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DOI
10.1016/B978-0-443-14120-1.00002-9

Publication date
2024

Document Version
Final published version

Published in
Non-destructive Testing of Impact Damage in Fiber-reinforced Polymer Composites

Citation (APA)
Tabatabaeian, A., Fotouhi, S., & Fotouhi, M. (2024). Visual inspection of impact damage in composite materials. In M. Saeedifar, & M. N. Saleh (Eds.), *Non-destructive Testing of Impact Damage in Fiber-reinforced Polymer Composites: Fundamentals and Applications* (pp. 43-67). Elsevier. https://doi.org/10.1016/B978-0-443-14120-1.00002-9

Visual inspection of impact damage in composite materials

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2.1 Introduction

Recent decades have seen a growing use of composite materials in various industries such as automotive, sports, civil and wind turbines, and, in particular, aerospace structural components due to mass criterion's crucial importance. The wide use of composites should still be addressed despite several advantages they can offer over metallic counterparts. Among their drawbacks, for instance, are their fragility and complex response to impact. Hence, composite damage tolerance maintenance practices should be standardized. In structural engineering, damage tolerance refers to assessing a damaged structure's ability to withstand loads before failing catastrophically. This has also been defined by European certification JAR 25.571 (JAR 25, Part 1 requirements, part 2 acceptable means of compliance and interpretations, n.d) as "the damage tolerance evaluation of a structure is intended to ensure that should serious fatigue, corrosion or accidental damage occur within the operational life of the airplane, the remaining structure can withstand reasonable loads without failure or excessive structural deformation until the damage is detected." There are two factors contributing to composite material's impact damage tolerance:

1. The impact-induced residual strength loss of the structure: Practically, the loss of strength can reach 50%−75% of the strength without impact.
2. Impact detectability: Even though impact damage is visible on the nonimpacted side of a composite structure before the impacted side, it is not detectable damage yet because, in practice, "detectable impact damage" refers to the damage on the impacted side, as the visual inspection of the nonimpacted side is not straightforward, for example, inside the wing, or the fuselage, in aircraft systems (Bouvet & Rivallant, 2016).

A well-established method to evaluate impact damage tolerance in aerospace composite structures is the visual inspection of the permanent indentation left on the impacted side of a composite after the impact event. This can be used in assessing the residual compressive strength and the level of the damage to determine whether it is visible impact damage (VID) or barely visible impact damage (BVID).

Non-destructive Testing of Impact Damage in Fiber-reinforced Polymer Composites.
DOI: https://doi.org/10.1016/B978-0-443-14120-1.00002-9

Visual inspection can be defined, according to the FFA advisory circular AC 43-204 (Erhart et al., 2004), as follows: “Visual inspection is the process of using the eye, alone or in conjunction with various aids, as the sensing mechanism from which judgment may be made about the condition of a unit to be inspected.” It is a fast and inexpensive method for structural health monitoring (SHM) of engineering systems, especially those with indentations or cracks on the surface. This process does not only rely on the human eye but also includes sensory and cognitive factors to enhance the accuracy of the tests and improve the visibility of the structure. For example, the angle and intensity of the light, or illumination, can be a critical factor in achieving high-quality visual inspection results. Test equipment may include but is not limited to borescopes, cameras, digital video magnifiers and video borescopes, and digital image correlation (DIC) facilities for improving detailed inspections (Zhong & Nsengiyumva, 2022) (see Fig. 2.1).

Figure 2.1 Examples of direct (in the center) and assisted visual inspection.
Sources: From PCTE. https://www.industrial-ndt.com and Aviation Pros. https://www.aviationpros.com and Aerocorner. https://aerocorner.com.

This chapter will present principles and different levels of visual inspection, followed by highlighting the role of effective parameters in impact damage inspection. Next, recent progress in the field is discussed and some case studies are highlighted. Finally, the challenges and future research directions of this nondestructive evaluation (NDE) method are reported and discussed.

2.2 Principles

In addition to the permanent indentation, impact loading can cause other types of damage in composite structures. These can vary from microscale damages, such as matrix cracks, to macroscale delamination and fiber breakage. In laminated composites, fiber breakage and delamination are often the dominant damage types affecting the residual compressive strength and impact damage tolerance. Therefore, critically identifying and categorizing different impact-induced damage types is of great interest to develop meaningful relations between the internal invisible, surface visible damages and remaining residual strength. Transverse loading causes matrix cracking in a ply in the form of shear cracks and transverse cracks running parallel to the fiber direction. These are the initial damage modes, taking place at an early stage of impact and static indentation due to the relatively weak mechanical properties of the resin. Cracks in the matrix do not significantly affect the laminate's residual properties and transverse stiffness. Nevertheless, if accumulating over time, it can cause more serious damages, such as delamination of adjacent plies. Contrary to other matrix-dominated damage modes such as delamination, matrix cracks cannot be detected by instrumented impact testing or conventional NDE techniques such as ultrasonic inspection (Abisset et al., 2016; Sun & Hallett, 2017). Delamination occurs due to high interlaminar shear and normal stresses exceeding the strength of the laminate interface, especially at areas of discontinuities such as holes and free edges or as a result of thermal loading during the curing process. This is more likely to happen between the plies with dissimilar fiber orientations (Abdallah et al., 2009; Sun & Hallett, 2018). Other impact-induced damage types are fiber breakage due to high tensile stress at the nonimpacted side or compressive fiber failure at the impacted side of the structure. These failure modes occur after matrix cracks and delamination and are easier to detect by visual inspection. At this stage, a large amount of energy is absorbed through fiber failure mechanisms, which significantly reduces the load-bearing capability of the composite structure (Dubary et al., 2018; Kristnama et al., 2021). The next section will explain how these damage types can be connected to permanent indentation, which is known to be a practical damage metric for visual inspection of impact damage in composite materials.

2.2.1 Damage metrics

For visual inspection of impact damage, permanent indentation is considered the most practical damage metric. However, this is defined differently by various organizations (Bouvet et al., 2012). For example, based on the Airbus damage definition, "BVID is the minimum impact damage surely detectable by scheduled inspection. BVID corresponds to a probability of detection of 90% with an interval of confidence of 95%. Two values for the BVID criterion are typically established dependent on the visual inspection type: Detailed visual inspection (DVI) and general visual inspection (GVI). Dent depth is the damage metric for transverse impact. For an edge impact, where internal cracks and delamination become visible, the damage metric is the dent depth and/or the crack length" (Fualdes, 2006). Boeing, however, defines BVID as "small damages which may not be found during heavy maintenance general visual inspections using typical lighting conditions from a distance of five feet. The damage metric is typically a dent depth of 0.01 to 0.02 inches. Dent depth relaxation must be accounted for" (Fawcett & Oakes, 2006). According to the inspector's experience (Rouchon, 1990; Thomas, 1994), it is possible to say with 95% confidence that a dent depth of 0.2−0.23 mm is detectable at a 2-m distance. Chen et al. (2014) used the dent depth and diameter to optimize the inspection intervals for maintaining high structural reliability and minimizing maintenance costs. According to general guidelines, permanent indentations between 0.3 and 0.5 mm can indicate BVID, whereas permanent indentations of 2 mm or perforations of 20 mm indicate minor VID. Also, perforation with a diameter of 50 mm can be related to large VID (Alhammad, et al., 2022b; Bouvet & Rivallant, 2016; Hasebe et al., 2022). Fig. 2.2 shows the evolution of impact damage and different visual inspection levels concerning the permanent indentation size and impact energy level. At the first stage, the dent size is so small, and damage happens in the form of matrix cracks. As impact energy increases, damage appears in the form of delamination, and dent size becomes larger. In the second stage, all three damage types can occur, and visual inspection becomes easier due to a larger dent size (dent depth and diameter). The fiber breakage in this stage can help achieve better inspection results. However, this can have a detrimental effect on the residual strength after impact, which explains the complexity of the interaction of different damage types during an impact event and the necessity of detailed studies of damage mechanics during and after the impact (Bouvet & Rivallant, 2016). To date, no damage metric can replace permanent indentation for visual inspection purposes. Ideally, such alternative damage metrics would be easy to implement and fast to assess with only a few tools needed. New SHM technologies could be a promising alternative to visual inspection of the dent depth, especially in the future of the aircraft industry. Recent progress in visual inspection of impact damage will be discussed in the next sections.

2.2.2 Visual inspection levels

Visual inspection of impact damage can be categorized into four main levels. The standard visual inspection aids are a flashlight, mirror, and magnification glass. For special inspection tasks, further inspection aids may be required (Visual Inspection of Composite Structures, 2009; Wang et al., 2021).

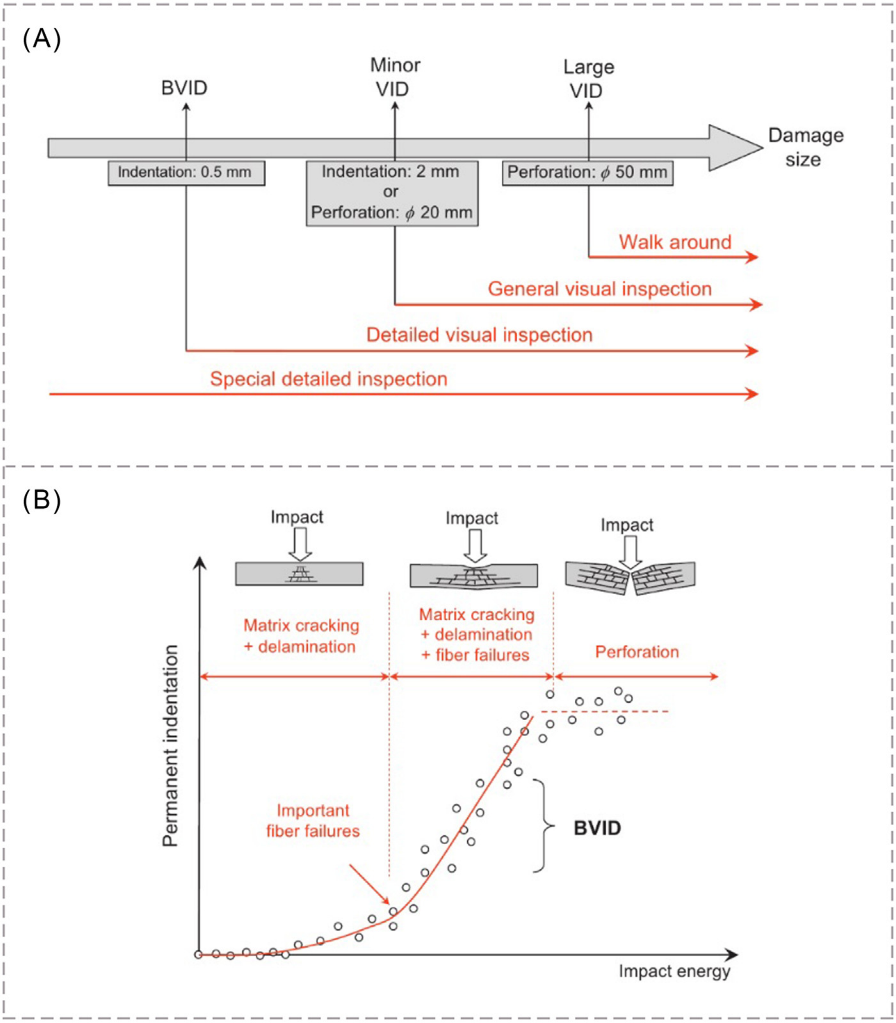

Figure 2.2 Damage size in different (A) inspection levels and (B) impact energies.
Source: From Bouvet, C., & Rivallant, S. (2016). Damage tolerance of composite structures under low-velocity impact (pp. 7–33). Elsevier BV. https://doi.org/10.1016/b978-0-08-100080-9.00002-6.

2.2.2.1 Walk-around inspection

A general check is conducted from ground level to detect discrepancies and assess general condition and safety. This inspection is conducted on a daily basis and is expected to detect large visual impact damages such as fiber breakage.

2.2.2.2 General visual inspection

It is made of an exterior with selected hatches and openings open or an interior, when called for, to detect damage, failure, or irregularity. This inspection level is expected to detect minor visual impact damage and may require suitable lighting conditions, surface cleaning, and equipment such as a mirror.

2.2.2.3 Detailed visual inspection

An intensive visual evaluation of a specific area, system, or assembly to detect damage, failure, or irregularity. This inspection level is expected to detect the BVID and may require surface preparation and elaborate access procedures.

2.2.2.4 Special detailed visual inspection

An intensive evaluation of a specific item, installation, or assembly to detect damage, failure, or irregularity. This inspection level may require intricate disassembly and cleaning as well as specialized techniques and equipment.

2.3 Effective parameters

An early study by Megaw (1979) suggests that the four influential parameters affecting the visual inspection are the inspector's visual acuity, the workplace lighting conditions, the time available for inspection, and the provision of feedback or knowledge of results to the inspector. In a study by Erhart et al. (2004), the visual detectability of 0.05-inch deep dents was investigated by considering different parameters. A list of the variables that were identified for further research in aircraft industries was provided accordingly. Comprehensive research by the European Aviation Safety Agency characterized the influence of parameters mentioned in previous research in detail (Visual Inspection of Composite Structures, 2009). A list of effective parameters and key findings for each parameter is presented and shown in Fig. 2.3.

2.3.1 Lighting and illumination

Visual inspection relies heavily on light, as the human eye sees nothing but light patterns. Visual Inspection of Composite Structures (2009) suggests that illumination can significantly influence damage visibility in composite structures. Visual inspection of a damaged structure may require different lighting conditions, as each damage type needs a specific lighting setup. In the automotive industry, for example, it is important to inspect painted surfaces for paint defects, which are often topographical. There are several methods to optimize lighting conditions for inspecting small topographical defects on glossy surfaces (Lloyd, 1999). However, the typical small paint defect is topographically different from an impact dent on a

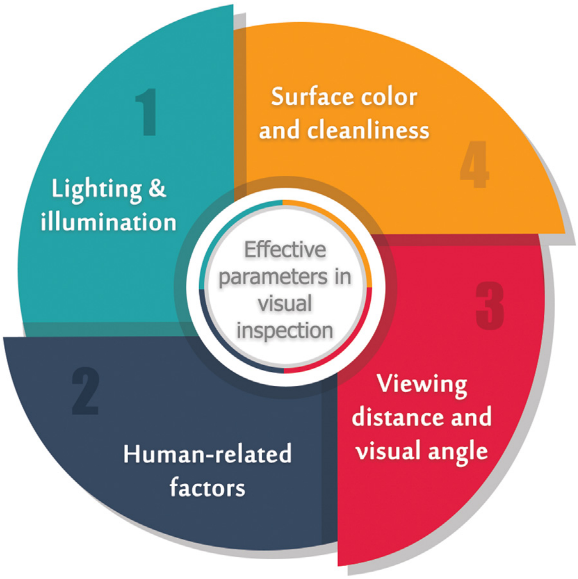

Figure 2.3 Effective parameters for visual inspection of impact damage in composite materials.

composite surface. Light brightness is a crucial factor in test environments since excessive light within the field of view leads to an unpleasant sensation called glare that interferes with a clear view for the inspector (Zhong & Nsengiyumva, 2022). The light intensity measured during the inspection can be evaluated by using the inverse square law as follows:

$$E = \frac{I}{d^2} \tag{2.1}$$

where E shows the luminance, I is the light intensity at the source, and d is the distance between the source and the surface of the test structure. This equation is accurate within 0.5% when d is at least five times the maximum dimension of the source (Zhong & Nsengiyumva, 2022). CAA, Safety Regulation Group (Aviation Maintenance & Human Factors, 2003) identified four fundamental light characteristics, which should be considered for maintenance tasks:

1. **Light level:** The use of task lighting allows for suitable illumination in most inspection and maintenance tasks.
2. **Color rendering:** Color rendering measures the degree to which the perceived colors of an object illuminated by various artificial light sources match the perceived colors of the same object when illuminated by a standard light source (i.e., daylight). Color rendering can be influenced by differences in the spectral characteristics of daylight, incandescent lamps, fluorescent lamps, etc.

3. **Glare:** Excessive lighting within the visual field can cause an unpleasant sensation called glare, obscuring the visual impression of details and adversely affecting damage detectability. This can be due to different reasons, for example, direct light sources in the visual field, reflecting surfaces, or reflections from light objects. A viable method to rectify the detrimental effects of glare is resorting to indirect lighting.
4. **Reflectance:** Another influential factor in the lighting conditions is the reflectance of nearby surfaces. A high reflectance surface can improve luminaire effectiveness, but it can also produce glare. Therefore, diffuse reflectance from a semimatte surface is often preferred.

2.3.2 Human-related factors

Person-related factors can also be an influential parameter in visual damage inspection. For example, human eyesight, characterized by its color vision capability and visual acuity, can affect visual inspection quality to a great extent. Colors and patterns around the test structure can substantially influence the inspector's attitude during the inspection. For example, high contrast on the pattern being inspected can cause eye fatigue and decrease inspection quality subsequently (Zhong & Nsengiyumva, 2022). Adding high-resolution cameras to endoscopes and fiberscopes and projecting the inspection images on projection monitors are viable methods to reduce eye fatigue caused by the prolonged use of these devices. Also, psychological factors such as tension may play a great role in the inspector's performance. The results of Visual Inspection of Composite Structures (2009) showed a clear trend for persons with greater experience in composite structures and visual inspection to find more damages on the same panel. This research also showed that the age and gender of the inspector could influence the probability of damage detection to a low extent.

2.3.3 Viewing distance and visual angle

Based on the viewing distance and viewing angle, visual inspection methods can be categorized into two main groups: direct and remote-based inspections. In direct visual inspection, the distance between the eye and the structure should not exceed a radius of 610 mm, and the angle should not be less than 30 degrees. The influence of the inspection angle is insignificant compared to other inspection parameters (Visual Inspection of Composite Structures, 2009). However, some studies suggest that an angle of 45 degrees can be slightly worse for inspection ability than an inspection angle of 65 degrees.

2.3.4 Surface color and cleanliness

Cleanliness can help achieve a better visual inspection. However, compared to other parameters, the influence of cleanliness is not significant. Literature suggests that there is no clear indication of whether color influences the detectability of damage. However, the subjective impression of the influence of color on damage detectability shows a clear advantage for the color red. Eight of the fifteen inspectors in a survey found the red panel easier to inspect, and six gave the color as the reason. Only one inspector found the blue panel easier to inspect (Erhart et al., 2004).

2.4 Recent progress (case studies)

Various indirect visual inspection equipment, including video cameras, endoscopes, borescopes, and unmanned aerial vehicles (UAVs), has been developed to inspect hard-to-reach composite structures (Sun & Hallett, 2017). Recent advances in artificial intelligence (AI) systems have significantly decreased inspection costs and increased inspection accuracy. Using new smart coatings to enhance the visual inspection of impact damage has shown great potential. The development of computer systems and digital storage technology has also improved the documentation of inspection records (Zhong & Nsengiyumva, 2022). These inspection systems are still being developed to address all related challenges. In the following, we present the recent progress in visual inspection of impact damage, particularly in three primary areas:

2.4.1 Remote visual inspection

The detection of BVID in safety-critical composite structures like aircraft and wind turbine blades is crucial. However, the current manual process is expensive and labor-intensive (Bossi & Georgeson, 2020; Dafydd & Khodaei, 2020). Visual inspection heavily relies on the skills of the operator, and there is a growing need to cover large areas that are typically difficult to access, thereby increasing costs, errors, and health and safety risks (Siegel & Gunatilake, 1997; The International Air Transport Association (IATA) Safety Report, AERO_Q207_article3.pdf boeing.com, n.d). For instance, over 80% of inspections on large transport category aircraft are conducted visually, and visual inspections for such aircraft can take up to 40,000 hours (Mainblades, n.d.). The prevailing methods of visual inspection involve the use of lift platforms for airplanes and rope access for wind turbine blades.

Therefore, there has been a shift towards remote visual inspection (RVI) systems that utilize automated computer vision inspection with a combination of fixed and moving cameras and deterministic image processing algorithms to detect BVID (Ostachowicz et al., 2016). RVI, also known as enhanced visual inspection (Forsyth et al., 1999), presents a promising alternative to traditional visual inspection methods as it addresses safety concerns, reduces time and costs, and enhances detection accuracy. With the integration of AI and machine learning, RVI has made significant advancements in detecting and characterizing impact damage in composite structures. The field of RVI has seen notable progress, ranging from simple borescopes and endoscopes to videoscopes, thanks to the development of miniature cameras and optical lenses that provide access to even small-bore locations like heat exchangers, drain headers, and stacks (Guo et al., 2008; Patel, 2022). Deterministic advancements in computer vision are further complemented by machine learning techniques, enabling reliable processing of large quantities of images (Wang et al., 2021) and facilitating decision-making processes. However, these optical techniques and instruments are typically heavy, require substantial power, and need stable positioning for seconds to achieve the necessary in-depth resolution of approximately 0.1 mm, with a typical in-plane size resolution in the range of 15−20 mm (Rice et al., 2018).

The use of automated UAV-based RVI systems can significantly reduce health and safety risks and cost as little as 20% of manual visual inspections, as reported by (Mainblades, n.d.), a company conducting inspection tasks for KLM Royal Dutch Airlines and other asset owners. This cost reduction is achieved by improving accessibility, facilitating immediate identification and assessment of damage, and providing high-quality images and videos for documentation and processing, as depicted in Fig. 2.4. The software utilized in these systems includes a dent-and-buckle feature, which allows for recording and reviewing all structural damages on the exterior of the aircraft, pinpointing the exact location of anomalies and damages.

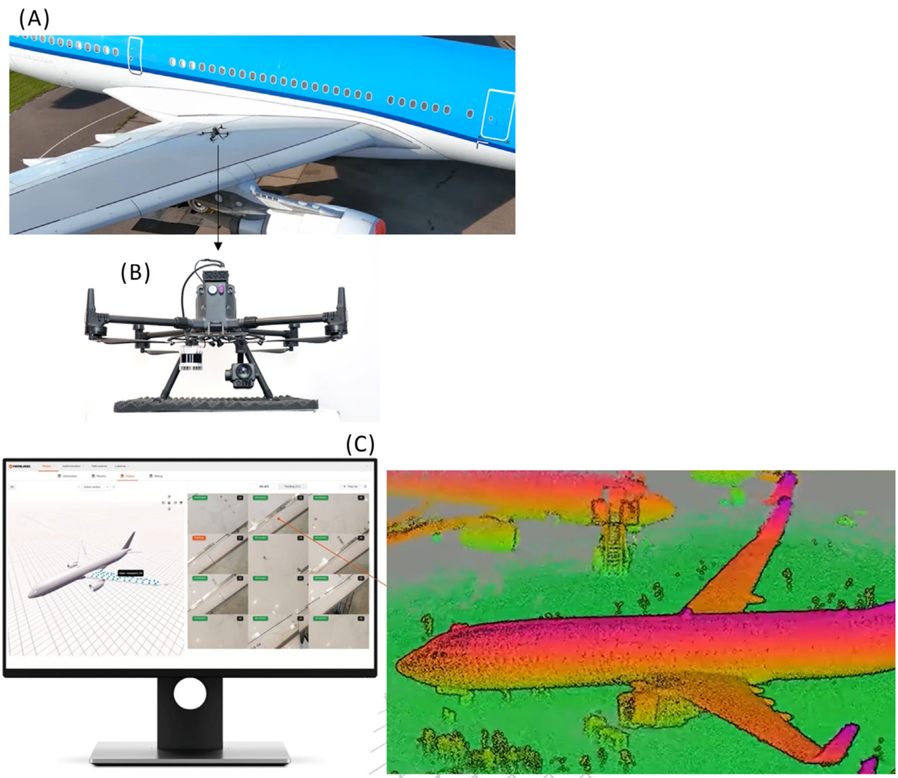

Figure 2.4 (A) An image of the aircraft inspection by Mainblades, (B) unmanned aerial vehicle, and (C) the software, and scanned surface of the aircraft.
Source: From Mainblades (n.d.). https://mainblades.com.

The current state-of-the-art approaches for RVI suffer from limitations in measurement resolution, making them unreliable for measurements below 1 mm (Papa & Ponte, 2018). These limitations arise from issues such as insufficient sharpness, exposure, high background noise, and the reliance on isolated frames and a predetermined visual trajectory for material state classification (Yang et al., 2020).

Drone-based photogrammetry, although used for RVI, exhibits an in-depth error of 1.3 mm (standard deviation) (Zhang et al., 2020). Moreover, it has limited applicability in detecting specific components like rivets (Miranda et al., 2019). While state-of-the-art drone-based development utilizing on-board laser line scanners offers a better in-depth resolution of 0.3 mm at a distance of 1.5 m, it is still insufficient for detecting the small BVID (Anisimov et al., 2021).

Furthermore, automated visual inspection systems lack the necessary reliability to match the capabilities of the human visual system. These systems struggle to create accurate 2.5D sketches solely from visual information, particularly when it comes to depth defects on curved and uneven surfaces. Consequently, there is a need for further research and development efforts to optimize inspection processes and enhance the capabilities of RVI.

2.4.2 Self-reporting coatings

BVID can pose different risks to structural integrity, as discussed in Section 2.2. A recent development is self-reporting mechanochromic coatings, which minimize these risks, reduce inspection time, and provide live information on the condition of a material. In response to external stimuli such as impact strikes, these chromogenic materials produce optical signals (change in transparency, fluorescence, and color), giving users a direct and eye-detectable indication of damage (Guo & Zhang, 2021). Many technology applications are possible with these self-reporting coatings, including SHM in the aeronautics, automotive, and construction industries and as sensors to inspect mechanical events such as impact (Calvino, 2021; Calvino et al., 2017). Generally, mechanochromic coatings can be divided into two main groups: chemical-based and physical-based. In the former, the color-changing process can occur by incorporating dye-filled materials such as microcapsules or hollow fibers that are ruptured upon impact damage. Alternatively, the polymer or fiber can become “smart” by adding functional groups that are sensitive to mechanical stimuli (mechanophores), into them.

On the other hand, physical-based coatings are connected to the material’s shape and refractive index and not to its chemical properties. Physical-based mechanochromism originates from how light is scattered and diffracted by random or periodic structures. Structural color materials and thin-ply hybrid glass/carbon composite sensors are prime examples of physical-based coatings. In the latter, the changes in light absorption at the interfacial glass/carbon damaged area can generate a clear visual cue by which damage, such as BVID, can be detected as an early warning to avoid catastrophic structural failure due to hidden damage. Some examples of recent progress in this area are highlighted in the following.

Fundamental and interesting research has been conducted by Pang and Bond (Norris et al., 2011a, 2011b; Pang & Bond, 2005a, 2005b; Williams et al., 2009). Developing the "bleeding composites" idea, they introduced a class of dual-function composites that could report damage by visual cues and heal it. Smart fiber-reinforced polymer composites equipped with hollow fibers were examined under low-velocity impact tests. Upon the fracture of the functionalized fibers, they released a healing agent into the damaged area. Also, given the fluorescent characteristics of the agent, a visual inspection of the BVID could be carried out. Kling and Czigány (2014) reported a more efficient dual-function system based on the application of very thin hollow fibers. The proposed SHM system could successfully visualize and heal the impact-induced damage with the help of a UV lamp. Research has shown that applying mechanophores can be more efficient in the interfacial area between the thermoset resin and reinforcing fibers, due to the mismatch in mechanical properties of these two phases and the activation of different damage modes. Lörcher et al. (2014) visually detected the BVID in carbon fiber-reinforced polymer (CFRP) composites by applying a yellow fluorescent protein at the resin/fiber interface (see Fig. 2.5A). Robb et al. (2016) demonstrated self-reporting mechanisms in CFRPs equipped with a smart coating. The coating was composed of 10 wt.% tetraphenylethylene (TPE) microcapsules and designed based on the aggregation-induced emission (AIE) concept, which enables the visual detection of microscopic damage in a wide range of polymeric materials under illumination with an appropriate excitation light source. The fluorescence signal is developed rapidly upon impact damage to polymeric coatings and reaches maximum intensity within minutes. This detection system does not rely on external or intermolecular interactions to elicit a response and provides outstanding contrast between intact and damaged regions with excellent sensitivity. Fig. 2.5B shows the efficacy of this self-reporting system for enhancing the visual identification of BVID in polymeric composite materials. Other studies also report the improvement in visual inspection of impact damage in encapsulated polymer composite structures, where the quantitative assessment of the damage is a priori possible. For example, as shown in Fig. 2.5C, the emission intensity in fluorescent polymeric composites embedded with encapsulated excimer-forming dyes can be correlated to the impact distance (impact energy) (Calvino et al., 2018, 2020). The BVID visual inspection in glass fiber-reinforced polymer (GFRP) composites has been studied by Shree et al. (2020), who used spiropyran (SP) as a self-reporting functional additive. SP mechanophores act through a reversible, mechanically-activated ring-opening reaction which converts the colorless and nonfluorescent Spiropyran into the highly colored and fluorescent merocyanine. It was observed that the GFRPs modified with Spiropyran could change their color from yellow to purple as a result of periodic impact strikes. The number of impact strikes could also be related to the color gradient (see Fig. 2.5D).

Fotouhi et al. (2023) applied a hybrid composite coating composed of a unidirectional ultra-high modulus carbon (YS-90)/epoxy and an S-glass/epoxy on a quasiisotropic $[45/0/90/-45]_{4S}$ laminate fabricated from unidirectional T800 carbon/MTM49−3 epoxy prepreg (see Fig. 2.6). Fig. 2.6A and B show the hybrid composite

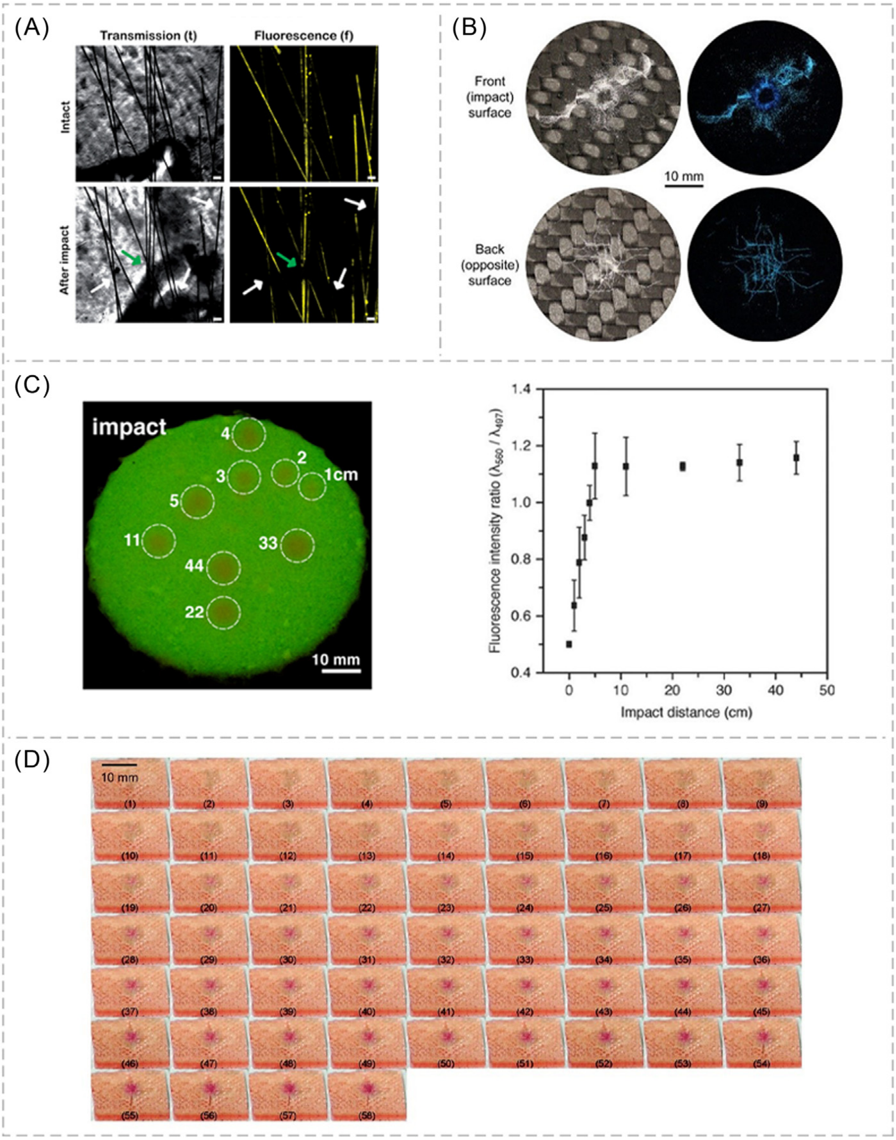

Figure 2.5 Visual inspection of barely visible impact damage (BVID) in self-reporting composites: (A) by means of fluorescent proteins. The yellow fluorescent protein stops fluorescing after the occurrence of BVID, (B) by means of embedded TPE microcapsules. The front face and back face images under white and UV light after impact show how using microcapsules can improve BVID visual inspection, (C) by means of embedded encapsulated excimer-forming dyes. Photographs recorded under UV illumination of microcapsules impacted from distances between 1 and 44 cm, and (D) by means of SP additives. The BVID in GFRP/SP composites can be visualized through periodic impact strikes.
Sources: (A) From Lörcher et al. (2014), (B) https://doi.org/10.1016/j.compositesa.2022.107236, (C) Calvino and Weder (2018), and (D) Shree et al. (2020).

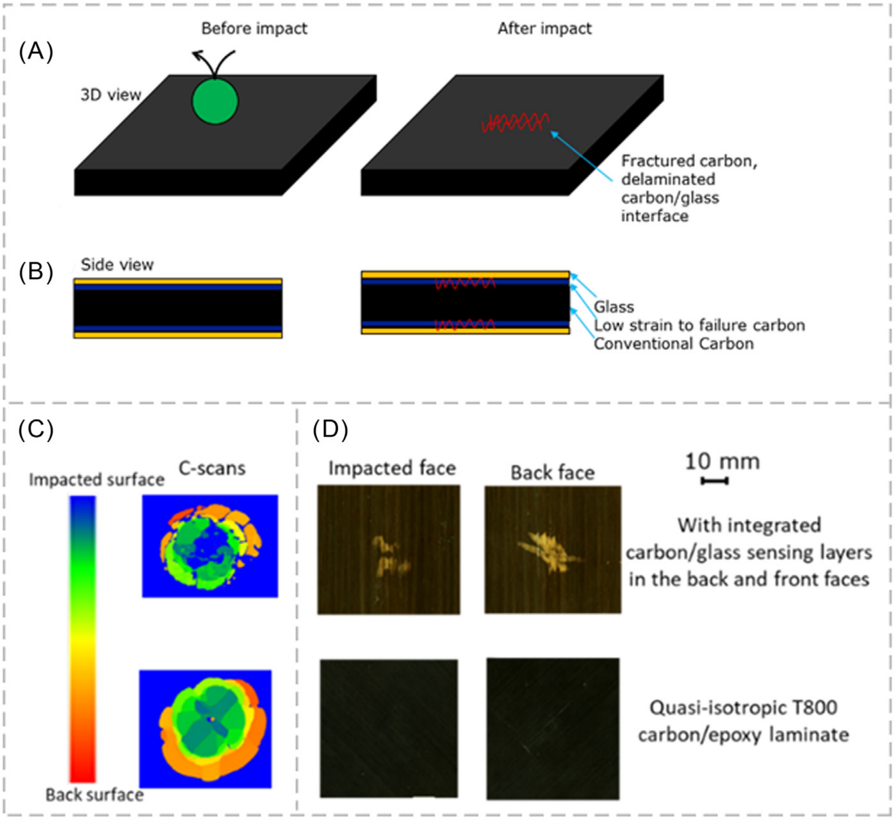

Figure 2.6 Visual inspection of barely visible impact damage in self-reporting composites by means of hybrid carbon/glass coatings: (A) schematic 3D view, (B) schematic side view of the substrate and the integrated sensor, (C) C-scan results, and (D) impacted face and back face images of specimens with (up) and without (bottom) carbon/glass coating.
Source: From Fotouhi, S., Jalalvand, M., Wisnom, M. R., & Fotouhi, M. (2023). Smart hybrid composite sensor technology to enhance the detection of low energy impact damage in composite structures. *Composites Part A: Applied Science and Manufacturing, 172*. https://doi.org/10.1016/j.compositesa.2023.107595.

sensor integrated on both the impacted face and back face of a quasiisotropic composite plate (cured together). An example of the impacted-face, back-face and c-scans for samples subjected to a 12 J drop tower test can be seen in Fig. 2.6C and D. The c-scan shows significant delamination damage for both samples, while the delamination size is slightly higher in the original sample compared to the sample with hybrid carbon/glass coating. However, there is no change in the appearance of the original sample on either the front or back faces. In contrast, a visible color change is observable on both faces for the sample with coating. These color changes are due to damage induced in the hybrid coating layer. The size of the visible damage area on the front face corresponds to the impact energy level. An in-depth discussion on self-reporting coatings is presented in a comprehensive review by Tabatabaeian et al. (2022b).

2.4.3 Artificial intelligence

Impact damage is traditionally assessed through manual feature parameter extraction, which is sometimes time-consuming and inaccurate. This has opened an avenue for new AI-based impact damage detection methods, such as vibration-based, acoustic-based, and image-based techniques to be applied to complex impact-related problems (Qing et al., 2022; Tabian et al., 2020). The AI algorithm is trained and validated using a dataset and then tested on an unseen dataset. These learning algorithms are divided into different types, each of which can solve a specific problem. An excellent feature of an AI-based inspection method is its adaptability, meaning that it can be tested and modified several times to achieve an accurate and efficient damage pattern recognition function. Moreover, some AI-based algorithms can benefit from few-shot learning and transfer learning methods (Saeed et al., 2019). The former is a machine learning technique that uses a pre-trained model to accelerate the training of a new model on a related task, by reusing features learned from some other tasks. However, these networks often have many layers with many trainable parameters that need to be estimated only from the data, which can become a problem in scenarios without access to big datasets (Azimi et al., 2020). Few-shot learning is a subfield of machine learning that deals with the problem of learning from a limited amount of labeled data. Therefore, thanks to these approaches, AI-based algorithms can work well with a small set of available data, and convey complex and qualitative empirical knowledge that is difficult to describe with mathematical formulas or conventional visual inspection practices. Unsupervised and supervised algorithms can be trained to perform different tasks such as damage detection, localization, classification, and severity estimation. However, unsupervised learning is mostly used for damage detection and supervised learning for all mentioned tasks (Yuan et al., 2020). As reported in Nelon et al. (2022), artificial neural networks are the most popular machine learning algorithms for damage evaluation applications. In the case of BVID visual inspection, where dealing with an image-based dataset, a more complex family of neural networks, such as convolutional neural networks (CNNs), might be needed. CNNs differ from other neural network architectures because of their convolutional layers (Bang et al., 2020; Gu et al., 2018; Sony et al., 2021; Wang et al., 2021). Recent examples of AI-based research in visual inspection of impact damage in composite materials are presented in the following.

Fotouhi et al. (2021) collected a diverse image dataset of both microscale damage (matrix cracking) and macroscale damage (impact and erosion damages) from the literature to train a CNN and explore the possibility of automating the visual recognition of damage. Particularly, they used a pretrained AlexNet for accomplishing three different tasks, including identifying damage type (impact, erosion, or undamaged), damage severity (low-energy impact or high-energy impact), and damage location (impacted side or nonimpacted side). The network could identify the macroscale damage type with a validation accuracy of 93%. The damage severity was identified on images of the impacted and nonimpacted sides with a validation accuracy of 96% and 87%, respectively. The third task achieved a validation accuracy of 78% for low-energy impact and 73% for high-energy impact datasets. These outcomes suggested that CNNs, in conjunction with transfer learning approaches, have a great potential for automating the visual inspection of impact-induced damage in composite materials. The authors also suggested developing high-quality datasets for different damage types in composite structures to correlate the damage extent to the residual lifetime of the structure in the next stages. Tabatabaeian et al. (2022a), conducted low-velocity impact tests with energies from 3 to 128 J, collecting an image dataset of the impacted and nonimpacted sides of damaged and undamaged composite panels. Then, a deep neural network adapted from (Haselmann et al., 2018) was used to classify the dataset into damaged and undamaged categories. This was an unsupervised method, meaning that no image masks were provided to the network at any stage of the process. The network's error was mainly due to a light reflection on the surface of some undamaged panels, giving the network the wrong impression of the presence of damage. The authors reported an accuracy of 81% and highlighted the importance of a high-quality dataset in training the AI-based algorithms for visual SHM. In another research (Tabatabaeian et al., 2023), two sets of composite panels, labeled as 'reference' and 'sensor-integrated' samples were subjected to low-velocity impact tests at varying energy levels. Subsequently, the outcomes, along with C-scan and visual inspection images, were scrutinized to establish the range of BVID and construct an original image dataset. Following this, four different deep-learning models were developed, trained, and tested for their ability to identify BVID exclusively from images depicting both impacted and nonimpacted surfaces. The results demonstrated the proficiency of all four networks in learning and detecting BVID. Notably, the inclusion of the sensor led to a reduction in training time and an improvement in the accuracy of the deep-learning models. Among all networks, ResNet stood out as the top performer, achieving an accuracy rate of 96.2% on the back-face of reference samples and 98.36% on sensor-integrated samples. Alhammad, et al. (2022b) conducted low-velocity impact tests on CFRPs with $[45/-45/90/0/90/0/90/-45/45]$ configuration. Then, pulsed thermography (PT) technology was applied to obtain healthy and defective datasets from custom-designed composite samples having similar dimensions but different thicknesses (1.6 and 3.8 mm). Two different methods were used to capture images, namely "reflection mode" and "transmission mode" as shown in Fig. 2.7. After that, a support vector machine algorithm was trained and tested to predict damaged and undamaged areas. This machine learning method was identified as the algorithm that provided the highest predictive accuracy in previous research by the authors Alhammad et al. (2022a). The results showed an accuracy of 93.5% and 82.1% for the reflection mode in thin and thick samples, and 79.4% and 78.7% for the transmission mode in thin and thick samples. This suggests that in AI-based impact damage detection when having a dataset of thermal images, the images of the impacted side would be preferred over the

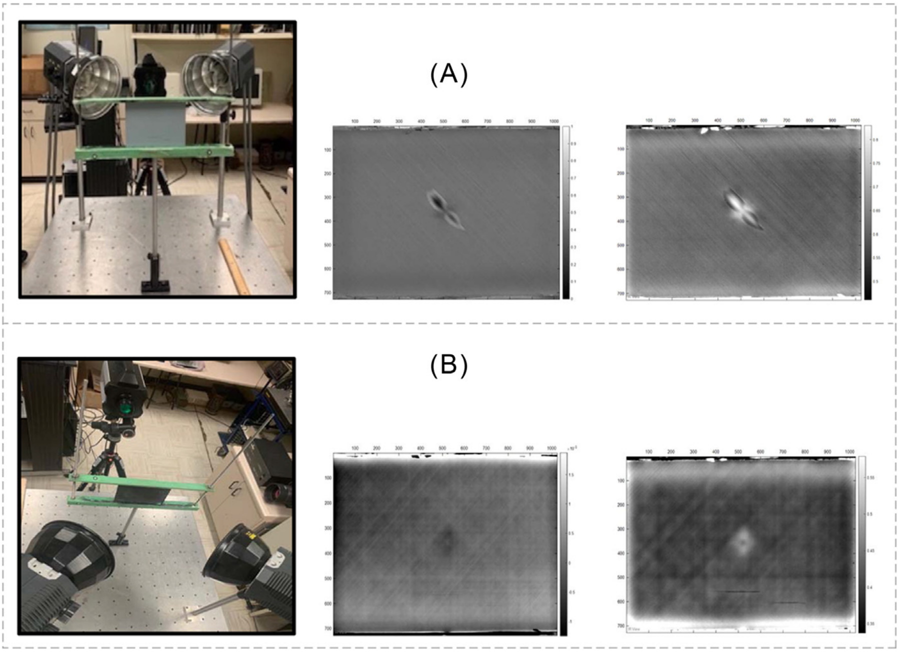

Figure 2.7 Methods for image capture presented in Alhammad et al. (2022). Reflect mode (A) captures the image from the impacted side and transmission mode (B) captures images of the nonimpacted side.
Source: From Alhammad, Avdelidis, Ibarra-Castanedo, Torbali, Genest, Zhang, Zolotas, and Maldgue (2022). Automated impact damage detection technique for composites based on thermographic image processing and machine learning classification. *Sensors, 22*(23). https://doi.org/10.3390/s22239031.

nonimpacted side because the crack in the samples is on the surface. Another example of using PT to construct datasets for the training of AI classification models is presented in (Deng et al., 2023), where authors used ResNet-50 to classify captured thermal photos from the nonimpacted side into different groups according to their corresponding impact energy levels, finding a relationship between BVID in CFRP materials and the related impact energy level. The results showed the best classification accuracy of 99.75%, suggesting that damage patterns introduced by slightly different energies (4 and 6 J) can sometimes be confused, negatively impacting the model's performance. Therefore, developing strategies to generate more diverse damage patterns is of interest for future work.

Hasebe et al. (2022) used three machine learning models, namely "ridge regression," "logistic regression" and "random forest," on a dataset extracted from low-velocity impact tests on CFRP composites. The aim was to study the possibility of inferring BVID information from the surface damage profiles. The low-velocity impact tests were conducted on 246 specimens under three different impact factors. The first factor was stacking sequence, where two different classes, cross-ply and quasiisotropic, were considered. The second factor was the impactor shape with six different classes, and the third was the impact energy with several classes. A total of 104 impact conditions were created accordingly. After analyzing the surface and C-scan images and dent measurements, the input data for machine learning models were prepared, and three impact factors, impactor shape, delamination area, and delamination length, were estimated, accordingly. The results showed that dent depth was the most effective feature for impactor shape prediction, the local deformed volume for the delamination area, and the projected dent area with a steep slope in addition to the delamination length in all laminates. It was also observed that the models could infer approximately 80% of results correctly using dent depth and the volume of indentation. As for further research, they suggested directly using the surface profiles as features without reducing raw data (surface profile) to human-designed features (depth, volume, etc.). Also, they suggested studying whether AI models are effective even if the target contains paint or other features, which may be found in real structures but not in laboratory-level research. In another study, they developed a multitask learning algorithm based on decision trees. The new algorithm was effective when the problem involved multiple objective variables related to each other or when it was difficult to collect numerous datasets. Furthermore, in addition to improving the prediction accuracy of objective variables, this model can also be used to find the features that contribute to the model by investigating the model detail (Hasebe et al., 2023).

2.5 Challenges and future path

Visual inspection offers several advantages over other NDE methods. For example, it does not require high-tech and expensive testing facilities or advanced testing setup, and its testing instruments are portable. Moreover, it is easy to train while providing fast inspection with reliable accuracy for surface damages. Nevertheless, there are some challenges in visual inspection of impact damage that can be addressed in future research. These challenges can be classified into three primary groups: accessibility, visibility, and human dependency (Böyük et al., 2021; Zhong & Nsengiyumva, 2022).

Inspection of very large or geometrically complex structures in hazardous environmental conditions in real-life applications can be challenging because there should be access to critical parts of the structure to have a direct observation. For example, access to damaged areas in wind turbine blades through the small passages or openings can pose health and safety risks to the inspector. Also, sometimes the whole system should be shot down or disassembled for a thorough visual inspection of a specific area, causing downtime issues and expenses. A viable method to deal with access restrictions that limit the inspection view is to use RVI and optical aids tools such as UAVs, magnifying devices, microscopes, borescopes, videoscopes, and thermal imaging cameras. This equipment can improve inspection safety, efficiency, and accuracy in a wide range of industries, including manufacturing, aviation, energy, and healthcare, particularly in areas that are difficult or dangerous to access. Another concern is that using such technologies might be expensive. Therefore, an area for future work would be to develop RVI strategies and devices that are both cost-effective and reliable, allowing for visual inspection of hard-to-reach or hazardous areas, without requiring direct access by an inspector.

Another major challenge of visual inspection, especially for impact damage detection is damage visibility. The application of this method is mainly limited to the inspection of surface damages, and subsurface damages cannot be monitored unless the structure has a transparent/translucent surface and the damage is large enough to be visually detected. Even in translucent materials such as glass fibers, in thick or painted sections, or where the surface layer has lost the resin due to environmental conditions, detecting and evaluating the severity of impact damage is complicated. In addition to the difficulties due to a small and barely visible damage pattern, surface illumination can also cause challenges in damage visibility. For example, shadows, glare, or uneven lighting conditions can obscure impact damage areas, making visual inspection difficult or impossible. In such cases, care should be taken to adjust the light source at an angle that minimizes glare, shadow, or uneven lighting. Moreover, additional tools such as borescopes, magnifiers, or microscopes can be used to perform a more detailed and accurate visual inspection.

As discussed earlier, permanent indentation or dent depth is considered a well-known impact damage metric. However, this cannot provide much information about the severity of the damage. Also, dent depth could be influenced by different parameters such as impactor shape and can decrease over time as a result of fatigue and humidity due to viscoelasticity (Thomas, 1994). In some cases, the initial dent depth just after impact is three times greater than at the end of life. To make it even worse, the decrease of dent depth over time can vary in different materials, too (Thomas, 1994). Some papers in the literature report that higher energy impact damage from a larger diameter hemispherical object results in damage with a lower depth and greater delamination than lower energy impact damage from a smaller diameter object (Cook, 2009). Therefore, BVID sizing tests should be carried out at end-of-life dent depth to use permanent indentation as a reliable damage metric. Also, visual inspection detection thresholds such as BVID must not be considered in terms of either dent depth or width alone. As a minimum, both the indentation width and depth are required to determine detectability thresholds. In general, for the most part, visual inspection can only detect VID, and BVID might be left undetected. A potential route for future studies might be developing smart coatings, which can generate larger and more visible damage patterns. This can be achieved by managing the damage mechanisms on the surface layer through the proper design of the smart coating layer (self-reporting coatings) (Tabatabaeian et al., 2022b).

Finally, a serious limitation of visual inspection stems from its dependency on an inspector, meaning that depending on the experience, age, gender, eyesight, and fatigue of the inspector, results may vary significantly, leading to missing or wrongly identifying BVID. In order to mitigate such problems, new SHM methods can be developed by combining visual inspection with other NDE techniques, especially by automating the inspection process using machine learning algorithms.

This can also help move from a qualitative to a quantitative and more accurate impact damage assessment.

2.6 Summary and conclusions

The chapter content can be summarized as follows:

1. Visual inspection is a widely utilized nondestructive testing method for assessing low-velocity impact damage in composite structures. It offers several advantages such as low cost, minimal equipment requirements, ease of training, portability, versatility, and the ability to inspect irregular shapes in the field. However, it has limitations in detecting BVID and relies on the skills of the inspector, as well as factors like fatigue, lighting, and surface conditions.
2. State-of-the-art RVI approaches also face limitations in measurement resolution and reliability. These techniques struggle to provide precise measurements below 1 mm, encountering challenges related to sharpness, exposure, background noise, and material state classification. Despite the exploration of drone-based methods such as photogrammetry and laser line scanning, achieving the necessary precision for detecting the smallest BVID remains a challenge. Furthermore, automated visual inspection systems have not yet matched the reliability and capabilities of the human visual system, particularly for complex surfaces. Therefore, further research and development efforts are necessary to optimize inspection processes and enhance the capabilities of RVI.
3. In order to improve real-life damage detection and evaluation systems, it is recommended to extend AI learning algorithms and models. By combining these algorithms with specific engineering damage detection and assessment systems, improvements can be made. This can include preprocessing input test data to enhance algorithm performance, classifying different damage detection scenarios, applying optimization modules for better results, and establishing reasonable classification criteria for damage assessment. The combination of multiple AI learning algorithms in different scenarios can enhance detection efficiency and improve the classification of damage features.
4. Color-changing coatings, such as the hybrid glass/carbon sensing technology can enhance the performance of visual inspection reliability by providing a higher contrast between damaged and undamaged areas. These smart coatings can also improve the accuracy of AI solutions and reduce their training time, thereby enhancing the computational efficiency of AI-based damage detection systems.

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