Critical review of shifting research from defect detection to defect modeling in computer vision-based structural health monitoring

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Abstract

The last decade has witnessed a plethora of studies on the applications of computer vision (CV) in structural health monitoring (SHM). While the research effort has been primarily focused on detecting surface defects from 2D images (known as defect detection), increasing studies are tapping into reconstructing the defects in 3D (called defect modeling). It remains unclear whether the shifting focus suggests a resolution of the defect detection problem, and thus constitutes a systematic transition. This article aims to answer the questions by conducting a critical review of CV-based SHM. It is found that the turning of limelight to defect modeling coincides with the proliferation of deep learning (DL) in defect detection. The shift is a structural change driven by (a) collective advancements of external technologies such as big data, computing power and algorithms, and (b) inherent need of the SHM discipline to strive for a data-enriched and evidence-based transformation. However, it does not mean a resolution of defect detection, but poses higher requirements on its performance in realistic settings (e.g., complex background and instance differentiation). A roadmap is proposed to synergize future defect detection/modeling research from five aspects, i.e., instance segmentation in context, 3D reconstruction, geometric modeling, semantic modeling, and formal representation. A case study was performed to demonstrate preliminary implementation of the roadmap. The research contributes to understanding the rapidly evolving landscape of CV-based SHM, and laying out an overarching framework to guide future research.

Keywords: Structural health monitoring (SHM); Computer vision (CV); Machine learning;

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Defect detection; Defect modeling; Damage information modeling.

1. Introduction

Structural health monitoring (SHM) plays a critical role in maintaining the serviceability of man-made structures (Farrar and Worden, 2007). It originated from the field of mechanical and aerospace engineering, and was gradually adopted for civil infrastructure monitoring in 1980s (Farrar and Worden, 2007). Technically speaking, inspection and monitoring are considered two different subjects with different space-time resolution — the former is sparse in time but dense in space while the latter being totally the opposite (Spencer Jr et al., 2019). However, for the sake of comprehensiveness, this research does not make the distinction, and adopts the broadest possible definition that encompasses the both (Dong and Catbas, 2020; D. Feng and Feng, 2018). Computer vision (CV)-based SHM is a non-destructive testing (NDT) approach that does not require direct contact with the structure concerned (Park et al., 2007). Compared with other NDT techniques such ultrasonic analytics (Brownjohn, 2007; Park, et al., 2007; Su et al., 2023), it stands out for its cost-effectiveness and the ability to cover relatively large area with its wide field of view (Dong and Catbas, 2020). The promise of CV-based SHM has been recognized as early as late 1990s.

As a subfield of CV-based SHM, defect detection generally refers to the methodologies, process, and technologies employed for automatically identifying structural flaws from digital images. Although a consensus has not yet been reached regarding the initial research attempt, relevant studies began to emerge in the 1990s. (L. Abdel-Qader et al., 2003; Klassen and Swindall, 1993; Tanaka and Uematsu, 1998). Early research efforts concentrated on identifying image pixels that represented defects by directly applying image processing techniques (IPTs), such as edge detection (L. Abdel-Qader, et al., 2003) and Otsu thresholding (Pakrashi et al., 2010). Another line of work aimed to train machine learning (ML) models, e.g., support vector machines (SVM), with the IPT-extracted features to detect the defects more robustly (Junjie Chen and Liu, 2021). Either way, manual efforts are required to test a wide range of IPTs and handcraft defect-sensitive features (Guo et al., 2024; L. Zhang et al., 2016). Due to this labor-intensive process, practical deployment of CV in SHM has been limited.

The situation was improved significantly with the resurgence of deep learning (DL). Unlike traditional approaches based on feature engineering, DL is an end-to-end model driven entirely by data (Koch et al., 2015; L. Zhang, et al., 2016). Given datasets of adequate size and diversity, a DL model such as a convolutional neural network (CNN) can automatically learn defect-sensitive features from the data and apply them for defect detection (Y.-J. Cha et al., 2017). As these features are automatically learned, they are statistically more adaptable to data variations, and thus have better generalizability over different defect types captured in different environments. The advantages of DL and the resulting superior performance have led to a skyrocketing number of publications in the field of defect detection over the past decade (Dong and Catbas, 2020; Hsieh and Tsai, 2020).

With the recent surge in defect detection performance, increasing attention is paid to a new territory in SHM called defect modeling (Artus and Koch, 2020a). Unlike the goal of defect detection to identify defects (typically from 2D images), defect modeling aims to reconstruct a digital representation of the defects (usually as 3D geometric models) (Artus and Koch, 2020a; Artus and Koch, 2020b; Hüthwohl et al., 2018). The modeling results provide valuable information on the defect geometry (e.g., length, width, and area) and can enable the extraction of their semantic properties. The implication to the broad field of SHM is immense. As noted by Spencer Jr. et al. (2019), defects identified at a local level (i.e., 2D images) must be analyzed within a global context to comprehend their scale and size. Many review papers share similar opinions. For instance, Dong and Catbas (2020) emphasized the importance of 3D defect information in assessing structural conditions and offered a review of the latest studies on defect 3D reconstruction. Zhang et al. (2022) envisioned the incorporation of defect information into finite element modeling (FEM), necessitating a 3D defect model. The growing interest in this emerging field gives rise to new research questions that require urgent attention:

(a) Does the shifting interest indicate a resolution of the defect detection problem?
(b) Is the current trend just a “a flash in the pan” or a systematic transition?
(c) If it is a systematic shift, what are the structural forces that underpin this transition?

In response to these research questions, this study presents a critical review of the latest developments in the field of CV-based SHM, with a focus on elucidating the nexus between the evolution of defect detection and defect modeling. The aim is to enhance our understanding of the transition from 2D detection to 3D modeling of defects and the driving forces behind it. Based on this understanding, a roadmap is proposed to outline the key aspects that future research should address to fully harness the potential of defect modeling.

2. Taxonomy revisited: Defect detection versus defect modeling

A cornucopia of terminologies has been generated in CV-based SHM. It would be beneficial to first clarify some of the most frequent terminologies in the respective fields of defect detection and defect modeling.

Formal definitions have not yet been established to differentiate between defect detection and its modeling. However, it is generally accepted that defect detection involves identifying defects from specific measurements of a concerned structure. While the definition itself does not imply any dimensionality, 2D images have been the most common form of measurement, and as a result, detection methods are primarily 2D. Numerous methods have been developed for this purpose, and depending on the granularity of their output, they can be broadly categorized into four clusters, as illustrated in Fig. 1. *Image classification* represents the coarsest level of granularity, as it can determine whether a given image contains defects and, if so, the types of defects present. However, the output results provide limited information on either semantic (e.g., specific defect types) or geometric (e.g., position, shape, and morphology on images) aspects. *Object detection* surpasses *image classification* in terms of geometric granularity, as it not only identifies the presence of defects in an image but also indicates their position and aspect ratio using bounding boxes. Nevertheless, *object detection* cannot provide information about defect geometric shapes and appearances. Conversely, *semantic segmentation* can decipher specific semantic types of multiple defects and thus lies a step further along the semantic granularity continuum. However, it cannot differentiate instances of the same defect type. The two continuums converge at *instance segmentation*, which achieves the finest level of granularity in both aspects. It can not only distinguish defect instances and their semantic types but also extract defect geometry at a pixel level.

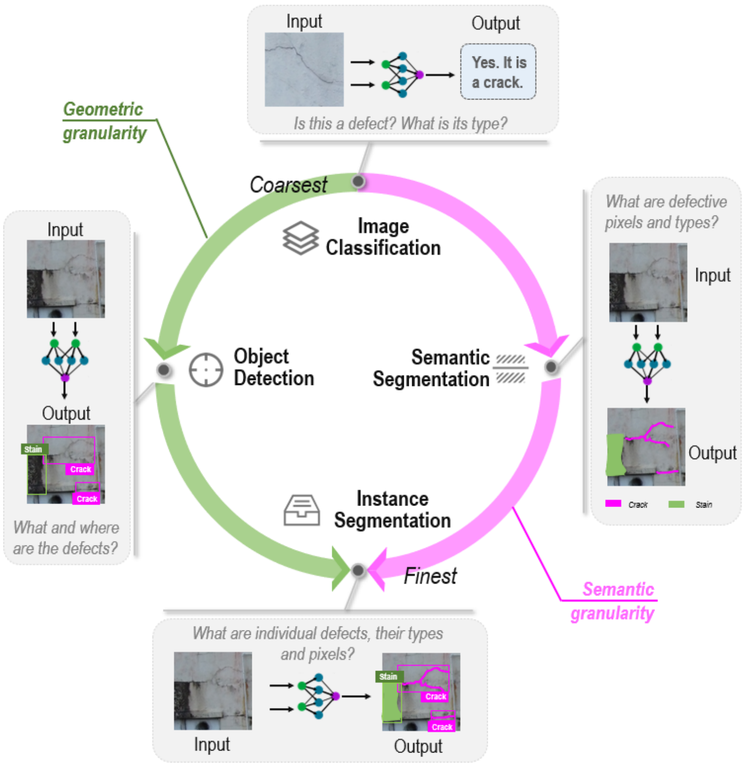


Fig. 1. Terminologies of widely used defect detection methods.

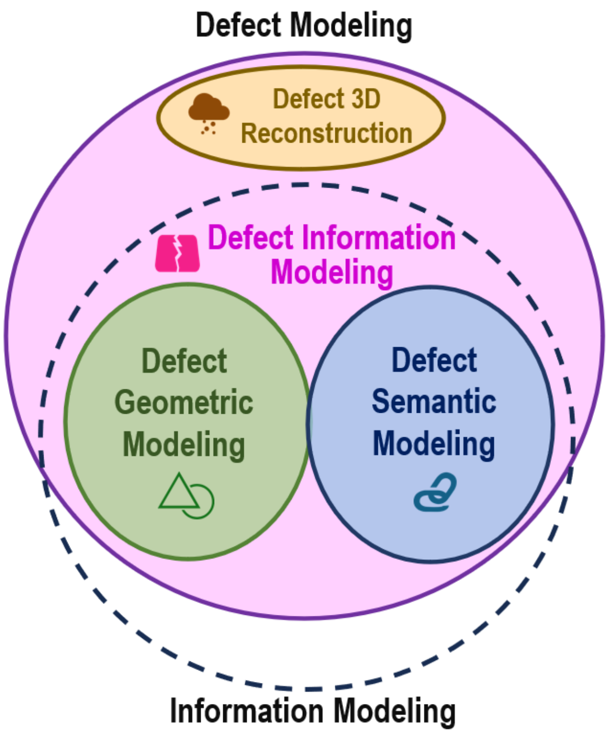


Fig. 2. Relationship of defect modeling terminologies.

Defect modeling aims to create an abstract representation of the identified defects. Since defects occur in 3D physical space, the preferred form of abstraction is also 3D. A defect modeling process consists of several activities, as illustrated in Fig. 2. An emerging area of interest is defect information modeling, also known as damage information modeling (DIM) (Artus and Koch, 2020b). As the name implies, DIM combines defect modeling and information modeling, involving the organization and representation of information related to defects. DIM comprises two main tasks: geometric modeling and semantic modeling. Defect geometric modeling concentrates on generating 3D digital models that replicate the geometry of defects in the physical world. Prior to geometric modeling, a process called defect 3D reconstruction is required to convert defects detected from 2D image sequences into points in 3D space. Intermediate or final outputs of 3D reconstruction and geometric modeling can take various forms, such as point clouds, defect point clouds (DPC) (Junjie Chen et al., 2023), mesh, boundary representation (BREP), and constructive solid geometry (CSG). Table 1 provides a summary of these terms. Defect semantic modeling, on the other hand, focuses on compiling a range of defect properties (types, ratings, etc.) and providing a structured digital representation. The resulting semantic models can also take various forms, from the most general linked data models to domain-specific industry foundation classes (IFC), as outlined in Table 2.

Table 1. Possible forms of defect geometric models.

Geometric forms	Definition
Point cloud	A discrete set of data points in space, which may represent a 3D shape or object.
Defect point cloud	A cluster of point cloud that represent structural defects.
Mesh	A digital representation of a 3D object or surface
Boundary representation	A method for representing a 3D shape by defining the limits of its volume.
Constructive solid geometry	A method for representing a solid as a combination of primitive solids, as contrastive to the boundary representation.

Table 2. Possible forms of defect semantic models.

Semantic forms	Definition	Level of specificity
Linked data model	A model to represent and organize structured data on the web to facilitate data sharing, integration, and interoperability.	Low
Entity-relationship diagram	A visual representation of the major entities, attributes, and relationships within a database system.	Medium
Industry foundation classes	An open, standardized data model for the exchange and sharing of built asset-related information across platforms and throughout project lifecycle.	High

3. Research methods

A desk research is conducted to understand the changing CV-based SHM landscape, which involves a combination of critical review, thematic analysis, trend analysis and comparative study.

(1) Critical review. At the center of the research is a critical review method (Grant and Booth, 2009), which aims to derive new conceptual model to decipher the current research trend by deeply interpreting existing body of work in CV-based SHM. It does

not aim for systematicity and comprehensiveness in covering past literature, which is normally necessitated by a systematic review approach (Grant and Booth, 2009). To identify a list of representative works, the authors leveraged their extensive experience at the intersection of CV, SHM, and 3D reconstruction. This was supplemented by a literature search on major databases such as Web of Science (WoS) and Google Scholar. In total, 110 scholarly works were reviewed, all of which were published in English. The majority of the articles were peer-reviewed journal papers, with a small number of conference papers published in authoritative outlets. Through the critical review, the authors aim to understand the driving forces behind the shifting research landscape in CV-based SHM and develop a novel conception of a systematic roadmap towards defect modeling.

(2) Thematic/Trend analysis. The collected papers undergo a thematic analysis to make sense of their content. As a widely used analytical approach in qualitative research, thematic analysis focuses on identifying, analyzing, and interpreting patterns of meaning (or "themes") within qualitative data. The objective is to uncover the internal mechanisms and driving forces behind the current shift from defect detection to defect modeling. Therefore, it is natural to use "defect detection" and "defect modeling" as selective themes for analysis. Special attention is given to the development of the respective research fields. To understand their evolution from a historical perspective, a trend analysis method is employed. Key indicators for the trend analysis encompass factors such as annual publication numbers for each field, accuracy and other performance metrics of related models or algorithms (e.g., mean average precision (mAP) for defect detection models).

(3) Comparative study. The trend analysis of the respective themes, i.e., "defect detection" and "defect modeling", will be holistically examined through a comparative study. Defined as a research methodology that compares multiple subject matters to uncover inherent patterns among them, the comparative study method is well-suited for achieving our research objectives. By comparing the evolution trajectories of the two aforementioned themes, we expect to illuminate the nexus and interplay between advancing data inspection platforms, enhanced defect detection performance, and the emergence of defect modeling research. In doing so, the current shift from defect detection to defect modeling can be better understood, and a more systematic approach to defect modeling can be established.

4. Results analysis

4.1. Evolvement of defect detection research

Among the reviewed articles, the earliest defect detection research can be traced back to 1993. Since then, the research field has undergone 30 years of polynomial growth, as illustrated by Fig. 3. This 30-year development can be roughly divided into three phases: the infancy stage, the development stage, and the explosive stage.

4.1.1. Infancy stage (pre-2006): Sporadic exploration

Before 2006, the research area was still in its infancy. This period is characterized by a sluggish development, as evidenced by the small number of annual publications (or without publications at all) during the time. Only sporadic exploration was made on and off, with a lack of continuous research input.

A closer look into the research during this period reveals a primary interest in the development of robotic systems capable of detecting defects in hard-to-reach civil structures, such as buried pipelines (Bradbeer et al., 1997; Nickols et al., 1997) and underwater bridge piers (DeVault, 2000). The emphasis was on designing mechanical systems that ensured the safe navigation of robots in challenging environments. In terms of defect detection, these systems predominantly relied on human inspectors to review footage captured by on-board cameras and to identify defects that may have occurred. Only a handful of studies aimed to automate data analysis for defect detection. For instance, Klassen and Swindall (1993) developed an automated crack detection system for road pavements, which incorporated a series of image analysis algorithms. Similarly, Tanaka and Uematsu (1998) proposed a morphological approach for road crack detection that includes black pixel extraction, saddle point detection, linear feature extraction, and connection processing. Abdel-Qader et al. (2003) presented a study that compared the performance of four distinct edge detection algorithms in bridge crack recognition.

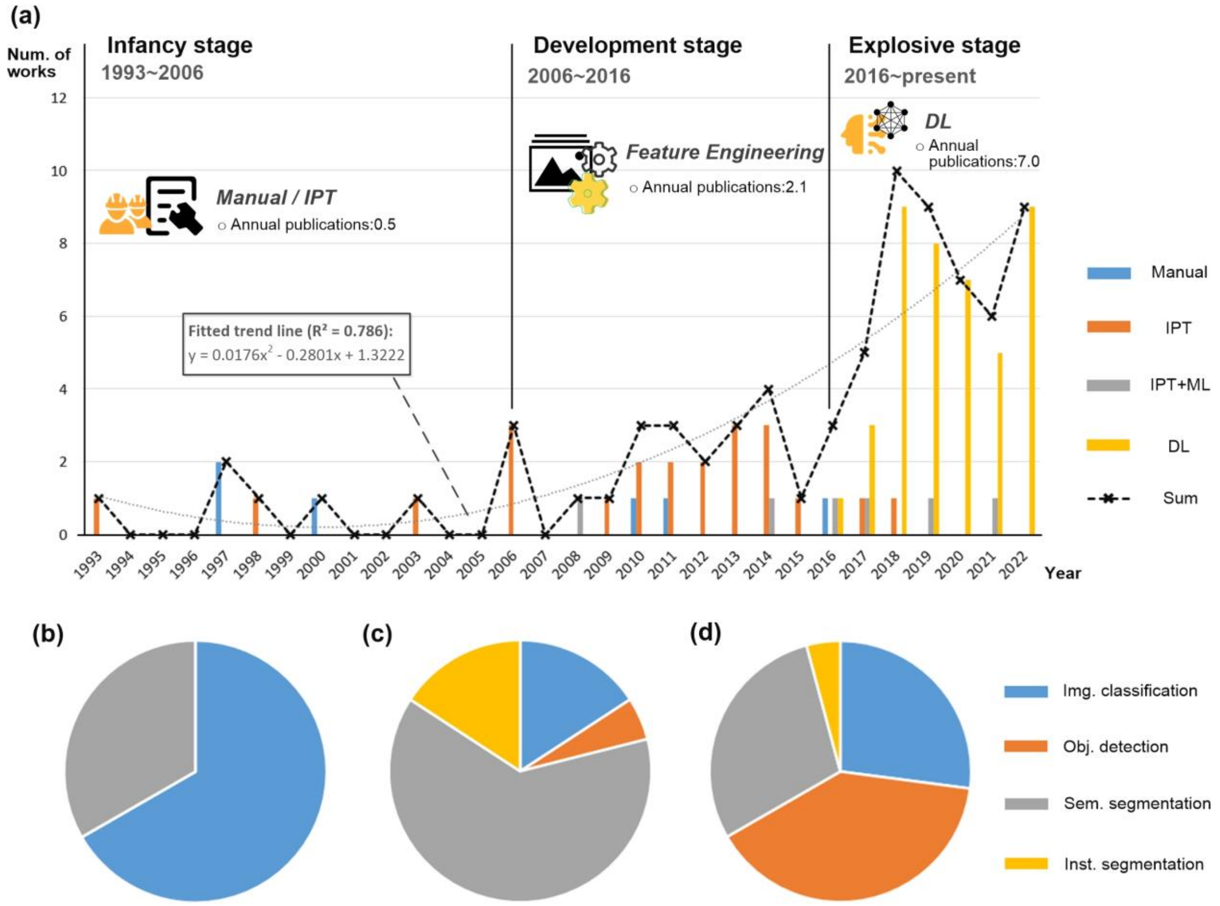


Fig. 3. (a) Annual publication numbers in defect detection since 1993; and Distribution of research on the tasks of image classification, object detection, semantic segmentation, and instance segmentation in (b) infancy stage, (c) development stage, and (d) explosive stage.

In retrospect, considering the enormous workload in infrastructure maintenance (L. Abdel-Qader, et al., 2003), researchers had already realized the importance of inspection automation in SHM as early as the 1990s. However, more focus was directed towards automating data collection rather than data processing (Bradbeer, et al., 1997; Nickols, et al., 1997). This is understandable, as even the most effective defect detection algorithm would be rendered useless without scalable devices (Schempf et al., 2010; Tătar and Pop, 2016) in place to gather necessary data for processing. The slow progress in this area can also be attributed to the fact that personal computers at that time lacked the computing power needed to handle resource-intensive tasks such as image processing.

4.1.2. Development stage (2006~2016): Semi-automation based on feature engineering

Defect detection publications have experienced a steady growth since 2006. This pattern of growth continued towards to 2016. The ten-year development stage is featured by stable research input, with in average 2.1 papers published annually.

Research during this stage was all based on IPT. In the context of defect detection, this involves leveraging various IPTs to manipulate digital images and extract useful defect-related information. It can range from identifying image pixels that correspond to defects (Y. Huang and Xu, 2006; Sinha and Fieguth, 2006; Tsai et al., 2010) to extracting high-level defect properties based on the identified pixels (German et al., 2012; Nishikawa et al., 2012; Zhu et al., 2011). IPT-based defect detection is problem-oriented and domain-specific. It relies on primitive knowledge about the objects of interest to select appropriate IPTs for defect-sensitive feature extraction. Take crack recognition as an instance. Abdel-Qader (2006) observed that cracks are formed by the continuation of darker-colored pixels distributed linearly, and developed a convolution-based linear structure detector for bridge crack detection. This linearly distribution assumption is followed by many other crack detection researchers (Oh et al., 2009; Qin Zou et al., 2012).

Unlike cracks, spalling or corrosion appears as clusters of pixels expanding in both dimensions of a plane. Pakrashi et al. (2010) took advantage of the visual contrast between corroded areas and neighboring pixels, applying Otsu's thresholding to extract corrosion in harbor structures. German et al. (2013) developed an entropy-based method to detect spalling from images, based on the observation that spalling areas tend to exhibit rougher textures. Koch and Brilakis (2011) conducted a pre-segmentation of road images into defect and non-defect regions using histogram shape-based thresholding, which was followed by an elliptic regression for the extraction of cyclic-like potholes. There are many other types of defects, such as bolt loosening (Y. J. Cha et al., 2016; Ramana et al., 2019), underwater cracks (Z. Zhang et al., 2018), and pavement distress (Doycheva et al., 2017). It is unrealistic to expect a one-size-fits-all collection of IPTs; rather, the choice of techniques and their implementation sequence should be determined on a case-by-case basis, depending on the specific type of defects to detect and the detection environment. The general principle of remains the same (Mohammad R Jahanshahi et al., 2009; C. M. Yeum and Dyke, 2015). It first relies on domain experts to identify visually distinctive patterns of the defects of interest. Then, based on these patterns, image features are engineered using an array of IPTs to extract the defects.

As presented in Fig. 3 (c), studies during this stage primarily focus on semantic segmentation. The emphasis on semantic segmentation can be attributed to the inherent nature of IPTs. Since an IPT typically processes images pixel by pixel in a bottom-up manner, it directly outputs pixel-wise binary maps where zero and non-zero values indicate non-defect background and defects, respectively. This is precisely the function of semantic segmentation (L.-C. Chen et al., 2017). This hard-wired binary division is inherently limited when dealing with multi-classification problems or when there are statistic uncertainties. To address the limitations, a line of research attempted to combine the generalizability of ML with the characterizability of IPT-extracted features (Junjie Chen and Liu, 2021; Halfawy and Hengmeechai, 2014; Yang and Su, 2008). Yang and Su (2008) compared the performance of three different ML algorithms—back-propagation neural networks, radial basis networks, and SVMs—in classifying sewer pipe defects based on texture features described by wavelet transforms and co-occurrence matrices. To ensure detection robustness, Halfawy and Hengmeechai (2014) trained an SVM classifier to identify root intrusion defect instances based on the histograms of oriented gradients (HOG) features. Cha et al. (2016) designed a series of damage-sensitive features using Hough transform and used them as input to an SVM for loosened bolt detection. The synergistic integration of IPT and ML enhances the robustness of hand-engineered features and the overall defect detection performance.

Data samples are essential to iteratively configure the hand-engineered features using IPTs. This is even more critical when ML is utilized. A close analysis of research published between 2006 and 2016 reveals a predominant reliance on private datasets collected by the respective research teams. The only exception is (Zou, et al., 2012), which was further expanded into a dataset called CrackTree260, consisting of 260 road pavement crack images and made public in (Q. Zou et al., 2012). Due to the requirement for manual feature engineering, methods proposed during the development stage (2006-2016) can only be considered semi-automated.

4.1.3. Explosive stage (post-2016): Fully automation by end-to-end learning

The research field has experienced an explosive development stage since 2016, which can be attributed to the resurgence of DL. This is evidenced by a decomposition of the growth curve in Fig. 3 (a), where defect detection studies based on DL surged and became dominant, while IPT-enabled detection gradually diminished. Inspired by the success of DL in other areas (e.g., the historic triumph of AlphaGo in 2016), Zhang et al. (2016) developed a road crack detection method based on deep CNN. Cha et al. (2017) applied DL to detect civil infrastructure crack damages, demonstrating its viability.

The most groundbreaking aspect of DL is its end-to-end training mechanism. Instead of relying on human-engineered features, a DL model can automatically learn the features by gradually adjusting its internal weights and parameters to fit the defects labeled by humans (X. Zhang et al., 2023). It accepts raw inspection images as input and directly output defect detection results. As long as the training data covers sufficient variations, DL can learn more generalizable defect features than those extracted by IPTs. The pioneering work by L. Zhang et al. (2016) demonstrated the superiority of the learned deep features, which can lead to better defect detection accuracy. The promise demonstrated has stimulated a plethora of studies (C. Feng et al., 2020; Hoskere et al., 2018a; Qi et al., 2022; Yang Zhang and Yuen, 2021). Kim et al. (2019) compared traditional ICP-extracted features and deep features learned by CNNs, and found that the CNN-learned features outperformed their counterparts in differentiating cracks and non-crack noise patterns. Cha et al. (2018) applied Faster Region-based CNN (Faster R-CNN) in multi-defect detection, accurately locating five types of defects with bounding boxes. Since DL features are automatically learned, there is no need to customize different features for different types of defects. This significantly lowers the barrier to multi-class defect detection, as seen in Yeum et al. (2018), Cheng and Wang (2018), Hüthwohl et al. (2019), S. Li et al. (2019), and many others. In addition to 2D images, attempts have also been made to harness the power of DL to process complementary data modalities. For example, Tong et al. (2017) designed an ensemble of CNNs for ground-penetrating radar (GPR) scan processing to detect concealed pavement cracks. Beckman et al. (2019) complemented DL-detected concrete defects with depth information provided by RGB-D cameras to achieve volumetric quantification of spalling. Wu et al. (2019) integrated the visual images and laser-scanned 3D point clouds for road pothole assessments.

In terms of task types, research at this stage presents significantly greater diversity than the monotonous focus on semantic segmentation during the Development Stage (see Fig. 3 (c) and (d)). While the number of publications focusing on semantic segmentation remains largely the same, attention paid to image classification and object detection has substantially increased. A significant proportion of research effort was devoted to classification between 2016 and 2019. Apart from early works by (L. Zhang, et al., 2016) and (Y.-J. Cha, et al., 2017), Gao and Mosalam (2018) conducted a classification of damage types by introducing Transfer Learning to train VGGNet (Visual Geometry Group). Similarly, Feng et al. (2019) reported an automatic dam defect classifier based on Inception-v3 CNN model. The output of classification does not convey information concerning defect location and appearance (A. Zhang et al., 2017). Therefore, research interests in this task gradually diminished after 2019, with a shift towards object detection. Maeda et al. (2018) employed the Single Shot MultiBox

Detector (SSD) to detect eight types of road damages from a large self-collected dataset. Deng et al. (2020) modified Faster R-CNN to ensure concrete crack detection performance in complex scenarios where handwriting scripts co-exist with defects on structural surface. Huang et al. (2022) proposed a dam damage detection method based on Faster R-CNN, which can efficiently identify and locate three types of defects in images. Object detection still fails to provide the highest level of information granularity required by practical applications (Junxin Chen et al., 2023). Instance segmentation can achieve defect property quantification to instance-level, but unfortunately, only two articles have addressed this topic (Wei et al., 2019; Wu, et al., 2019).

The DL revival would not have been possible without big data. Large DL models, with their millions of internal network parameters, require sizable datasets to train (Pan and Yang, 2020). To address this fundamental need, many large-scale defect datasets have been created and shared within the research community. When the amount of data is insufficient, researchers often resort to a technique called data augmentation to expand the dataset. Common data augmentation approaches involve image manipulation such as flipping, resizing, cropping, and adjusting brightness and contrast (Junjie Chen and Liu, 2021). Tang and Chen (2020) proposed a novel data augmentation technique based on the scale-space theory, which is fully analytical and tractable. More advanced approaches use generative models, such as Generative Adversarial Nets (GAN) and Stable Diffusion, to generate synthetic samples. Gao et al. (2019) demonstrated the effectiveness of GAN-based data augmentation in improving defect detection performance. Maeda et al. (2020) augmented a road damage dataset by combining GAN with Poisson blending, which can generate high-quality samples. Table 3 lists details of five typical defect datasets. With such publicly available datasets and consistent evaluation metrics, it is viable to objectively evaluate the progress of the research field (Arya et al., 2022).

Table 3. Representative defect image datasets.

Name	Num. of classes	Defect classes	Num. of images
Structural ImageNet	4	No damage, Flexural damage, Shear damage, Combined damage	36,413
RDD	8 *	Longitudinal cracks (×2), Transverse cracks (×2), Alligator cracks (×1), and other corruption (×3)	47,420
METU	2	Crack, and Non-crack	40,000
CrackTree260	2	Crack, and Non-crack	35,100
CrackForest	2	CrackForest	11,800

* Refers to the total number of subclasses, of which the number for each class is presented in brackets of next column

Despite the generally perceived success of DL, little effort has been made to comprehensively compare the state-of-the-art defect detection results across studies, which is critical to position the current progress. Yet, due to the huge variations in task targets, evaluation metrics and data complexity adopted by different studies, such cross-study comparison is challenging. As a counter-measure, this research categorizes the results into the three tasks of image classification, object detection and semantic segmentation. For each task, the most prevalent performance metric is chosen, i.e., accuracy, mAP, and mIoU for classification, detection and segmentation, respectively. When different metrics were used by the reviewed studies, they will be normalized if possible; otherwise, they are excluded from the evaluation. For example, some studies used F-score to measure their defect semantic segmentation results. For these cases, we converted the F-score results to IoU before comparison (Dawood et al., 2017; A. Zhang, et al., 2017). As for data complexity, we divided the used datasets into three level of complexity, i.e., low complexity (small scene with only defect present), medium complexity (medium defect scene with certain background and/or foreground objects), and high complexity (large-scale scene with only small portions of defects).

Fig. 4 shows defect detection results compiled by the aforementioned method. Task-wise, unlike the commonly over 0.9 score achieved by classification, the tasks of object detection and semantic segmentation have experienced relatively less satisfactory results, with mAP/AP and mIoU/IoU falling in the range of [0.7,0.9], and [0.6,0.8], respectively. Regarding the effect of data complexity, the performance was unanimously found to drop as more variations and contextual items are presented in images. To solve practical problems in SHM, it is important to achieve effective defect detection from images featuring complex scenes instead of idealistically simple backgrounds (Hsieh and Tsai, 2020). This is also driven by the rise of new hardware (e.g., drones) that tend to capture unstructured images in large complex scenes, as opposed to dedicatedly designed devices (Jiang and Zhang, 2020). One straightforward solution to this complex-scene detection problem is to confine the detection to only ROIs that are subject to the occurrence of defects. The identification of ROI can be either done by DL-based component recognition (Kim et al., 2023; Liang, 2019; Xiao et al., 2024) or guided by primitive knowledge from the Building Information Model (BIM) (Junjie Chen et al., 2019; Junjie Chen, et al., 2023). Another direction is to improve the robustness of DL-enabled defect detection against background noise, as demonstrated by Bang et al. (2019), Kang et al. (2020), and Kang and Cha (2021). Nevertheless, given the still stagnant progress in defect segmentation in complex scene (average mIoU of 0.601), more needs to be done.

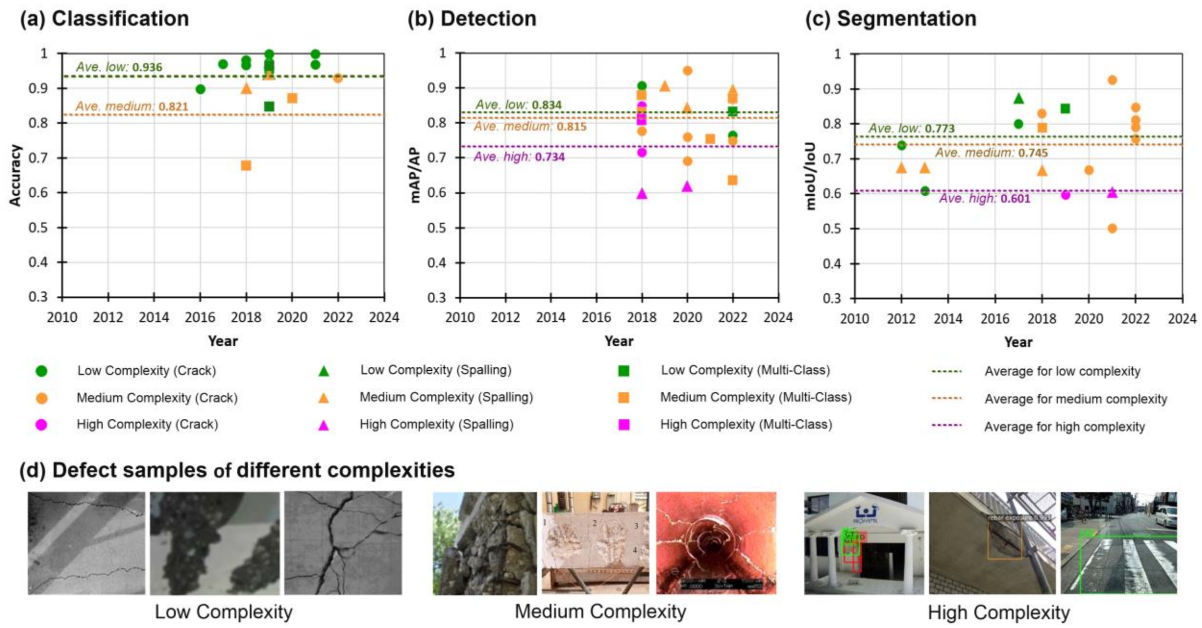


Fig. 4. Statistic summary of the state-of-the-art defect detection performance: (a) Image classification; (b) Object detection; (c) Semantic segmentation; (d) Examples showing different level of data complexity.

4.2. Evolvement of defect modeling research

It was not until recently that research on defect modeling emerged as a significant trend. The exploration has given rise to two distinct streams of work: one addressing the geometric aspects of defects, and the other concentrating on data modeling of defect properties and semantic information. Some early works a decade ago had already begun to investigate some of the objectives defect modeling seeks to accomplish, e.g., characterization of defect properties. To gain a comprehensive understanding of the current state, this section will first delve into its past by examining these early works on defect characterization.

4.2.1. Early defect characterization works driven by the need of property measurement

The ultimate purpose of defect detection is to derive properties that hold practical value for engineering analytics, e.g., defect types, positions, dimensions, areas, and volumes. This goal partially aligns with the mission of defect modeling and has been investigated early on through a myriad of studies.

Prior research on defect detection has primarily concentrated on 2D images. This 2D detection suffers from the lack of depth information, which hampers accurate characterization of defects' 3D geometry in physical space. To address this issue, scholars have introduced relative metrics to assess the severity level by comparing the dimensions of defects to those of the affected components (German, et al., 2012; Zhu, et al., 2011). Zhu et al. (2011) argued that crack properties measured in pixels are of little value unless they are correlated to the measurements of structural elements. German et al. (2012) quantified severity of concrete spalling by comparing its pixel-represented dimensions to the width of the structural elements. At the meantime, some researchers attempted to derive absolute defect measurements by certain predetermined primitives such as the pixel-to-metrics ratio, which is either deterministically measured (Nishikawa, et al., 2012; Wei, et al., 2019) or statistically regressed (Adhikari et al., 2014; Dawood, et al., 2017). Nishikawa et al. (2012) estimated crack width by applying a known image resolution measured by mm/pixel. Wei et al. (2019) adopted a similar approach to measuring concrete bugholes. Adhikari et al. (2014) trained a neural network to estimate crack depth after obtaining crack length and width using the pixel-to-metric conversion method. In practice, it is unrealistic to obtain primitives like the pixel-to-metrics ratio beforehand. With the principle of photogrammetry, Lee et al. (2013) established a theoretical model to derive the relationship between pixel and metric measurement, which eliminates the need of pre-calibration. Jahanshahi and Masri (2013) improved this photogrammetry-based method by considering situations where the camera orientation is not perpendicular to the defect plane.

Early defect characterization works also sought to obtain geo-spatial location of the defects. The purpose is to correlate the defects detected from 2D images, which usually only depict a local part of the concerned structure, to the global context for better interpretation (Lim et al., 2014). To achieve this purpose, Li et al. (2018) proposed a defect detection and localization network (DDLNet) to detect and locate civil structure defects simultaneously, wherein the geo-localization was achieved via content-based image retrieval. Kang and Cha (2018) applied ultrasonic beacon to guide the navigation of UAV in GPS-denied environments, and used the geo-tagged information to position bridge defects. Ma et al. (2021) realized coarse building defect localization by dividing a floor area into discrete grids. Defects detected are automatically assigned to corresponding grids, and visualized in BIM with different colors.

4.2.2. Exploration on modeling defect geometry in 3D

Early efforts in defect characterization addressed some practical engineering demands, but did not adequately capture the defect geometry and its spatial context in an intuitive manner. The limitation gives rise to defect geometric modeling in the holistic 3D contexts of facilities.

Explorative efforts in geometric modeling have been undertaken in a decentralized and bottom-up manner. A notable characteristic of such decentralized endeavors is the lack of consensus on the appropriate forms of representation for the modeling (Zlatanova, 2017). Some has resorted to naïve 3D representation like pseudo-3D (Insa-Iglesias et al., 2021; Mohammad R. Jahanshahi et al., 2011; Oh, et al., 2009). Insa-Iglesias et al. (2021) developed a panorama-based defect visualization system called 3D Virtual Inspector for tunnel SHM. As the defects are presented by highlighted pixels in stitched 360° photographs, it can only be considered a pseudo-3D representation. A more popular, and perhaps more unarguably, type of simplistic 3D representation is point cloud. A typical workflow usually involves (a) the application of the multi-view stereo vision to recover a sense of depth from multiple mutually overlapped images, (b) the use of algorithms such as Structure from Motion (SfM) to reconstruct a point cloud of the structure from a collection of inspection images by iteratively applying the multi-view triangulation, and (c) a backward projection to correlate the defects detected on 2D images to clusters of 3D points in the point cloud (referred to as DPC).

Liu et al. (2016) presented one of the earliest works on defect geometric modeling using point clouds. They demonstrated the feasibility of SfM reconstructed point clouds for measuring defect properties, irrespective of the photo-taking positions. Khaloo et al. (2018) and Zhao et al. (2022; 2021) expanded the use of 3D reconstructed photogrammetric point clouds for large-scale civil infrastructure inspection. Lu et al. (2020) conducted an exploratory investigation into the geometric accuracy of point clouds for infrastructure SHM. Chaiyasarn et al. (2022) applied a CNN-based semantic segmentation technique for pixel-level crack detection from photogrammetrically reconstructed 3D models, inherently correlating detected defects with the geometric model. Point clouds generated by SfM are up-to-scale, meaning they only reconstruct relative spatial positions among points that do not necessarily adhere to the identical scale and origin of the physical assets. To avoid cumbersome calibration using ground control points (Zhao, et al., 2021), Chen et al. (2022; 2023) leveraged BIM as a natural landmark to register the point cloud to the actual scale. The resulting DPC offers a geometric model that can be directly measured for property extraction.

Despite its simplicity, point cloud can be redundant in modeling the numerous defects a facility may have. It is particularly evident given that defect geometry often follows certain primitive patterns. For instance, a crack is usually linearly distributed and can be effectively represented by a few polylines with vertices capturing its turning points, which is more efficient than using hundreds of points to detail every aspect of it. The undesirable redundancy of point cloud prompts researchers to seek for more effective representations. Mesh is perhaps the most common among various alternatives. Hoskere et al. (2018b) generated mesh models of damaged facilities by applying Poisson surface reconstruction to the SfM-derived point cloud, onto which different types of defects (cracks, spalling, debris, etc.) were modeled via UV mapping. Similarly, Isailović et al. (2020) employed triangular meshes to represent bridge spalling damages. In contrast to mesh representations that only model boundary surfaces, Taraben and Morgenthal (2021) proposed a voxel-based method, which can be advantageous when volumetric quantification is required. Zhang and Lin (2022) introduced an automatic remeshing method to dynamically update the FEM with defect information for structural analysis.

Many other representations were proposed for different defect types. Liu et al. (2020) and Hamdan et al. (2021) modeled bridge pier cracks with polylines, which follows the observations that most cracks appear as linear structures. Hüthwohl et al. (2018) projected photorealistic texture of defects to facility models for representation, whereas Artus and Koch (Artus et al., 2022; Artus et al., 2021; Artus and Koch, 2020a) conducted a series of works to explore the effectiveness of different defect geometry representation methods, e.g., texture-based and void-based.

4.2.3. Exploration on defect semantic representation

Abstraction of a defect entity goes beyond its geometry. The past decade has witnessed an uprise of research to formally model semantic properties of structural defects. To improve defect information reusability and facilitate machine-processable evaluation, Hamdan et al. (2021) developed a linked data model for semantic representation of recorded damages based on semantic web technologies. Musella et al. (2021) formally defined a data scheme for representing masonry and concrete building defects, and achieved a dynamic linkage between the quantitative (position, shape, and extent of damage) and qualitative (building component affected, possible mode of failure, etc.) information.

Defect semantic modeling research is accompanied by rapid proliferation of BIM (Tan et al., 2022), and thus a major line of research aims to come up with an IFC data model or extends it for defect information modeling. Ma et al. (2015) built upon existing IFC schema to propose an information model for post-earthquake assessment of reinforced concrete structures. The study also extends IFC by introducing two new classes to represent segments of broken building elements and the relationship between segments and cracks. To automate post-earthquake damage assessment, Anil Engin et al. (2016) developed an automated method to generate damaged model from BIM and recorded damage information. As for common defects obtained by daily inspection, Hüthwohl et al. (2018) conducted an in-depth examination for the development of an IFC information model to organize inspection data related to reinforced concrete bridges. Sacks et al. (2018) compiled an Information Delivery Manual (IDM) to specify the technical components, activities and information exchanges in bridge inspection, and specified a data exchange schema based on IFC4 Add2 for bridge damage information. Artus and Koch (2020a) stressed the importance of efficiently storing and exchanging defect information, and explored different ways to model the geometry and semantics of physical damages based on IFC. They further examined the performance and compatibility of existing BIM software in supporting the newly developed IFC model view (Artus and Koch, 2021). Artus et al. (2022; 2021) presented an object-oriented data model utilizing standard IFC format for representing defect related information encompassing both geometry and semantics.

4.3. Comparative analysis and findings

This section aims to unravel the shifting research landscape in CV-enabled SHM by directly contrasting the development trajectories of defect detection and defect modeling research. As illustrated in Fig. 5, the emergence of defect modeling research is found to be coherent with the Explosive Stage of defect detection.

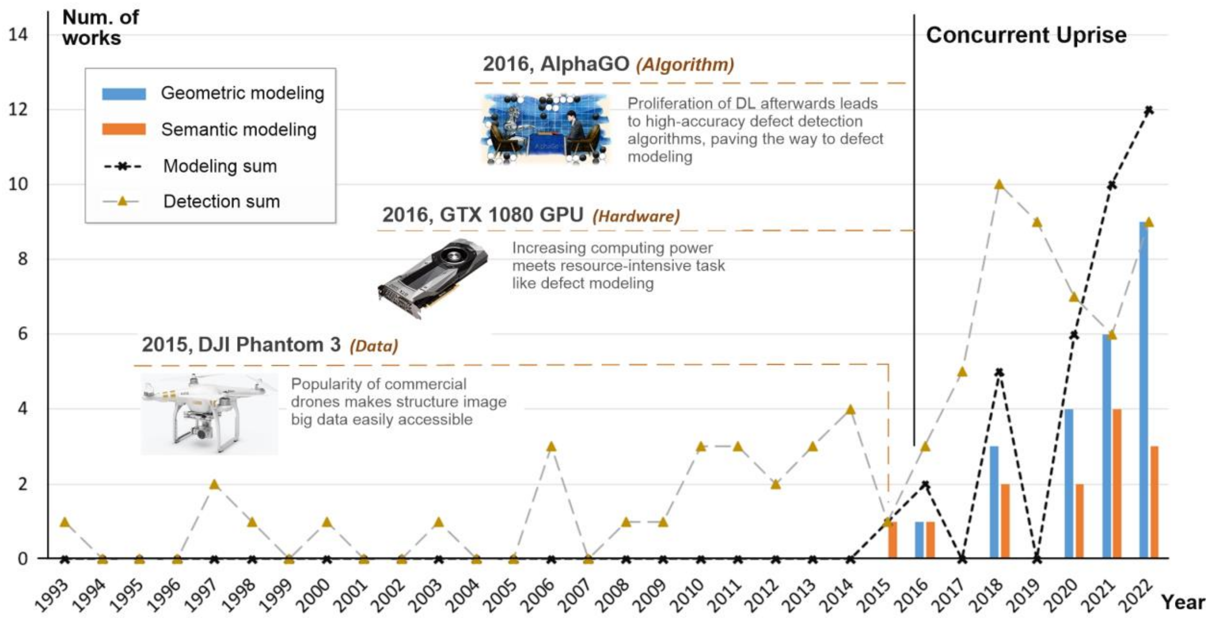


Fig. 5. Evolvement of defect modeling research, and its aligning uprise with defect detection research since 2016.

The alignment is not coincidental; rather, it could reveal the underlying structural reasons behind the current shift. One can easily draw a connection between the rise of defect modeling research and the application of DL in SHM. After all, it was not until 2016 that the research community began to investigate defect modeling at scale, aligning perfectly with the DL boom (L. Zhang, et al., 2016). In many ways, DL has proven to be superior to its preceding IPT-based counterparts. This superiority is evident in the significantly improved precision and robustness of defect detection, as quantitatively demonstrated in numerous studies (Y.-J. Cha, et al., 2017; Kim, et al., 2019) and reflected by the diminishing number of IPT research in Fig. 3. DL's advantages also involve its adaptability to a wide range of defect detection tasks, including classification, object detection, semantic segmentation, and instance segmentation. This enhancement in precision and versatility is crucial, as it enables SHM researchers to move beyond the minor implementation details of defect detection and focus on broader and more practical concerns, such as defect modeling.

Behind the defect detection-modeling nexus is a more implicit and thus somehow overlooked factor — data. DL-based defect detection is data greedy, and so is defect modeling. Recovering a 3D model of a structure (or even a part of it), removing outliers from the reconstructed 3D points through bundle adjustment, or fitting defect points with parametric models all necessitate a sizable collection of images. Consequently, the increasingly easy access to large-scale inspection data could be a confounding factor causing the seemingly mysterious concurrence. The argument is re-affirmed by the timing when the commercial drone industry took off. For example, Amazon announced its ambitious drone-based delivery initiative in 2013. It was in 2015 that DJI released its flagship drone model – DJI Phantom 3, which offered high-performance drone products at affordable prices. The popularity of commercial drones and other robots has significantly reduced the cost of inspection data collection, leading to an abundance of available data whether for training DL-based defect detection algorithms (K. Lee et al., 2022; Sajedi and Liang, 2021) or for 3D reconstruction in defect modeling (Junjie Chen, et al., 2023; Isailović, et al., 2020).

In addition to the factors mentioned above, the shift towards defect modeling would not have been possible without the fundamental support provided by increasing computing power and advancements in algorithms. Since defect modeling involves processing large amounts of data (e.g., SfM reconstruction and point cloud processing), powerful computing tools are essential. This is also a prerequisite for DL-based defect detection, further elucidating its simultaneous emergence with the growing focus on defect modeling. The continuous improvement of algorithms is another foundational factor. While SfM was proposed as early as the 1980s, the development of scale-invariant local features like SIFT (Scale-Invariant

Feature Transform) and SURF (Speeded-Up Robust Features) has made it more practical to implement due to their ability to extract abundant feature correspondences across images. Emerging variations, such as COLMAP (Schonberger and Frahm, 2016) and HashSIFT (Suárez et al., 2021), also enhance traditional SfM in terms of efficiency and applicability in textureless scenarios. Algorithmic improvements of this nature contribute to defect modeling in large-scale scenario reconstruction.

The easy access to computing power, the surge of inspection data, and the continuous improvement of algorithms are driving forces behind the development of defect modeling. However, it is crucial to remember that for something to become prevalent, it must offer fundamental utility to its subject area. In the case of defect modeling, the primary reason for its popularity lies in the benefits that the resulting defect model provides in guiding more comprehensive and objective facility maintenance decision-making. This has significant implications for promoting a cultural shift in SHM towards data-driven and evidence-based facility maintenance.

5. A roadmap towards defect modeling

Based on the above findings, a roadmap is formulated to synchronize future efforts towards defect modeling on a solid footing. As illustrated in Fig. 6, the roadmap outlines key research activities, as well as assesses the progress made in their respective fields.

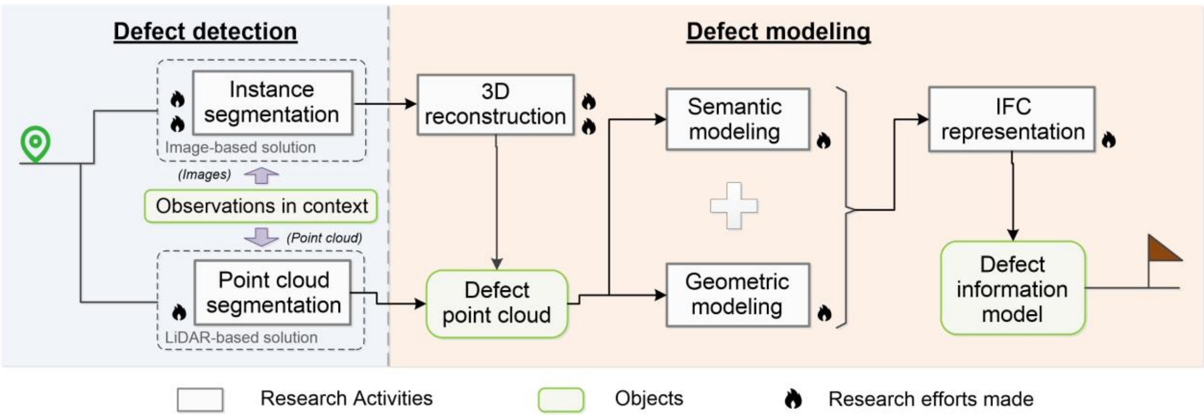


Fig. 6. The proposed roadmap towards defect modeling.

Step 1. Instance segmentation in context. The shift towards defect modeling does not render defect detection obsolete. On the contrary, it imposes higher demands. This is because defect modeling always begins with defects detected from specific observations (e.g., images), and the accuracy of defect detection significantly influences the quality of the resulting defect model. Prior research has devoted considerable attention to defect detection based on image data, resulting in substantial progress. However, most of the defect detection research is focused on object detection/semantic segmentation from idealistically simple background, which does not provide instance-level and pixel-wise information that is crucial for modeling individual defects at later stages. In addition, large-scale modeling involves observation data with both defects and their contexts captured. Therefore, future research should focus more on defect instance segmentation in contexts. In this regard, DL models with instance discrimination capabilities, such as Mask R-CNN, will be highly relevant. Another promising approach is to directly segment defects from 3D point clouds rather than 2D image collections. The advantage is clear as it avoids the computationally intensive and sometimes error-prone 3D reconstruction required by image-based solutions (Hua et al., 2022). However, research in this field has been limited, possibly due to the prohibitive cost of LiDAR devices and the lack of mature point cloud processing algorithms (Xie et al., 2020). Limited attempts made in this field include those by Bahreini and Hammad (2021), Erkal and Hajjar (2017), and Stałowska et al. (2022). With the increasing affordability of LiDAR and the development of more powerful algorithms (e.g., PointNet, 3P-RNN, DGCNN), a surge in this research area is anticipated.

Step 2. 3D reconstruction. The detected defects play a crucial role in generating DPCs, the fundamental elements for defect modeling. Different DPC generation approaches should be adopted depending on how the defects are detected. If the detection is conducted on a point cloud, the output automatically forms a DPC in which the defect instances have presumably been identified. When the defects are detected from images, a 3D reconstruction is required to transform the detected 2D defects into 3D space (Kim et al., 2022). This area has received most of the recent attention. A classical 3D reconstruction approach is SfM (Saputra et al., 2018), which has been actively explored in recent years for SHM (Khaloo, et al., 2018; Liu, et al., 2016; Zhao, et al., 2022; Zhao, et al., 2021). The point cloud produced by SfM is up-to-scale, making the normalization of an SfM-generated DPC to the real scale a highly relevant topic (J Chen, et al., 2022; Junjie Chen, et al., 2023). As precision of the reconstructed DPC (Lu, et al., 2020) directly affects the quality of the resulting defect model, further research is suggested to improve 3D reconstruction performance.

Step 3. Geometric modeling. With DPCs available, the next steps are to model the defects both geometrically and semantically. Geometric modeling aims to determine a 3D representation of a defect based on its DPC. Fundamentally, this is a regression problem with a target to find a geometric expression that best fits the DPC. For example, cracks can be modeled by a series of line segments organized in a tree structure. This tree-organized linear structure provides a parametric model that can be used to fit a DPC of cracks. The same concept applies to other defects. A mouldy element on a flat surface can be represented by a polygon, while bulging can be modeled by mesh or NURBS. For potholes or spalling, which exhibit significant volumetric damage, BRep or CSG might be a sensible choice. A geometric model provides a structured representation of defects that allows geometry-based analytics and facilitates information management (Artus and Koch, 2020a). Despite its significance, little research has been conducted. The few existing studies only aim to convert DPCs into mesh composed of excessive vertices and faces (Hoskere, et al., 2018b; Isailović, et al., 2020; Youqi Zhang and Lin, 2022). These mesh representations are redundant and unstructured, which requires demanding storage and computing resources. Future research should focus on defect modeling with parametric geometry based on BRep, CSG, and other forms. In this regard, useful references may be found in geological modeling, an active research field focused on modeling the geometry of underground fractures, faults, and rock strata (Han et al., 2018; Zhong et al., 2006). However, compared to defects, point samples used in geological modeling have a sparser pattern. Implications of sampling density in terms of uncertainty, precision, and efficiency should be considered.

Step 4. Semantic modeling. The goal of semantic modeling is to organize related properties of defects into a designated structure, so they are interpretable to both humans and machines. The well-organized defect properties can be easily retrieved for structural condition assessment (Artus, et al., 2022; Artus, et al., 2021), and can be combined with domain knowledge to form an expert system for causal inference (H.-M. Chen et al., 2013; Yu et al., 2023). As shown in Table 4, the semantic information to be model can be divided into four categories:

- Descriptive semantics. The first category is descriptive, and concerns basic factual information, e.g., inspection basics (inspector ID, inspection time, etc.), defect types (cracks, bulging, etc.), and measurement of defect dimensions (length, width, etc.).
- Relational semantics: The second category concerns the relationships among different defect instances or their relationships with external structural components. For intra-defect relations, potential groupings between defects should be considered. For example, certain defects (such as cracks, spalling, and corrosion) may be regarded as individual instances at a local level, while their combination as a whole can represent a larger defect (e.g., a defective column) at the global level. In terms of defect-component relationships, data fields should be reserved to describe the element to

which a defect is occurring.

- Diagnostic semantics. Another aspect for semantic modeling is concerned with diagnostic information related to the causes and rating of the defects, and their potential counteracting measures.

- Prognostic semantics. Corresponding to the diagnostic is the prognostic information, which serves to predict the future evolution of the defects. Examples include their implications in terms of the whole structure and their likely future development.

Although some previous research has addressed the topic of semantic modeling, these efforts tend to be fragmented and only focus on a part of the information listed in Table 4. Moreover, existing research is primarily concerned with data structure rather than automation of the entire pipeline, from defect information extraction to encoding it into a high-level semantic model.

Table 4. Aspects for defect semantic modeling.

Category	Content	Remarks/Examples
Descriptive	Inspection basics	Inspector, Time, etc.
	Defect types	Cracks, Bulging, Mouldy, etc.
	Measurements	Length, width, area, volume
Relational	Affecting components	Elements the defects occur, e.g., walls and façade
	Grouping	Nexus among defects, e.g., union and intersects,
Diagnostic	Causes	Inferred factors causing the defects
	Ratings	An assessed score assigned to defects
	Measures	Suggested actions for mediation
Prognostic	Implications	Implications of the defects
	Evolvement	Forecast future development
	Affected components	Surrounding elements that will be affected

Step 5. Formal representation. The final step involves a formal representation of defect information. The objective is to enhance cross-platform interoperability by modeling the defect geometry and semantics using formal data schemas. With improved interoperability, defect information can be better utilized for various purposes, such as numerical simulation (Min et al., 2023; Youqi Zhang and Lin, 2022) and digital twinning (J Chen, et al., 2022). Given the prevalence of IFC in the construction industry, a sensible choice is formal representation based on IFC. Pioneering research has been conducted to develop IFC-based data models for defect information representation (Artus, et al., 2021; Artus and Koch, 2020a; Artus and Koch, 2020b). These studies provide a solid foundation for formal defect representation by outlining the required IFC MVD (Hüthwohl, et al., 2018; Sacks, et al.,

2018). However, more research is needed to address two important questions: (a) whether the current IFC schema is well-suited to represent the domain-specific information presented in Table 4; (b) how to automate IFC-based defect representation and integrating it with the preceding steps in Fig. 6. The final output is a defect information model described by a formal data schema like IFC.

6. Pilot study

A small-scale pilot study was implemented to demonstrate key steps in the proposed roadmap. The structure of interest is a 10-story residential building near The University of Hong Kong (HKU), which occupies an area of around 26 m × 13 m, and is around 31 m tall. An image-based solution was adopted for defect detection. A total of 260 images were taken by an airborne camera with a 24 mm focal length and a 4000×2250 resolution.

In order to extract defect instances from the images, a classical instance segmentation model, Mask R-CNN, was used. The network weights previously trained on the COCO (Common Objects in Context) dataset were used as the base model, and fine-tuned on our custom task of defect detection. The number of training epochs, steps per epoch, learning rate, and weight decay were set as 30, 100, 0.001 and 0.0001, respectively. There are two types of defects for the pilot study, i.e., Cracks and Mouldy. Fig. 7 shows the defects detected by the trained model. It is found that not only the types and corresponding pixels areas of the defects have been successfully detected, but also individual instances of the defects were accurately distinguished by the model. This eliminates the need to cluster defective points into instances during later 3D reconstruction and modeling stages.

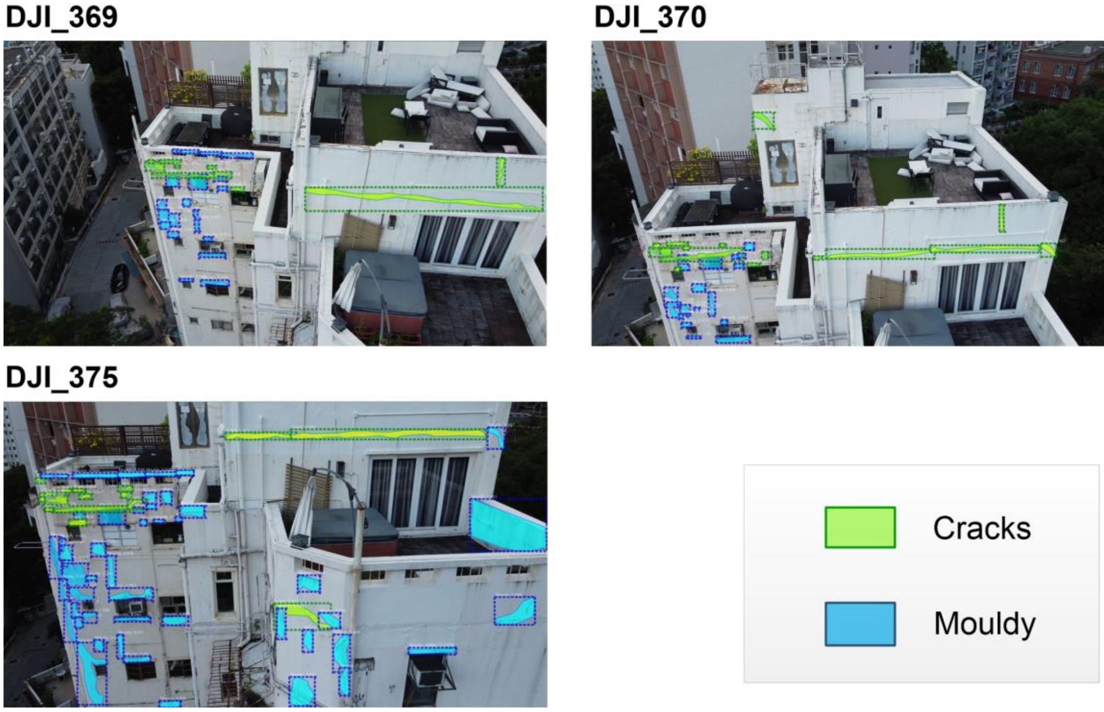


Fig. 7. Defect detection results based on instance segmentation techniques.

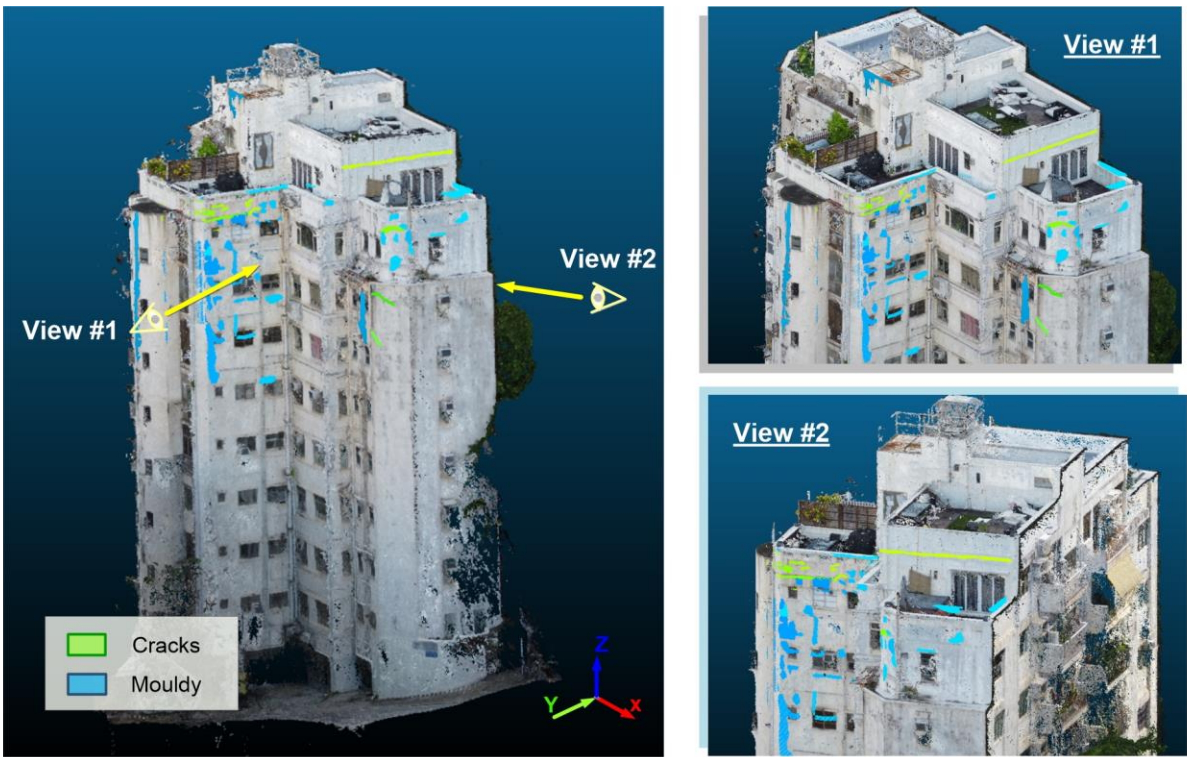


Fig. 8. 3D reconstructed point cloud with defect instance and types recognized.

A 3D point cloud model of the target building was reconstructed from the collected aerial images. It should be noted that the point cloud has been transformed to an equivalent scale of its physical counterpart in real world. The defect instances recognized in the last step were back-projected onto the point cloud model, forming clusters of DPC. Fig. 8 demonstrates the reconstructed 3D scene associated with instances of different DPCs highlighted in different colors. Points in lime green represents the cracks, and others in light blue denote the mouldy. As shown in Fig. 8, instances recognized in the 2D images have been successfully associated with the point clusters that form them in the 3D space. These clusters of DPCs lay the foundation of geometric modeling.

3D geometry of the reconstructed DPCs was modeled with primitive shapes such as lines and polygons. An automated script using Python was written for this purpose. Point clusters of different defect instances are treated as separate entity for modeling. Different types of defects were treated differently. For the cracks, they are fitted with polylines. While this can be done by various methods, the study applied Hough Transform to detect lines in the 3D point clouds. The lines detected for the same crack instance are then merged to form a polyline as its representation. As for mouldy, polygon is used for its representation. Alpha shape, which is a generalization of the concept of convex hull, is selected to model mouldy as polygons containing a set of points. A Python library called alphashape was used to realize the polygon fitting. Note that the coplanar points in 3D space are first converted to 2D space for polygon fitting. Afterwards, the control points of the fitted polygons are converted back to original 3D space as the final parametric representation of the mouldy geometry. Fig. 9 shows the results of geometric modeling, wherein five typical examples are marked with their instance ID and offered with close-up looks of their geometric representations. It can be observed that the geometric representations of the defects have been successfully reconstructed based on the DPC (back dots in close-up views in Fig. 9). Table 5 lists key information of the reconstructed geometric models.

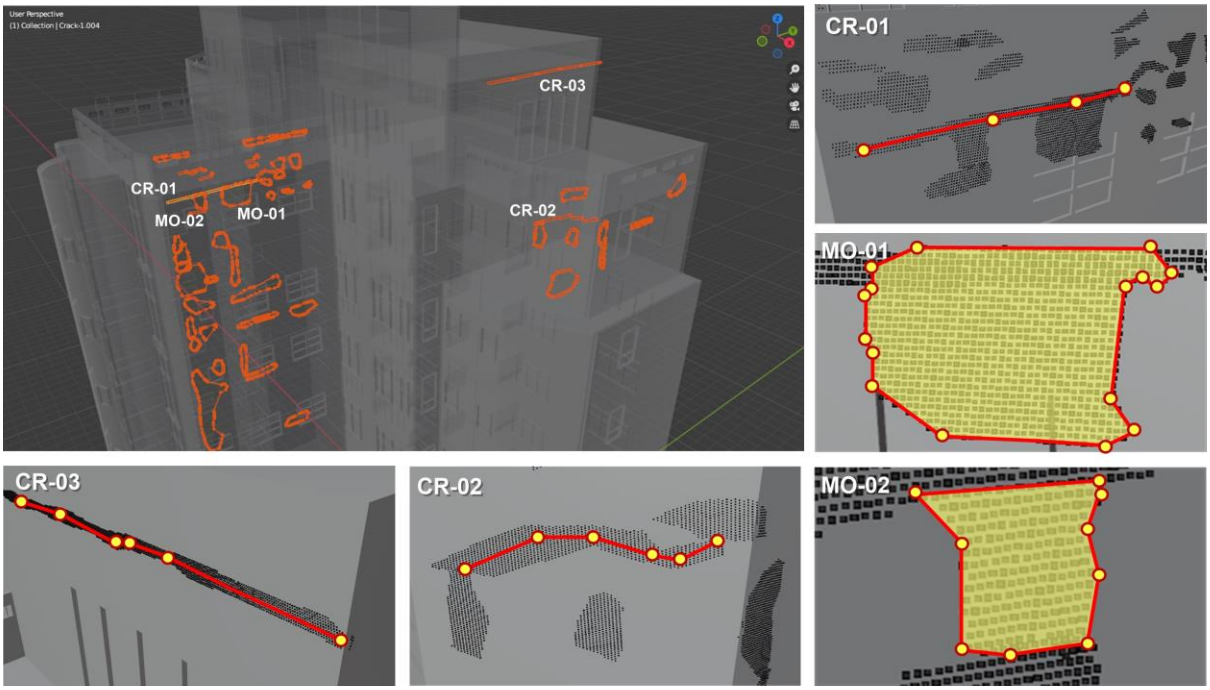


Fig. 9. Examples of geometric modeling results.

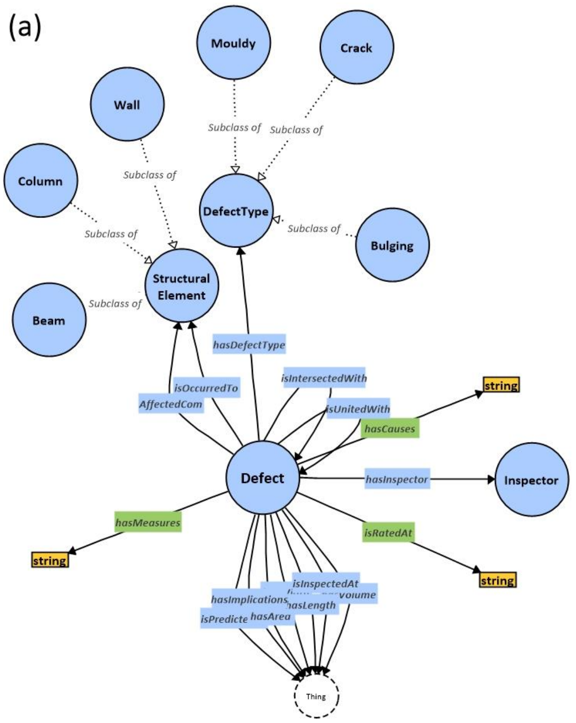
Table 5. Parameters of defect geometric modeling results.

Instance ID	Type	Geometric form	Geometric Control Points
CR-01	Crack	Polyline	{(0.23, -13.42, 26.29), (0.23, -12.86, 26.33), (0.23, -12.86, 26.33), (0.23, -10.65, 26.38)}
CR-02	Crack	Polyline	{(7.37, -6.04, 26.15), (7.94, -5.71, 26.40), … (8.50, -5.37, 26.43), (8.78, -5.21, 26.50)}
CR-03	Crack	Polyline	{(4.73, -5.41, 29.37), (4.73, -4.41, 29.39), … (4.73, -1.41, 29.46), (4.73, -0.45, 29.45)}
MO-01	Mouldy	Polygon	{(0.23, -11.56, 25.76), (0.23, -11.60, 25.78), … (0.23, -11.53, 25.76), (0.23, -11.56, 25.76)}
MO-02	Mouldy	Polygon	{(0.23, -12.60, 26.35), (0.23, -12.57, 26.35), … (0.23, -12.66, 26.27), (0.23, -12.60, 26.35)}

Semantic properties of the detected defects were extracted and represented by a linked data model as shown in Fig. 10 (a). The four aspects of semantic information were substantiated by the linked data model using the Web Ontology Language (OWL) in Protégé. Key descriptive properties of the selected defects have been listed in Fig. 10 (b). Take “CR-01” for instance. Basic information such as inspector name (Y** Wong) and inspection time (2021-10-05 07:52:13) has been successfully modeled. Defect type (crack) and dimensions such as length (2.77 m) were automatically extracted from the geometric modeling results. Finally, defect information regarding both geometry and semantics was formally represented by IFC schema. Following (Artus, et al., 2021), the defect is substantiated by the

IfcBuildingElementProxy entity. The geometry of crack and mouldy, for their geometric characteristics, was represented by the IfcPolyline and IfcPolyloop entity, respectively. In this pilot study, only descriptive properties were considered. For their representation, a set of single-value properties were defined and linked to the defect instances. Fig. 11 shows the resulting IFC representation of the case study building defects in BIMvision.

(a)



(b)

CR-01	
DefectType	Crack
Inspector	Y*** Wong
Time	2021-10-05 07:52:13
Length	2.77 m
CR-02	
DefectType	Crack
Inspector	Y*** Wong
Time	2021-10-05 07:52:13
Length	1.73 m
MO-01	
DefectType	Mouldy
Inspector	Y*** Wong
Time	2021-10-05 07:52:13
Area	0.28 m^2

Fig. 10. (a) Linked data model to represent semantic relationship of the defect properties; (b) Semantic properties of selected defect instances.

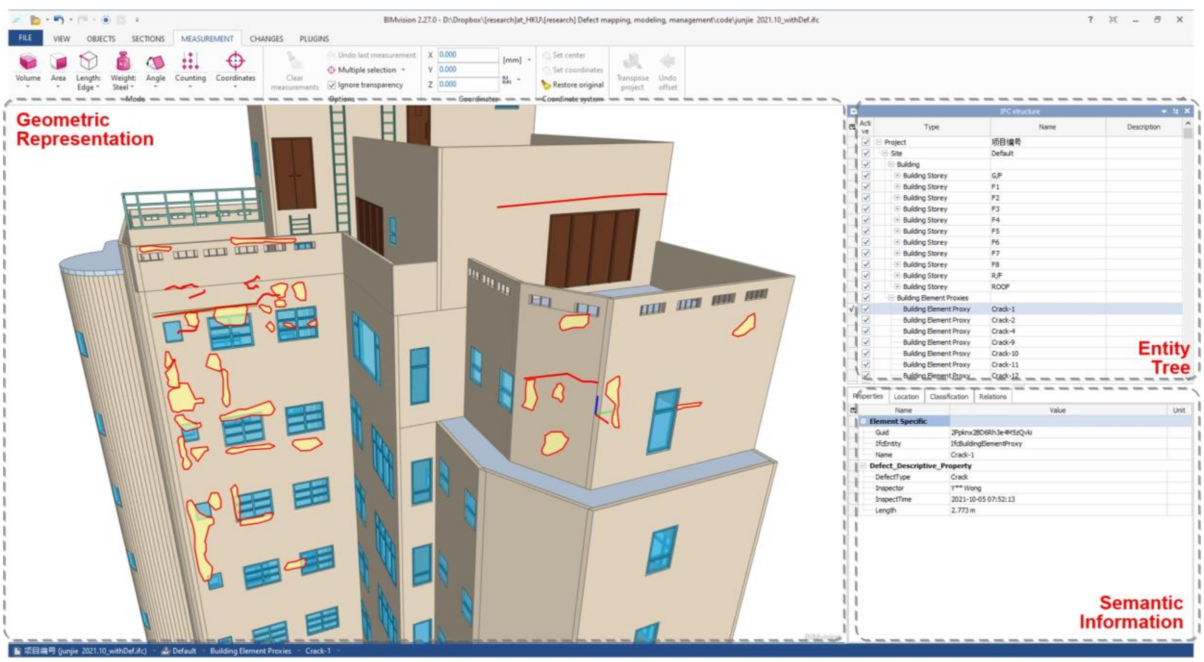


Fig. 11. IFC representations of the case study building defects.

Although this pilot study presents preliminary results for each step outlined in Fig. 6, it only targets to demonstrate the general principles. Due to its demonstrative nature, many steps in the pilot study have been simplified. For instance, in crack geometric modeling, only linearly developed cracks were considered, while in reality, many cracks may evolve into different branches and form a tree structure. Another example is that only coplanar defects were considered in the pilot study. For defects with more complex shapes, more sophisticated geometric representations should be adopted.

7. Conclusions

A critical review of CV-enabled SHM over the past three decades was conducted. The aim was to decipher the current shift in research focus from defect detection to defect modeling by addressing three questions: (a) does the shifting interest indicate a resolution of the defect detection topic? (b) is the shift a temporary trend or a systematic transition? (c) if the latter is valid, what are the underlying structural forces driving the transition? Through an in-depth analysis of 110 papers, it was discovered that the emphasis on defect modeling coincides with the rise of DL in defect detection. While the DL drastically improved defect detection models, the high performance was mainly achieved by simple tasks such as classification on idealistic datasets without contexts and background presented. The shifting focus is not "a flash in the pan" but rather a structural transition driven by the collective advancements of big data, computing power, and algorithms. However, this shift to defect modeling does not mean a resolution of the defect detection problem; instead, it urges the community to address more practically relevant problems in detection such as the presence of complex background and the differentiation among defect instances. Based on the review findings, a roadmap is proposed to align future research efforts on defect modeling in five key areas: instance segmentation in context, 3D reconstruction, geometric modeling, semantic modeling, and formal representation. A case study is presented to demonstrate a preliminary implementation of the roadmap. This research contributes to the understanding of the rapidly evolving landscape of CV-based SHM and establishes an overarching framework to guide future defect modeling research.

Following the key research topics and milestones in the roadmap, future research is suggested to fuel the field of defect modeling from the following five aspects:

(1) Addressing 2D or 3D instance segmentation in context. The generalizability of DL has enabled defect detection to achieve near or even superhuman precision for relatively simple tasks, such as classification, on datasets with monotonous backgrounds. However, to remain relevant in the evolving field of defect modeling, detection methods need to address large-scale scenarios where defects are captured within the contexts in which they occur. Exploring instance segmentation is also essential, as it provides crucial instance-level information for modeling individual defects. The presence of noisy background and the increased complexity introduced by instance segmentation would render existing detection algorithms less effective. This is why future defect detection research should pay primary attention to segmenting defect instances from context-related observations, whether in 2D images or 3D point clouds.

(2) Building data infrastructure for benchmarking 3D defect modeling performance. Publicly accessible common data infrastructure is essential for benchmarking performance, forging consensus, and synergizing research efforts. Several 2D defect image datasets, such as RDD and Structural ImageNet, have been made available for defect detection research and have positively contributed to the field's development. However, for defect modeling, such data infrastructure has yet to be established. Additionally, a system of evaluation metrics needs to be created to objectively measure defect modeling performance. With the data infrastructure and evaluation metrics in place, an overarching framework can be set up to guide future defect modeling research.

(3) Incorporating defect physics for geometric modeling. The emerging field of defect modeling is deeply rooted in the disciplines of structural engineering and material mechanics. Scientific models explaining how defects occur, develop, and evolve provide insights into the geometric appearance of these defects. Such defect physics can and should be leveraged to inform geometric modeling. For instance, defect physics confirms that cracks can only develop linearly, following a tree structure. Accordingly, it is reasonable to model crack geometry with parametric polylines organized in a tree structure. Moreover, crack depth can be modeled as a function of multiple variables, including its surface appearance and material properties. Establishing such a physics-informed model can help generate a more comprehensive crack geometric model that considers depth.

(4) Representing defect knowledge for semantic modeling. Semantic modeling of defects entails organizing defect properties that are of engineering interests in a structured manner. To this end, it is necessary to represent domain knowledge in SHM and defect inspection with a formalism, e.g., in a linked data model. This process is usually referred to as knowledge engineering. While some exploratory studies have been conducted, they are generally confined to specific civil structure types, e.g., bridges, tunnel, or buildings. A universal defect knowledge representation is in absence.

(5) Formalizing defect representation model for interoperability. The digitalization of defect information as virtual models does not necessarily make the information easy to use. In fact, the excessive digital formats and data schemes often results in numerous gaps between different defect models, making the reuse and exchange of defect information nearly impossible. These gaps highlight the need to formalize defect representation models with a universal scheme. The positioning of IFC as a vendor-neutral and sharable built asset data schema makes it a suitable option for defect information interoperation, which should be further explored.

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