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Research Survey

A Review on Visual Inspection Methods for Aircraft Maintenance

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Abstract

During aircraft maintenance, the control of damages such as crack, burn, corrosion should be done precisely. Therefore, the process can take a long time. In the case of rapid control, errors cannot be detected properly. However, since the control process is usually carried out by naked eye, it is quite open to human-induced risks. In recent years, with the expansion of the application area of artificial intelligence, the use of modern techniques in aircraft maintenance and breakdown operations has been increasing in the aviation industry. In this study, deep learning-based visual inspection methods involved in aircraft maintenance and repair are surveyed.

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Uçak Bakımında Görsel Muayene Yöntemleri Üzerine Bir İnceleme

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Özet

Uçak bakımı sırasında çatlak, yanık, korozyon gibi hasarların kontrolü hassasiyetle yapılması gereken bir işlemdir. Bundan dolayı yapılan işlem uzun bir zaman alabilmektedir. Hızlı kontrol yapıldığı zamanlarda ise hataların takibi sağlıklı bir şekilde gerçekleştirilemememektedir. Bununla birlikte kontrol işlemi genellikle göz ile gerçekleştirildiği için insan kaynaklı risklere oldukça açıktır. Son yıllarda yapay zekanın uygulama alanının genişlemesi ile birlikte hava taşıtları bakım ve arıza işlemlerinin gerçekleştirilmesinde modern tekniklerin kullanımı havacılık sektöründe giderek artmaktadır. Bu çalışmada, uçak bakım ve onarımında yer alan derin öğrenme tabanlı görsel inceleme yöntemleri incelenmiştir.

1. INTRODUCTION

Safety and security are among the most important issues in airline activities. One of the most important stages of ensuring safety and security in aircraft is the maintenance of these vehicles. Many maintenance operations are carried out periodically or after and before each flight, and troubleshooting operations are applied when necessary. Considering that even a missing screw can endanger the safety of the flight [1], it becomes clear that maintenance operations must be performed with great care. There are two basic types of maintenance according to the modern care planning procedure [2]. These are named as "Line maintenance" and "Base maintenance". While line maintenance is a more superficial process than base maintenance, it is performed more frequently than base maintenance. Pre-flight, daily, weekly or after a certain flight time are considered as line maintenance operations. The critical step of aircraft base maintenance is the control of impact loads [3]. The impact of natural events such as foreign body strikes, bird strikes or lightning strikes on aircraft can be given as examples of impact loads. The fatigue strength decreases in the areas with impact load and corrosion may start in that area because the paint and coating layer are damaged. In addition, the impact damage of a tired or corroded surface accelerates the aircraft out of fault tolerances. In aviation, impact loads are mainly controlled visually by traveling around the aircraft using various elevators. Although this process seems like an economical method at first glance, it involves human-induced risks in addition to the difficulty of maintenance and the length of the maintenance period. Considering the aircraft accidents experienced in the past, the fact that most of them are maintenance-related shows how important the maintenance process is in ensuring flight safety. Table 1 shows some important aircraft accidents and the reasons of these accidents [4].

Table 1. Important aircraft accidents in the past.

Airline company	Location	Time	Cause of the Accident
Aloha Airlines Flight 243	Hawaii	April 28, 1988	Damage to the fuselage during flight due to lack of control.
United Airlines Flight 232	Iowa	July 19, 1989	Loss of control in flight due to lack of control causing engine silence
Continental Express Flight	Texas	Sep. 11, 1991	Horizontal stabilizer breaks due to maintenance personnel not installing bolts
Northwest Airlines	Tokyo	March 1, 1994	Motor separation from the body due to improper assembly

Impact loads can be inspected visually or with various optical devices, but the visual inspection method is more preferred. During maintenance, starting from the nose area of the aircraft, the entire circumference is controlled by traveling through various elevators. The nose radar cone, body outer surfaces and wing attack edges, which are riskier in terms of impacts, and different types of object on the airframe such as damage caused by impact or cracks must be detected. Although this process can last up to 8 hours, the error size that can be detected during visual control is evaluated as at least 2-3 cm [5]. For more detailed inspection, the aircraft surface should be examined more closely. Considering that this process should be carried out with great care, it is clear that the process will take a long time and error-prone [6]. In addition to these, risk analysis of defects such as cracks, dents, scratches and quality of markings detected during these controls must be carried out. Crack and scratch images are given in Fig. 1 and Fig. 2, respectively.

On the other hand, there are many types of cables in aircraft for supplying power and control signals to electronic systems and are installed in the cavities of the aircraft according to the ARINC specification described in [7]. Aircraft cable performance directly affects flight safety due to various reasons such as pollution, physical damage, aging and environmental impact, malfunctions such as open circuit failure, short circuit failure.

Aviation maintenance is a complex and demanding process. The success of maintenance affects the ability to fly safely. Aircraft maintenance activities are carried out with various hardware and software, and diagnostic and prediction-based methods to minimize the malfunctions caused by maintenance personnel. In terms of today's conditions and possibilities, maintenance activities are based on test technology, computer technology, information technology and diagnostic technology. With the widespread use of artificial intelligence in recent years, the use of modern techniques in aircraft maintenance and breakdown operations in the aviation industry has been increasing.

Deep learning studies have gained a very good pace with the development of GPUs and the increase in the amount of data. Today, one of the most used areas of artificial intelligence is computer vision. There are many other application areas such as surveillance [8], health applications [9], search and rescue, detection of chemical wastes [10], control of rails on railways [11]. With the help of computer vision aircraft inspection processes can be automated, eliminating situations in which aircraft maintenance personnel may not notice critical damage. Another benefit of computer vision-based inspection is that it reduces inspection time and human effort, allowing for the detection of cracks, painting errors, damage caused by lightning strike instantly.

Figure 1. Corrosion on the surface of the aircraft [12].

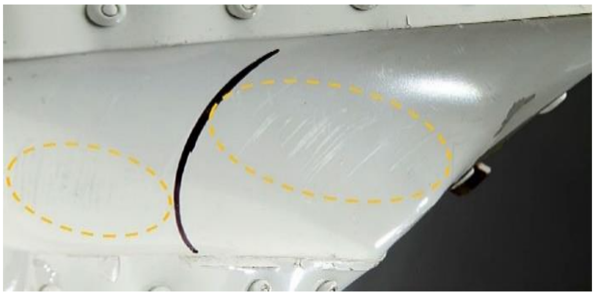

Figure 2. Scratches on aileron rib [13].

The contribution of this paper is to provide a comprehensive and systematic review of state-of-the-art deep learning based visual inspection methods in aircraft maintenance. To the best of our knowledge, there are very few literature reviews on the application of deep learning to aircraft maintenance, and this study will be the first survey conducted on computer vision-based methods used in aircraft maintenance.

In the next section, the details of the vision-based inspection methods and deep learning-based object detection approaches in literature are presented. In Section 3, experimental results are provided, and conclusions are given in Section 4.

2. VISION BASED INSPECTION METHODS

In [14], visual inspection is carried out with the help of drones. In this study, the detection of damages on the surface of the aircraft was performed using deep learning algorithms with the images taken by a camera placed on an UAV (Unmanned Aerial Vehicle). During the inspection, the UAV is steered along a pre-prepared path along the aircraft wings and surfaces and high-resolution images are obtained from camera mounted on the UAV. It is of great importance in terms of determining the exact location of the damaged area and comparing it with previous examinations. Since the inspection process is carried out in the hangar where the global positioning system is not working, an internal navigation system is used for the inspection environment. In the considered internal navigation system, the cameras placed on the upper regions are used to detect the position of the UAV. The problem of detecting a UAV in real time is achieved based on computer vision techniques where YOLOv3 [15] is employed. YOLOv3 is one of the fastest and accurate deep learning algorithms used in computer vision for real time object detection. The reason why YOLO algorithm is so fast is that it can predict the class and coordinates of all objects in the picture by passing the picture through the neural network in a single pass. The 3D coordinates of the drone are obtained by cameras mounted on the walls and transmitted to autopilot software of the drone. After the 3D coordinates are calculated, the UAV is guided by the internal navigation system along the aircraft wings to detect defects and their location with DCNN (Deep Convolutional Neural Network) on the plane surface. The system setup is shown in Figure 3.

Malekzadeh et al. [16] proposed a method in which convolutional neural networks are also used to detect damage to the airframe. Accordingly, a dataset consisting of two classes, with and without deformation, is created with the images taken from the fuselage of the aircraft, and this dataset is used in the training of the deep neural network. The images obtained in this study are divided into parts at various scales from 20x20 to 100x100 pixels, so classification accuracy and computational complexity are compared according to pixel size. As the image size increased, the calculation complexity increased, but it was observed that the accuracy increased at a similar rate, and they obtained the best results from images with a size of 65×65 pixels. The feature extraction process from images is obtained by using deep neural network, AlexNet [17] and VGG-F [18] architectures, which are pre-trained with ImageNet, and the classification process is performed by SVM. In addition, classification operations are performed on the same dataset with classical feature extraction methods such as SURF, RGB, HSV histogram and local binary pattern (LBP) [19] methods. The results are given in Table 2.

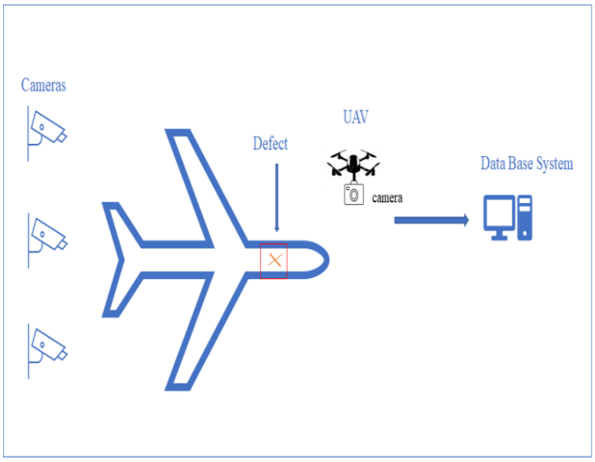

Figure 3. Visual damage assessment application with internal global positioning system and drone.

Table 2. Model performance comparison [16].

Method	Accuracy	Sensitivity	Specificity
RGB Histogram	0.60372	0.2950	0.8089
HSV Histogram	0.60299	0.3097	0.7980
LBP	0.60383	0.1263	0.9213
SURF	0.63667	0.2742	0.8446
VGG-f	0.87623	0.8543	0.9053
AlexNet	0.84631	0.7062	0.9394

Ramalingam et al. [20] has developed a robot that can be reconfigurable and climb onto aircraft surfaces to detect faults such as stains, rust, and deformation on the surface of aircraft that will cause surface corrosion. Thanks to the camera placed on the robot, it can detect stains using deep learning techniques. With this method, it is aimed to reduce the safety risks that maintenance personnel will encounter during inspection on surfaces. Convolutional neural network-based SSD model is used to detect stains such as machine oil and dirt on the surface of the aircraft. The SSD [21] divides the images into square regions, and each square is responsible for detecting the area objects. If there is no object, that square region is assigned to the background class and the location of that object is tried to be determined with structures whose size is known as an anchor. One of the important reasons for using the SSD - Mobilenet is the need for lighter and faster models to perform image processing applications with a mobile robot. The flexibility of the inspection robot enables it to easily climb hard to reach areas on the plane surface and successfully perform the visual inspection process.

Using computer vision techniques, Bouarfa et al. [22] detected the damages such as holes, dents, cracks and lightning strikes on the outer surfaces of the aircraft. They used Mask R-CNN model to perform visual inspection. Mask RCNN is a kind of region based convolutional networks and consists of three neural networks which are Feature network, Region Proposal Network (RPN), and Detection Network respectively. The feature network is responsible for extracting features by using convolutional layers. RPN's task is to produce bounding boxes called region of interest that contain possible objects. Detection Network is responsible for final prediction of class and bounding box coordinates and masks. They used 55 images in total for model training, and due to the low number of data, they aimed to obtain a more accurate result by performing data augmentation and 10-fold cross validation. The result is given in Table 3.

Li at al. [23] with the YOLOv3-Lite model, they designed a lightweight network that detects cracks in aircraft structure. They used the convolutional network model as a backbone to solve the problems encountered in detecting relatively small objects with a complex background. In this study, a high resolution and rich semantic structure is obtained from a structure with low resolution but semantically strong features by using feature pyramids. In this way, the cracks in the body or motor blades are detected.

The combination of augmented reality and artificial intelligence has become increasingly common in recent days. In [24], a deep learning-based approach has been developed to inspect connectors on aircraft (Fig. 4), by using augmented reality glasses. In this way, connector inspection in aircraft, detection of pins in the connector and detection of mismatching pins can be done with the help of augmented reality. The stages of this work were as follows:

- Images containing structural information and template images are shared with augmented reality glasses, then connector images are taken with the camera on the augmented reality glasses.
- RetinaNet [25] model is used for connector detection, so the connector type is defined and the area containing the connector object detected on the image is clipped for the next step. In this cropped image, the feature pyramids network was applied to detect the pins on the connector.
- The pin distribution recovery approach is used to obtain the original distributions of the pins. Then, the pins are sorted by their serial number based on the clustering algorithm. Since the assembly information is obtained beforehand, the assembly status of the incompatible pins is determined by comparing the correct one.

It has been discovered that there is an excessive foreground class imbalance problem in the single stage detector. This is thought to be the main reason that makes the performance of single-stage detectors lower than two-stage detectors. By using Focal Loss in RetinaNet, a single-stage detector developed by Facebook AI, it has been tried to increase the prediction accuracy by focusing on the error in more difficult samples, since the lower loss comes from easy negative samples. It provides very good performance with ResNet + FPN (Feature Pyramid Networks) as the backbone for feature extraction and also task-specific two subnets for classification and bounding box regression. Augmented reality glasses transmit the warning message and mismatched pins to the operator. Since the pins and plugs on the connector are of different scales, feature pyramids networks can extract the features between deep and shallow layers. In addition, BiLSTM [26] has been adopted to replace the convolution process in deep layers to extract the spatial attributes of the pins and fits distributed to the connectors thus, a feature pyramid network was formed by obtaining both graphical features and spatial location information. For training, a data set consisting of 1346 images is created and trained on the FPN, Faster R-CNN, SSD, YOLO v2, RetinaNet and YOLO v3 networks respectively, and the results are compared. The network with the feature pyramid approach with 0.99 mAP achieved the best result.

There are hundreds of cables that perform many functions in aircrafts [27]. Since the assembly time of the cables increases in direct proportion to the amount of the cable, methods are required to shorten the maintenance time. The assembly and arrangement of the cables are carried out with various equipment such as cable brackets and clamps. Today, the detection and recognition of the cable brackets in aircraft assembly scenes is made with two-dimensional drawings or graphics and is still based on manual labor. An easy-to-retraining hybrid artificial neural network design is implemented to recognize cable brackets on aircraft in [28]. In this system, the images taken from the industrial camera are transmitted to the cloud server, the server detects the target area with the Faster R-CNN algorithm. In this study, a multi-stage artificial neural network is designed in which weights are shared for feature extraction from cable bracket images. If a new type of cable bracket is added to the system, instead of retraining the whole network, SVM classification process at the end of the network are retrained and feature extraction is performed. The feature extraction network consists of four layers, namely the initial network, the middle network, the high-level network, and the feature fusion network, respectively. While the first layer was designed to extract deep features, general and detailed feature extraction was performed with the transversely expanding network design in the middle layer. In the last layer, vertically and horizontally spatial features extraction was performed with a convolutional network with 1×3 and 3×1 filters.

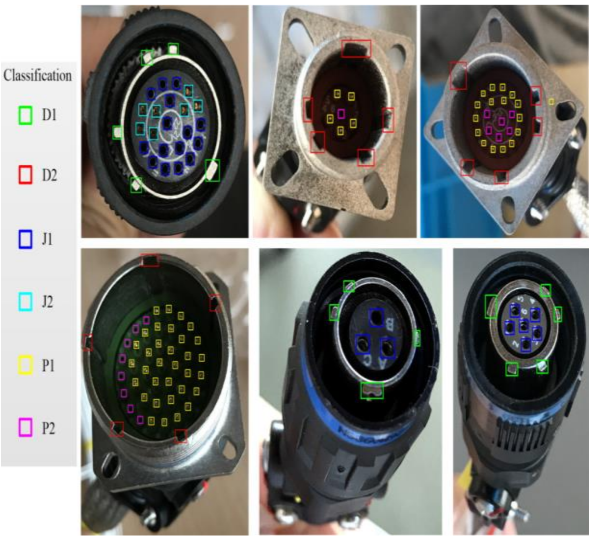

Figure 4. Images from pin detection [24] © [2020] IEEE.

3. COMPARISON AND EVALUATION

In this section, studies based on visual inspection are examined and the frequency of use of deep learning methods are compared. Fig. 5 shows the class distributions of the problems encountered in aircraft. Accordingly, methods for detecting defects such as cracks were proposed in 40% of the examined studies and the locations of these cracks are mostly located in outer surface, but very few of them are located in inner part of the aircraft. Each of the research for the detection of defects such as corrosion, stains and dents constitute 10% of the total studies.

It has been observed that the YOLO model and its derivatives are mostly used to overcome defect detection problems. YOLO architecture is preferred in many studies due to its easy applicability and its high performance on mobile devices. It has been observed that the RetinaNet model gives better results in detecting small scaled objects. In Table 3, the studies in the literature and the methods used are compared. The best accuracy for detecting defects is obtained by Blokhinov et al [14]. They developed DCNN with the YOLOv3 architecture. Malekzadeh et al. [16] achieved 87.62% score when they used VGG Net to classify defects on aircraft. The best accuracy for classification of crack and corrosion images with a score of 83.5% is achieved by Siegel and Gunatilake et. Al [29]. It is observed that convolutional neural network-based methods give better results than traditional object detection methods.

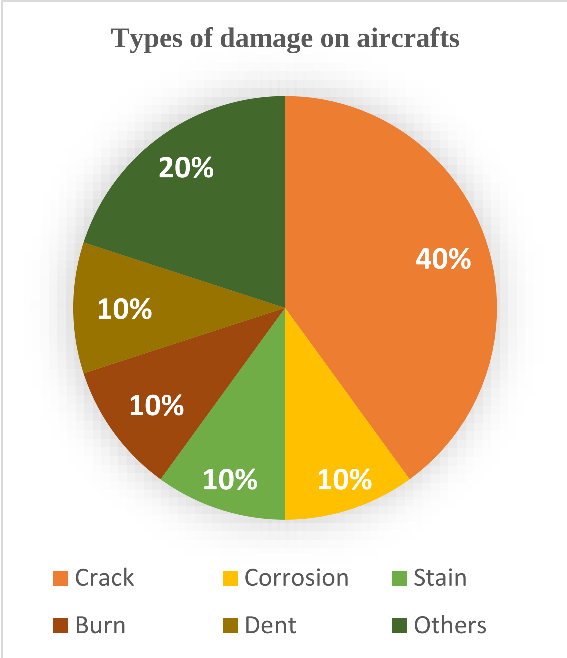

Figure 5. Types of damages on aircraft.

4. CONCLUSION

In this review, recent methods for detecting defects in aircrafts are surveyed. In most of the studies reviewed, various defects such as cracks, dents, scratches in aircraft with convolutional neural networks are used and it is observed that deep learning-based methods achieved better results in damage detection. It is observed that the mostly used object detection methods among the investigated studies are YOLO and Faster R-CNN. The size of the data set used to perform visual inspection in the evaluated studies is much less than data sets in other domains and increasing the size of the data sets can boost the performance of the models.

Table 3. Studies in literature.

Reference	Classes	ROI extraction	Method	Result
Malekzadeh et al. 2017 [16]	Defect	Cropped	VGG Net AlexNet	Acc =87.62 % Acc =84.73 %
Ramalingam et al. 2019 [20]	Stain, Defect	Cropped	SSD MobileNet	Acc =96.2 %
Siegel and Gunatilake at. al 1999 [29]	Crack, Corrosion	Cropped	ANN	Acc =83.5 %
Bouarfa et al. 2020 [22]	Dent	Segmented	Mask-RCNN	Precision =57.32 % Recall= 69.13 %
Li et al. 2019 [23]	Crack	Cropped	YOLOv3-Lite SSD-MobileNet YOLOv3 YOLO-Tiny	Ap= 38.7 % Ap= 17.1 % Ap=3.1 % Ap=2.5 %
Blokhinov et al. 2019 [14]	Defects and foreign objects	Cropped	DCNN - YOLOv3	Acc=98.57% Ap = 86.97%
Li et al. 2020 [24]	Pin	Cropped	Faster R-CNN SSD YOLOv2 YOLOv3 RetinaNet Hibrit	mAP =0.7268 mAP =0.512 mAP =0.4982 mAP =0.9757 mAP =0.7483 mAP = 0.990
An et al. 2020 [28]	Cable bracket	Cropped	Faster R-CNN SIFT+SVM HOG+SVM ANN	Mean acc=85.69 % Mean acc=55.99 % Mean acc=21.99 % Mean acc=76.97 %

Abbreviations: ROI: Region of interest, mAP: mean average precision, Ap: Average Precision, Acc: Accuracy

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VITAE

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