Computers in Industry 141 (2022) 103695

Contents lists available at ScienceDirect

Computers in Industry

journal homepage: www.elsevier.com/locate/compind

Aircraft visual inspection: A systematic literature review

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A R T I C L E I N F O

Article history:
Received 18 January 2022
Received in revised form 20 April 2022
Accepted 22 April 2022
Available online 21 May 2022

Keywords:
Aircraft visual inspection
Systematic literature review
Defect detection
Deep learning

A B S T R A C T

Aircraft visual inspection is a procedure that aims at identifying problems with the vehicle structure. The visual inspection of aircraft is part of the activities of aircraft Maintenance, Repair and Overhaul (MRO), and combines multiple observation processes conducted by human inspectors to find irregularities and guarantee vehicle safety and readiness for flight. This paper presents a systematic literature review of methods and techniques used in procedures for the visual inspection of aircraft. It also shows some insights into the automation of these processes with robotics and computer vision. A total of 27 primary studies were considered, including methods, conceptual works, and other literature reviews. To the best of our knowledge, this is the first systematic literature review about vision-based aircraft inspection. The findings of this review show the deficiencies in the literature with regards to requirements specifications for the development, testing, and validation of methods. We also found a scarcity of publications in the aircraft inspection area and a lack of complete intelligent inspection systems in the literature. Despite these deficiencies, our findings also reinforce the potential for automating and improving visual inspection procedures. In addition to these findings, we also present the complete methodology we used for performing this systematic review. This methodology provides documentation of the process and the criteria for selecting and evaluating the studies. Researchers can use this review framework for future investigations in this area of interest. These results should encourage further works on computer vision and robotics techniques, requirements specification, development, integration, and systematic testing and validation.

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https://doi.org/10.1016/j.compind.2022.103695
0166-3615/

1. Introduction

Aircraft traveling is one of the safest transportation modes, capable of moving long distances and carrying many passengers and considerable cargo loads Oster Jr et al. (2013); Savage (2013). According to the study by Barnett (2020), the risk of death per passenger boarding has been falling consistently over the decades. The author shows that accidental deaths caused by equipment failure have sharply dropped since the 1960 s as aviation safety has increased over the years by technological improvements in aircraft, avionics, and engines. Commercial airline safety also dramatically improved with the development of ground proximity warning devices, more sophisticated pilot training with simulators, enhanced regulations due to a better understanding of human factors, navigational aids, air traffic management, and more accurate weather forecasting Oster Jr et al. (2013).

Even though aviation safety is constantly improving, the scientific and technical communities have not solved several related challenges yet, and others emerge with new and advanced technologies. As an example, the extensive usage of composite materials alters maintenance and inspection procedures since they require different techniques and equipment Oster Jr et al. (2013). Newer aircraft that travel longer distances have original demands for reliability and performance. Maintenance and safety checks for non-scheduled operations, as well as for older airplanes, may be limited by time and resources. The cost of maintenance in operation phase is the highest and most unpredictable among the phases of an aircraft life cycle Mofokeng et al. (2020).

Operators from maintenance centers and airports execute several of these procedures manually or visually, and they commonly use their judgment and experience to make subjective decisions Chen and Huang (2014); Gramopadhye and Drury (2000). Some tasks involve visually inspecting parts of the aircraft, where trained workers look for manufacturing defects, assembly faults, components failures, or damages that may have happened during a flight event (departure, flight, landing). These inspection tasks are part of the activities of aircraft Maintenance, Repair and Overhaul (MRO). It is critical to identify these issues and correct them before the aircraft is approved for flight, as they could cause accidents and unforeseen events.

According to Baaran (2009) and FAA advisory circular AC 43–204: “Visual inspection is defined as 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-". The FAA describes four categories of visual inspection:

Walk around inspection: This inspection is performed by aircraft maintenance and aircraft operating personnel. It serves as a quick check for damages and should be performed periodically.

General Visual Inspection (GVI): This inspection is performed by aircraft maintenance personnel. It serves as a check for damages and should be performed periodically or scheduled when needed.

Detailed Visual Inspection (DET): This detailed inspection is performed by aircraft maintenance personnel. It is performed when a specific problem is suspected.

Special Detailed Visual Inspection: This inspection is performed by aircraft maintenance personnel. It is periodically scheduled to ensure the airworthiness of the critical structure of an aircraft.

As we found in this review, identification of fuselage defects and visual checks are the most commonly addressed topics in the aircraft inspection literature. These visual checks are inspections performed before takeoff and after landing to guarantee that the vehicle is in good condition and ready to fly. The exterior of airplane fuselages is generally composed of metallic alloys or composites. Impacts during maintenance or flight with objects, birds, lightning strikes, and hails will cause damages to the fuselage and exterior components. These materials present different visual cues when damaged, and the operators must identify these damages during an inspection procedure. Operators perform examinations before and after flights based on checklists, which describe items and their correct states. These items, such as doors, valves, sensors, and other manually operated components, may cause accidents if left unattended at an inappropriate state.

There are automatic inspection systems in the literature and commercial solutions used to detect defects in metal (dents, scratches) and composite fuselage (cracks, fractures) and to perform pre and post-flight checks (vents, doors, tires, sensors). Autonomous visual inspection of the exterior of airplanes is possible with the use of drones (a.k.a. UAVs) and other mobile robots. These robots acquire images from around the vehicle and send them to a computer for data processing and identification of damages and irregularities. Commercial examples of this kind of approach, which includes an autonomous drone and the system for visual inspection, are the solutions developed by Donecle (France) Anon (2021), Mainblades (Netherlands) Anon (2021), Customdrone (Netherlands) Anon (2021), Rapid (UK) Anon (2021), Autaza (Brazil) Anon (2021), Luftronix (US) Anon (2021), and Rizse (US) https://rizse.io/. These companies use drones developed by themselves or by drone manufacturers, such as DJI (China) Anon (2021) or Parrot (France) Anon (2021).

This paper presents a systematic literature review (SLR) that helps researchers and engineers to identify, evaluate, and interpret the most relevant research publications on visual inspection of an aircraft. More specifically, it aims at identifying the most popular methods and techniques for an automated and intelligent aircraft inspection in a dynamic indoor or outdoor environment based on the computer vision. It also aids readers in understanding how to implement, validate, and integrate these methods into the standard inspection procedures conducted by aircraft manufacturers, airlines, and related companies. We also investigate the benefits that computer vision provides to the inspection process and how close current solutions are to a complete and fully automated general-purpose aircraft inspection system. Therefore, this paper contains the common terminology, existing solutions for aircraft inspection based on the computer vision, analysis of publications in this area, and insights into the current state of visual inspection.

This SLR expands traditional reviews since it has a well-defined methodology comprised of a review protocol, research questions, and a search strategy. It includes documentation of the search strategy for assessment of rigor, completeness, and repeatability. It also defines explicit inclusion and exclusion criteria, specification for the information extraction, and the definition of quality criteria to evaluate each study.

This paper is organized as follows: Section 2 presents the background of aircraft visual inspection and related works. Section 3 introduces the research methodology used for this systematic literature review. Results and discussions related to the research questions are shown in Section 4. In Section 5, we state an overview of our findings and the conclusions of this review.

2. Background and related works

2.1. Definitions

In this subsection, we present and explain the terminology used in this SLR report. We sorted the terms alphabetically and compiled their definitions from the references included in this paper.

CNN: Convolutional Neural Network, a.k.a. ConvNet, is a class of artificial neural network commonly used for image analysis. It has application in image classification, segmentation, recognition, video analysis, and many others where data is represented in multiple arrays. CNNs are able to extract characteristics from a dataset, learn patterns, and identify objects, such as visual defects on the fuselage.

Environment: The environment is any place where a component of an aircraft is manufactured, assembled, or inspected for quality evaluation. It could be a hangar, an airport, or another location in which the vehicles go through inspection processes during maintenance checks.

HW: Hardware is any physical component or equipment that is part of the system. It includes sensors, actuators, stands, mechanical devices, electronic circuits, computers, power sources, and connections.

MRO: Maintenance, Repair, and Overhaul are the compilation of facilities, procedures, and work for keeping aircraft and equipment operational. MRO procedures include preventive, corrective, and predictive maintenance, where parts and systems are repaired or replaced according to their quality condition. The aircraft is considered operational when it passes aviation regulation checks defined by regulatory authorities.

NDT: Non-Destructive Testing is a group of testing equipment and methodologies for acquiring data and analyzing the physical state of an object without altering its properties. Inspection of aircraft components that are still in operation generally uses this type of analysis.

Photogrammetry: Photogrammetry is the process of extracting reliable information from photographic images. In robotics and computer vision, systems based on it generate 3D topographic maps of locations and surfaces from acquired 2D images.

RGB: Red, Green, and Blue is a common representation of images acquired by digital cameras. Images are represented by matrices of pixels, and color images usually have three channels for the red, green, and blue hues, which are the primary colors. Some cameras capture images in RGBD format, adding a Depth channel to each pixel representation containing the distance between objects and the sensor.

Shearography: Shearography is the projection of laser patterns and image acquisition with a CCD camera to evaluate aircraft surfaces. This technique detects deformations, cracks, and other defects on the fuselage and its structure.

SW: Software is the suite of programs that control the Hardware or that process the acquired data. The Software might be developed by the authors of the related work or by a third party, such as paid or free commercial programs and libraries.

TRL: Technology Readiness Level is a system developed by NASA for assessing the level of maturity of a technology. Each level of the TRL evaluation method represents the confidence in the solution and the environment in which it was tested and validated.

UAV: Unmanned Aerial Vehicles, also known as drones, are aerial mobile robots powered by motors and propellers. There are two main categories of drones based on how they fly: vehicles with fixed wings and with multirotor. The multirotor UAVs can stay still in the air, while the ones with fixed wings require movement to generate lift.

2.2. Related works

This section presents works related to this review. Some of them came from the list of selected papers of the systematic review, and we added others to provide a valuable background of the state-of-the-art. There are not many works covering the complete process of visual inspection of an aircraft in the literature. Several reports about methods used in aircraft inspection were included in this review and presented throughout this paper (Section 4 presents these papers in more detail). The lack of studies about complete visual inspection systems further motivated us to conduct this review.

In Kamsu-Foguem (2012), the author presents a review of several NDT (Non-Destructive Testing) methodologies for the inspection of aircraft structures. Conventional inspections of maintenance checks commonly use these methodologies to evaluate the integrity of the aircraft. Each inspection task should follow the list of tools and methods in the aircraft manuals, but some procedures are based on visual inspections by a human operator. After identifying several testing methodologies, the paper categorizes them based on their primary method, equipment, specific techniques, and dimensional parameters. These categories and descriptions of methods aid in finding equivalent tools for similar jobs and help to develop automatic visual inspection systems and compare them to the traditional procedures.

The survey presented by Saadat and Cretin (2002) compares several measurement systems for aircraft manufacturing and maintenance. The authors described systems designed for large aircraft components within three common categories: optical systems, photogrammetry systems, and lasers. The comparison includes conventional optical tooling, electronic triangulation, electronic trilateration, photogrammetry, laser trackers, and laser scanners. These computer-based technologies could also help automatic inspection systems to identify problems during the production and assembly of an aircraft.

As long as people judge some of the testing results, human reliability will still matter during quality inspections and checks. The

Table 1
Research Questions for this literature review.

ID	Research Question	Motivation
RQ1	What are the stages in the process of visual inspection of an aircraft?	To better understand the items and parts of the aircraft that require inspection during the production and maintenance procedures and the sequence of events involved in the process.
RQ2	What are the existing methods used for visual inspection of aircraft by drone?	To raise the state-of-the-art and methods adopted by industry, to identify gaps and potential improvements with the help of automation and computer vision, and to investigate existing methods from other closely related areas that could be adapted and applied to aircraft inspection.
RQ3	How can computer vision techniques and methods help in the inspection of aircraft?	To improve accuracy and efficiency of visual inspection by adding automation and intelligence to the inspection process, from image acquisition to analysis and reporting.
RQ4	What is required for drones to navigate in indoor environments around aircraft autonomously, efficiently, and safely?	To evaluate the current technology readiness level of state-of-the-art solutions and identify potential improvements for a drone to perform a completely autonomous visual inspection of an aircraft.
RQ5	What are the requirements (SW, HW, environment) for a drone and camera system to visually identify characteristics and defects of an aircraft in a similar way to a human inspector?	To identify minimum system configuration such that it performs equally or better than human inspectors, following industry and safety standards for aircraft inspection.

works by Chen and Huang (2014); Gramopadhye and Drury (2000) present an overview and an investigation on how humans can harm the results of these manual procedures. They describe accident occurrences due to human error Gramopadhye and Drury (2000) that could potentially be avoided by an automatic system inspection. Using a probability network model, they identified significant factors of visual inspection related to common human errors that resulted in poor performance Chen and Huang (2014).

These four reviews Dhillon and Liu (2006); Latorella and Prabhu (2000); Shanmugam and Robert (2015); Sheikhalishahi et al. (2016) present studies about human factors in the inspection and maintenance of aircraft and the impact of human errors in these areas. The work by Latorella and Prabhu (2000) reviews the identification, reporting, and management of human errors in aviation maintenance and inspection. Authors present a human error taxonomy, reliability analysis, error classifications, responses to these errors, and some challenges in the tasks and environments related to inspection activities. The review by Dhillon and Liu (2006) lists publications related to the importance of human error in maintenance in the industry, presenting their impact and how to mitigate them. In Sheikhalishahi et al. (2016), the authors present a framework to aid maintenance practitioners in evaluating human factors, including ergonomics, work planning, and performance. Another review by Shanmugam and Robert (2015) shows human factor concepts used in aircraft maintenance, where principles are applied to enhance safety and follow regulations.

The author See (2012) presents a review of visual inspection that includes 212 documents. They investigate inspection models, techniques to measure performance, and the parameters that may impact the execution of this task. They discuss that human visual inspection is subjective since it is prone to errors, variability, and execution misunderstanding. They concluded that more effective training, well-defined inspection procedures, and the availability of tools could improve the visual inspection process.

Machine learning and deep learning are also gaining popularity in the field of aircraft visual inspection. Recent publications presenting the usage of neural networks show promising results and encourage further investigation in this area of research. A comparison of machine learning techniques for defect detection is presented by Miranda et al. (2019). The authors compare SVM (Support Vector Machine) with neural networks for detection of paint defects on images acquired with a UAV (Unmanned Aerial Vehicles).

The work by Malekzadeh et al. (2017) shows the application of a CNN (Convolutional Neural Network) for detection of defects on aircraft fuselage, such as dents and scratches. Authors use SURF (Speeded-Up Robust Features) key-point detector to identify defect candidates and a linear SVM classifier. A crack detection network for aircraft structures is described by Li et al. (2019), which uses a CNN to extract crack features and detect defects on images of the fuselage and engine blades. The work presented by Bouarfa et al. (2020) uses a Mask R-CNN to detect dents in the aircraft fuselage. The authors also provide ideas to extend their work for further improving their method. They expand their work in Doğru et al. (2020) and improve accuracy for dent detection.

Yasuda et al. (2020) present a systematic literature review on autonomous navigation of mobile robots. In this work, the authors show several methods for building a complete and autonomous navigation system that could be applied to different robots and dynamic indoor environments. They also present open challenges in the field, such as poor requirements specification for the development of autonomous navigation systems, the deficiency in testing and validation of these solutions, and the lack of complete navigation systems ready for application in the real world.

Other literature reviews about autonomous navigation of mobile robots consider different sensors besides vision for navigation in dynamic environments. Bagnell et al. (2010) present a review about using machine learning to solve the autonomous navigation problem in rough terrain and dynamic environments. Cheng et al. (2018) show a survey of odometry approaches for the localization of a mobile robot. Mohamed et al. (2019) surveyed data fusion techniques for autonomous navigation based on vision and laser sensors. These autonomous navigation systems provide solutions that inspection centers may use for automating the inspection process of aircraft and large vehicles or structures. The autonomous mobile robots move around the vehicle or large structures and acquire data for inspection.

3. Methodology

When we combined the necessities of the review with the knowledge we acquired while studying the background and related work, we could define five research questions. We show and explain these questions in Table 1, describing the motivation for answering each one of them.

We automated the searching process by using eight selected digital libraries: ACM Digital Library, CiteSeerX, Emerald Insight, IEEE Xplore, Sage, ScienceDirect, SPIE Digital Library, and Wiley Online Library. We defined the search strings based on the research questions and executed some trials to find the ideal combination and variation of keywords. The primary search string presented below allowed us to include the most relevant studies in the results: ((aircraft* OR airplane*) AND (visual OR vision OR imag*) AND (inspection OR analysis OR evaluation OR detection OR verification)).

We had a few thousand results from some of the selected digital libraries when we used this exact search string. This high number of articles would make the review impossible in a feasible time. Some search engines also have a maximum number of logical operators that are allowed in the search string. Therefore, we modified the search string for each library to restrict the number of results and increase their relevance to this systematic review. We describe the specific search strings and how we conducted the searching process for each digital library in Appendix A.

This systematic review includes traditional reviews (surveys) and studies published in journals and conferences related to the use of computer vision, solely or as a complement, to detecting and inspecting aircraft and aircraft components. We excluded short papers, documents not written in English, older publications (before the year 2000), and studies about the use of computer vision for applications that are not related to aircraft inspection. The selection considered the following inclusion and exclusion criteria: .

- Inclusion:
  - Papers from proceedings, conferences, magazines, journals.
  - Systematic Literature Reviews, Surveys, regular Reviews, Mappings.
  - Methods that use vision, solely or as complement, for aircraft inspection.
  - Studies about the use of drones for aircraft inspection.
  - Publications since 2000.
- Exclusion:
  - Works not in English as main language.
  - Inspection systems that do not use vision.
  - Commercial publications, products, papers with lack of technical information, papers that do not contribute academically or scientifically.

We used a quality checklist composed of 13 questions to assess each included paper assigning a quality score to them. The complete list of questions is in Appendix B. These were "yes", "no", or "partially" answer questions that covered the main goals of the studies, the used or proposed methods, their definition, results, validation, relevance, and any experimental hardware and software. Studies with more positive answers (higher score) were considered more relevant to this review.

The protocol also contains details about the extraction of data, including information about the publication, used methods and implementation techniques, identified problems and aircraft characteristics, differences from traditional inspection methods, relevance in the academic environment, and applications in the aerospace industry. We did the data extraction along with the quality assessment of the selected papers. The complete list of extracted data and their descriptions is in Appendix C. We answered 19 questions and combined them with the quality checklist and the score, resulting in 33 fields of information for each reference.

3.1. Review execution

The search engines of selected digital libraries returned 376 results after using the proposed search string and its variants. We used the Mendeley (https://www.mendeley.com) software and the Parsifal (https://parsif.al/) tool to organize all the searches and papers, to extract metadata, detect duplicates, and export formatted references. We executed the last search on these libraries in October 2020.

We divided the selection process into four stages, where we applied the inclusion and exclusion criteria. We also used the snowballing strategy to raise additional relevant papers, increasing the total number of included papers in this review. The first stage represents the total number of results from each digital library before any filtering or selection. In Table 2, we present the number of papers selected in each stage.

Table 2
Number of selected papers per stage.

Library	Stage 1	Stage 2	Stage 3	Stage 4
ACM Digital Lib.	117	1	1	2
CiteSeerX	0	0	1	1
Emerald Insight	42	4	0	4
IEEE Xplore	87	7	3	10
Sage	45	1	1	2
ScienceDirect	38	6	1	7
SPIE Digital Lib.	38	0	1	1
Wiley Online Lib.	9	0	0	0
Total	**376**	**19**	**8**	**27**

We applied the filters in the second stage before downloading the articles, removing papers published before 2000, without any annexed files, not written in English, and short papers. We read the titles and abstracts of the remaining papers to apply the inclusion and exclusion criteria to them. After this selection, we included 19 works in the final stage analysis.

The third stage represents the process of snowballing, in which we considered potential relevant studies from the selected paper references. After reading the referenced publications, we added another eight papers to the list.

In the final stage, we combined the selected studies from the initial search and from snowballing. Along with this process, we also fulfilled the checklist for the papers and extracted their data. In the end, we selected 27 papers for inclusion in this review.

We did the quality assessment based on the checklist by assigning a point for each positive answer and a half-point for a "partially" answer. The higher the score, the more relevant the paper is for this review. We used the scores to aid in interpreting the results, synthesizing the data, and analyzing them. Table 3 shows the results from the quality assessment with the number of answers for each quality question (QQ) from the checklist.

3.2. Threats to validity

In a systematic review, all data are analyzed objectively, following the research protocol. This procedure helps to minimize the bias present in most traditional literature reviews. But even after following the guides and planning the systematic review, there are still potential threats that can affect the results and introduce some bias in the conclusions.

One threat to the selection of a representative set of search libraries is the sparseness of the works. We selected popular digital libraries in computer science, robotics, and aircraft manufacturing and inspection, but there may be other sources for relevant papers. Including more libraries would increase the number of search results and demand extra researching time. If someone is interested in

Table 3
Results from the Quality Assessment.

ID	Yes (%)	Partially (%)	No (%)
QQ1	**25 (92.6%)**	2 (7.4%)	0 (0.0%)
QQ2	6 (22.2%)	**21 (77.8%)**	0 (0.0%)
QQ3	**23 (85.2%)**	4 (14.8%)	0 (0.0%)
QQ3.a	5 (18.5%)	**17 (63.0%)**	5 (18.5%)
QQ4	**18 (66.7%)**	5 (18.5%)	4 (14.8%)
QQ5	2 (7.4%)	4 (14.8%)	**21 (77.8%)**
QQ5.a	1 (3.7%)	3 (11.1%)	**23 (85.2%)**
QQ6	**17 (63.0%)**	0 (0.0%)	10 (37.0%)
QQ6.a	6 (22.2%)	1 (3.7%)	**20 (74.1%)**
QQ6.b	1 (3.7%)	5 (18.5%)	**21 (77.8%)**
QQ6.c	3 (11.1%)	9 (33.3%)	**15 (55.6%)**
QQ7	10 (37.0%)	1 (3.7%)	**16 (59.3%)**
QQ8	7 (25.9%)	**20 (74.1%)**	0 (0.0%)

enhancing this research or updating it, we made the complete protocol and search process available. One may include new sources of content and combine them with the current results by the same criteria.

Another threat comes from the definition of the search strings. We performed tests with different combinations of related words and logical operators to find a suitable string. Additionally, we adjusted this string for each search engine based on the available options and rules. Relevant works may not fit the search string for all the libraries, but changing the search protocol to collect more relevant results would probably increase the number of irrelevant ones, demanding more research time.

Paper selection by enforcing the inclusion and exclusion criteria is one of the most relevant threats in systematic literature. One of the goals of these criteria is to minimize the subjectiveness of the decisions. Still, this stage relies on the researcher's experience and how each publication presents the information.

The quality assessment stage also relies on the researcher's understanding while reviewing the works. Other relevant factors are the writing quality, efficiency, and conciseness in showing the information or abstracting data due to publication rules or confidentiality. The lack of standardization in the presentation of methods, implementations, tests, and results also contributes to this threat.

A final threat to the consistency of the extracted data occurs while answering our research questions. We only investigated data relevant for reaching the goals of this review, but data extraction is a long process, and it may change during its execution.

4. Results and analysis

This systematic review includes a total of 27 papers, listed in Appendix D. Among the selected publications, there are three literature reviews Gramopadhye and Drury (2000); Jordan et al. (2018); Saadat and Cretin (2002), three experimental works Dubinskii et al. (2019); Erchart et al. (2004); Růžek et al. (2006), one conceptual work Kamsu-Foguem (2012), and the remaining 20 papers consist of visual inspection methods and techniques. We did not find any systematic literature reviews while using the defined research protocol. We found one review Jordan et al. (2018) that presented the methodology that the authors used to select papers, even though it is not as detailed and strict as a systematic review. Additionally, these reviews are related to aircraft inspection, but neither of them covers vision-based processes. Based on this information and other findings that we will explain in the following sections, it is possible to notice a difficulty in finding publications in this research area. Also, definitions and methodologies in the studies are poorly structured and standardized.

Even though the total number of publications we included in this review is not large, we notice an increase in the number of publications in the area over the last few years (see Figure 1). This review considers studies that use images and videos. One possible reason for this growth is the popularity and affordability of digital cameras since images can provide a large amount of information for visual inspection. Another reason is the availability of computing power to process all the collected data. Figure 2 shows the number of publications per country, which are mainly from the USA (7) and France (6), two of the largest aircraft manufacturers in the world. China (3) and the UK (3) follow them, which are also among the most significant airline industries and scientific communities in technology and automation.

4.1. Process of visual inspection of an aircraft (RQ1)

The inspection of an aircraft occurs at two different phases considering its life cycle: 1) Manufacturing (or Production), and 2) Maintenance. During the production phase, components go through visual inspection after being manufactured or received from a supplier. Technicians assemble these parts and inspect them again in different stages of production until the aircraft is complete. When the factory finishes the aircraft production and painting, operators visually inspect it again before the final delivery to guarantee the quality of the final product.

4.1.1. Manufacturing

Among the studies that we found in this review, there are five papers related to manufacturing processes, of which four are new methods for the inspection of fuselage Chady et al. (2016); Nayak et al. (2020); White et al. (2005); Zhang et al. (2020) and the other is a review about technologies and instruments for measuring large components Saadat and Cretin (2002). The review from Saadat and Cretin (2002) provides a comparison of available measurement systems used while manufacturing aircraft. Operators will use these measurement systems to compare and verify parts against their specifications. They may also use them during the assembly of components to guarantee the correct positioning of all elements.

In Chady et al. (2016), the paper presents a method to detect defects and issues in metallic panels and components welding, which occurs while assembling panels to build the aircraft fuselage. In Nayak et al. (2020), the authors present a solution to detect defects in the manufacturing of composite components, more specifically in the lamination process. The manufacturing of an aircraft fuselage also uses these prepreg composite panels. The work presented by Zhang et al. (2020) consists of a method for detecting and measuring the profile of panels, as well as surface defects, during assembly in a busy and complex environment. In White et al. (2005), authors developed a climbing robot for NDT of fuselage surfaces.

These five studies present methodologies and techniques used in the process of aircraft fuselage manufacturing. The fuselage is the exterior structure of the vehicle, and defects on panels (metallic or composite) or their welding and assembly represent a risk for operation and flight safety. Even if the defect is minor, there is still a possibility that it will be visible after painting and coating, which also affects the presentation of the product. Other papers from this review also mention different inspection processes from the manufacturing phase, but it is possible to notice the lack of publications specifically about the visual inspection of aircraft construction and assembly.

4.1.2. Maintenance

The second phase where operators must inspect an aircraft occurs during the MRO (Maintenance, Repair, and Overhaul) procedures Kinnison et al. (2013). The aircraft manufacturers require multiple inspections to ensure safe operation and acceptable maintenance of aircraft conditions. Certain events will require these checks according to the usage of the vehicle, which may be due to the time passed since the last visual inspection or the number of hours of flight. Operators also perform checks before and after flights, especially for commercial airplanes. They must inspect several items according to a checklist before every flight to guarantee a safe and smooth operation. After landing, they also search for damages that may have occurred on-air. Some causes for these damages could be impacts with objects (hail, birds), lightning strikes, loosened fasteners, corrosion or paint damage Findlay and Harrison (2002); Kinnison et al. (2013); Lee et al. (2008).

When an aircraft is in operation, there are several types of required checks during its lifetime. Planned maintenance occurs during A, B, C, and D checks based on the overall elapsed time, flight hours, or the number of flights since the last inspection Kinnison et al. (2013); Lee et al. (2008). These checks vary according to the manufacturer and aircraft model, and the procedures range from quick visual inspection to full disassembly of the aircraft for testing,

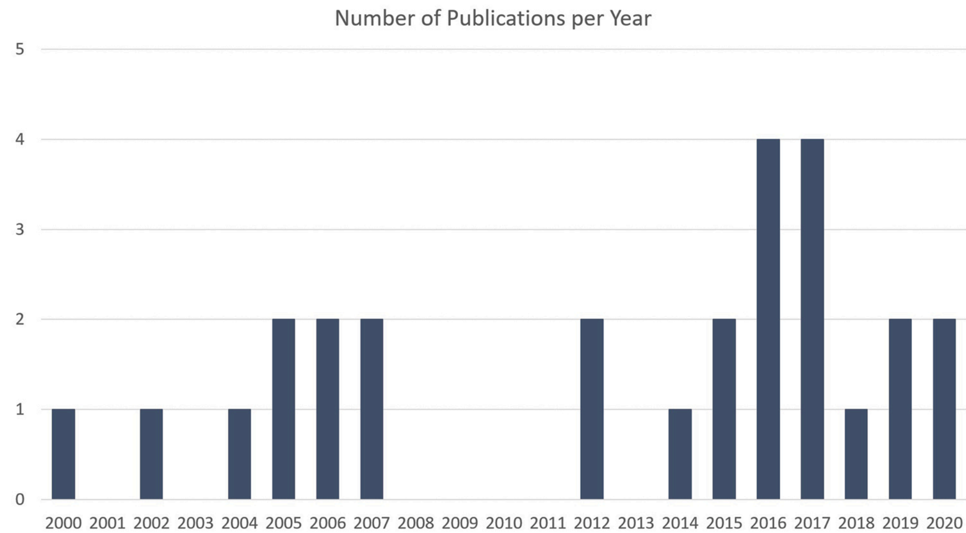

Fig. 1. Number of selected publications per year.

repairs, and component replacements. Another type of check is the pre-flight and post-flight inspection, which are inspections for the verification of systems and the state of aircraft components before and after a flight, respectively.

These inspections commonly use NDT, which allows for the analysis of the components without affecting their characteristics, performance, and reliability. Every part of an aircraft is critical to its safety, and inspectors will perform individual tests to guarantee their required quality. Most complete procedures go as far as disassembling almost the whole aircraft to its bare parts. Other more regular checks include visual inspection and other NDT analyses. In one commercial airplane, thousands of rivets must be visually inspected Liu et al. (2006). Rivets attach the fuselage, panels, and other external devices to the main structure, meaning their health is critical to flight safety.

The study by Gramopadhye and Drury (2000) is an editorial that presents a review of maintenance and inspection of aircraft and how they are affected by human errors during the processes involved in this phase. The article shows that human error during maintenance of the vehicle caused multiple aircraft incidents. It also shows how manual processes conducted by technicians is susceptible to undetected problems. They also report that several of these processes are laborious and subjective, with results directly dependent on the personal, and their mental and physical disposition, while performing the procedure.

There are many tools and techniques for the inspection and maintenance of an aircraft. The vehicle manufacturer specifies them for each maintenance procedure. The article by Kamsu-Foguem (2012) presents a conceptual work about identifying characteristics of NDT methods and tools. They use these characteristics to find similarities and equivalencies among the methods. These equivalencies are especially efficient in choosing the most appropriate tool for a given job, knowing which of them are equally adequate for it.

Operators also visually inspect the fuselage and structure of the aircraft to identify damages that could compromise the integrity of the vehicle. We included in this literature review works that describe the evaluation of joints between metal components Pandurangan and Buckner (2007), presenting quantitative NDE (Non-Destructive Evaluation) methods to characterize structural defects. Other projects use crawling robots for the analysis of the fuselage surface such as Shang et al. (2007), as well as wheeled

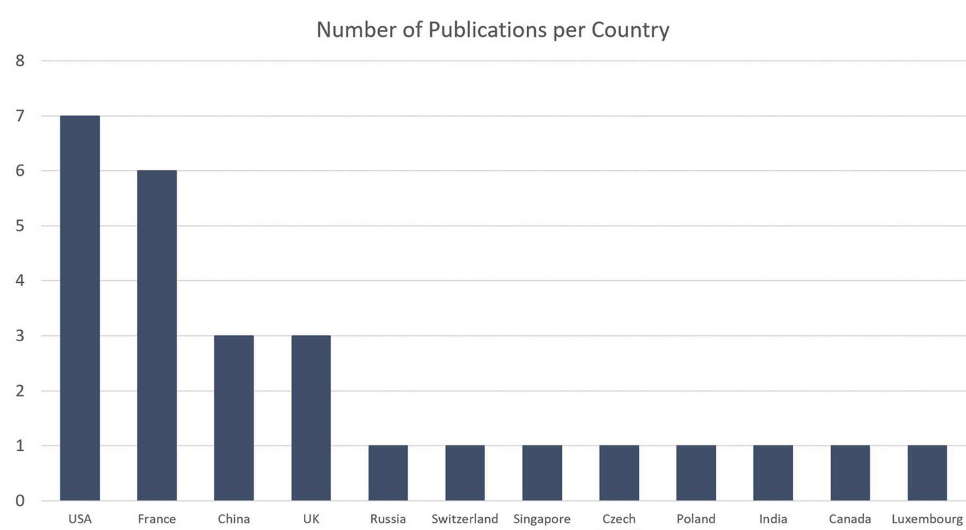

Fig. 2. Number of selected publications per country.

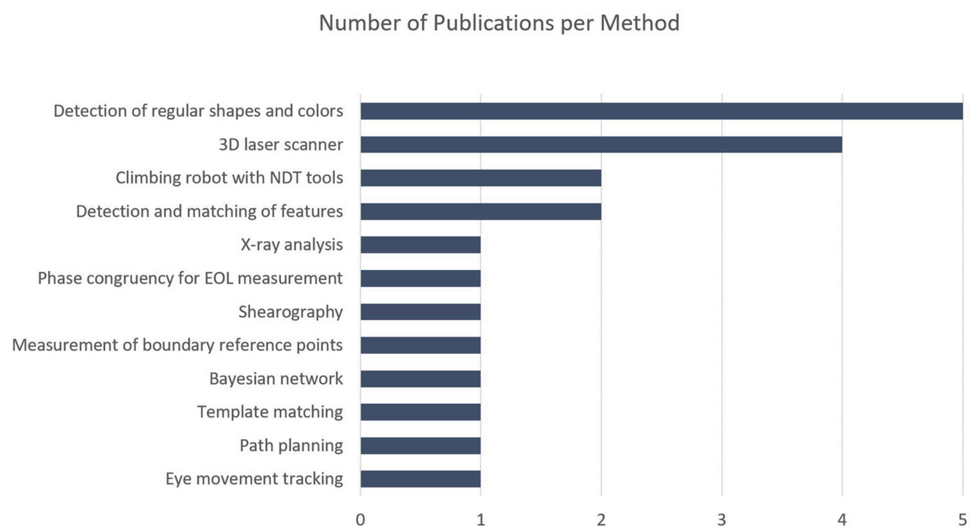

Fig. 3. Number of selected publications per inspection method.

mobile robots Jovančević et al. (2015), (2016b) and drones Cazzato et al. (2019) for farther visual inspection.

Before an aircraft takes off, dozens of items must pass visual investigations to guarantee that all systems are operational and ready for a safe flight. Multiple exterior elements are visually inspected, such as tire conditions Jovančević et al. (2016a), ports, inlet valves (vents), handles, and engine blades Jovančević et al. (2015); Leiva et al. (2017). After landing the aircraft, several of these items are submitted again through visual inspections. Operators will look for any damages or failures that may have occurred during the take-off, flight, or landing and report them as soon as possible. Identifying these nonconformities and potential hazards is critical for taking corrective or preventive measures, and avoiding risks during the next flights.

Some exterior damages occur to the fuselage when an object hits the aircraft, causing dings, dents, or scratches Ostrom et al. (2012); Wilhelmsen and Ostrom (2016), which technicians must fix if there is a possibility that they compromise the structure of the vehicle. Another adopted procedure after an aircraft lands is to check for residual ice Zhuge et al. (2017). The detection of ice on the fuselage is necessary for a faster deicing procedure, which must occur before the plane can take off again.

Some procedures serve to aid in other tasks, which are not necessarily directly related to the aircraft's health. One of these procedures is the connection between the bridges and the doors of the airplane. The control of the bridge is done manually in every flight and could also be improved by an automated system Andonovski et al. (2017). Another important task is to detect navigable paths Bauda et al. (2017) so that robots can move between locations safely and efficiently.

4.2. Methods for visual inspection (RQ2)

In the MRO procedure and during flight checks, there are multiple specified items that an inspector is required to identify and evaluate. Most items in the checklist of a flight inspection are well defined, e.g., doors open or closed Jovančević et al. (2015); Leiva et al. (2017), and shapes, colors, and other characteristics are either standardized or consistent between models of the same company. In these cases, it is possible to tailor the detection and analysis algorithms to a specific part of an aircraft model where the devices' states and conditions are known and more easily identifiable. Figure 3 shows the methods available for performing the visual inspection of an aircraft.

Automatic inspections require hybrid systems for data acquisition, sensors to capture and digitize the inspected parts data, robots to automate the movement of these sensors, and a processing system to analyze the data and identify irregularities or patterns. Figure 4 shows the types of sensors and robots used for acquiring data.

Based on these conditions, several methods for visual inspection of an aircraft implement the detection of simple shapes and colors Andonovski et al. (2017); Jovančević et al. (2016a); Jovančević et al. (2015), (2016b); Leiva et al. (2017). The detection of these characteristics is, in most cases, sufficient for an algorithm to determine when the parts are following the requirements or if they require intervention and correction. In Saadat and Cretin (2002), multiple instruments and measurements systems are presented. These systems are mostly visual, where cameras and laser scanners acquire dimensional data from large components.

Damages that occur during flight and maintenance, such as dents, scratches, and other surface deformations, are most commonly searched by visual inspection as well Dubinskii et al. (2019); Erchart et al. (2004); Ostrom et al. (2012); Wilhelmsen and Ostrom (2016). A trained operator inspects the areas of interest from the fuselage of the aircraft while searching for irregularities. This procedure is done with the human eye and depends on adequate access to the inspected region. It also requires good illumination and control over other human factors Chen and Huang (2014); Gramopadhye and Drury (2000).

The focus in quality inspection during manufacturing lies on each produced component, which means the methods are tailored and more specific than those used during maintenance. The verification of welded elements Chady et al. (2016) occurs by visual analysis of the parts, where a human will observe these regions and look for defects and unusual characteristics. These defects may be cracks and pores, where there are visible artifacts in the area or misalignment or deformation of the element. This analysis may also use radiography for the identification of irregularities beneath the surface of the object. The process of layering several sheets of material produces the composites based on prepreg Nayak et al. (2020), and during this process, inclusions may occur. These inclusions are defects where the layering may be irregular or has air bubbles or dirt between the layers, which are all visually detected by the human eye.

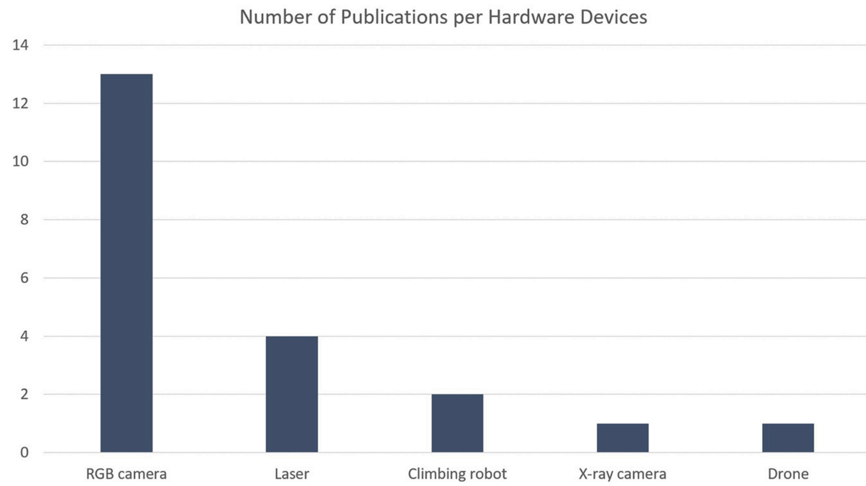

Fig. 4. Number of selected publications per hardware equipment.

We also included other aircraft inspection methods we found in the literature to add to the list from the systematic review. The work from Deng et al. (2006) shows a crack detection method using a magneto-optic imager. Ockerman and Pritchett (1998) and Vora et al. (2002) describe an investigation of using wearable computers and virtual reality to aid inspectors in training and aircraft inspection tasks. Favro et al. (1993) show a thermal wave imaging method for detecting corrosion and disbonds in aircraft skins. Siegel et al. (1993) used a robot for measuring and detecting skin cracks during the inspection in difficult environments. Donadio et al. (2016), Bugaj et al. (2020), and Papa and Ponte (2018) present works about collaboration between humans and robots for aircraft inspection. Rice et al. (2018) detail a system for automating the aircraft visual inspection.

4.3. Computer vision techniques (RQ3)

These methods for visual inspection combine years of experience and procedures to identify the states of aircraft parts. After evaluation, technicians will fix any defects or irregularities. There are several image processing and computer vision techniques from other applications that developers can use and combine to create novel automatic inspection systems. The processing techniques from studies included in this review use images from different cameras and sensors (e.g., color, monochromatic, infrared, x-ray) and 3D data (e.g., point clouds from Lidar, 3D scanners, virtual models, ultrasonic C-Scan).

In Chady et al. (2016), authors use algorithms for image normalization, features extraction, and data classification to identify welding defects in x-ray data. In the normalization phase, they filter the images, adjust their contrast, binarize, and apply morphology operations. They filter and binarize images again to extract features, as well as profile reconstruction with spline fitting. Finally, they use artificial intelligence algorithms to classify the extracted data into the categories of weld defects.

The work described by Nayak et al. (2020) uses a 3D laser scanner to generate a point cloud of composite surfaces during the layering process. After processing the reconstructed surface, the developed algorithm calculates the curvatures to identify inclusion problems between the layers. Other authors Ostrom et al. (2012); Wilhelmsen and Ostrom (2016) also use Lidar sensors to scan composite parts of the fuselage and transfer them to a virtual environment for further visual inspection by the inspectors.

Authors Liu et al. (2006) use edge of light images to identify rivets. The described process uses two templates for convolution, and the results of the template matching represent rivets from the fuselage of the aircraft.

The works in Pandurangan and Buckner (2007); Růžek et al. (2006) use shearography to identify surface defects. Impacts on the surface from other objects will cause defects such as deformations, ruptures, dents, and delamination. This technique uses the projection of a laser speckle pattern onto the surface of the inspected part while a CCD camera captures images from these patterns. Ultrasonic C-Scan is combined with shearography by Růžek et al. (2006) to aid the detection of defects.

The study by Saadat and Cretin (2002) shows a comparison of several visual measurement systems for large aircraft parts. The authors present techniques based on conventional optical tooling, photogrammetry, laser trackers, and scanners. These techniques are commonly used in the industry to measure the dimensions of a part.

A stereo vision system is used by Zhang et al. (2020) to acquire 3D data from the surface of a panel. Contour detection algorithms are applied to the images to identify the boundaries of the inspected part and remove the background.

In Zhuge et al. (2017), near-infrared images from four cameras capturing different wavelengths are matched with the detection of Harris corners to create SIFT feature descriptors. This feature-matching provides references to align all images and combine them for another process to detect ice on the aircraft after it lands.

The work by Jovančević et al. (2015) presents an inspection of exterior aircraft elements, where the authors use different techniques for each inspected component on color images from RGB cameras. The first step is to use texture analysis and remove background from these images. Line detection algorithms identify oxygen bay handles, circle detection algorithms find air inlet vents, and the contrast in the region of interest (ROI) will determine their state (latched, unlatched). Static ports are gray, and their covers are commonly red, so authors use color to detect these covers in the images. The inspection of fan blades occurs by calculating the derivatives of the images to find the center of the engine. After, they apply the Fourier transform to the image to measure the frequencies in a circular shape around the center. In Jovančević et al. (2016a), authors present a method for detection and inspection of aircraft tires. They use template matching and Grabcut segmentation to find the contours of the tires and evaluate the conditions of the threads.

The work presented by Andonovski et al. (2017) also uses detection of regular shapes that match door windows, arrows, texts, frame lines, handles, and footplates to determine the localization of the aircraft doors. Authors use the Hough transform algorithm, detection of lines and circles, and template matching to find these shapes, and the detected objects are combined to find the doors and compute the confidence level of the results.

Navigation of robots uses a visual aid in Bauda et al. (2017), where the authors use edge detection with a declivity operator to estimate lanes on the ground of an airport. These lanes are used as guides for the locomotion of autonomous mobile robots after the perspective correction through homography. For the localization of drones around the aircraft, the work presented by Cazzato et al. (2019) uses FAST and ORB features, combined with the RANSAC method, to identify landmarks and compute homography to estimate drone poses in the real world and the inspected aircraft. We present more details about the navigation and localization from this paper in 4.4.

In Jovančević et al. (2016b); Leiva et al. (2017), authors use a mobile robot on the ground to acquire data. They combine the detection of regular shapes and the 3D model of an aircraft to localize the robot w.r.t. it. After, they identify its parts for inspection, such as static ports, air inlet valves, angle-of-attack probes, trap doors, engine blades, and pitot probes. The visual inspection of items that may have two or more states considers features extracted with the SURF algorithm. The algorithm compares these features to those from the correct state to identify the condition of the part.

4.4. Autonomous navigation of drones (RQ4)

In this review, we selected and included three published works about robot navigation based on their relevance and contributions. The first work Jordan et al. (2018) presents a review of the state-of-the-art technologies for UAV inspections. The objective of this study was to show concepts for the usage of drones in the inspection of large structures in indoor and outdoor environments. The authors did not contemplate visual analysis of aircraft, but it is possible to translate and adapt some of these methods for this purpose. The authors covered multiple application areas, such as inspection of power lines, bridges, buildings, geographical sites, sewers, railways, and wind turbines. The usage of drones for data acquisition replaces the requirement for a human inspector to be close to the object. When humans visually inspect surfaces, they must be close to the region of interest and have a clear line of sight to it.

The second work Cazzato et al. (2019) is a method for vision-based aircraft pose estimation for autonomous inspections with UAVs. The presented methodology uses the detection of natural landmarks from outside of the aircraft, such as flag stickers, ports, vents, and other exterior elements. The detection and pose estimation work without the need for fiducial markers, which are custom objects placed on or around the environment to aid the visual navigation system. Even with a defined trajectory and accurate odometry, errors are accumulated over time and may result in a divergence in the drone's actual path with relation to the original plan. Since the visual inspection of aircraft is performed inside the hangars, and the drone is flying close to it and other obstacles, there should be alternatives to verify and correct the drone pose. Precision in localization of detected defects and other characteristics also requires an accurate pose estimation relative to the aircraft.

The third study Bircher et al. (2015) presents a path planning methodology and algorithm for drones. The algorithm automatically generates these paths from the CAD model of the inspected object. It also computes the optical parameters, like the distance between camera and surface and the view angle of the lenses. This algorithm can plan optimized paths around the aircraft based on time of flight or for area coverage. The flight time is critical for drones since batteries do not last very long while the drone is flying. The area that the camera covers has an impact on the amount of detail it will acquire. Obstacles, such as other aircraft, structural elements from the environment, equipment, and safe zones can also be considered in path planning, improving flight safety and avoiding collision risks.

4.5. Requirements for automated visual inspection (RQ5)

According to our findings, the works we included superficially address requirement specifications. These primary studies provide information about equipment and tools that authors used and developed to solve the automated inspection problem, with no details about application area solution requirements. The requirement specification is an essential documentation that projects must provide during development, for decision-making and technological advancements associated with product development. These specifications are more crucial for aviation applications and mission-critical tasks such as quality inspection and safety checks.

We divide the identified requirements into two categories: data acquisition and visual anomaly detection. Data acquisition requirements describe methodologies and equipment to acquire the images and complementary aircraft data to guarantee an accurate and agile analysis. Requirements for defect detection relate to computer vision concepts and methods used for their detection and classification. They also should follow and comply with standards and engineering protocols from the industry.

Data acquisition represents the methodologies and equipment to obtain aircraft information for anomaly detection. Since this review is about visual inspection, most data is represented by images acquired from the exterior of aircraft, which could be from RGB Andonovski et al. (2017); Jovančević et al. (2016a); Jovančević et al. (2015), (2016b); Leiva et al. (2017); Liu et al. (2006); Pandurangan and Buckner (2007); Saadat and Cretin (2002); Zhang et al. (2020); Zhuge et al. (2017), X-ray Chady et al. (2016), laser Chady et al. (2016); Nayak et al. (2020); Ostrom et al. (2012); Saadat and Cretin (2002); Wilhelmsen and Ostrom (2016), or ultrasonic sensors Růžek et al. (2006). These images focus on resolutions similar to those of the human eyes for detecting discrepancies and identifying characteristics. They are also NDT techniques, which means they do not affect the quality of the parts while measuring them.

The way sensors move around the aircraft for complete surface coverage is another aspect of data acquisition. Inspectors can carry equipment while walking around the vehicle and inspecting it, or they may automate the acquisition using mobile robots, such as drones (air navigation) Bircher et al. (2015); Cazzato et al. (2019); Jordan et al. (2018), wheel-based vehicles (ground navigation) Bauda et al. (2017); Jovančević et al. (2015), (2016b); Leiva et al. (2017), and crawling robots (surface navigation) Shang et al. (2007); White et al. (2005). The robots may be manually controlled or embedded with autonomous navigation for fast and precise acquisition. The usage of autonomous mobile robots requires perceiving and understanding the aircraft and the surrounding environment to compute the best trajectory and execute safe movements, avoiding collisions Yasuda et al. (2020).

Anomalies include aircraft part defect detection such as manufacturing defects or assembly mistakes that could potentially compromise the structure of the vehicle Chady et al. (2016); Nayak et al. (2020); Saadat and Cretin (2002); Zhang et al. (2020). Manufacturing must comply with the project and procedures to assert the product quality according to specifications of each part and assembled components. Anomaly detection also involves the identification of damages due to accidents, usage, and time. Accidents may happen during flight, while maneuvering on the ground, or during maintenance procedures Chady et al. (2016); Dubinskii et al. (2019); Erchart et al. (2004); Jovančević et al. (2015); Liu et al. (2006); Ostrom et al. (2012); Pandurangan and Buckner (2007); Růžek et al. (2006); Wilhelmsen and Ostrom (2016).

Until now, humans subjectively inspect the aircraft for damages from accidents, following procedures and requirements that vary between maintenance centers. Inspectors and technicians also look for irregular components that they must check before every flight, such as vents, doors, tires, sensors, and other checklist items

Andonovski et al. (2017); Jovančević et al. (2016a), (2015); Leiva et al. (2017); Zhuge et al. (2017). Aircraft manufacturers and regulatory bodies define and regulate these checklists according to the model and flight information.

Overall, requirements should include automated inspection system needs. The specification should also detail how the industry will validate these systems for an acceptable solution. Most requirements in product development come from clients and industrial standards, which are not always available as a new technology appears in its early stages of conceptualization and development. There are some concepts related to aircraft engineers and maintenance crew visual inspection, but we conclude, as a review finding, that it is difficult to obtain accurate information about these processes and standards. Manual inspections are prune to variability and subjectivity, even when they were well-documented and readily available to researchers. Therefore, their validity and applicability in real world applications are questionable.

5. Conclusion

In this paper, we presented a systematic literature review about the visual inspection of aircraft. We investigated the processes, methods, technologies, and characteristics of visual analysis in manufacturing and maintenance. We also analyzed the usage of mobile robots, such as drones and wheeled vehicles, for the automation of these processes. From this analysis, combined with the available equipment and industry procedures, it was possible to answer the questions from Table 1. We selected 27 studies through the filtering and snowballing process of four stages, from the initial number of 376 querying results from the selected digital libraries.

After inspecting the studies included in this review and analyzing the collected data, we identified a potential for automating inspection procedures, but we noticed a few issues related to aircraft visual inspection development and reporting such as poor specification of requirements, poor testing and validation of solutions, and the lack of consideration for complete systems in the literature. These findings show that the technology still is at an early stage of development, represented by a low Technology Readiness Level (TRL), resulting in a barrier for the adoption of these automated solutions in the aviation industry. This review should guide new research projects and improve the overall quality of aircraft inspections based on computer vision. In the following subsections, we discuss and raise awareness of these findings, hoping researchers consider them in future studies.

5.1. Potential to automate aircraft inspection with computer vision

Visual inspections performed by humans require several hours or even days. This time depends on the type of check they are performing or the anomalies they are seeking. Operators assemble scaffolding or place elevated platforms and lifts around the aircraft to perform safety checks and inspection procedures. During this period, the maintenance crew will ground the plane until they finish all inspections and eventual repairs. Humans also make mistakes, and their results vary over repetition since they are subjective and prone to errors.

Automated visual inspection systems can acquire the data faster and safer with the aid of robots and cameras. This way, humans can focus on the evaluation of data and the identification of anomalies. Intelligent algorithms aid in data processing objectively to identify anomalies within an acceptable degree of certainty. We can achieve the automation of inspection procedures by guaranteeing that the camera sees the aircraft with the same or higher resolution than the human eye. Algorithms using artificial intelligence (such as deep learning) have the potential to identify anomalies and detect defects with higher accuracy, repeatability, and reliability than humans.

5.2. Poor specification of requirements for inspection systems

The works we found, in general, did not present a well-defined description of the inspection problem. It was hard for us to understand the main requirements that they intended to fulfill and solve. We also found it difficult to conclude if they achieved their goals as they were often vague and subjective. One of the reasons for this may be the difficulty in finding reliable and comprehensible sources of information about the visual inspection of aircraft. Another concern is that the aircraft manufacturers already provide instructions and tools for inspecting their products. Several regulatory organizations define strict procedures and methodologies to standardize the aviation industry and guarantee flight safety.

We noticed that the solutions for inspection problems are not mature, requiring advancements for addressing real world industrial applications. The lower level of maturity and understanding of the technology may also contribute to the poor specification of requirements we found. Advances in this research area will help in establishing the advantages and limitations of the technology, allowing authors to write a thorough specification of requirements that comply with industry standards and complement other procedures to increase flight safety.

5.3. Poor testing and validation of automated solutions

The lack of well-defined specifications of the problems and requirements also affects the testing and validation of results. These final procedures in the development of methods are essential for the acceptability of the work, and researchers must execute them following standards that guarantee their correctness. Deficient testing and validation may also be due to the difficulty in acquiring and analyzing relevant data from aircraft. The acquisition requires adequate equipment to collect reliable data and protocols to manage and analyze the data. It also requires access to damaged or faulty vehicles and components, which may not be readily available, or manufacturers may not want to share that information. Since most of the related data is confidential and strictly regulated, it makes this analysis even harder, which is unlikely to happen without cooperation between industry and scientific research.

Another reason for poor testing and validation is the low TRL of existing solutions. The experimental phase of proof-of-concept projects is often not as scrutinized as solutions ready for real applications. This relaxation occurs when people are still learning and trying to discover possible innovations in the area. When solutions become mature and reliable, we expect authors to be more confident in their work and expand to more restricted and regulated testing.

5.4. Lack of consideration for complete inspection systems in the literature

We also had difficulties in finding completely automated inspection systems that covered all the steps and processes, from visual checks to reporting. This systematic review includes works presenting autonomous robots to acquire data and automatic inspection of aircraft exterior. These visual inspections followed two main categories: identification of anomalies on fuselage and wings; and visual checks of tires, doors, valves, and other exterior components. However, we did not find works presenting a complete system that considers these anomalies and checked items in an integrated and modularized form. When developing an automated inspection system for daily use during routine operations and MRO procedures, it is required to understand how the inspection modules will integrate with other systems. It would also be interesting to see a framework that describes the data flow from the acquisition, which autonomous robots could perform, to the processing algorithms that will detect and identify defects.

5.5. Regulations and acceptance by the aviation industry

There are several solutions for automatic visual inspection that can detect defects and anomalies or perform flight checks. Even though some of these methods were tested and validated with actual data, they still require more testing and comparison with other works before they are proven ready for commercial and industrial use. The lack of thorough testing with several conditions in the inspection environments means it is unknown if these methods will work as expected in the real world. Regulatory bodies will trust these automated intelligent systems when they become widely accepted by the scientific community, engineers, and maintenance specialists. There is room for improvement in the accuracy and reliability of defect detection algorithms and their application for daily usage.

Despite these concerns about the generalization of algorithms, some methods successfully presented the detection of dents, lightning strikes, and other structural damages with neural networks. Other methods using detection of features and shapes identified the state of ports, vents, handles, and tires correctly. Some concepts used in these algorithms can evolve into more robust and accurate implementation with new techniques aided by artificial intelligence. Mature inspection systems with higher TRL will combine algorithms into a complete solution that will perform the inspection of multiple aircraft parts, considering a diverse set of anomalies that require further investigation.

5.6. Final remarks

The potential for automating aircraft inspections with computer vision we presented in this paper should motivate further studies and the development of new technologies in this area. Poor requirement specifications, poor testing and validation of published works, and the lack of consideration for complete systems in the literature indicate that this technology still is at a low level of readiness. A low TRL presents a challenge for acceptance of a solution, especially in aviation for the transportation of people and goods.

If not well understood and addressed, these issues and conditions could impede the contribution of new ideas and solutions to the aviation industry. Researchers and engineers must overcome these challenges, so they can bring improvements and innovation to current industry standards. This insertion of new technology will happen with the increase in the solutions TRL and the interest in the development of aviation and space technology, as more researchers start to investigate and tackle open questions.

Availability of reliable and open data will also aid in the evolution of methods and solutions, since these must be tested and validated rigorously before being considered for real world application. This includes information about vehicles and MRO procedures, as well as collected (or even simulated) examples of healthy parts and defects for research and development of novel methods. The use of databases for large availability and version control of these data aids researchers and facilitates their work.

Finally, the advances in machine learning, robotics, and artificial intelligence for data processing and control will bring several new approaches for solving current and future problems. The capability of methods from these areas are increasing at an accelerated rate, and they can be leveraged to improve current solutions, especially those that require manual operations.

Declaration of Competing Interest

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

Acknowledgement

The authors would like to thank CNPq (National Council for Scientific and Technological Development), FAPESP (São Paulo Research Foundation) under the grant #2019/09396-0, and CAPES (Coordination for the Improvement of Higher Education Personnel) for their funding and support. They also thank Autaza Technology for

Table A1
Search strings and execution for each digital library.

Library	Search String	Execution
ACM Digital Library	(aircraft* OR airplane*) AND (visual OR vision OR imag*) AND (inspection OR analysis OR evaluation OR detection OR verification)	Regular search in Title or Abstract
CiteSeerX	(aircraft* OR airplane*) AND (inspection OR analysis OR evaluation OR detection OR verification)	Regular search
Emerald Insight	(aircraft* OR airplane*) AND (visual OR vision OR imag* OR scan*) AND (inspection OR analysis OR evaluation OR detection OR verification)	Regular search in Title or Abstract
IEEE Xplore	(aircraft* OR airplane*) AND (visual OR vision OR imag*) AND (inspection OR analysis OR evaluation OR detection OR verification)	Command search in Document Title
Sage	(air* OR aero*) AND (visual OR vision OR image) AND (inspection OR analysis OR evaluation OR detection OR verification)	Advanced search in Title and Abstract
ScienceDirect	(aircraft) AND (visual) AND (inspection OR analysis OR evaluation OR detection) AND (damage OR structure OR fuselage)	Advanced search in Title, Abstract and Keywords
SPIE Digital Library	(air* aero*) AND (visual vision imag*) AND (inspection analysis evaluation detection verification)	Advanced search in all fields
Wiley Online Library	(air* OR aero*) AND (visual OR vision OR image) AND (inspection OR analysis OR evaluation OR detection OR verification)	Advanced search in Title, Abstract and Keywords

providing resources used in this work and colleagues Everton, Enivaldo, Renan, Thiago, Isadora for their help and support.

Table A2
Checklist for the Quality Assessment.

ID	Quality Question
QQ1	Are the objectives clearly defined?
QQ2	Is the work related to our research questions?
QQ3	Are the methods clearly defined?
QQ3.a	If yes, are they capable of being generalized to different conditions?
QQ4	Does the paper present a good literature review?
QQ5	Is comparison with other works presented?
QQ5.a	If yes, were they conducted in similar/equivalent means?
QQ6	Was a robot or physical equipment used for experimentation and validation?
QQ6.a	If yes, is the robot clearly specified?
QQ6.b	If yes, does the robot have autonomous navigation?
QQ6.c	If yes, is the environment clearly specified?
QQ7	Is the vision system intelligent (automatic)?
QQ8	Does the paper present relevant contributions to the research area?

Appendix A. Search strings and execution

The Table A1 contains the search strings and how the search was executed for each digital library.

B. Quality checklist

The Table A2 contains the checklist used for the quality assessment of the included papers.

C. Extracted data

These are the data extracted from the included papers and their descriptions.

- Digital library: in which digital library the paper was found;
- Title: original title of the publication;
- Source: name of the journal, magazine, conference, or any other source where the paper was originally published;
- Year: year in which the paper was first published;
- Author: name of the main author of the paper (first person credited in the document);
- Affiliation: affiliation of the main author (first organization credited in the document);
- Country: location of the main affiliation;
- Citations: total of citations the paper received (taken from Google Scholar);
- Citations per month: total number of citations divided by number of months since publication;
- Type of document: classified as description of a method, literature review, introduction of a new model or concept, or presentation of experiments and their results;
- Method: main method presented or used by the authors, categorized to show which navigation tasks it accomplishes;
- Method description: details of the main method with enough information to differentiate studies that used the same approach;
- Strengths: positive points of main method and its advantages;
- Weaknesses: negative points of main method or areas where it needs to be improved;
- Differences to traditional methods: comparison between main method and methods traditionally used in industry;
- System requirements: software, hardware and environmental requirements for application of main method;
- Features: characteristics, defects, problems identified by the method;

Table A3
List of included works from selected libraries.

Library	Included Papers
ACM Digital Library	Jovančević et al. (2016b); Sadasivan et al. (2005)
CiteSeerX	Erchart et al. (2004)
Emerald Insight	Chady et al. (2016); Saadat and Cretin (2002); Shang et al. (2007); Zhang et al. (2020)
IEEE Xplore	Andonovski et al. (2017); Bauda et al. (2017); Bircher et al. (2015); Cazzato et al. (2019); Jordan et al. (2018); Jovančević et al. (2016a); Leiva et al. (2017); Ostrom et al. (2012); Wilhelmsen and Ostrom (2016); Zhuge et al. (2017)
Sage	Chen and Huang (2014); White et al. (2005)
ScienceDirect	Dubinskii et al. (2019); Gramopadhye and Drury (2000); Kamsu-Foguem (2012); Liu et al. (2006); Nayak et al. (2020); Pandurangan and Buckner (2007); Růžek et al. (2006)
SPIE Digital Library	Jovančević et al. (2015)

- Hardware: devices and robots used for development, tests and validation;
- Software: programs and libraries used for development, tests and validation;
- Score: score from the quality assessment process;

D. Included papers

The Table A3 contains a list of all 27 papers included in this SLR grouped by the digital libraries they were extracted from.

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