succeed in outdoors cannot be transferred and applied indoors without accommodating the special needs of the indoor construction environment [56]. The authors have categorised these in to challenges related to indoor objects, lighting conditions and camera movements.

4.1. Indoor objects related challenges

The complexities in object detection can occur when multiple components of interior walls, equipment, and temporary materials present in images [57,58]. Cluttered indoor scenes are also caused by the movements of construction personnel [21]. In the indoor construction operations, the progress is mostly associated with changes in wall surfaces and this causes capturing a large amount of overlapping images [12]. Moreover, the slender objects such as steel studs, and small objects, such as electrical boxes in high clutter indoor scenes suffer from robust feature extraction and object classification [12,20]. The minimally textured and achromatic objects constrain the feature extraction [56], mainly because some different objects have similarities in colour, shape and surface roughness [12].

4.2. Lighting-related challenges

Unfavourable and changing light conditions are mostly related to back-lights, shadows, missing artificial light sources during interior fittings. Non-uniform illumination patterns can cause difficulty in extracting the shape and outline of construction elements and as a result, visual recognition algorithms must be adjusted accordingly [12]. Quality and consistency of lighting affect accurate detection of the edges of the objects. Detecting the region-of-interest (ROI) can be constrained by changing lighting conditions [42,59]. The artificial light sources are inadequate to operate cameras during most of the interior phase and this intensifies the noise on the device affecting robust image data capturing [56].

4.3. Camera movements related challenges

Fixed cameras lose their effectiveness when the work moves indoors and get hindered by the limited data capturing range [60]. Continuous relocation of cameras can be an exhausting exercise [8]. On the other hand, the data collection process is manual, because it requires someone to inspect and capture images of the active areas in the site [61]. In addition to that, uncertainties in unsupervised camera movements and different perspectives on objects (scale, rotation, transition) can affect object recognition [17]. To generate complete as-built models for indoor construction sites, a large set of overlapping images is required due to the limited visibilities and field of view of cameras [23].

Each of the three types of challenges can independently create limitations on robust object detection in the indoor images [12,13]. In an indoor setting, however, these may co-exist, as illustrated in Fig. 3, and therefore, make the object detection process extremely difficult.

5. Discussion on CV-based indoor construction progress monitoring studies

In spite of challenges, the research into CV-based ICPM has been developing over the past decade. This section presents seven aspects of the CV-based ICPM based on a detailed review of the studies published between 2009 and 2020. Table 2 summarises these previous studies.

5.1. Visualisation of indoor progress deviations using 3D walk-through models

In the early days of automated progress monitoring systems, although the progress deviations were detected, visualisation of these deviations in real time was challenging [72]. Among the initial attempts to enable 3D walk-through visualisations in the indoor environments, the prototype introduced by [14] is prominent. This prototype uses interior construction images superimposed over a 3D model and user's view point information to visualise the progress deviations in augmented reality (AR) 3D walk-through model [14]. As proposed in this study, when the user gathers the images, a wireless transmitter attached to the digital camera automatically sends photographs to a database server and stores in 3D environment in real time. According to the user's context information, a walk-through model in AR is retrieved from the BIM. Colour and pattern coding are used for visualisation of interior construction progress deviations.

More improvements to the previous prototype was proposed through an approach to represent the progress of an activity completion, where the activities are treated as objects [5]. This is used to update the schedule for the installation of HVAC ductwork in ceiling spaces and drywalls [5]. As-built construction photographs are superimposed over an as-planned BIM to represent interior construction progress. The SFM technique is employed to automatically register camera viewpoints in an existing 3D model.

Although this method offers avenues to improve visualisation of progress deviations, due to the object-based approach in representing

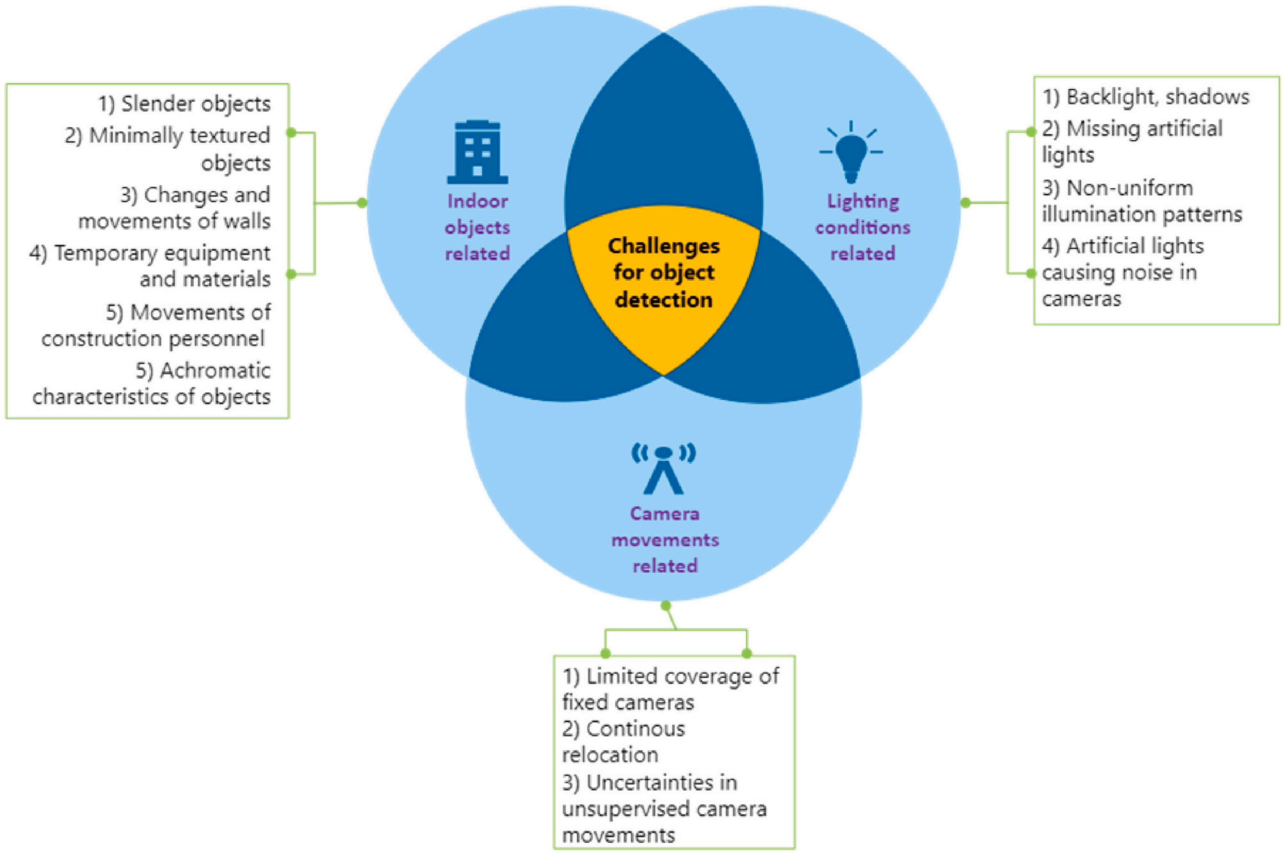

Fig. 3. Challenges related to CV based indoor progress monitoring.
Source: The Authors.

activities, detecting deviations of processes and objects that are not modelled in BIM is limited. Although both colours and patterns are used to visualise the state of progress, it requires the user to manually enter spatial-temporal information including the time, location and viewpoint for each photograph, which makes this approach labour intensive [5].

5.2. Automated activity state recognition and delay prediction of indoor works

As discussed earlier, interior works are highly prone to schedule overruns and the average cost share of these works lies between 25% and 40% of the total budget [21]. The use of CV-based real-time monitoring at the level of the elements has been explored for the components of under-construction indoor partitions i.e. drywalls, studs, insulation, electrical outlets [12,13,15,62]. These past studies have exploited distinctive features related to characteristics such as shape, colour and texture of indoor objects [12], thus employing handcrafted features to achieve object detection. These handcrafted features are associated with traditional ML approaches for object detection, where features such as edges, corners are manually extracted through feature extraction algorithms like edge detection, corner detection [73].

With the aim of automatically predicting delays in finishing works, a conceptual framework using video data and 4D BIM was proposed focussing on installation of heaters, electric outlets, painting, and tiling [21]. This approach proposes to estimate the camera motion in reference to BIM as the user traverses the indoor site. The registered video data is used to match the corresponding items in BIM. Based on items' presence and finishing state, as-performed version of the 4D BIM is generated. This updated schedule is compared with the initial schedule to predict delays [21].

Further to that, an approach for activity state recognition of a heating device, which uses the data from schedule loaded BIM models and motion registered videos was presented [17]. This approach discusses how the image data is pre-processed with filters, so that the images are prepared for robust object detection. The histogram of oriented gradients (HOG) features are extracted to train and classify image data using support vector machine (SVM), reducing object detection to a simple 2D classification problem [17].

The earlier CV-based applications on interior finishes were further improved to determine the different states of drywall completion using a two staged cascaded approach [62]. The camera position and the pose are required to be known from the motion estimation. A 4D BIM model is used to derive drywall extents and identify a ROI containing the relevant drywall. The first stage focusses on the line and dot characteristics to identify the edges for detecting panelled drywalls. The second stage determines the difference of the reflecting properties of materials on plastered drywalls and using pixel intensity, plastering and painting is distinguished. Edge distribution and histograms of pixel intensities are used to train cascaded SVM classifiers and differentiate states of progress for drywall installation, plastering and painting [62].

The study of [13] integrates the previous studies of [17,21,62] for more robust radiator state recognition (unprepared background, prepared background, radiator wrapped in packaging foil, and unwrapped radiator) and drywall completion (installed drywall panels, plastered drywall and painted drywall). This approach enables registering each image of a sequence to the 4D BIM in terms of its origin and its point in time in the construction schedule. Taking the as-built video frames as input, the first block registers image data to BIM. After registration, the recognition block represents the actual state of activities. Firstly, the search space for objects related to relevant activities is reduced to avoid analysing negligible video frames. Secondly, a rectification of the considered image regions is performed to enable a more homogeneous

Table 2
Overview of the previous studies.

Key emphasis	Data capturing method	Key algorithms	Source
Prototype to enable the 3D walk-through o visualise progress discrepancies	Digital camera with a wireless transmitter	–	[14]
3D walk-through modelling with AR and IFC based BIM for activity monitoring, where activities are treated as objects	Digital camera with a wireless transmitter	Cascade of Haar like feature-based classifiers	[5]
Conceptual framework to predict finishing delays based on items' presence and state to generate an as-performed 4D BIM	Videos (IMU and a camera integrated into a tablet computer)	–	[21]
Pre-processing images with filters to reduce object detection to a classification problem and estimating correspondences between images and 4D BIM	Videos (IMU and a camera integrated into a tablet computer)	Perspective-n-point algorithm, HoG features, SVM classifier	[17]
Determining the states of drywall completion using line and dot characteristics and differences of the reflecting properties of materials	Videos	Compass edge distribution and pixel intensity histogram features, CLAHE parameters, SVM classifier	[62]
Comparing algorithms for proper estimation of camera localization	Videos	SFM, VO and VSLAM	[56]
Detecting steel studs and electrical boxes using an integrated shape and colour-based approach	UAV mounted camera	CIELAB, Otsu thresholding, morphological transformations, Hough Transform, Canny edge detector	[12]
Potential of UAV and UAS for indoor site monitoring	UAV mounted camera	–	[20]
Automatically detecting partition's current state using four CV-based modules based on an algorithm which uses edges, texture and colour features of each of the module	UAV mounted camera, smartphone	HoG, bi-lateral filter, Otsu cluster-based image thresholding, L-channel, PPHT, voting system, k-means clustering, Gaussian filter, CIELAB, LBP, SVM classifier, CLAHE, Sobel kernel, multistage thresholding algorithm, CDF histogram, inverted binary thresholding, morphological transformations,	[15]
The objects' progress ratios are automatically incorporated to IFC based BAUS	UAV mounted camera	The algorithmic modules in [15]	[63]
Accuracy of partitions progress tracking with respect to the UAV's velocity and photo capture configuration	UAV mounted camera	–	[64]
Use of UAV and IFC schema to automatically update BIM based on inspection of building elements	UAV mounted camera	–	[65]
IFC schema to automatically update BIM based on inspection of building elements for defect analysis	UAV mounted camera	–	[16]
Each image of a sequence is registered to the 4D BIM in terms of its origin and its point in time in the construction schedule	Videos (captured with a monocular camera system)	Line segment extraction approaches, camera pose estimation approaches i.e., modified RANSAC for pose estimation, VO, SfM and HOG features, compass edge distribution and pixel intensity histogram features, SVM classifier	[13]
Developing a hybrid SFM-SLAM 3D reconstruction algorithm	Videos (walkthrough video)	Hybrid SFM-SLAM 3D reconstruction algorithm built upon ORB features, MVS, RANSAC	[66]
Leveraging the mapping strengths of SFM and MVS and real-time localization strengths of SLAM to monitor scattered work locations	Videos (walkthrough video)	SFM, MVS, SLAM, Direct Linear Transformation and Single Value Decomposition, ORB and HaHoG features	[67]
Registering video frames to a BIM for detecting and matching the vanishing points and vanishing lines of the image frames.	Videos captured from an UGV mounted monocular camera	SLAM	[68]
Discovering the camera poses of image frames in BIM coordinate system by performing an augmented monocular SLAM	Videos	Augmented monocular SLAM, multi-view environment, Canny edge detector, voting and searching schemes, gradient descent–based algorithm, perspective projection using vanishing points and lines	[69]
Mask R-CNN based building object recognition, segmentation and IFC BIM object generation	2D photos collected from handheld digital cameras/ smartphones	Mask R-CNN, corner pixel detection, edge construction in segmented masks, coordinate transformation	[70]
Determining the engineering quantity in real time for activities which are calculated by area	2D photos captured from fixed site cameras	SVM classifier based on LBPs, canny edge detection algorithm Hough transform algorithm, camera calibration algorithm, tile orientation determining algorithm	[10]
UAVs and UGVs are proposed to be used collaboratively and simultaneously for data capturing	UAV is mounted with a wide-angle camera and UGV is mounted with a LiDAR	–	[71]

Legend: CDF - Cumulative distribution function; CLAHE - Contrast-limited adaptive histogram equalization; HOG - Histogram of oriented gradients; IMU - Initial measurement unit; LBP - Local binary patterns; LiDAR - Light Detection and Ranging; MVS - Multi view stereo; ORB - Oriented FAST and Rotated BRIEF; PPHT - Progressive Probabilistic Hough Transform; RANSAC - Random sample consensus; SLAM - Simultaneous localization and mapping; SFM- Structure from motion; SVM – Support vector machine; UAS – Unmanned aerial system; UAV – Unmanned aerial vehicle; UGV- Unmanned ground vehicle; VO – Visual odometry; VSLAM – Visual simultaneous localization and mapping.

basis of the image data for the succeeding state recognition [13].

When detecting components of interior partitions such as steel studs and electrical boxes, the inherently distinctive features of each component was exploited using a shape and colour-based approach [12]. These two components are distinctive mainly because steel studs are large in number, slender in shape and achromatic. Electrical boxes are relatively small in size and their appearance changes before and after installing the sockets [12]. The object detection procedure firstly considers differentiating the objects from the background using colour and illumination intensities. Secondly, it carries out processing of the extracted shape and localises the objects of interest using Canny edge detector and Probabilistic Hough Transform.

The above object detection method was further used to develop more advanced CV-based progress monitoring through a sequence of indoor partition elements. Four CV-based modules designed to detect the components: steel studs, batt insulation, electrical outlets, and three states for drywall sheets using an algorithm which uses edges, texture and colour features of each of the module [15]. First, the algorithm detects the studs, then the insulation followed by drywalls state completion and electrical outlets installation using feature extraction [15]. Fig. 4 illustrates how the studs are detected using feature extraction.

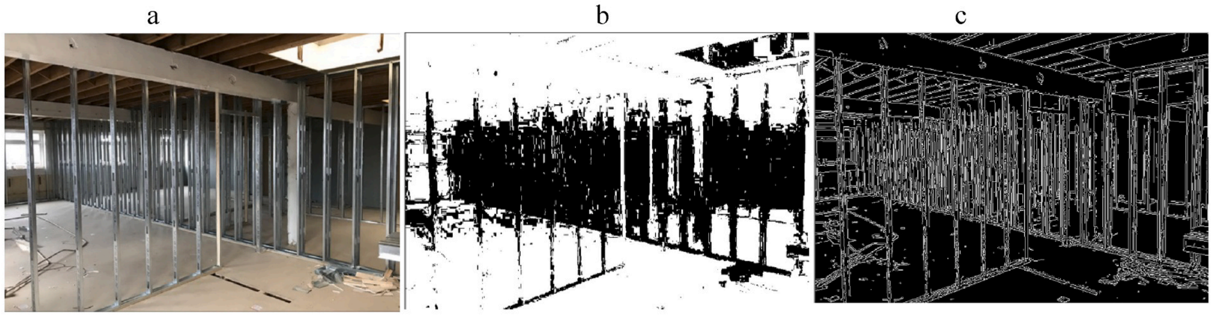

Fig. 4. Automated detection of studs in a fit-out project a) original image; b) thresholding image c) Canny edge detected image.
Source: The Authors.

The automated updating of industry foundation classes (IFC) based 4D BIM in terms of progress of detected indoor partitions' elements from the previous study was invented as BIM Automated Updating of Schedules (BAUS) [63]. In this method, the progress information is translated into IFC data schema, and the IFC-based 4D BIM is analysed in terms of task-object relationship and schedule. The elements' progress ratios are automatically incorporated into 4D BIM. Colour coding is used to reflect the progress deviations [63].

5.3. Unmanned vehicles-based image capture platforms for progress monitoring

As discussed before, the use of fixed cameras in indoor sites can be challenging due to the limitations in range and continuous relocation [8]. These limitations can be remedied by using image capture platforms such as unmanned aerial vehicles (UAV) and unmanned ground vehicles (UGV) [51,71]. Both technologies have distinct advantages and disadvantages stemming from their measuring positions in the indoor environment [74]. Since a ground robot/vehicle can be more easily stabilised with higher payloads than an aerial robot/vehicle UGVs hold multiple sensors and they are mostly mounted with Light Detection and Ranging (LiDAR) for 3D point cloud generation [74–76]. The UAVs typically use a camera to capture image data. Moreover, UGVs have a stop in-place safe strategy enabling dynamic obstacle avoidance unlike air collisions caused by UAVs in a cluttered indoor environment [51]. However, the ground-based measurement methods used by UGVs are affected by blind spots behind vertical obstacles and they are unable to capture horizontal surface data located higher than the UGV. In contrast, UAVs can even capture horizontal obstacles such as roof [51].

The navigation strategy of UGVs and UAVs is either GNSS-based or simultaneous localisation and mapping (SLAM) based. SLAM algorithms are mainly used for indoor navigation due to limited GNSS signals indoors. SLAM enables a robot to estimate its current position and orientation from a map of the environment created by LiDAR or cameras. [51,77]. Localising the camera poses with respect to a BIM in real time is challenging in cluttered indoors. The method proposed by [68] registers video frames from an UGV mounted camera to a BIM for detecting and matching the vanishing points and lines of the image frames to that of the viewpoints in the BIM. This method can be employed as a localisation method, because the viewpoints of the BIM are iterated to align with the cameras, to correct the actual location of the UGV [68].

Because of their in-flight agility and capacity to hold cameras while flying, UAVs are efficient for data capturing [16,20,64,65]. UAV's velocity and photo capture configuration are crucial for the accuracy of automatically detecting the components of indoor partitions such as studs, insulation, electrical outlets, and state of drywalls [64]. It was found that the best results are achieved when the UAVs are operated at a partition's mid heights aligned perpendicular to the wall's longitudinal axis. In terms of planning the flight path, it can be mapped in BIM and enhanced with path optimisation algorithms [20,65]. However, UAVs can pose safety risks to construction workers due to their flight path and can cause distractions with the noise [16,20,64,65]. On the other hand, although the layout of the project is initially known, it can be changing affecting the flight path. Moreover, UAVs' rotational velocity and sudden angular movements, can cause motion blur in the captured image.

Alleviating the limitations when employed individually, UAVs and UGVs are proposed to be used collaboratively and simultaneously for data capturing [71]. A custom-built indoor blimp is designed as the UAV for this study instead of other types of UAVs such as quadrotors, hexacopters because of the lower cost, energy consumption, and noise. A wide-angle camera is mounted on the blimp for localisation and tracking from air. The UGV in this study was a custom-built robot with a LiDAR sensor mounted to generate a map of the occupancy in a university laboratory, which resembles an indoor construction site. The relative pose between the two vehicles is estimated consistently, which enables the UAV to follow the UGV's path during its navigation if the place of interest is not accessible by the UGV.

5.4. Use of CV to update as-built/as-is BIM using progress inspection data

Progress monitoring of building elements is sometimes merged with defect analysis. Hamledari, et al. [16] introduced a technique that uses the IFC schema to automatically update an as-planned BIM based on inspection details of building elements in accordance with the progress of the as-is images of the particular element. The CV-based algorithm automatically analyses the IFC data model to retrieve the element's semantics and identifies discrepancies between the as-is condition with the as-planned object conditions. In this method, updating the model in terms of type and geometrics is automated for an element, for which a defect has been detected. This includes elements such as outlets, fixtures, doors, windows, and furniture [16].

5.5. Visual 3D mapping of scattered indoor locations and real-time image localising

Indoor construction activities are mostly performed by different teams working in dispersed locations. A large number of images is needed to map all locations, particularly the corridors and hallways [66]. The comparison of CV-based processes and techniques such as SFM, visual odometry (VO) and visual simultaneous localisation and mapping (VSLAM) for determining a method of proper estimation of the camera localisation within the building was conducted to overcome this challenge [56]. SFM reconstructs the camera motion and reveals the observed structure of the scene, whereas VO estimates the path of the camera that provides an image sequence. VSLAM estimates the path of the camera while creating a map. In order to make pose estimation inside buildings during interior finishing, the use of a filter based VSLAM in terms of scale and pose was proposed [56].

In another study, a pipeline of SFM to register images taken by different teams on a daily basis and feed them into multi view stereo

(MVS) to produce point clouds for each work area was performed [66]. Videos captured on a weekly basis are then fed into SLAM to connect the locally produced dense 3D point clouds. VisualSFM, a graphical user interface application [78] estimates camera poses of image sequences or videos and generates a very sparse map. In the approach of [66], OpenSFM is used to generate the dense point clouds for each work location. OpenSFM [79] is a CV- based library to reconstruct camera motions and the structure of a scene by using ordered or unordered photographs. Moreover, a modified version of Oriented FAST and Rotated BRIEF simultaneous localisation and mapping (ORB-SLAM2) [80] is used to create the global map of the site. By doing so, this approach leverages the mapping strengths of SFM and MVS and couples it with the real-time localisation strengths of SLAM. After generating a locally dense as-built map of all work locations, such as corridors, hallways, and other connecting areas, registering to BIM allows for as-planned vs as-built analysis [66].

A hybrid SFM-SLAM 3D reconstruction algorithm was proposed in [67]. The SLAM procedure is built on ORB-SLAM2 [80] and both SFM and SLAM reconstructions are performed using binary ORB features. This method aimed at mapping the work done at two different and scattered indoor locations and registering them together in BIM [67]. After video data is used to create a sparse point cloud of the entire site using the SLAM thread of the algorithm, while the local sets of images are used to create local dense point clouds of every work location separately using the SFM + MVS thread of the algorithm. The local point clouds are then registered with the global point cloud by finding matching points [67].

As an extension to previous works, an augmented VSLAM to improve point clouds and create more accurate camera trajectory, compared to ORB-SLAM2 was proposed by [69]. To facilitate as-built and as-planned data comparison, an automated registration of as-is video sequence was proposed to an as-planned BIM in real time by detecting and matching between the image frames and their corresponding BIM view. This method discovers the camera poses of image frames in the BIM coordinate system by performing an augmented monocular SLAM, which is robust in indoor image localisation [69].

5.6. Real time engineering quantity calculation

In the indoor environment, the progress of many non-structural activities measured using metrics such as area and volume is not properly quantified [10]. To fill that research gap, a method for determining the engineering quantity in real time for activities, which are calculated by area was proposed [10]. The SVM classifier-based local binary patterns (LBP) are established to classify tile and non-tile areas captured through 2D images. In an image, the contours of all objects are identified by an edge detection algorithm and the straight lines are separated from these contours by a Hough Transform algorithm. In the BIM model, the location of the paved tiles is known, so the boundary line of the tile paving area identified through on-site images should correspond to the tile segmentation line in the BIM model [10].

5.7. Use of neural networks to generate CV-based object detection platforms

The automation level of CV-based studies is improving with the advent of DL-based CNN algorithms. Compared to handcrafted features that are designed to extract chosen characteristics, CNNs can learn the features from training image datasets for object detection. As a result, DL models outperform ML object detection models that use manually extracted features [73]. On the other hand, the algorithms relying on handcrafted features for object detection are sensitive to input images and it is difficult to extend to new building objects. To address these limitations, a Mask R-CNN based approach was developed to construct as-is BIM objects in IFC format from indoor images of an existing building [70].

Mask R-CNN is a DL-based CNN method used for instance segmentation [70], which refers to as detecting all interested objects in a given image while precisely segmenting each instance [81]. Due to the automatic feature learning ability, Mask R-CNN-based building object recognition is robust to complex environmental conditions, and scalable to customised building object types in the indoor environment. Furthermore, Mask R-CNN predicts pixel-accurate masks of objects in images to construct building objects with arbitrary-shapes [70]. Three types of building objects (walls, doors, and lifts) are used in this study. The approach is conducted in three modules as follows; (1) Building object recognition and segmentation involves collecting 80% of images for the training, 10% for testing and 10% for validation. Then the labelled image data are trained with Mask R-CNN for instance segmentation. (2) building object geometry construction involves shape extraction and coordinate transformation for constructing the objects' geometry. (3) IFC BIM object generation involves defining constructed building objects as IFC objects.

Various applications of CV-based technologies for ICPM have been progressing over the past decade. Fig. 5 illustrates how these studies have been contributing to the advancements in CV-based ICPM based on the aforementioned 7 categories. Main contributions of each of the category are summarised with the corresponding years of studies to form a timeline.

6. Future research directions

Study of CV-based ICPM has been evolving. In order to accelerate this evolution, this section discusses a number of directions that present significant potential for improvements on the current achievements and open new avenues in a broader sense in this domain by exploring their full potential.

6.1. Integrating imaging technology with other technologies

The point clouds generated through laser scans and 2D and 3D camera images are only capable of capturing volumetric data [49,52,82]. Few research works have so far been conducted on approaches that can integrate imaging technology with position data capture technologies to collect progress data from interior construction sites. This is mainly because the applications of radio frequency and geospatial based technologies in the interior construction environment is constrained [13,49]. However, integrating one data capturing technology with another alleviates limitations associated with each of them when employed individually [83–85]. The data fusion model integrating UWB and imaging technologies created by [49] for progress monitoring of piping and ductwork installation is a good example. In this study, UWB is used for tracking location, presence and time of arrival of pipes, whereas volumetric data captured from laser scans and imaging is used for feature extraction to generate the as-built model to be integrated with as-planned CAD model.

The approach to integrate RFID data with point clouds introduced by [82,85] was employed for furnished interiors. The interior structural elements are detected using the point cloud data, while the furniture is identified through RFID tags attached to them and sensed by a reader mounted alongside the laser scanner. These fusion approaches provide a good direction on combining imaging technology with positioning technology for the interior environment. More robust methods are necessitated to integrate positioning data captured from UWB and RFID to be integrated with volumetric image data and thereby link to the BIM platform.

6.2. Use of DL neural networks for object detection and activity tracking

Application of DL neural networks is significant in the context of CV as they automatically learn features from training data themselves [86]. This ability can be beneficial compared to handcrafted feature

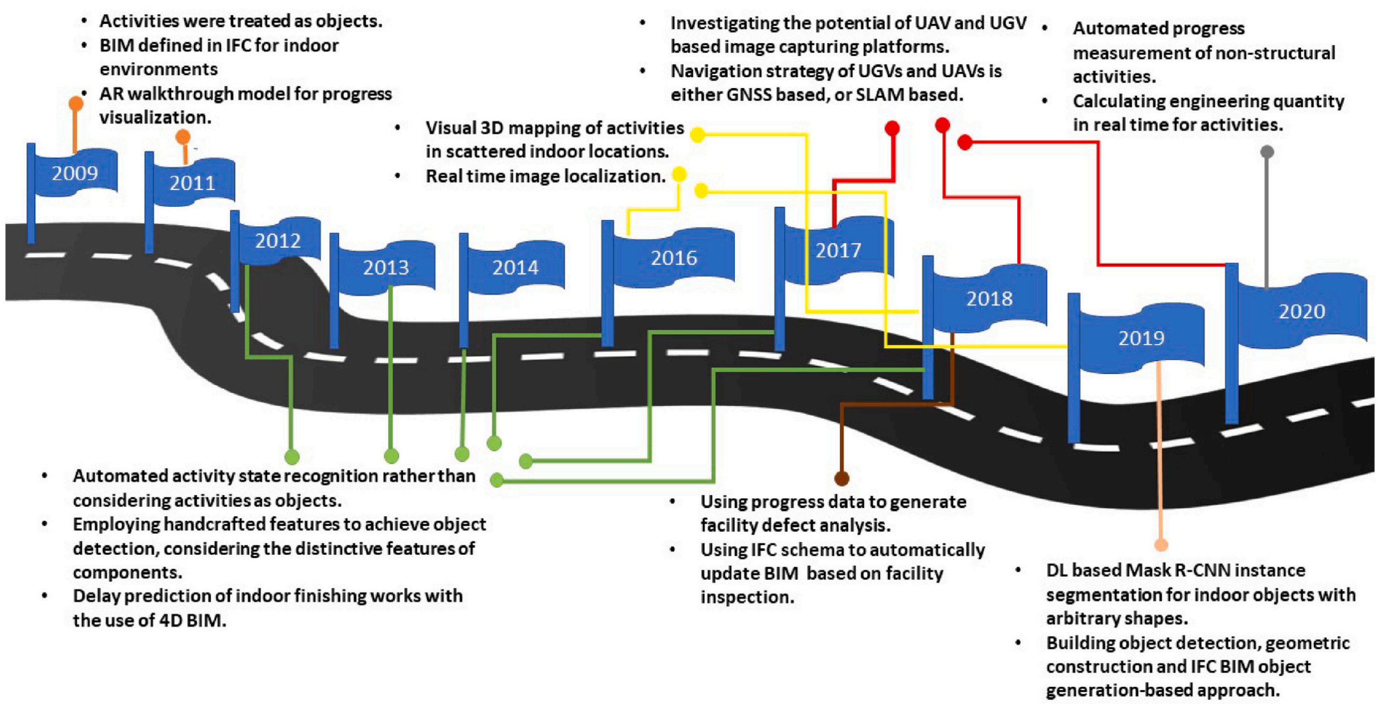

Fig. 5. Timeline of the CV based indoor progress monitoring studies.
Source: The Authors.

extraction such as edges and lines of objects in low lighting indoors. It can be discerned from the study of [70], the more advanced form of object detection i.e. instance segmentation by DL-based Mask R-CNN can be customised to various object types in the indoor environment. In addition to R-CNNs, which use region proposal-based framework for object detection [87], regression/classification-based object detection algorithms [87] such as You Only Look Once (YOLO) [88], Single shot multi-box detector (SSD) [89] are other DL algorithms that can be used in object detection for ICPM. Once the object is detected, it needs to be tracked through long periods of occlusions [90]. The tracking-by detection using DeepSORT, which is built upon a CNN architecture [90] is one of the effective methods that can be applied for activity tracking in ICPM.

For such DL-based models to work effectively, it is essential to build an extensive training image database with annotation of target objects [91–93]. Deep active learning [94,95] is a promising approach to automatically evaluate the uncertainty of unlabelled training data, select the most meaningful-to-learn, and thereby train the DL model to reduce human intervention. Another solution to reduce the training effort would be to use a pre-trained DL model [96], which uses transfer learning to refine the pre-trained model. This process requires an existing network such as GoogLeNet, AlexNet, ResNet [97]. However, since a few ICPM based studies have been conducted so far, the availability of image databases of indoor objects is limited.

6.3. *Automated progress measurement based on the earned value*

Application of 4D BIM integrated with CV to reduce delays is already researched for the interior construction environment. However, for progress measurement approaches to be useful in practice, tracking earned value (EV) is promising [1,41,98] because EV is used for periodic measurement of both actual expenditure and physical scope accomplishment [98,99]. Among the past studies, Shahi, et al. [49] presented a data fusion model integrated with a 3D CAD model for EV tracking in

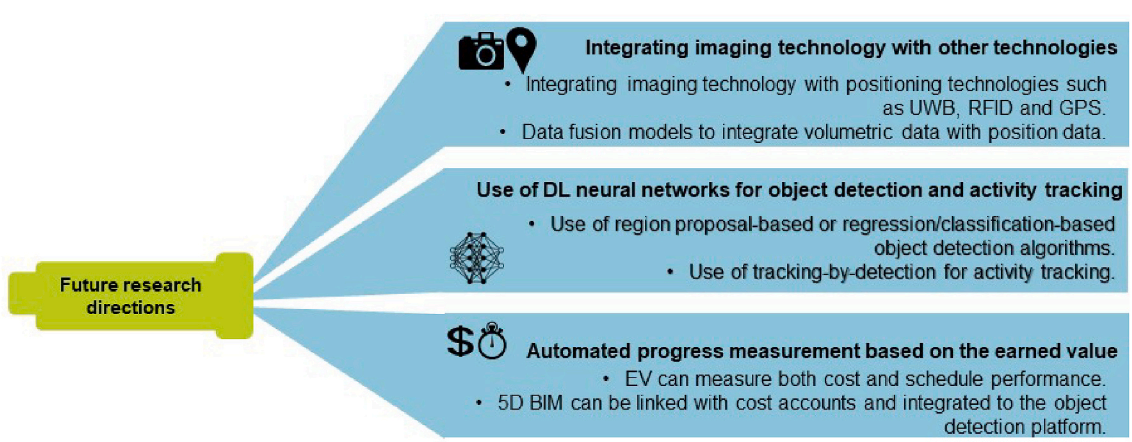

Fig. 6. Future research directions.
Source: The Authors.

indoor environment. The application of 5D BIM linked with the cost information of the project has potential to benefit establishing progress payments in relation to their planned cost schedule thus reducing delay and budget overruns [100]. Integrating CV with 5D BIM can direct the focus on automating EV tracking in the interior construction environment. Automated EV tracking of interior works will be specifically beneficial to human-less resolution of financial conflicts.

Fig. 6 demonstrates the above discussed future research directions.

7. Discussion and conclusions

This paper provides an overview of the current applications of CV for ICPM. Existing research deficiencies and future research directions have been determined. Following is a discussion of the challenges, applications, and future research areas of CV-based ICPM.

This study categorised the challenges that hinder robust object detection for ICPM. These challenges are related to the indoor objects, lighting conditions and camera movements. The very few studies on ICPM are mainly focused on automated progress monitoring of indoor finishing works and predicting the delays with the use of 4D BIM. There is a limited focus on both cost and schedule updates and controls in the indoor activities. In this context, the automated EV tracking with the integration of 5D BIM and object detection platform can be recommended as a future direction. Compared to handcrafted features that were used in those studies, the use of DL-based CNNs for object detection and tracking is robust. Future studies should consider more advanced uses of neural networks for object detection and activity tracking. This is affected by overcoming the need of collecting large number of training data using deep active learning. Moreover, CV-based technologies are not suitable to capture positioning data. Since the indoor environment poses challenges to employ positioning data capturing devices like UWB, RFID and GPS, the fusion models with CV offers a great potential in creating integrated models for indoor progress data capturing.

Despite the strengths of this review study, there are few limitations to be indicated. While there are many studies on the application of CV technologies and BIM adoption for buildings, this study mainly focusses on the physical progress monitoring of indoor construction environment. CV-based progress monitoring in construction projects is rather a new and emerging area with a history of slightly over a decade and not many studies have been conducted specifically on the indoor environment. Although a rigorous procedure was followed to retrieve articles in this context, some relevant publications may have been missed.

With the increasing growth of refurbishment projects and the complications in the interior construction environments in new building constructions, indoor progress monitoring is becoming crucial for the construction professionals. On the other hand, the advancement in artificial intelligence research is unlocking the potential of CV in automated object detection and its linkage to other platforms like BIM and AR. It is anticipated that such advancements will contribute to strengthening the research on automated ICPM. Towards achieving that end, this review is an effort on presenting the holistic view of the extant literature on CV-based ICPM.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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