Computer Vision Techniques in Construction, Operation and Maintenance Phases of Civil Assets: A Critical Review

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Abstract –

Throughout the life cycle of civil assets, construction, operation and maintenance phases require monitoring to assure reasonable decision makings. Current methods always involve specially-assigned personnel conducting on-site inspections, which are work-intensive, time-consuming and error-prone. Computer vision, as a powerful alternative to manual inspection, has been extensively studied during the past decades. On the basis of existing summary papers, this paper reviews a wide range of literatures, including journal articles, conference proceedings and other resources. Current applications of computer vision during construction, operation and maintenance stages of civil structures are concluded, with a special focus on operation and maintenance phase. This review aims to provide a comprehensive insight about the utilization of computer vision in civil engineering and an inspiring guidance for future research.

1 Introduction

In construction, operation and maintenance phases of civil assets' life cycle, monitoring is required for reasonable resource allocation and decision making. To be specific, monitoring of construction sites paves way for progress tracking, quality control, safety assurance and productivity analysis. When it comes to in-service structures, understanding of their current situations can help engineers to determine repair, retrofit and replace plans. Traditional methods always involve specially-assigned personnel conducting on-site inspections, during which physical measurements can impose extensive workload and potential danger to inspectors [1]. Such manual inspection processes are also time-consuming and prone to the biased judgement of inspectors. Alternatively, the development of reality capture technology and image processing techniques facilitate the utilization of computer vision in Architecture, Engineering & Construction and Facility Management (AEC & FM) industry. As an interdisciplinary field, computer vision aims to generate human-like understanding from digital images or videos, and thus attracts focused attention from researchers worldwide. Numerous studies have been done and impressive progress has been achieved. This paper goes through computer vision's applications in construction, operation and maintenance stages of built assets in a large scale, with a focus on recent researches that are published after existing review papers [2, 3].

The structure of this paper is as follows. Section 2 illustrates research methods. Section 3 presents analysis results and in-depth discussions about current researches. Section 4 provides envisions for future work.

2 Research Methods

2.1 Data Collection

Aiming to obtain a comprehensive insight about vision-based practices in civil engineering, the research started with initial searching and scanning in both web search engine, google scholar, and academic databases such as ScienceDirect and IEEE Xplore. Direct search method based on title, abstract and keywords was employed to collect a wide range of literatures, so as to form a fundamental concept about how computer vision is combined with civil engineering. "Computer vision", "civil engineering" and other related terms such as "machine vision" were search keywords. Different types of literature including journal articles, conference proceedings, even book sections were collected and reviewed. Apart from the relevance, publishing date was regarded as another sift criteria. The emergence of this topic was largely facilitated by the development of computer science and image processing techniques, thus the time limit was set to year 2000 to exclude unrelated studies. After the initial stage of review, top journals embodying high-quality articles in this field were identified, some (but not all) of which are: Computer-Aided Civil and Infrastructure Engineering, Automation in Construction, Advanced Engineering Informatics, Journal of Computing in Civil Engineering and IEEE. Key authors who made advanced contributions to this field were also recognized. Existing review papers were referred to and set as a time mark for further selection of data. Focused search was then conducted centring on the above-mentioned journals and authors. In total, 71 papers were collected and analysed (Figure 1), including 54 journal articles, 16 conference proceedings and 1 book section. EndNote X7 was used for data storage, management and citations.

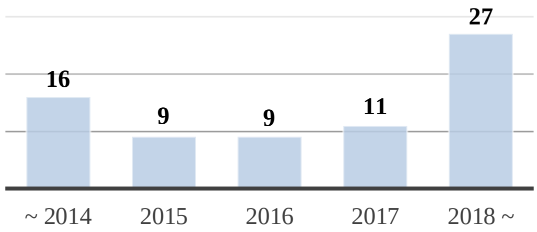

Figure 1. Chronological distribution of articles

2.2 Data Analysis

Preliminary data analysis was completed during data collection by scanning titles and abstracts, followed by context analysis, a typical method for qualitative data analysis. Regarding the application scenarios of computer vision, the literature was divided into two blocks: one that focused on construction phase and the other on operation and maintenance phase. Papers in two parts were then analysed separately. Excel tables were created for note takings while reviewing, with critical information and peculiar contributions of each article highlighted. Notable information included the main purpose of application, area of use, equipment demand, methodology, outcome quality, and future agenda. A comparison was made based on the systematic review.

3 Results and Discussions

Current applications of computer vision in civil engineering are categorized into two groups: (1) construction phase and (2) operation and maintenance phase in structure’s life cycle.

3.1 Computer Vision in Construction Phase

Due to an early start of computer vision on construction sites, a thorough research in this area has been developed in the last decade. Summaries and overviews are available in existing literatures [2].

The utilization of computer vision technology in construction jobsites can be categorized into four classes regarding the main purpose of application, namely progress monitoring, quality control, operational productivity analysis [4-7] (which is to what extent onsite resources are being utilized) and safety assurance [8-12]. Combination of multiple purposes was achieved in some researches [13, 14]. Apart from fatality prevention, there is another safety concern named occupational health assessment, referring to [15]. Seo, J., et al. integrated vision-based human kinematics data to biomechanical analysis, so as to evaluate the risk of musculoskeletal disorders faced by workers when conducting lifting tasks.

One important constitution in a vision-based monitoring system is object detection. Typical methods follow two sequent steps, feature extraction and object classification. The most frequently employed image descriptors include, but are not limited to, shape-based features like edges [16] and texture-based ones like Histogram of Oriented Gradients (HOG), which is a local spatio-temporal feature particularly suitable for action recognition. Extracted features are then fed into classifiers for object recognition. In addition to traditional classification algorithms like support vector machine (SVM), deep learning techniques, e.g. faster region-based convolutional neural network (faster R-CNN) in [11], are rising up in recent studies. Its core part is an artificial neural network (ANN) as an analysis kernel during object recognition, categorization and other information extraction [17]. Luo, H., et al. [6] presented a three-stream CNN dealing with RGB images, optical flow images and grayscale images, separately, then fused the results together to identify workers’ states in reinforcement installing activities.

Another core task in job sites involves the tracking of detected construction entities (i.e. workforce and equipment). Xiao, B. and Z. Zhu [18] summarized and compared 15 2D tracking methods in past studies regarding the outcome quality (i.e. overlap score and centre location error), highlighting the superiority of methods using sparse representations and generative classification algorithms. The 2D tracking results are then transformed into 3D space through triangulation to gain trajectories of the target, for example, crane jib [19] and excavators [16].

Subsequently, activity recognition of either workers [6, 9] or equipment (especially excavator and dump trunk in earthmoving operations [4], and cranes [19]) constitutes the next level of image processing, allowing the detection of un-safe behaviour and understanding of onsite situations. Moving personnel and equipment were monitored in [20] and by fuzzy inference, potential dangers like struck-by accidents were evaluated in a numerical way for an efficient safety management. Luo, X., et al. [21] managed to identify 20 activity patterns in sites assisted by prior knowledge (i.e. whether two certain objects cooperate in an activity and their proximity). Similar relevance information was adopted in [5] for interactive analysis of individualized action recognition. Both one-to-one- and group-level analysis led to a precision of 91.27% in situation understanding.

Combination of computer vision and other state-of-the-art technology is also emerging. For example, Jeelani, I., et al. [10] utilized eye-tracking techniques to obtain workers' viewing patterns, which was then integrated into a computer-vision-based localization system to indicate workers' ability to recognize onsite hazards.

3.2 Computer Vision During Operation and Maintenance Phase

The utilization of computer vision in structural health monitoring (SHM) and performance evaluation has been increasingly studied in recent years. Such a scheme can positively contribute to a reasonable management of construction resources, leading to a sustainable built environment. Koch, C., et al. [3] concluded the achievements and challenges faced in this field and since then, notable improvements have been accomplished.

3.2.1 Reality Capture Technology

For data acquisition, two main reality capture techniques include laser scanning and photogrammetry, where point clouds and images/ videos are input and analysed, respectively. Aiming to lower inspection cost, digital imaging was favoured in the literature. 49 out of 51 studies extracted information from photos or video frames, most of which relied on consumer-grade devices like digital single-lens reflex (DSLR) camera [22-25], action camera [26], video camcorder [27], existing closed-circuit television (CCTV) [28], or even smart phone cameras [29-32]. Un-manned Aerial Vehicle (UAV) [33] or flying robot [34] can be utilized to mount cameras to free workers from hand-held cameras and on-site tour for inspection. To note, Dorafshan, S. et al. [35] studied the robustness of crack detection in steel bridges against various camera specifications. Three types of cameras, i.e. Nikon COOLPIX L830, DJI Mavic and GoPro Hero 4, were tested, indicating different crack-to-camera distance requirement for a desirable result.

3.2.2 Image Processing Algorithms

A typical computer vision-based defect detection method involves four levels of image processing, namely image pre-processing, segmentation, feature extraction and pattern recognition. Satisfactory segmentation results can lead to a high accuracy of detection, which, in most cases, was ensured by the use of thresholding-based segmentation algorithms. Defect detection leverages similar features as job-site monitoring, covering edges, diverse interest points, region proposals (especially in R-CNN algorithms), HOG, gradient magnitude and orientation, entropy, and even colour-based ones. Edge detection dominates in previous studies, and Qizhen, H. et al. [36] concluded two classes of edge detection algorithms: ones dependent on first-order derivative, i.e. image gradient, and ones based on second-order derivatives.

In higher-level image processing, deep learning algorithms have gained popularity as mentioned. The form of the core network, ANN, evolves from CNN [37, 38], fully convolutional neural network (FCN) [39], fast R-CNN [29], to faster R-CNN [24, 28]. Along with the superiority to eliminate multi-step image processing, such algorithms are further supported by acceptable performances and adaptability to diversified structures and defect types.

3.2.3 Area of Use

In real life, defect inspection and condition assessment procedures are carried out both regularly (routine inspection) and after disasters.

- Post-disaster inspection

Past work for post-disaster inspection focuses on damaged reinforced concrete (RC) columns due to their critical role to resist lateral seismic loads. Lattanzi, D., et al. [40] established relationship between visual defects (e.g. cracks and spalls) and the maximum experienced displacement of concrete bridge columns for post-earthquake condition assessment. The peak drift estimated through machine learning regression models can facilitate triage evaluation. Similarly, German, S., et al. [41] first adopted computer vision algorithms (e.g. edge detection, region-growing detection, thresholding, etc.) to identify and measure cracks and spalling on RC columns, based on which, a framework for vision-based structural analysis is completed.

- Routine inspection

The allocation of past researches in different areas of use is shown as Figure 2.

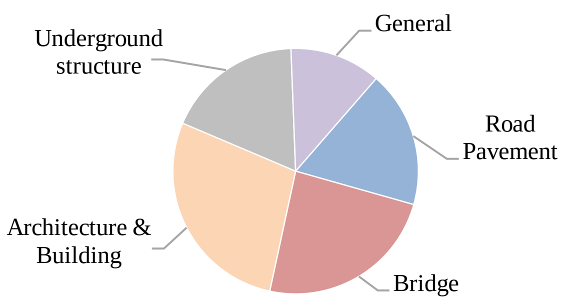

Figure 2. Literature distribution (area of use)

Comparatively, a wider range of civil structures are studied in routine inspection, and an almost even distribution is shown. The aging problem of architectures and buildings attracts the most attention (making up 28% of the literature). 12 out of 51 studies focus on the health of bridges. Roadways (asphalt pavements in particular) and Underground structures (including sewer pipes [28, 42], tunnels [38, 43, 44] and subway system [17]) are also frequently studied fields, accounting for 9 out of 51 papers equally. Different from the majority of studies, Kamal, K., et al. [45] classified various knot defects in wood structures.

There are about 12% researchers developing their proposals in a general scale, testing on laboratory specimen [46] and existing point cloud datasets [47], and aiming to tackle prevailing or critical challenges encountered during applications.

3.2.4 Defect Types

Figure 3 illustrates the allocation of past work in various defect detection.

Cracks appeal the most intensive studies by far, accounting for more than 35% of the literature. Among them, 17 articles study on concrete structures, 3 researches target fatigue cracks on steel structures and 5 papers recognize cracks on road pavement. Around a quarter of past work focus on displacement, based on which structural vibration properties (e.g. natural frequency and mode shapes [48]) are further retrieved. Pothole, as a distress peculiar to roadways, are recognized in 3 out of 51 papers. Other defects include cavities [29, 49], spalling [50], rebar exposure [29, 50], moisture marks on subway structures [17], loosened bolts [44], etc.

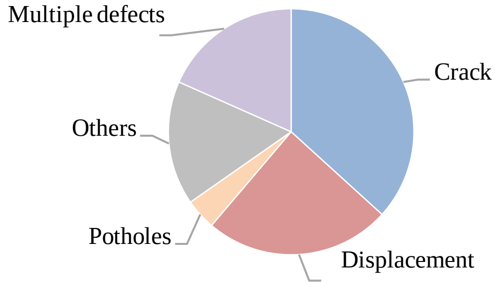

Figure 3. Literature distribution (defect types)

In addition, a few of studies (nearly 20%) recognize multiple defects [51] and cover more damage patterns, such as deposits, tree root intrusions and water infiltrations on pipes [28], steel corrosion, bolt corrosion and steel delamination on general structures [24].

Particularly, artificial markers or specific objects (e.g. lane marker, manhole and patches on roadways) on the asset were utilized to clarify novel methods in [52].

3.2.5 Level of Detection Details

To what extent computer vision can benefit maintenance decision making is fully dependent on the level of detail of the inspection results. The outcome of a computer-vision-based inspection system develops from the mere detection of defects' presence, classification of multiple damages, defect localization, to numerical measurement of critical properties. The progress so far is shown in Table 1. And detailed achievements in each category are illustrated below.

Table 1. Current research progress

Level of detail / Defect type	Defect detection		Defect property retrieval
	presence	localization	
Crack	[23-25, 30, 33, 34, 37, 53-55]	[28]	[22, 39, 56-59]
Pothole		[60, 61]	
Spalling			[50]
Cavity		[49]	
Moisture marks			[17]
Displacement		-	[26, 27, 46, 48, 62-65]
Dynamic responses		-	[66]

Note: The grey area means that this level of defect details has been successfully retrieved using computer vision techniques in the literature (with relevant references listed), while blank area means that few researches included the extraction of such information so far.

- Classification. Identification across defect types were realized in [31] to classify pothole, longitudinal-transversal cracks, and fatigue cracks on pavement. Other researches define category based on damage severity (major/ minor cracks in [42]), defect features (crack orientation in [56]), or different maintenance demand (sealed or ordinary cracks in [67]).
- Localization. Several researches locate the defect-included bounding box in the identified image [28, 60, 61], requiring further processing to gain their positions in global coordination. Additional devices

are deployed as supplementary, such as GPS [31], infrared camera and laser range finder for cavity localization on roadways [49].

- Property quantification. For crack measurement, its length, orientation, max width and mean width are extracted either through skeletonizing operations in static images [39, 68] or by tracking surface discontinuities in video streams [22]. Properties of spalling area, i.e. its length and depth, are obtained by analyzing the region with exposed longitudinal reinforcement [50]. The severity of wet marks on subway structures is quantified in terms of the area's percentage [17]. Displacements are retrieved in almost all relevant researches. One notable improvement is that early studies rely on manually-created markers [64] or speckle created by a laser pointer [66], while recent work achieve target-free inspection using "key points" [63, 69] on structures. Another progress is multi-point displacement measurement using multiple synchronized low-cost cameras [26] or a multithread active camera with Galvano-mirror [48]. Displacements can be further converted to natural frequencies through the Fast Fourier Transform (FFT) [63].
- Structural analysis. Limited research manages to complete this step with vision-based defect information. Post-earthquake fragility curves of RC columns were generated in [41], indicating structural damage states and estimated retrofit cost. Davoudi, R. et al. [32] estimated structural load levels of RC beams and slabs based on crack patterns. Combination with other technology like robotics [58] further facilitates this process.

4 Conclusions and Future work

This paper presents an overview about the applications of computer vision in civil engineering. Researches in construction sites start early and form a relatively mature system, and there are considerable advances in defect property retrieval for existing civil assets. However, challenges remain in this field and promising future work on the basis of current achievements is demonstrated as below.

Currently, vision-based defect information is underutilized due to the lack of relationship between visual data and structural responses. Thus, the integration and utilization of defect information in structural analysis so as to facilitate maintenance decision makings is in the future agenda.

Another task is to establish an enlarged dataset for computer vision. For construction phase, images with a wider range of personal protective equipment (PPE) [8], construction entities, and their activity patterns [11] should be collected. As for operation and maintenance stage, images containing more defect patterns under various environmental conditions can largely contribute to this field. Such enlarged datasets can be used to train classifiers for higher detection accuracy and achieve comprehensive monitoring of both construction sites and aging structures.

Robustness of analysis results against adverse factors encountered during data acquisition should be tested and improved. In jobsites, though effects of various illumination, varying object-to-camera distances, and different levels of occlusion on the accuracy of object tracking have been studied [7], further evaluation concerning other uncertainties, like shadows, should be included in future work. Similar envision applies to in-service assets, even if the impacts of surrounding lighting conditions on crack detection have been assessed [35].

For practical considerations, real-time analysis is desired. In routine inspections, real-time defect recognition and feedback to inspectors are enabled by the simplification of image capturing devices [31]. The leverage of Graphics Processing Unit (GPU) can further shorten computation time. However, when faced with cluttered construction sites and existence of various deterioration patterns, further improvements are in need.

In the future, combination with other advanced technology is encouraged. The utilization of deep learning methods has been proved efficient. Data-driven algorithms also facilitate the vison-based condition assessment [32] , calling for more multidisciplinary applications. Moreover, devices like GPS providing additional information for vision-based system also deserve consideration.

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