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Robotic and intelligent technologies in composite material inspection: a review

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Abstract: The increasing use of composite materials in sectors like automotive and aerospace poses serious problems for preserving their material performance and integrity. Because they provide automated, accurate, and effective inspection capabilities, advanced inspection techniques—in particular, robotic intelligence technologies—have emerged as viable options. This paper provides a comprehensive review of the key robotic intelligence technologies used in the inspection of composite materials, highlighting advancements in vision-based, tactile-based, and force-based traditional approaches, as well as the development in modern advanced deep learning methods such as Convolutional Neural Network (CNN) based image processing techniques for inspection. In order to guarantee accurate and steady manipulation during inspection jobs, robot control strategies are also investigated. The robot's capacity to navigate intricate composite constructions while preserving constant inspection quality has also been greatly improved by the use of clever path-planning algorithms. The paper concludes by outlining future directions for improving inspection accuracy and efficiency through AI integration and advanced sensor technologies.

Keywords: composite material inspection; robotic intelligence; image processing

1. Introduction

Over the past decade, the increasing demand for automation has driven significant advancements in robotic technologies, encompassing areas such as perception, control, and decision-making [1]. The integration of artificial intelligence (AI) and machine learning (ML) is further accelerating these developments, allowing robots to interact autonomously with their environments and execute more complex tasks [2]. Robotics has been widely used in manufacturing, healthcare, agriculture, transport and logistics industries [3–6].

In manufacturing, robots are utilized in various processes, such as assembly, packaging, and welding [2], due to their precision, speed, and reliability. In the composites manufacturing industry, robotics plays a particularly dominant role. This is largely because composite materials are widely used in the automotive and aerospace sectors, where components tend to be large and complex, making it challenging for human workers to manufacture them efficiently. For instance, as shown in Figure 1 [7,8], two important methods for producing composite materials are (a) Automated Tape Laying (ATL) and (b) Automated Fiber Placement (AFP). ATL offers speedier manufacturing but is less suitable for complex geometries since it uses wide tapes, which are perfect for huge structural components like wings and fuselages and flat or slightly curved surfaces. AFP, on the other hand, lays narrow fibre tows, which allow for accurate placement and little material waste. As a result, it is more appropriate for high-precision applications and complicated, curved surfaces, especially in aerospace. In some complicated manufacturing cases, this process requires a collaborative robotic arm system to carry out the entire manufacturing operation [9]. Furthermore, in manufacturing processes involving complex geometrical components, the collaborative system between robots and humans is often necessary to complete the task. This collaboration is particularly essential in tasks where precision and adaptability are required. For example [10], the system consists of a draping robot responsible for laying up the composite sheets, while two grasping robots assist by holding and positioning the material. This coordinated effort allows for greater accuracy and efficiency, especially when handling large or intricate parts. Such collaborative systems leverage the strengths of both robots and human workers, where robots provide consistency and speed in repetitive tasks, and humans contribute flexibility and problem-solving capabilities. In addition, the integration of advanced sensors, such as depth cameras and tactile sensors, alongside machine learning algorithms, improves these systems by enabling real-time adjustments and adaptive decision-making throughout the production process [11]. These technologies ensure precise handling and deposition of composite materials, even in complex geometries, reducing the chances of defects and material waste. To further enhance quality control, several defect detection methods, such as ultrasonic C-scan (UT) [12], infrared thermography (IRT) [13], X-ray computed tomography (CT) [14], and computer vision [15], have been incorporated into these systems. Although some of these methods can be used during production for in-process monitoring, most are still primarily applied after manufacturing to ensure final product integrity.

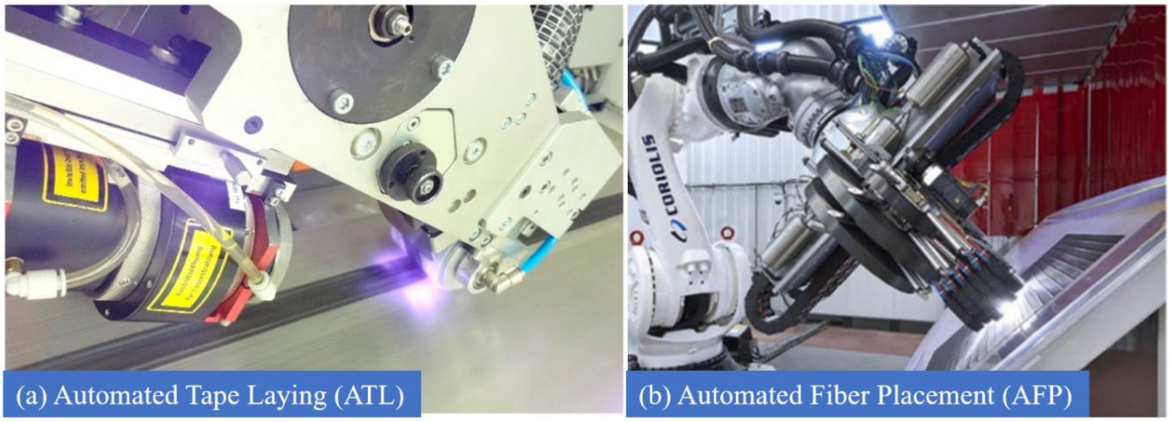

Figure 1. Two main manufacturing methods of composites **(a)** Automated Tape Laying (ATL) [7] and **(b)** Automated Fibre Placement (AFP) [8].

Moreover, the detection of defects has made extensive use of image processing techniques, especially in the production of composite materials. Flaws in composite materials like cracks, wrinkles, and foreign objects and debris (FODs) have been found using techniques like edge detection, feature extraction, and pattern recognition [16]. These technologies enable automated inspection systems to discover faults with improved accuracy and efficiency compared to traditional manual examinations.

For example, image processing algorithms in vision-based systems can evaluate visual input from cameras or sensors to detect possible defects instantly [17]. The system's capacity to identify intricate patterns and abnormalities is further improved when these methods are coupled with machine learning models. By using bigger datasets for training, this kind of integration makes it possible to continuously increase the accuracy of defect classification [18]. Furthermore, deep learning like convolutional neural networks (CNNs) has been used to identify and pinpoint defects in composite materials with little assistance from humans [19]. The need for sizable annotated datasets, the difficulty of real-time processing in industrial settings, and the generalization of models across various manufacturing processes are some of the obstacles that still need to be overcome in order to fully realize the potential of image processing and machine learning for defect detection [20]. In order to further increase the precision and resilience of robotic inspection systems in the composite manufacturing process, it will be imperative to address these issues.

The demand for composite materials in the automotive and aerospace industries has made it challenging to ensure efficient material quality control. Conventional inspection methods, such as visual inspection by hand and ultrasonic testing, frequently cannot handle complicated geometries, find defects instantly, or scale up for large-scale applications [21]. The need for automated and non-destructive testing (NDT) is rising, and these labour-intensive, human error-prone approaches cannot keep up with the demand. Increased precision and the complexity of composite materials mean that increasingly sophisticated inspection methods are needed. Robotic intelligence systems possess the capability to tackle these issues by performing precise, automated, and instantaneous inspections, particularly in settings where human involvement is restricted [22]. However, there are still many obstacles to overcome before AI and robotic control can be fully integrated into composite inspection systems. These include issues with processing speed, accuracy, and adaptability to various composite environments and structures.

This review offers a comprehensive overview of recent advancements in robotic intelligence technologies for composite material inspection, aimed at addressing these challenges. Section 2 examines key strategies, applications, and current limitations of various composites inspection techniques, including wave-based, optical, radiation, vision-force, and tactile methods. Section 3 explores image processing techniques in composites inspection. Section 4 explained the applications of robotic and intelligent technologies in materials inspection, while section 5 reviews robot path planning and control methods. Finally, section 6 discusses future industry prospects for composite manufacturing.

2. Intelligent inspection technologies

2.1. Wave-based inspection techniques

Cross-sectional scan, or ultrasonic C-Scan Testing is the main technique used to assess a part's internal quality using pictures as shown in Figure 2. To find flaws, a probe emits high-frequency sound energy pulses into the material [23,24]. The C-scan provides a detailed two-dimensional (2D) map of the inspected region, in contrast to the A- and B-scans, which provide single-dimensional and cross-sectional views, respectively. This makes the C-scan indispensable for accurate inspections where the precise location, size, and extent of faults must be recognized. As a result, the aerospace industry frequently uses ultrasonic c-scan for composite inspections as well as material integrity checks throughout manufacturing operations.

Using the properties of ultrasonic propagation in the time domain, the depth-direction ultrasonic C-scan detection technique was originally proposed in 2001, allowing for the development of multiple scanned images of the interior of carbon fibre composites. Defect identification is the exclusive purpose of this technique [25]. Utilizing ultrasonic C-scan technology, Hasiotis *et al*. found artificial faults inserted into CFRP composites. This technique made it possible to precisely measure the specimen's thickness and to identify and characterize flaws [26].

Fu *et al*. investigated ultrasonic testing in carbon fibre composites with layer-dropping structures using finite element simulations in recent years. They discovered that ultrasonic reflection becomes less effective the more angles there are between layers, especially when the angle is more than 60 degrees, which makes flaw identification more difficult. Additionally, thicker structures decrease signal amplitude, indicating that different techniques could be required for the trustworthy examination of such composites [27].

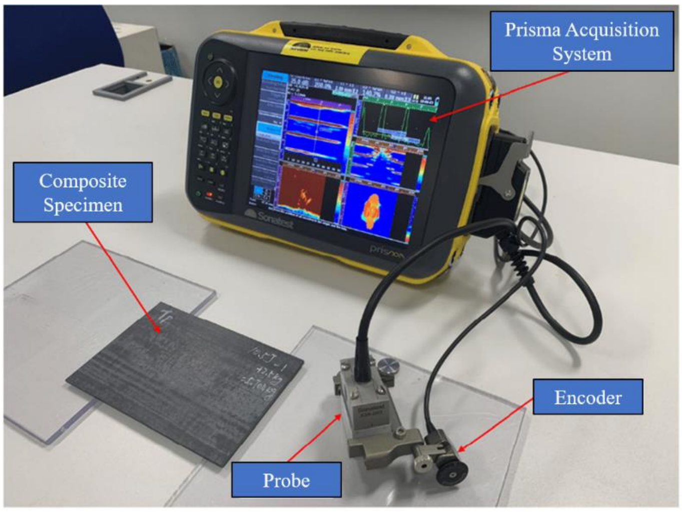

Figure 2. The ultrasonic C-scan equipment [24].

2.2. Optical-based inspection techniques

Another potent method for finding flaws in a variety of materials, including composite structures, is infrared thermography (IRT). This technique utilizes infrared imaging to detect localized thermal variations caused by material flaws, making it ideal for in-situ inspections of complex geometries and widely used in composite material inspection [28,29]. The pictures show how infrared thermography (IRT) is used for material inspection and its guiding principles. The active thermography system is depicted in Figure 3, where a material's surface is heated by a pulsed heat source, creating temperature variations that are recorded by a sensor to identify underlying flaws or properties [30]. Furthermore, the integration of a sensor for automated inspections is illustrated by its installation on a robotic arm. The application of infrared thermography (IRT) for aircraft defect detection is illustrated in Figure 4 [31], where a robot equipped with an IRT system scans the aircraft fuselage and collects thermal data.

There have been several advancements in the development of IRT approaches. Pulsed thermography became a standard technique in the early 2000s [32], followed by the introduction of Lock-in Thermography [33]. The invention of Line Scan Thermography (LST) by Ley *et al*. in 2010 was a major breakthrough [34]. In contrast to static thermography techniques, LST offers enhanced fault identification capabilities thanks to its real-time scanning of the specimen using an infrared detector and a moving heat source. However, maintaining constant scan speeds and heat dispersion is difficult when applying LST manually.

In order to overcome these constraints, scientists started combining IRT methods with robotic systems. Robotic-assisted LST was introduced in 2013 and has been shown to reduce operating expenses and improve scanning accuracy and reliability [35]. Due to this integration, the scanning process could be precisely controlled, guaranteeing uniform inspection quality and even heat dispersion throughout vast, intricate composite constructions. In the years that followed, more advancements in robotic-assisted IRT were shown. For example, a work by Jeroen *et al.* demonstrated the use of active thermography to evaluate a carbon fibre reinforced polymer (CFRP) bicycle frame using a six-axis robot fitted with an excitation source and an infrared camera [36]. With this configuration, complex geometries may be inspected with extreme accuracy and repeatability, demonstrating the potential of robotic systems to improve IRT's capabilities.

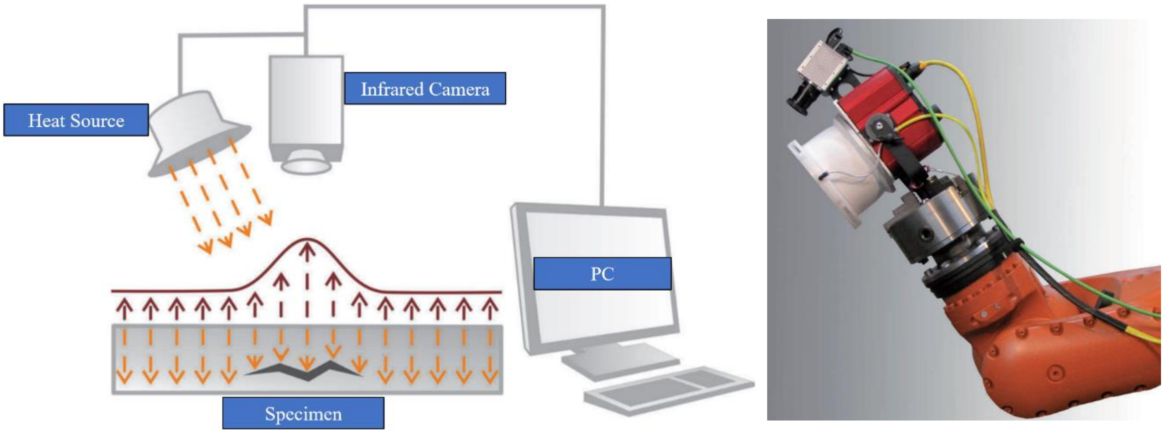

Figure 3. This diagram (Left) illustrates the working principle of infrared thermography inspection. A heat source applies thermal energy to the specimen, and the infrared camera detects the resulting temperature variations. These variations are processed by a computer to identify subsurface defects, such as delamination or voids, in composite materials. The picture (Right) showcases an automated robotic infrared thermography setup. The robot-mounted infrared camera system enhances inspection precision and efficiency, allowing for real-time detection of defects in complex geometries [30].

Apart from the advantages, IRT inspections still have several issues that need to be resolved. Variability in results can arise from the technique's sensitivity to defects' size, shape, and material qualities [37]. The accuracy of fault identification can still be impacted by optical problems and unequal heat dispersion [38]. Furthermore, evaluating things with several integrated components comes with special difficulties. Variations in material emissivity can also lead to misinterpretation or concealment of defects in thermal images, while environmental factors like background reflections, thermal noise, and external interferences also affect the effectiveness of infrared thermography (IRT) inspections [39,40]. To address these problems and strengthen the reliability of IRT inspections, researchers are hard at work creating sophisticated image-processing algorithms and machine-learning strategies [41]. Combining many NDT and robotics techniques and to build more complete inspection systems is a recent trend in IRT research.

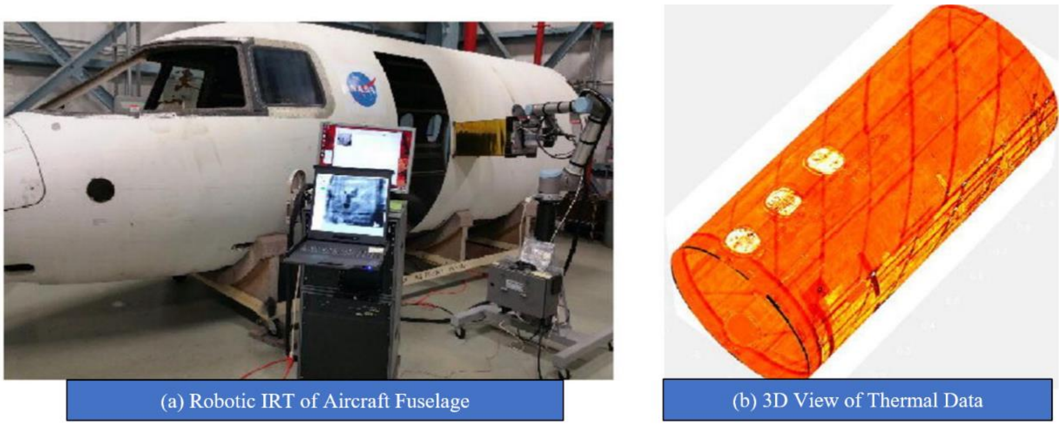

Figure 4. The thermal imaging results reveal critical defect information in composite material inspection: **(a)** shows the robotic Infrared Thermography (IRT) system in operation on an aircraft fuselage, while **(b)** presents a 3D view of the collected thermal data, highlighting defect areas [31].

2.3. Radiation-based inspection techniques

In composite materials inspection, X-ray computed tomography (CT) has been widely used in material quality assurance. It is one of the most extensively used non-contact technologies for flaw detection in the composites manufacturing sector because of its capacity to provide intricate three-dimensional (3D) subsurface images of components [42,43]. As shown in Figure 5, this is an example of the process for sampling, scanning, and analysing Carbon Fiber Reinforced Thermoplastic Sheet Moulding Compound (CFRTP-SMC). When it comes to viewing interior structures, flaws, and damage mechanisms—all of which can be difficult to identify with conventional non-destructive testing methods—this methodology has some distinct advantages. Both hardware and software advancements have significantly improved the resolution and processing power of X-ray CT in composite inspection, overcoming the limitations of its early applications.

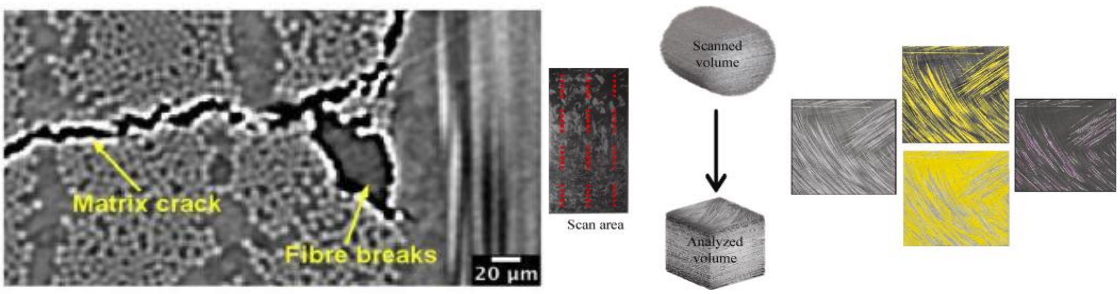

Figure 5. Schematic of the sampling, scanning and analysis process for CFRTP-SMC [44,45].

Nonetheless, notable advancements in these fields have occurred recently, making it possible to identify and characterize progressively smaller flaws and minute material changes [45]. The advent of interactive software tools for advanced visual analysis of flaws in composites has been one of the major advancements in the field. Garcea *et al*. [46] developed a precise 3D inspection system to model defect shapes, enhancing understanding of defect morphology and its impact on material properties. Building on this, Cognigni *et al*. [47] used the ORS Dragonfly tool to detect micro flaws like voids and cracks, providing critical insights into failure mechanisms. Senck *et al*. [48] further advanced X-ray CT capabilities by integrating it with optical coherence tomography (OCT) for multi-scale analysis of carbon fibre reinforced polymers (CFRP). The integration of X-ray CT with AI and machine learning has facilitated automated flaw detection and improved the accuracy of void identification in composite materials. Additionally, in situ X-ray CT enables real-time monitoring of damage progression under load, providing important insights into material behaviour under stress [49,50]. In order to get better picture quality with less radiation exposure, Villarraga-Gómez *et al*. [51] explored a novel X-ray source technology for high-resolution CT imaging of composites, while Recur *et al*. [52] proposed an iterative reconstruction technique that improved defect visibility and reduced artifacts, contributing to more efficient processing and enhanced image quality.

Despite its advantages, X-ray CT still faces limitations in composite material inspection, such as being time-consuming, costly for large components, and involving bulky equipment that is difficult to transport, making it less suitable for field inspections. Additionally, radiation safety remains a concern, particularly in industrial settings. However, these challenges could be mitigated by the use of robots, improving practicality and safety in such environments [53].

2.4. Vision-based inspection techniques

In the material quality assessment of composite materials, machine vision has become an indispensable technology, providing quick, automated, and very precise inspection capabilities. The development of machine vision techniques in composite inspection is reviewed in this part, covering both conventional image processing methods and more recent developments in data-driven approaches.

Machine vision, the primary technique to determine defects in composite inspection in the past, is based on digital image processing techniques incorporating some combination of preprocessing, edge detection and thresholding [54]. These techniques have been successfully explored to detect defects such as dents and fractures in composite surfaces, fibre orientations and impact damage. For example, the fibre orientations in dry woven and cured unidirectional (UD) prepreg composites have been exacting inspected using a polarisation vision method [55]. Atkinson *et al*. studied the in-plane shear behaviour of different composites, as shown in Figure 6, impact-loaded with various energy inputs using the same technique and obtained an accuracy of 0.1°–0.2°. While effective, traditional machine vision methods often face limitations related to camera resolution, lighting conditions, and the reflective nature of some composite surfaces, particularly carbon fibre composites [56].

This shift toward data-driven methods of machine vision using machine-learning and deep-learning algorithms highlights the potential for achieving higher detection, and more automation, over the past few years, especially in automating defect detection and classification in composites [57]. For instance, Zambal *et al*. [58] describe a system that automates the detection and classification of three types of defects (delamination, in-situ foreign objects and localised resin-rich regions) in carbon fibre-reinforced polymer (CFRP) in components using data from thermography. The machine learning approach achieved a good level of accuracy. In related work, Tabernik *et al*. [59] presented a segmentation-based, deep-learning approach for detecting the surface defects in a composite. To address the issue of limited labeled data in composite material inspection, researchers have explored few-shot learning and transfer learning methods. Kesavan *et al*. [60] improved defect detection accuracy in composites using transfer learning with a small dataset, while Duan *et al*. [61] proposed a multimodal deep learning approach combining visual and infrared images for detecting defects in CFRP materials.

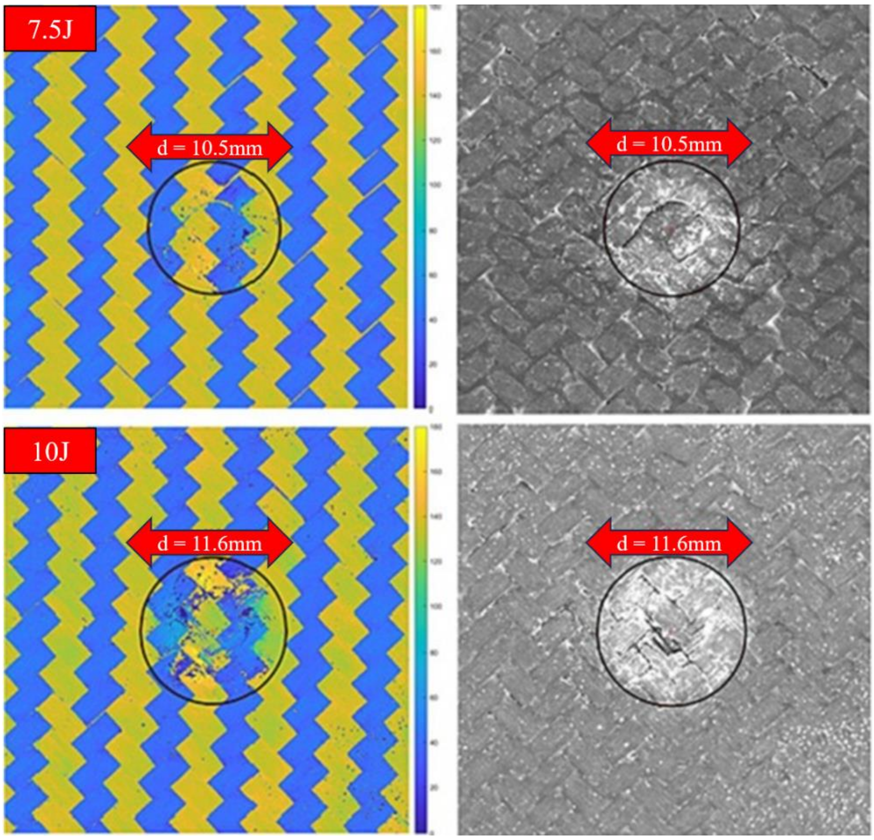

Figure 6. Polarized images (left) of the impacted specimens and greyscale images (right) depict the damage for all impact energy. For impact energies of 7.5 J and 10 J, respectively, the damage's diameter is 10.5 mm and 11.6 mm [56].

Meanwhile, to find surface-level flaws including wrinkles, cracks, and foreign objects, visual-based assessment methods use cameras and sensors. However, the precision of these methods depends heavily on the robot's ability to follow exact trajectories. To guarantee that the robot covers the whole surface of intricate composite structures, highly accurate path planning is necessary. Furthermore, in order to compensate for geometric abnormalities in the material, adaptive control algorithms allow for real-time adjustments to the robot's position and orientation. This guarantees consistent image quality and lessens the possibility of missing important areas, leading to more accurate fault identification. The reliability and efficiency of composite material examinations can be greatly increased by robotic systems by combining precise motion control with sophisticated visual inspection techniques.

2.5. Force-based inspection techniques

Recent years have seen a notable increase in the use of force feedback-based non-destructive testing methods as a supplementary for composite materials. In order to detect mechanical changes on the surface or within a material, these approaches mostly rely on tactile or high-precision force sensors [62]. A force signal that is aberrant is registered by the force feedback device when it detects voids, delamination, or fissures inside the material. The force-displacement relationship can be examined for various regions by applying force and monitoring the material's displacement response; aberrant force-displacement characteristics typically correlate to flaws in the composite material [63].

More accurate detection is possible when force feedback technology is combined with robotic manipulation. By carefully adjusting the applied force and utilizing force feedback techniques, robots may precisely scan the outside or interior of a material, detecting abnormal areas through force feedback information from their end-effectors [64]. Villa-Tiburcio *et al.* [65] utilized a six-degree-of-freedom force sensor to ensure consistent contact force during the AFP process, as shown in Figure 7, By combining a PI controller with an Artificial Neural Network (ANN), their method achieved precise force tracking and robust compensation for disturbances under complex conditions. The study provides a robust foundation for further exploration of force-based defect detection in automated manufacturing processes. In order to identify features relevant to material flaws, the collected force feedback signals usually need to be processed using signal processing algorithms, such as Fourier transform or waveform analysis [66]. Furthermore, force feedback data can be combined with machine learning algorithms to automatically classify and identify defects [67].

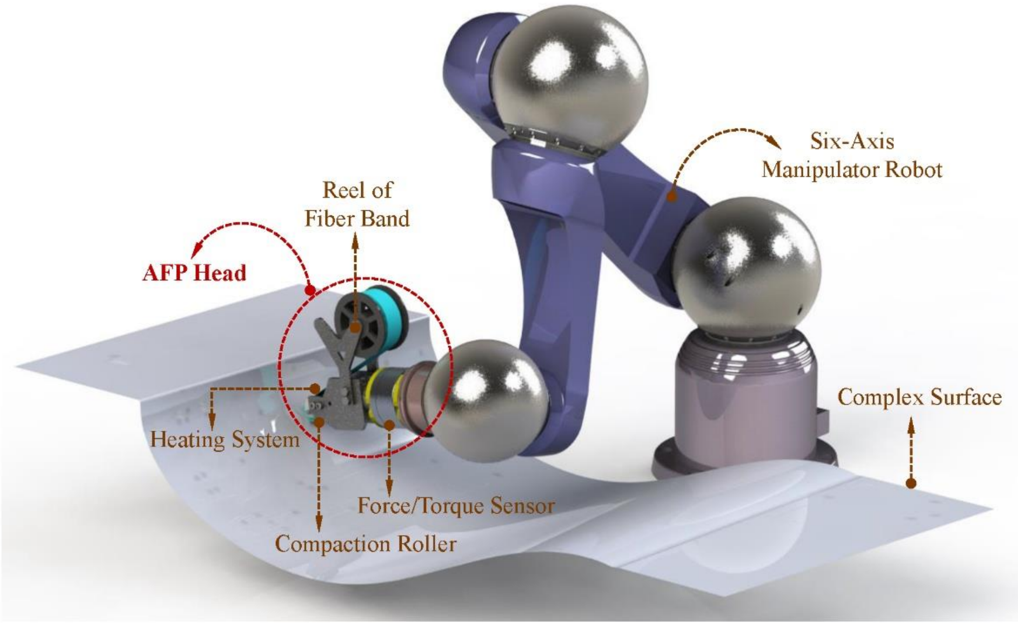

Figure 7. Robotic contact measurement system [65].

Force-based inspection techniques measure the material's response to applied controlled forces in order to evaluate the mechanical characteristics of composite materials, such as stiffness and bonding strength. Precise and consistent application of forces is made possible in large part by robotic control systems. Using adaptive force control in conjunction with real-time sensor feedback, the robot can identify minute changes in the material's response that could point to flaws like holes or delamination. Moreover, real-time force sensor data can be processed and interpreted by machine learning algorithms, which enhances the robot's capacity to recognize and categorize flaws according to the mechanical properties of the material.

2.6. Tactile-based inspection techniques

Tactile-based defect detection has emerged as an innovative approach to identifying defects in composite materials, offering a complementary method to traditional visual inspection techniques. Unlike visual methods, which are limited to surface-level defects, tactile sensing can potentially identify subsurface anomalies and provide information about material properties through direct contact with the material surface. Some examples of tactile sensors have been developed lately to fulfil the requirement of composites defect detection, such as the Gelsight sensor from Yuan *et al*. [68] have gained notoriety for their optical tactile sensor. It uses a three-color light source with a symmetrical distribution of the circumference to create a symmetrically distributed tactile image of red, blue, and green. What makes this sensor innovative is that it uses the photometric stereo method to reconstruct the contact geometry with high precision. Similarly, Meta Corporation (USA) has developed the open-source DIGIT haptic sensor [69], which is a fully optimized sensor design for better application in robotics tasks. Moreover, Lin *et al*. [70] suggested a monochromatic light-based phototactile sensor called 9DTact, which uses a black silica gel to cover a semi-transparent elastomer in order to achieve the shadow change in the contact region. This reduces the complexity of creating a three-color light source. In order to detect defects in the surfaces of dry fabric and composite prepreg, our previous research [71] proposed a new vision-based tactile sensor roller prototype, TacRoller, which is a three-colour reflective membrane roller-shape sensor. This new tactile sensor is anticipated to enhance the automation of the hand layup process. Because it allows for real-time quality monitoring, it drastically reduces the need for extensive manual inspections. Figure 8 shows the TacRoller developed in the authors' group.

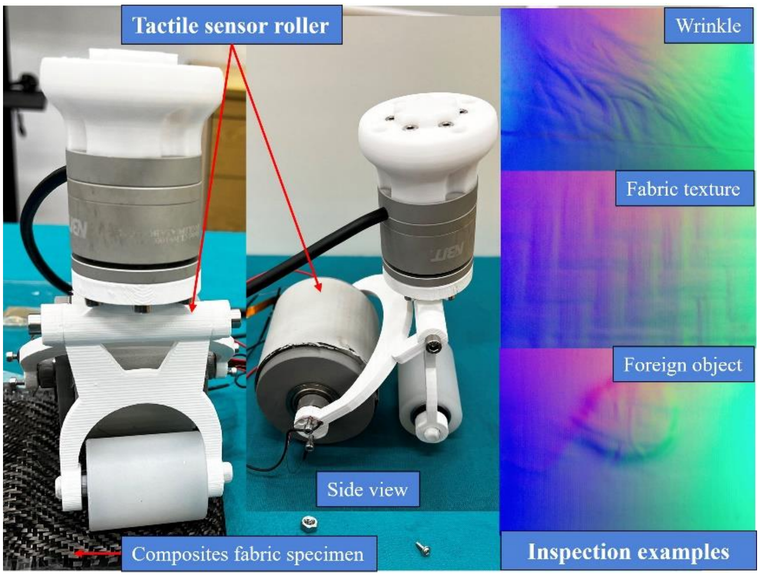

Figure 8. The TacRoller developed by the authors.

In addition to improving real-time monitoring and revolutionizing flaw identification, tactile sensing has found new uses in a variety of production processes, most notably in composite materials. Krombholz *et al*. [72] highlighted that traditional post-manufacturing inspection of high-performance composite parts can take up to 6 hours, significantly impacting production efficiency. In contrast, tactile sensing enables real-time, in-process monitoring, allowing for layer-by-layer inspection throughout the manufacturing process. This facilitates immediate defect detection and potential corrective actions, as demonstrated by Sacco *et al*. [73] in their work on automated fibre placement (AFP) systems. The applications of tactile sensing in composite materials are diverse. Fang *et al*. [74] showcased its capability in identifying fabric defects, including irregular dyeing patterns, revealing that tactile images could provide clearer background textures compared to visual images for certain materials. However, they noted limitations in sensor size and the need for repeated lifting and pressing of the sensor, which could impact detection efficiency. In a related field, Shimonomura *et al*. [75] developed a tactile sensor capable of identifying foreign objects based on hardness variations, a principle that has potential applications in detecting inclusions or contaminants in composite manufacturing. Recent advancements in tactile sensor technology have addressed some of these limitations. Kim *et al*. [76] developed large-area capacitive sensor arrays to overcome the issue of small sensor size, while Zang *et al*. [77] reviewed progress in flexible pressure sensors that can better conform to curved or complex composite surfaces. The integration of multiple sensing modalities and machine learning algorithms, as discussed by Zou *et al*. [78] and demonstrated by Zhao *et al*. [79], has further enhanced the ability to detect and characterize various types of defects.

Notwithstanding these developments, issues with sensor robustness, attaining fast inspection across wide regions, interpreting data in real time, and smooth integration with current production procedures still need to be resolved. The creation of self-healing tactile sensor skins, investigation of biomimetic tactile sensing concepts, and combination with additional non-destructive testing techniques are potential future research avenues. Tactile-based defect identification is expected to become more and more important as these issues are resolved in guaranteeing the dependability and quality of composite structures in a variety of industries.

The robot's capacity to regulate the force used during the inspection is crucial to tactile-based methods of inspection. Robots may control how much pressure is applied to a material to avoid damaging it while maintaining a constant contact point between the surface and the sensor thanks to adaptive force control. Robots can now navigate more complex surfaces thanks to advanced control algorithms, which also guarantee high-resolution data collecting from touch sensors even in hard-to-reach places. Its accurate and efficient flaw detection is enhanced by the combination of tactile sensing and precise force control, making it an invaluable instrument for composite material inspection.

2.7. Comparison of various inspection methods

Wave-based, optical-based, radiation-based, visual-based, force-based, and tactile-based composite inspection methods each have unique capabilities, limitations, applications, defect type covered and success rate as shown in Table 1. Wave-based techniques (ultrasonic testing) are ideal for robotic inspection of large structures due to their high sensitivity and deep penetration, demonstrating an impressive 85%–95% defect coverage [23,25,27]. Particularly in multi-layered composites, these methods are highly effective at detecting delamination, voids, and fibre breakage. However, they face challenges with complex internal geometries that may distort readings and require precise calibration, with high model complexity and reliance on coupling media constraining automation potential. Optical-based methods, such as infrared thermography, are non-contact and provide excellent precision in surface defect detection, achieving an 80%–90% success rate [28,30,33] while being sensitive to environmental conditions. They are well-suited for robotic automation due to their non-contact nature, enabling quick and precise flaw detection. Radiation-based techniques, including CT scans and X-rays, offer unparalleled 90%–99% accuracy for internal defects [42,46,53], providing high-resolution internal images when combined with high-precision 3D imaging. However, they are less suitable for direct robotic integration, are costly, and require stringent safety precautions. Visual techniques achieve a cost-effective 75%–90% success rate in surface defect detection [57–60], while force-based methods (70%–85% success rate) [62,64–67] and tactile-based approaches (60%–80% accuracy) [68,71,76] provide precise feedback on contact pressures, material deformations, surface roughness, and micro-defects.

Table 1. Comparative overview of inspection methods.

Methods	Capabilities	Limitations	Application	References
Wave (UT)	- Effective for detecting delamination, voids, and fibre breakage. - Can penetrate multi-layered structures.	- Requires coupling medium and precise calibration - Limited by complex geometries	- Aerospace components - Thick composite structures	[23–27]
Optical (IRT)	- Infrared thermography can detect subsurface defects like delamination by measuring heat flow.	- Sensitive to environmental factors - Limited to near-surface detection	In-process monitoring of composite layups	[28–41]
Radiation (CT)	- Excellent for detecting internal defects like voids and delamination. - Non-contact, high-resolution results.	- Expensive, high radiation safety requirements - Not real-time	Critical component inspections in aerospace and automotive	[42–53]
Visual (CV)	Quick and easy for surface-level defects like cracks or wear.	- Limited to surface defects. - Dependent on lighting conditions	Quality control in manufacturing environments	[54–61]
Force (sensor)	Assesses mechanical properties like stiffness and bonding strength.	Limited resolution for small-scale internal defects	- Precision assembly - mechanical property evaluation	[62–67]
Tactile (sensor)	Effective for detecting surface roughness or cracks.	- Limited to surface-level defects - slow scanning speed	Real-time monitoring during hand layups	[68–79]

Methods	Defect Types Covered	Success Rate (%)	Model Complexity	References
Wave (UT)	Delamination, voids, fibre breakage, thickness variation	85%–95%	High	[23,25,27]
Optical (IRT)	Subsurface delamination, cracks, voids, foreign objects	80%–90%	Medium	[28,30,33]
Radiation (CT)	Internal voids, cracks, fibre orientation, delamination	90%–99%	High	[42,46,53]
Visual (CV)	Surface cracks, wear, impact damage, fibre alignment	75%–90%	Low	[54–57]
Force (sensor)	Surface ridges, resin excess, mechanical property variations	70%–85%	Medium	[62,63–66]
Tactile (sensor)	Surface roughness, microcracks, texture irregularities	60%–80%	Medium	[68,76]

From a robotic integration perspective, each technique finds its specific domain as demonstrated in Table 2. Wave-based and optical methods are highly suitable for automated inspection due to their non-contact nature and precision; radiation-based methods, despite their accuracy, face application limitations from cost and safety concerns; visual, force-based, and tactile methods excel in continuous monitoring and scanning through rapid, precise feedback. Both tactile and visual approaches are easily integrated with robotic systems for continuous monitoring and scanning. Ultimately, selecting an inspection method demands careful consideration of sensitivity, penetration depth, cost, safety, and automation potential to achieve optimal composite material defect detection.

In conclusion, the inspection technique selection is based on the particular needs of the composite material application, taking into account cost, robotic integration potential, and flaw detection capability. The real-time performance and automation ease of visual (CV) and optical (IRT) approaches make them useful for quick, economical surface examinations. However, despite their slower speeds and greater prices, wave-based (UT) and radiation-based (CT) technologies are preferable for detecting complicated interior problems. Although they are less appropriate for real-time applications, tactile and force-based approaches offer insightful evaluations of surface conditions and mechanical characteristics, which makes them perfect in situations where material strength is crucial. Robotic integration provides a road to completely automated, high-precision inspections by improving the efficiency and accuracy of existing methods, especially for big or complex composite constructions. Through deliberate selection and fusion of several techniques, sectors can maximize the velocity and precision of their evaluations of composite materials.

Table 2. Comparison of real-time inspection capabilities and robotic arm integration for composite material inspection methods.

Methods	Real-time Capability	Suitability for Integration	References
Wave (UT)	**Moderate:** Near real-time data with some processing delays depending on equipment.	Suitable	[23–27]
Optical (IRT)	**High:** Near real-time feedback, especially effective for surface and near-surface defect detection.	Suitable	[28–41]
Radiation (CT)	**Low to Moderate:** Immediate results possible with X-rays, but CT scans require significant processing time.	Partially Suitable	[42–53]
Visual (CV)	**High:** Immediate feedback, highly suitable for surface inspections.	Highly Suitable	[54–61]
Force (sensor)	**Low to Moderate:** Results require post-processing, reducing real-time capability.	Suitable	[62–67]
Tactile (sensor)	**Low:** Slow due to physical contact requirement, not suited for real-time monitoring.	Suitable	[68–79]

3. Image processing techniques

Image processing is now crucial for flaw detection due to the growing demand for composite material inspection. While image processing allows for the quick, automated detection of minute flaws on intricate surfaces, traditional inspection techniques frequently call for physical labour or specialized equipment. Image processing provides increased precision and consistency for minute problems such fibre misalignment, microcracks, or foreign objects in composite materials. A more intelligent, automated inspection procedure that can adjust to the many conditions and geometries found in composite materials is made possible by this multi-technology approach.

The two main categories of image processing algorithms utilized in composite material inspection are machine learning/deep learning algorithms and traditional computer vision (CV) techniques. Both conventional computer vision techniques and deep learning algorithms have merits in the field of composites inspection; nevertheless, the most popular algorithms are primarily determined by the particular application situation and inspection needs. Due to their ease of use, simplicity, and efficiency, conventional computer vision algorithms are still frequently employed in many industrial inspection situations today. However, the use of machine learning and deep learning algorithms is rapidly expanding, particularly in automated and intelligent inspection, as the amount of data grows and the standards for automated inspection accuracy improve.

3.1. Traditional CV methods

Because of their computational efficiency and ease of use, traditional computer vision techniques continue to be essential in the inspection of composite materials. Otsu's thresholding technique is still a mainstay for image segmentation, especially in situations with constant contrast [80], while advanced imaging techniques like edge detection are frequently used to detect surface flaws and structural irregularities in composite materials [81,82]. In ultrasonic and X-ray imaging, a variety of filtering techniques, such as Gaussian and median filtering, are widely utilized for picture improvement and noise reduction [83]. These traditional methods, which are the foundation of many industrial inspection systems, are excellent at identifying and evaluating surface flaws, edges, and fundamental structural irregularities [84]. For example, Zhao *et al*. [85] showed how well wavelet transforms and Canny edge detection work to identify delamination in composite laminates, while Gao *et al*. [86] successfully used a combination of Gabor filters and Otsu thresholding to detect and classify defects in carbon fibre reinforced polymer (CFRP) components. Because they are simple, computationally efficient, and reliable in certain environments, traditional computer vision techniques are perfect for real-time industrial applications. However, their reliance on predetermined traits and standards often limits their ability to adjust to complex or highly varied inspection tasks. These methods may therefore not be as successful in scenarios with intricate fault patterns or low-contrast images, where more advanced algorithms or machine learning techniques may be more useful.

3.2. Machine learning and deep learning methods

Building upon these traditional methods, the field has witnessed rapid adoption of machine learning algorithms, particularly deep learning models, which have demonstrated superior performance in complex defect detection and segmentation tasks. Convolutional Neural Networks (CNNs), which is a type of deep learning, have completely changed machine vision in composite inspection and U-Net architectures have shown remarkable capability in processing complex images and accurately localizing various types of defects [87,88]. The necessity for human feature engineering has been eliminated by CNNs' amazing abilities to automatically learn pertinent characteristics for fault identification [89]. CNNs are useful for identifying flaws in CFRP materials, as evidenced by a recent study by Meister *et al*. [90] that used X-ray computed tomography data. Their method provided accurate defect localization and achieved great accuracy in identifying a variety of defect types, such as pores, delamination, and foreign objects. Support Vector Machines (SVMs), often combined with traditional feature extraction methods, prove effective for specific defect classifications, especially with limited datasets [91]. Clustering algorithms like K-means offer powerful solutions for the automatic segmentation of composite materials, particularly when defect locations are uncertain [46]. This integration of advanced machine learning techniques with traditional methods provides a comprehensive framework for composite material inspection, addressing a wide range of defect types and inspection requirements in various industrial settings [92].

Recent research highlights the power of these advanced techniques. Li *et al*. [93] successfully applied a hybrid CNN-SVM model for automated defect detection in aircraft composite structures, demonstrating improved performance over traditional methods. In the realm of X-ray Computed Tomography (CT), Andre *et al*. [94] proposed a method using CNN for image segmentation to identify cracks and failures in composites. Xu *et al*. [95] presented a unique approach combining CNN for fibre orientation classification with a separate code for measuring the fracture process zone (FPZ). Further advancing the field, Yang *et al*. [96] and Chen *et al*. [97] utilized U-net CNNs to reconstruct composite structures from micro-CT images, demonstrating the potential of deep learning in material characterization. However, the strong feature extraction capability of CNNs can sometimes lead to the recovery of unnecessary features [74], potentially affecting defect detection accuracy. To address this, Niu *et al*. [98] introduced the attention mechanism, a powerful machine learning tool that enhances CNNs by reducing extraneous feature input and allowing for more effective model training focused on relevant features. These advancements illustrate the evolving landscape of composite material inspection, where traditional computer vision techniques provide a solid foundation, while machine learning and deep learning methods offer enhanced capabilities for complex defect detection and analysis. The synergy between these approaches continues to drive improvements in inspection accuracy, efficiency, and applicability across various industrial domains.

Although deep learning and machine learning approaches improve the accuracy of fault identification, the precision and adaptability of robotic systems are critical factors that determine how well these techniques work in practical applications. Robotic control systems are essential for guaranteeing the precise application of force, tactile, and vision-based techniques in composite material examinations. Robots can navigate complex geometries, adapt to changing material qualities, and produce consistent, high-quality inspection findings thanks to sophisticated control strategies like adaptive force control, learning-based systems, and real-time motion planning. Intelligent robotic control not only increases the efficacy of inspections but also makes it easier to make changes in real-time and receive ongoing feedback—both of which are critical for finding problems in complex or large-scale composite structures. The convergence of sophisticated machine learning algorithms and intelligent robotic control systems produces notable enhancements in inspection precision, flexibility, and effectiveness for a range of industrial uses. The subsequent sections will analyse the ways in which particular advancements in robotic manipulation and control tactics directly improve the accuracy and efficiency of various composite material inspection methods.

4. Applications of robotic and intelligent technologies in materials inspection

Non-destructive testing (NDT) has been transformed by robotic systems in a number of industries, providing increased accessibility and efficiency. As shown in Table 3, in aerospace applications, complex-geometry composite components can be inspected using six-axis robotic manipulators fitted with phased array ultrasonic testing (PAUT) probes [99]. Lamb wave-based mobile robotic devices hold potential for automated NDT of aircraft surfaces by fusing flaw identification and structural mapping [100]. Unmanned Aerial Vehicles (UAVs), which have historically used high-resolution cameras for visual assessments, have become an invaluable tool for remote NDT inspections [101]. Internal inspections of industrial assets are now possible thanks to recent developments that have included ultrasonic contact measurement capabilities in autonomous UAV systems [101]. Collaborative robots (cobots) integrated with advanced sensors are revolutionizing manufacturing quality control. These systems combine robotic precision with human flexibility, enabling real-time inspection and reducing defects [102].

In addition, current developments in AI and machine learning have greatly enhanced industrial quality control and fault detection. In several industries, such as the production of steel and semiconductors, Convolutional Neural Networks (CNNs) have become an essential tool for automated surface defect classification [103]. Real-time fault identification and improved decision-making are made possible by these deep learning models' exceptional ability to extract fine information from product photos [104]. Efficiency gains, waste reductions, and operating cost reductions have resulted from the incorporation of AI-powered systems into production workflows [104]. CNNs have demonstrated efficacy in tackling Industry 4.0 difficulties, namely in domains like anomaly detection and defect detection for maintenance [105]. Sensor accuracy and computational demands often limit the efficiency of intelligent systems. The integration of AI with robotic systems for adaptive control and defect prediction shows great promise. Emerging technologies like digital twins and augmented reality could further enhance inspection processes by providing real-time visualization and analysis [105].

Table 3. Comparison of applications of robotic systems in materials inspection.

Robotic System	Inspection Method	Applications	References
Robotic Arms	UT	Internal defect detection	[23,99]
Mobile Robots	IRT	Surface and near-surface defect detection in large structures	[100]
Autonomous UAVs	CV	Inspection of large-scale structures like wind turbines and bridges	[101]
Collaborative Robots	Force/Tactile sensing	Real-time surface roughness and defect detection in manufacturing	[102]

5. Robotic path planning and control techniques

Robot perception systems offer crucial environmental data and feedback for control and manipulation, and sophisticated control and manipulation strategies let robots behave with flexibility and precision depending on this sensory input [106]. To handle complicated and changing work conditions in composites manufacturing, modern robots commonly use algorithms like learning-based control and force control [107]. The goal of manipulation techniques is to increase the dexterity and adaptability of robots; compliant control enables robots to demonstrate greater flexibility in their interactions with their environment [108]. Furthermore, robots may now continuously optimize their control and manipulation tactics by learning from experience thanks to the development of artificial intelligence and deep learning [109]. In a variety of application settings, robots are able to exhibit ever-higher degrees of autonomy and intelligence because to the close integration of these technologies with perception systems [110].

5.1. Path planning

Robotic path planning is essential for accurate material placement in composite material layup processes because of the intricacies of curved surfaces, the necessity to prevent material wrinkling or stretching, and the continuity of layup routes [111]. The most established and often used algorithms in the field of robotic path planning for composite material layup are the following three: offline programming with trajectory planning [112], curve fitting and smoothing path planning [113], and A* algorithm with optimization techniques [114]. Building upon these robotic perception and control foundations, the traditional three primary path-planning algorithms have evolved to address the specific challenges in composite manufacturing while leveraging modern technological advances. Offline programming with trajectory planning has become increasingly sophisticated through the integration of digital twin technology and machine learning approaches, enabling more accurate simulation and optimization of paths before physical implementation [115]. Curve fitting and smoothing path planning methods have been enhanced to better handle the complexities of curved surfaces and material properties, incorporating advanced optimization techniques to prevent material deformation while maintaining motion efficiency [116]. Meanwhile, the A* algorithm continues to evolve through modern optimization techniques, particularly in addressing dynamic environmental changes and real-time planning requirements [117], with recent developments integrating adaptive strategies to better handle complex manufacturing scenarios. Despite that, an Inverse Reinforcement Learning (IRL) system was presented by Omey *et al*. [10], which is an advanced modern technique, with the goal of improving robot trajectory planning, specifically for task sequencing in manufacturing applications. Expert knowledge of task order and motion execution is captured by this framework, which efficiently learns task sequencing policies from human demonstrations. The approach makes it possible to transfer these rules to robots by modelling expert preferences and incorporating them into the learning process. As a result, robots can now perform trajectory planning and automatically create optimal task sequences for intricate manufacturing processes like composite layups without the need for extra human demonstrations for new parts. These algorithmic advances, coupled with improved perception and control systems, have significantly enhanced robots' capability to perform precise and adaptive composite material layup tasks.

5.2. Robot control

5.2.1. Force control

Motion control of robotic end-effectors is crucial for ensuring inspection quality. Three control approaches are the main emphasis: force control for managing contact interactions with composite surfaces, velocity control for ensuring smooth inspection processes, and position control for accurate inspection trajectory tracking. Recent breakthroughs in control have resulted in more sophisticated and adaptive systems that integrate multiple control algorithms to perform complex inspection tasks [118,119].

Force control has become increasingly common in robot contact tasks, often combined with position control to achieve precise inspection operations [120]. PID control is widely used for its simplicity and effectiveness in achieving precise trajectory tracking. For example, by creating a novel variable target stiffness (NVTS) control method, Zhang *et al*. [121] made substantial progress in force control in compliant, force-tracking interactions within unknown inspection environments. Mazumder [122] developed a PID-based dynamic controller for soft robots, addressing the challenges of precise control in these flexible systems. Lee *et al*. [123] introduced a practical method to improve PID control performance in nonlinear systems like robot manipulators, enhancing tracking without adding complexity. However, PID control may struggle with dynamic or highly nonlinear environments due to its fixed parameter structure, requiring manual tuning for optimal performance [124].

Advanced control methods such as demonstration-based stiffness/force controllers [125,126] have shown advantages in contact-rich manipulation tasks. For example, the robot can learn force-controlled inspection skills from human demonstrations [10], producing more accurate and fluid strokes on a variety of materials. In order to ensure stability and agility in execution, the hierarchical architecture combines high-level planning with low-level real-time force adaptation. Experiments where the robot effectively completed tasks requiring precision force control, such as cleaning uneven surfaces (similar to inspection of composite materials), verified this strategy [126].

Research in this emerging field suggests that force control, as an advanced solution for contact-rich tasks, holds promise for composite inspection—a similarly contact-intensive application in robotics. This technique effectively prevents damage to sensitive composite surfaces, and when combined with advancements in sensor technology and artificial intelligence, it has greatly enhanced the capabilities of composite inspection systems [127].

5.2.2. Learning-based control

Learning-based control methods, such as reinforcement learning and neural network control, enable robots to learn control strategies for complex inspection tasks through data-driven approaches. These methods excel in handling unstructured or dynamic environments, particularly in scenarios where traditional control models are difficult to implement or inadequate.

In order to optimize robot-environment interaction in composite inspection, Peng *et al*. [128] presented an adaptive admittance control approach enhanced by radial basis function neural networks (RBFNN). This method improves trajectory tracking in uncertain settings by dynamically controlling contact torque. In a similar vein, Petit *et al*. [129] created a learning-based force control system that integrates parallel position/force control and admittance control with reinforcement learning (RL). The system incorporates safety features to allow for secure training on actual inspection systems, and real-world tests and simulations show that it is effective at handling contact-intensive tasks.

By allowing robots to automatically adjust to novel materials and inspection environments through experience accumulation, learning-based control systems provide a scalable solution for upcoming composite inspection problems. These systems gradually improve control strategies as jobs become more difficult, using vast datasets and developing algorithms to manage complex situations. This flexibility reduces the need for lengthy reprogramming and improves inspection safety and precision, opening the door for more adaptable robotic frameworks in the workplace. There are still issues, though, such as the requirement for substantial data training, decreased interpretability, and stability issues. These problems have started to be addressed by recent developments in learning efficiency, model robustness, and safety [130,131]. Furthermore, hybrid systems that blend traditional control theory with learning-based methodologies have demonstrated encouraging outcomes in real-world applications [132,133].

6. Conclusion

Composite material inspection is changing as a result of the combination of robotic intelligence technology and sophisticated inspection techniques, which provide increased automation, efficiency, and accuracy. From solo detection techniques to the integrated solutions of today, traditional composite material inspection technologies have seen significant development. The most common methods in the past were manual inspection and purely wave, optical, radiation, etc. detection, which took a lot of time and required a high level of operator skill. Nowadays, this subject has undergone a revolution thanks to the combination of advanced inspection techniques with robotic intelligence, which makes automated, accurate, and efficient inspections possible. When paired with image processing algorithms, machine learning models, and robot technologies, advanced non-destructive testing techniques like X-ray computed tomography, infrared thermography, and ultrasonic C-scan have shown impressive capabilities in identifying flaws in composite structures.

Nonetheless, a number of issues still exist with the present inspection systems, such as their susceptibility to environmental changes, limited model generalization, and real-time processing limitations. Three main areas are anticipated to be the focus of composite inspection in the future: (1) the creation of increasingly complex robotic control systems with improved precision and adaptability; (2) the incorporation of cutting-edge AI technologies, especially in the areas of transfer learning and few-shot learning for improved generalization; and (3) advancements in sensor fusion technologies for more thorough and dependable defect detection.

The way forward is to create more resilient and flexible systems that effectively integrate robotic capabilities with human knowledge. Together with ongoing developments in AI and sensor technologies, this human-robot collaboration method will not only overcome present constraints but also make inspection procedures more dependable and effective in a variety of industrial applications. In order to satisfy the rising need for quality assurance in increasingly complex composite materials and structures, such evolution will be essential.

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Conflicts of interests

The authors declare no conflict of interest.

Authors' contribution

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