Digital tools for aircraft maintenance: prototyping location-aware AOI for engine assessment and cable routing solutions

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***Abstract* — Aircraft maintenance plays a vital role in ensuring not only public safety but also aircraft availability and financial viability. However, carrying out such activities traditionally leaves gaps for processual optimizations with the potential of increasing the overall performance and satisfaction of operators and engineers who deal with these responsibilities. Currently, available technologies may enable the increment of quality in aircraft maintenance processes, namely, the ones based on xReality and deep learning. Therefore, this paper proposes two use-cases based on real aircraft maintenance context requirements: one employing augmented reality for cable routing, enabling cataloguing and also previewing the position and paths of cable systems inside the fuselage kit; and another making use of deep learning and virtual environments to aid in the activities related with engine baroscopic inspections, with position awareness capabilities. Results regarding a few functional and usability tests are also presented and discussed. In spite of their still incipient maturity, both these tools showed potential for being involved in the pipelines of aircraft maintenance in the future.**

Keywords — Augmented Reality, Human-Computer Interaction, Artificial Intelligence, YOLO, Head-Mounted Display, Usability, HoloLens, Computer Vision.

I. Introduction

In the aircraft industry, maintenance is an activity of major importance [1]–[3], wherein procedures of variable complexity are carried out in the form of inspections and preventive/reactive interventions. While public safety stands as an obvious priority, being able to reduce the time required for maintenance activities and, at the same time, ensuring operational reliability is a challenge that must be addressed to improve aircraft availability and financial sustainability.

The scope of maintenance is vast, and complex, and requires approaching each aircraft according to specific contexts, prioritizing prevention instead of reaction. This demands to keep in mind factors such as the relation between flight times and costs. Usually, more hours in the air are associated with the highest aircraft maintenance cost [4]. With periodic maintenance procedures, it is possible to prevent costly component damages [5] that, in extreme situations, may result in disastrous accidents involving critical human losses.

This paper identifies two challenges in aircraft maintenance, through direct contact with a Portuguese company – AEROMEC[1] – acting in the field: a) the cable routing management and tracking; and b) the baroscopic inspections performed to monitor the health of aircraft engines. The former issue is associated with the successive maintenance and modifications done in the aircraft that require rerouting cables and, therefore, moving them from their original positions, creating a tracking issue for future interventions. The latter is associated with mandatory procedures that consist of inspecting the interior part of an aircraft engine after a certain number of flight hours. Using a thin camera (borescope), defects and damages are checked. This is a dull process and demands the visual

[1] AEROMEC – The Aero Maintenance Experts Company. Available online: https://www.aeromec.pt/. Accessed 18 October 2023.

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attention of an operator, which sometimes loses track of the sensor's position and needs to restart the task from the beginning. To effectively address these challenges, two different solutions were developed, exploring the potential of technologies like augmented reality (AR), deep learning (DL), and virtual environments (VE) to establish visually representable digital twins (DT).

The first is in an AR tool that was planned and developed to provide the necessary means for technical operations in the context of the cable routing topic. It consists of a hands-free holographic application that allows to virtually catalogue cables systems in the form of 3D data, as well as their locations' history. This catalogue can also be used whenever a technician needs to consult and visualize 3D representations of the cable systems, with the following main objectives: a) to analyse the transformations done to those elements over time, for traceability purposes; and b) upon intervention necessity, to harness AR capabilities for performing direct eye-contact with a 3D representation of the latest version of the cable set of interest, avoiding tedious trial-and-error procedures that traditionally involve removing the physical fuselage panels towards the identification of the element requiring attention. The other solution is based on DL and is also proposed to assist engineers/technicians in the borescope assessments, specifically resorting to an automatic optical inspection (AOI) approach oriented for the detection of defects and damages in engines' inner parts. Moreover, a borescope camera was instrumented with a small-sized inertial motion unit (IMU) that intents to track inspection device's orientation and displacement. This set of data is reflected into a faithful DT component, developed to complement the DL solution, and provide an intuitive 3D visual tracking to the operator regarding the borescope probe location inside the engine. Therefore, the issues related with the loss of visual contact with the physical inspection equipment by the technician are approached.

The remainder of this paper is organized as follows: besides this introductory section, the next section will present a brief background related to aircraft maintenance, followed by an explanation of the proposed tool. In Section 4, both the methodology and implementation are described. Experimental results will be presented in Section 5, followed by conclusions and future work, in Section 6.

II. BACKGROUND

The use of intelligent systems in aircraft maintenance and troubleshooting has greatly helped the aviation industry. Today, intelligent systems using computer vision (CV) technologies and artificial intelligence (AI) have reduced errors in maintenance and troubleshooting. In this section, approaches that have used CV technology are presented. For example, Cusano et al. [6] proposed a visual recognition module for aircraft mechanical parts. They used methods based on local descriptors for feature matching and then estimating the geometric transformation. Alternatively, various methods using convolutional neural networks (CNN) have been proposed for different aircraft maintenance purposes. The DL model based on Xception [7] was used by [8] to detect burn and crack occurrences through borescope imaging. Buarfa et al. [9] proposed a method to detect dents in aircrafts. The authors used transfer learning [10] from COCO dataset and employed mask region CNNs (Mask R-CNN) to perform such detections. Later, the same authors [11] improved their research, by: a) incorporating images without dents; b) using augmentation techniques – such as flipping, rotating, and blurring; and c) combining feature pyramid networks (FPN) [12] backboned by ResNet101 with Mask R-CNN. The conclusion was that extending the dataset and using a pre-classifier improved the prediction performance. Li et al. [13] proposed the YOLOv3-Lite method, which is a combination of depth-wise separable convolution [14], FPN, and YOLOv3 [15]. The authors used depth-wise separable convolution as the backbone network to reduce parameters and to extract crack features. Since there are cracks with a variety of sizes, the authors concatenate the feature pyramids and then pass them to YOLOv3 for detection. The approach has been proven to be faster and more accurate than YOLOv3 alone. Furthermore, a comparison with SSD-Mobilenet [16] showed that the proposed method is less erroneous. In [17], the authors also used the SSD MobileNet framework to detect the stains and defects in aircraft skin. Then they enhanced the images before feeding the model, which resulted in an improved performance when compared with the original work. Furthermore, the authors compared their approach performance with ANN for the CIMP robot [18], Contourlet transform [19], VGG Net [20], AlexNet [21] They concluded that the enhanced method had better accuracy. Fotouhi et al. [22] presented a method for the classification of damage in laminated composite structures, such as aircraft and wind turbine blades. The authors employed the pre-trained version of AlexNet. To evaluate the proposed approach, they have used pre-trained ResNet-50 and five other user-defined CNNs: Net1(one Convolutional Layer (CL) and one Pooling Layer (PL)), Net_2(3 CL and one PL), Net_3(3 CL and 3 PL), Net_4(5 CL and 3 PL), Net_5(5 CL and 5PL). AlexNet outperformed the other methods.

Underlying the advantages of using AR lies the possibility of enhancing physical environments with digital content, as studied by Khan et al. [23], who had explored the use of ArUco markers to accurately align virtual objects with real-world structures. These markers are fiducial patterns extensively used in AR for encoding information, as described by Avola et al. [24], building upon Garrido-

Jurado et al. [25]. Each marker contains Recognition Data (R-Data) for real-world identification, and Information Data (I-Data) related to the target object and error correction. The supporting ArUco library is freely accessible for research.

In turn, AR technologies and related approaches, such as mixed reality (MR), have been proven useful to enhance workers ability and product quality in Industry 5.0, while ringing attention to the importance of incorporating the human-centric manufacturing concept [26]. In [27], a comparison of conventional devices and AR tablets for assembly tasks was performed, showing an error reduction associated to the use of the former devices. Furthermore, classifying AR and virtual reality (VR) as subsets of MR, Henrik Eschen et al. [28] refer the advantages of MR in aviation, highlighting the significant cognitive support that it can offer.

More focused in concrete aircraft procedures, other works have been documenting the potential of AR/MR applicability in the specific context of maintenance [29]. For example, AerinX, a smart AR application, integrates drones to scan aircraft surfaces for damage, eliminating the need for manual inspections [30]. In another work [31] , the application of augmented reality technology in the development of aircraft maintenance manuals is presented. Using a leakage inspection example as a starting point, the process of publishing augmented reality technical manuals for aircraft maintenance is explored.

Having in mind the aforementioned lines of research, the next section presents a couple of tools oriented to aircraft maintenance, combining AR, DL, IOA, VE, and DT concepts.

III. Digital aircraft tools for Location-aware AOI and Cable Routing

This section reports the specification of the main tools proposed to support aircraft maintenance operations. One of them is the location-aware AOI (LAOI) to assist engines' borescopic inspections, which leverages spatial information to enhance defect/damage detection, while allowing to keep track of the borescope/camera for operators' orientation purposes.

The other one, i.e., the AR-Based Cable Routing Previewer (AR-CRP) tool, consists in a hands-free holographic tool, which was designed for superimposing 3D representations of cables in real environment, not only for cataloguing purposes but also and mainly to aid technicians performing interventions in the cable groups more efficiently. Specifically, this is done by indicating the positioning of the latest known route for desired cable, with a 3D representation of it overlaid in airplanes fuselage. It is noteworthy that these requirements and respective technological solutions were developed considering the real needs of an aircraft maintenance company (see Section 1).

A. Requirements identification

This subsection will present the main requirements of both of the referred tools, partially following [32] guidelines. In this work, the technician is considered a user and the priority of the requirements is "Must".

1) LAOI tool

The main requirements of LAOI tool revolve around achieving specific functionality for having support to AI-based inspections of engine parts, assisted by a visual layer for an easier spotting of the inspection device, occluded by the casing that involves the mechanical components. After locating the sensors inside the engine, the real-time capturing should be visualized with the detected defects supported by the intelligent vision system. Also, the user must be able to see the camera's spatial information mapped on the 3D model (DT functionalities).

2) AR-CRP tool

With the user experience in mind, requirements – both functional and non-functional – for AR-CRP tool must encompass holographic interface, access control, the use of marker-based algorithm for tracking, precise 3D model positioning, and gesture-based AR interaction. The utilization of Microsoft's Mixed Reality Toolkit (MRTK), besides supporting some of the previous required functions, also enables the user to operate in a hands-free context.

B. Tool's general architectures

LAOI and AR-CRP architectures will be presented in the following subsections.

1) LAOI tool

LAOI tool combines CV-based defect detection with real-time location data and sensor visualization. It consists of three modules that are presented in Fig.1: AOI (with a DL agent), localization, and visualization module.

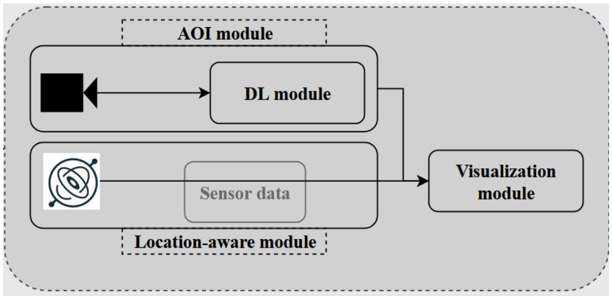

Fig. 1. Overview of the proposed LAOI architecture.

In the AOI module, the captured frames from the camera will be fed to the DL module for defect detection, while the processed data from the attached sensor will provide real-time information about the camera's location and orientation. The collected data from the sensors will proceed to the visualization module.

2) AR-CRP tool

The AR-CRP logic tool encompasses several key features, including secure user authentication, cables creation and manipulation, and an ArUco marker element that is used as an anchor for the initial positioning of the environment, as specified in the architecture proposed in Fig.2.

The AR-CRP holographic module offers a high-resolution immersive interface, featuring advanced display technologies and 3D capabilities. It vividly renders holographic content, augmented by motion sensors and spatial audio, providing a lifelike visual and auditory experience. Enhanced user interaction through motion tracking, voice recognition, and intuitive gestures promotes the overall user engagement.

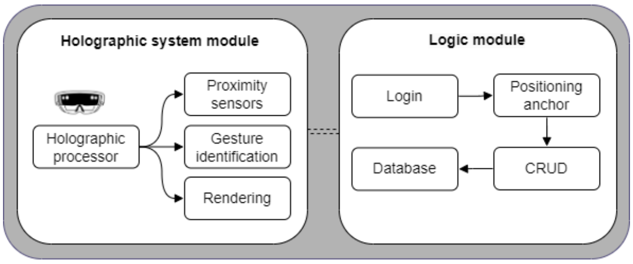

Fig. 2. AR-CRP– Overview of the proposed architecture.

The application's architecture incorporates several classes, each with unique responsibilities:

- Login Controller - handles the users' login details and related processes;
- Cable Routing Manager - manages the routing of cables, including data storage and event response;
- Aircraft and Cable System - have data containers related to aircrafts and cable systems;
- Storable Objects - is responsible for storing data about objects within the application;
- Storable Objects Controller - provides a mechanism to interact with storable objects, such as object search, cable routing waypoint (CRWp) creation/elimination, and line renderer updates;
- Waypoint Controller - covers the CRWp behaviour and manages the pointer events.

The interaction between these classes (Fig.3) forms the core of the AR-CRP tool, providing a comprehensive system for managing, interacting with, and visualizing holographic cable routing in an AR environment.

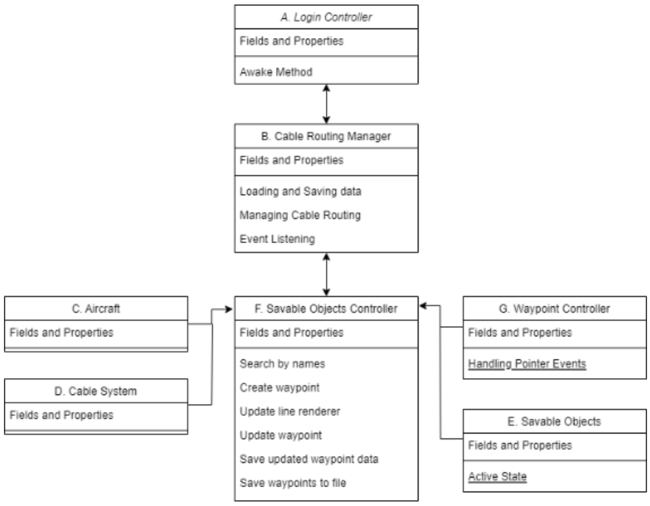

Fig. 3. AR-CRP classes.

IV. LAOI AND CABLE ROUTING TOOLS IMPLEMENTATION

Details regarding the implementation of both LAOI and AR-CRP are provided in this section.

A. LAOI tool

In the LAOI tool, an AI-based image analysis system and a specialized camera (instrumented borescope) for capturing real-time data (video and elements for estimating position and orientation) were implemented, along with the component that provides location-awareness, complying with the architecture previously defined for this module. This solution will be presented hereinafter.

1) AOI module

To properly address DL-based AOI, the dataset is the main key. Therefore, the first step in this module consisted in preparing a representative dataset. Data preparation encompassed collecting images and then, annotating them with related labels. To be able to perform such preparation, a set of images collected from borescope-based inspections inside four damaged engines with crack defects (Fig.4) was used. This resulted in a small dataset, with 83 images that were then labelled using the LabelMe annotation tool [33]. Before feeding the dataset to the DL model, the data needs to be split into three sets for training, validating, and testing groups, The proportion of 80%,10%, and 10%, respectively, was considered.


Fig. 4. Two examples of crack defects inside the engine.

To detect the cracks in the image, a YOLOv7 [34] object detector algorithm was trained with the previously collected and annotated dataset. The available pre-trained model yolosv7 is used to avoid overfitting. Predefined parameters were adjusted to the desired ones to approach optimization. Furthermore, data augmentation was used during the training process by adjusting the image translation, scaling, and horizontal flip with the values of 0.2, 0.5, and 0.5 in the configuration file, respectively (considering the batch size of 32 and image size of 320X320). YOLOv7 was trained for 500 epochs using Nadam, Adam, and SGD optimizers with an initial learning rate of 10^{-3}.

2) Location-aware module

To measure the camera's orientation and position, a MPU6050 sensor was adopted. By reading its raw accelerometer and gyroscope data and feeding them to further post-processing. The first step was to calibrate the sensor and set offsets of the accelerometer and gyroscope.

Raw data from the accelerometer and gyroscope will be passed to Mahony update to normalize quaternion. To determine the camera's orientation, *roll*, *pitch*, and *yaw* are computed using equations (1), (2), and (3) respectively, considering *q* as a quaternion.

$$\mathbf{roll} = atan2((q[0]*q[1]+q[2]*q[3]),0.5-(q[1]*q[1]+q[2]*q[2])) \quad (1)$$

$$\mathbf{pitch} = asin(2.0*(q[0]*q[2]-q[1]*q[3])) \quad (2)$$

$$\mathbf{yaw} = -atan2((q[1]*q[2]+q[0]*q[3]),0.5- (q[2]*q[2]+q[3]*q[3])) \quad (3)$$

Each was multiplied to $(180.0 \ / \ \pi)$ convert them to degrees, which is proper to be used in the visualization step. To compute the camera's location, a set of equations (from (4) to (7)), were employed using the values of the accelerometer to compute the 3D coordinates of the camera, considering the initial velocity in each direction as 0. These equations involve d_t or the time difference between the current time and the last computed time; *dx* or the displacement in the direction of *X*; and $V_{x\ last}$ or the last recorded velocity in the direction of *X.* Equations (5)-(7) are repeated for the *Y* and *Z* directions with the related parameters adjusted $(acc_y, V_y, and\ dy)$ and $(acc_z, V_z, and\ dz)$. This computed data is then passed to the visualization module, responsible for rendering the location and the orientation of the camera/borescope.

$$\mathbf{dt} = (t_{now} - t_{last}) * 1.0e\text{-}6 \quad (4)$$

$$\mathbf{V_x} = acc_x * dt + V_{xlast} \quad (5)$$

$$\mathbf{dx} = 0.5*acc_x*pow(dt,2) \quad (6)$$

$$\mathbf{X} = V_{tx}*dt + dx \quad (7)$$

3) Visualization module

The implementation of the visualization module was done resorting to Unity software[2] to create a real-time DT with a visual layer capable of providing insights regarding the position and orientation of the IMU module docked into the camera. This process involves producing faithful 3D models of mechanical parts of interest in a dedicated software studio, such as 3D Studio Max 2022 software[3], digitalizing not only shapes and details but also precise measurements. Once the components are produced, the developed Unity platform is the responsible component to rendering these 3D, allowing for a dynamic interaction and integration with the other components. Through Unity, this visual representation provides a powerful tool for inspecting and analysing the parts, using a virtual environment as support to have a glimpse of the location of the borescope.

As for hardware and software, the development of the LAOI module was carried out in a computer integrating the following components: an Intel(R) Core (TM) i7-8700 CPU 3.20 GHz 3.19 GHz processor, 16.0 GB of RAM, and a NVIDIA GeForce GTX 1080 GPU. An inspection HD camera with built-in white LED lights was utilized as the acquisition device for the AOI component. Additionally, an MPU6050 sensor module was docked to it, with an Arduino Nano board used to calculate the camera's displacements and orientation in Arduino IDE 2.0.0. These measurements were then reflected in the digital twin with 3D visualization capabilities implemented in Unity 2021.3.15f1. The implementations of AOI module were done by resorting to Python3.8. Furthermore, DL library was TensorFlow 2.8, deployed in the graphics processing unit (GPU) for maximizing computation speed resorting to the Yolo object detector algorithm, leading to the identification of regions of interest (ROI) corresponding to the estimation of cracks and other defects inside the aircraft engines.

4) AR-CRP tool

Unity was the main development tool used in the AR-CRP toll, mainly because it provides a seamless integration with Microsoft's HoloLens platform. Indeed, Unity forms the backbone of the AR-CRP tool, and its development leverages Microsoft's HoloLens for its robust AR capabilities and hands-free operation, essential for tasks needing both hands available for required interventions. As shown in Fig.2, this tool consists of two modules: a holographic system and a logic module. The deployment

[2] Unity software – Available online: https://unity.com/releases/editor/whats-new/2021.3.15. Accessed 18 October 2023.

I. [3] 3D Studio Max 2022 software – Available online: https://help.autodesk.com/view/3DSMAX/2022/ENU/?guid=3dsMax_ReleaseNotes_3dsmax_2022_2_releasenotes_html.Accessed 18 October 2023.

stage involves the packaging of the tool for the target device and its proper installation, which, in this case, occurs for HoloLens device.

The framework architecture of the AR-CRP tool designed for HoloLens, which leverages ArUco markers for precise alignment of the initial anchor and is built using the MRTK and the C# programming language, involves six distinct stages, as illustrated in Fig.5.

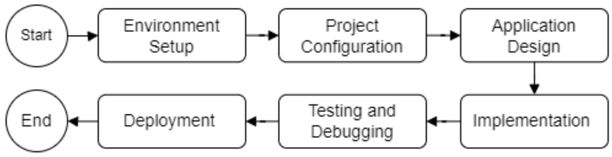

Fig. 5. AR-CRP framework stages.

The first stage is the environment setup, where the development environment is established to facilitate project implementation. This includes camera calibration, which focuses on performing a few adjustments to HoloLens' camera. In the subsequent project configuration stage, the development environment settings were tailored to meet HoloLens AR application development requirements. This stage includes the installation procedures within the Unity Engine, covering all aspects from scene acquisition to multimedia projection for AR application building. Object code optimization for device installation was also a concern. Moreover, resorting to a GUI that interfaces the framework, directing key interactive operations like associating multimedia information with markers, camera calibration settings, and metadata insertion, some implementation tasks could be accelerated. To facilitate AR application development, Microsoft's MRTK was incorporated, as well as ArUco markers and OpenCV for Unity imported into the Unity project. The application design stage involved the layout of the AR interface, including user interaction mechanisms and defining display and manipulation parameters for holographic cable routing. In the implementation stage, the code is generated to fulfil both functional and non-functional requirements. Finally, during the testing and debugging stage, a comprehensive examination of the application is conducted to rectify any programming errors and optimize the application.

V. DEMONSTRATIONS, TESTS AND RESULTS

Both the LAOI and AR-CRP tools were tested to assess functionality and performance. These tests were conducted to validate the efficacy of each tool in its respective domain. LAOI assessment focused on the evaluation of the AI models and on the demonstration of the DT-based location-aware feature, while the AR-CRP functionalities were also shown along with a few tests involving users.

A. LAOI tests, results and demonstrations

The implementation of LAOI has been tested and evaluated to assess its performance and effectiveness in defect detection and localization in maintenance environments. The key results obtained are presented hereinafter.

1) AOI module

To assess the AI-based optical inspection module's performance test set images were inputted into the trained model. Performance was assessed by using the accuracy metric, which quantifies the percentage of correct detections (equation (8)):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

Where TP, TN, FP and FN stand for True Positive, True Negative, False Positive, and False Negative, respectively. Table 1 presents the performance of Adam, Nadam, and SGD optimizers over the test set. By comparing the results, it is clear that Adam outperformed the others with an accuracy of 75%. Some results of detections using the trained models are shown in Fig.6, which also depicts the superior performance of the Adam optimizer.

TABLE I ACCURACY OF THE TRAINED MODELS

Optimizer	Accuracy
Adam	75%
Nadam	56%
SGD	50%

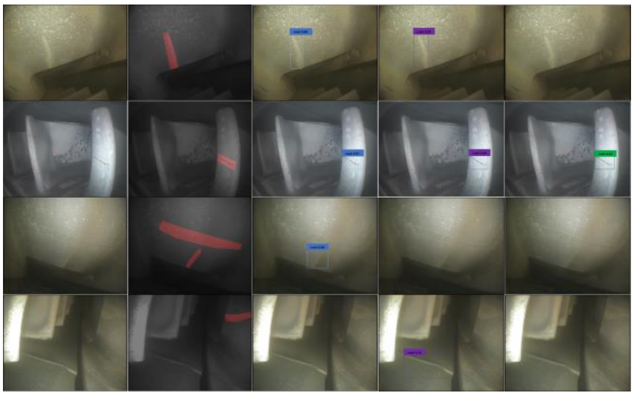

Fig. 6. Results of detections using trained models: column 1 shows the original images; column 2 is reserved for ground truth; column 3-5 shows the predictions made by YOLO models trained with Adam, Nadam, and SGD optimizers (starting from learning rate 10^{-3}), respectively.

2) Location-aware module demonstration

Functional demonstration of the location-aware module while operating is carried out in this subsection, in alignment with a series of steps. The first step to start using the location-aware feature in inspection procedures requires an initial calibration between both virtual and real probes. The physical instrumented borescope must be positioned in relation to the physical component to be inspected, just as the virtual probe needs to align closely with the corresponding position on the 3D model representing the part to be inspected, towards a close match between the real and the digital environments. In practice, the 3D probe assumes a predefined position that must be approached by the physical elements. Then, by moving the inspection camera slowly inside the 3D component – which, in this demonstration, consists of a faithful digital representation of an engine cylinder liner –, variations on the MPU6050 physical inertial measurement unit (IMU) were induced and mirrored simultaneously to the DT application developed for visually tracking the borescope. As shown in Fig.7, the defect area is specified in the captured frame and the computed orientation and 3D coordinates can be seen in the 3D model, wherein the probe is represented through a small red parallelepiped in the middle of a digitalized component.

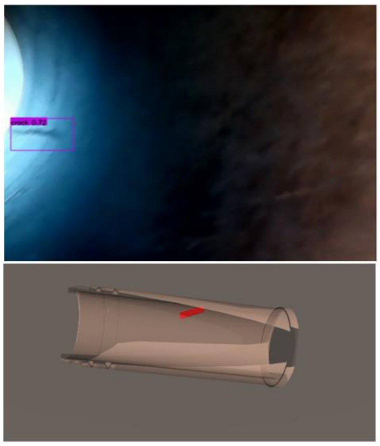

Fig. 7. Real-time LAOI visualization. Top: Results of DL module; Bottom: camera localization data visualization.

Despite the lack of numerical measurements to assess the deviance between the virtual and the real probe, the accuracy and sensitivity of that IMU does not seem to be ideal for this type of application.

B. AR-CRP tests and results

The AR-CRP tool was tested and evaluated resorting to functional experiments, but also considering users.

1) Functional assessment

Before the functionality testing, a standard usage scenario was defined, specifically, with the creation of a cable system with nine CRWp and demonstrated by updating waypoints and navigating between different cable routing versions.

The testing process begins with the login menu to initiate a session, as demonstrated in Fig.8-b. Subsequently, the AR-CRP's main menu automatically appears (Fig.8-c), enabling users to create a new cable routing encompassing the aircraft, cable system, and version. It also provides the option to import previously created cable routings. Moreover, the main menu offers access to the user guide and, for admin users, the ability to manage technician restrictions. Thereafter, users can easily comprehend the operation by consulting the holographic user guide menu, depicted in Fig.8-a.

Upon creating CRWp within the scene, the AR-CRP tool interaction set - specifically "tap", "drag", and "drop" functions - facilitate position adjustments for each CRWp, as shown in Fig.8-d. The system dynamically and continuously saves updates, ensuring data persistency.

It is important to highlight that the creation of a CRWp involves two options: a) initially, users may choose to create the CRWp in a specific location within the spatial mapping environment and then reposition it; b) users may create the CRWp via airtap near the desired location. While the former option ensures a close position of the CRWp in relation to user, the air tap alternative may pose difficulties, as the CRWp position may become physically hard to reach or inaccessible. By accumulated experience using HoloLens, it turns out that accuracy of the CRWp 's coordinates heavily depends on where the user air taps within the 3D space. Moreover, the tests made with users – presented as follows – indicated that the first method led to swifter detections of the CRWp, enhancing the user experience by providing more reliable results.

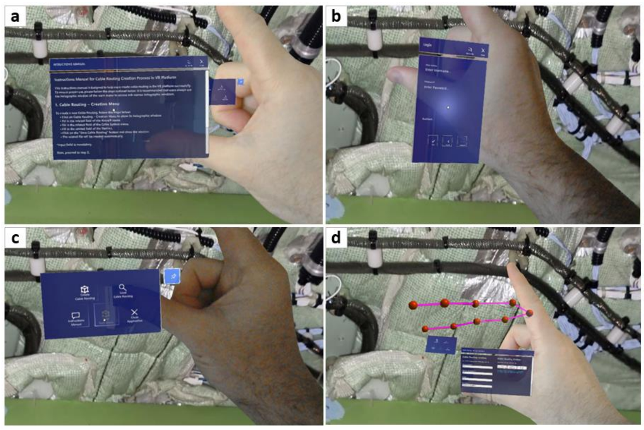

Fig. 8. a) AR-CRP user guide; b) AR-CRP login menu; c) AR-CRP main menu; d) AR-CRP import menu of CRWp.

2) User experience (UX) and usability assessment

In the tests with users, participants were instructed to engage with all previously discussed functionalities, with the objective of tracking their progress in relation to the end-user experience, focusing on usability. Validation took place within a real aircraft at AEROMEC facilities. Those steps consisted in operations such as loading the creation menu, inputting text in predetermined fields, and understanding the tool's feedback on each undertaken step's success or failure.

Participants were navigated through the menu that enables the import of a single cable routing created for testing purposes or selecting versions available in a logically structured dropdown sequence. This sequence comprised options like the specifying aircraft name, cable system, and version. Participants were also instructed on how to holographically create the necessary CRWp for the scenario when importing the cable routing. Access was granted to the editing menu, providing participants the ability to alter the position of each CRWp, and also to delete each CRWp from the respective cable routing. It was clarified that any changes made would be automatically saved to the respective cable routing.

The process of importing another cable routing into the HoloLens was explained and demonstrated. Throughout the test, participants received continuous support to cope with any challenges encountered while interacting with the HoloLens and the 3D holographic space, within a real aircraft (Fig.9).

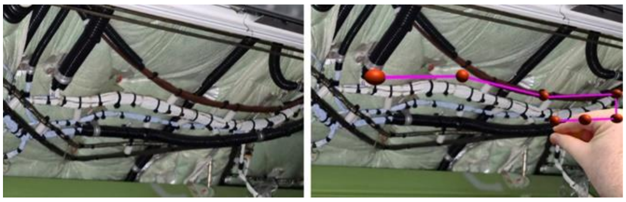

Fig. 9. Real demonstration of AR-CRP cable routing manipulation in an aircraft.

Environment

The test took place in a real environment, in a maintenance hangar at Cascais Municipal Aerodrome. A Falcon 50 airplane was selected as the setting for the AR-CRP tool, and the HoloLens device equipment was used as the AR device, as shown in Fig.10.

Fig. 10. The participant is handling AR-CRP cable routing in an aircraft.

Protocol

Participants were selected according to their roles, with the prerequisite of holding experience in the cable routing maintenance. Upon participant selection, the system's objective and the research were initially presented, along with the consent form. An introduction to AR was provided, and some initial procedures were performed. An initial demographic questionnaire was conducted, with questions related to age, position, experience time, use of AR equipment, visual acuity, and whether they experience any discomfort or pain when handling hands, arms, or neck.

For usability analysis, Umux-Lite [35] was used. This tool consists of two questions, and its score is converted to the SUS scale, with reliability between its responses, as studied by [36]. The conversion to the SUS score was done as following equation:

$$\textbf{\textit{UMUX-LITE}} = 0.65*((Item1 + Item2 - 2)*(100/12))+22.9 \quad (9)$$

In addition to the usability parameter, some open-ended questions were asked to gain a better understanding of the user's perception of the system, namely:

- What did you think of the system and its potential?
- What did you think of the augmented reality aspect?
- Did you experience any difficulty or ease in performing this procedure? If yes, could you tell us a bit about them?
- Do you think this system can help with your cable-locating work?
- Any additional comments?

Participants

Various usability studies indicate a magic number of five testers, as they can detect 80% of the issues, which provides a cost-benefit [37][38][39]. In this perspective, 5 participants (4 males, M = 34.8 years, SD = 11.01) were recruited, all working in the aeronautical field with contributions to this application (M = 14, SD = 10.7).

Four of the participants were engineers (three in aeronautics and one in mechanical engineering), and one participant was a maintenance technician. All the selected participants had experience in the maintenance and modernization of military and civilian aircraft. Participant 1 (P1) reported 25 years of experience and currently holds the position of aeronautical innovation for the improvement of aircraft modernization processes and services. P2 reported 30 years of experience and is responsible for managing the avionics system modernization program. P3 reported 3 years of experience with the responsibility of developing technical instructions for the execution of tasks related to avionics system modernization. P4 reported 1 year of experience with the responsibility of developing technical instructions for the execution of tasks related to avionics system modernization. And P5 reported 29 years of experience, and was the Team Leader of the Avionics team, and is responsible for the installation of electrical wiring in the avionics system modernization program. They were chosen based on their technical profile in the field and their willingness to participate in the research and all of them having a connection with the cable routing operations.

It is worth noting that all participants were right-handed with moderate to advanced AR experience. Four participants had myopia or astigmatism, but only one was wearing prescription glasses during the experience. None of the participants reported experiencing any type of pain in their hands, arms, neck, or any other part that would interfere with the device's use.

Results

From a usability perspective, it had an average score of 72.7, with the lowest value being 71.7 and the highest value 82.5. According to the parameters of the SUS score, to which Umux-Lite was converted, its margin of acceptability is 68 [40], good between a score of 73 and 85, and excellent above 85 [41]. However, Sauro and Lewis in 2016 [42] consider a score above 80 as the level of excellence. In this case, only one participant had a score below good, according to [41], while a single participant had a score above excellence, according to [42]. Thus, the usability level remained at a good level of acceptability (Fig.11).

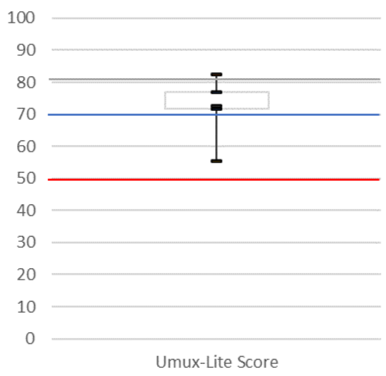

Fig. 11. Umux-lite results.

All participants recognized the AR-CRP potential. One participant stated, "It has great potential for aircraft maintenance and modernization", while another participant remarked, "The system is quite interesting and has enormous potential in the aeronautical industry. There are clearly improvements that can be made, but that’s normal for a prototype." Another participant highlighted the scenario, saying, "The system is very useful in the training area but also in modifications, just like in the scenario that was tested."

Regarding difficulties, two participants did not experience any difficulties, while two others mentioned the need for adaptation. One participant stated, "I think it's a matter of adaptation, but it's easy," and another participant mentioned, "I had difficulty gaining practice and initially understanding how the system works." Finally, one participant mentioned difficulties in selecting the boxes, stating, "Initially, I had difficulty selecting the boxes. It's necessary to understand the hand position, but then it becomes easy."

No additional comments, except for compliments about the AR-CRP tool, were recorded. All participants affirmed that the technology would assist in their work, with one participant even mentioning, "Without a doubt, we should explore this capability in more detail." It was also observed that some participants had difficulty reading certain information.

VI. CONCLUSIONS AND FUTURE WORK

This work proposes a couple of tools for aircraft maintenance and modification activities, covering both cable routing-related operations and location-sensitive DL-based engine inspections. On the one hand, the AR-CRP tool aims to addresses the challenge of managing and tracking cable routing in the context of aircraft maintenance. To that end, an AR-based solution targeting HoloLens was implemented, enabling technicians to catalogue and visualize 3D cable systems, as well as transformations made to those cables over time. As such, whenever an intervention is required, an intuitive visual identification can be provided through the AR-CRP tool, avoiding burdensome and time-consuming trial-and-error procedures, as for example, the need of physically removing aircraft panels or consulting manuals and paperwork regarding past interventions. On the other hand, LAOI is dedicated to support borescope inspections, tackling challenges related with the identification of defects, and with the zoning of those occurrences, also intending to mitigate the disorientation experienced by many technicians that perform that kind of analysis. It utilizes deep learning (DL) to automatically detect defects and damages inside the mechanical components (e.g., engines). The tool incorporates a borescope camera equipped with a small-sized IMU to track the inspection device's orientation and displacement. This data is used to create a visually intuitive 3D representation in a DT-like environment, intending to keep technicians oriented during inspection procedures.

Practical demonstrations of the proposed tools were conducted. While LAOI functionalities could be successfully demonstrated, space for improvements were identified in what concerns to the localization features, mostly related with the noisy sensor in use and the lack of a proper filter. The AR-CRP functionalities were thoroughly tested, as well, and no significant issues were identified during the experimentation process. Regarding the user experience evaluation involving AR-CRP, it became evident from participants feedback that the system is good and holds a real potential for modernizing aircraft maintenance activities. Like any system under development, there are still areas for improvement, such as interaction with the boxes and the font size of certain information, which made reading difficult.

For future endeavours, it is essential to compile an expanded dataset of engines’ anomalies with additional examples and classes to develop more accurate and versatile DL models for the LAOI tool. Furthermore, improvements should be made, focusing on enhancing sensors' accuracy and refining filtering algorithms to enhance the location-awareness feature. Regarding the AR-CRP, the emphasis will be on integrating the valuable feedback gathered from user tests to continuously enhance the prototype. Additionally, in-depth analyses of user experience and system usability need to be carried out, aiming to maximize the capacity of AR in providing increasingly effective assistance to operators involved in aircraft maintenance tasks.

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