

Predictive maintenance of pavement cracks in airport facilities based on drones and computer vision

Tarik Lahna^a

^aINPT, Toulouse, France

ABSTRACT

Manual inspection of damages in airport facilities such as pavement cracks is difficult due to the reliability objective and the high demands of time and costs. This can be automated using a system of unmanned aerial vehicles (UAVs) for aerial imagery of damages. Many computer vision-based approaches have been applied by several researchers to address the limitations of crack detection but they have their limitations. The purpose of this paper is to describe how the limitations can be overcome by using various hybrid methods based on artificial intelligence (AI) and deep learning (DL) techniques. Also, it shows how convolutional neural networks may be introduced in drones to automate the detection of pavement cracks in airport facilities. The outline of the proposed system is composed of three modules which are: Image acquisition, Crack detection, and Image-based 3D modeling. In addition, this paper has shown that this proposed system can participate in building a 3D digital representation of pavement cracks in airport facilities automatically from a DSLR camera within the context of the digital twin.

Keywords: Digital twin, Deep learning, Airport facility, Crack

I. INTRODUCTION

Maintenance in airport facilities (MAF) is attracting huge interest from the academic world. Therefore, maintenance practices have still not progressed since collecting data to inspect facilities is time-consuming and the budget and resources allocated for building maintenance are insufficient. Cracking is generally detected based on visual evaluations from an expert and the main cracks in airport facilities are the ones present in airport pavements (Lahna et al., 2023). However, detections of pavement cracks based on artificial intelligence techniques can be performed. These kinds of assistance are tested within the framework of the amelioration of predictive maintenance methods inside airport facilities. The objective of modernizing predictive maintenance in airport infrastructure is to skip different issues such as the safety of passengers during aircraft operations and the increased costs for maintenance departments. Additionally, these infrastructures are vital economically for any region in the world (Peneda et al., 2011). The purpose of the article is to propose an outline to detect automatically pavement cracks based on three modules which are: Image acquisition, Crack detection, and Image-based 3D

modeling. To answer all these research questions, the paper will focus on defining the main keywords of this article and describing the proposed system for detecting crack pavements in airport facilities.

First, the paper will draw partially on a literature review highlighting the main keywords of this paper. Second, a proposed system to detect automatically pavement cracks will be detailed.

Finally, limitations and a conclusion are presented including future research avenues.

II. LITERATURE REVIEW

2.1. Runway pavements in airport facilities

Airport infrastructure can be divided into three main categories (Lahna et al., 2023).

- 1. Essential operational services and facilities
- 2. Traffic-handling services
- 3. Commercial activities

These three main categories are detailed in **Table 1**:

Operational Services/ Facilities	Air Traffic Control
	Police and Security Department
	Ambulance, Fire and Rescue Department
	Maintenance Services
	Runway
	Terminals and Air bridges
Traffic Handing	Fuel, Ramp, Hanger
	Baggage and Freight facilities
	Immigration Services
Commercial Activities	Duty-Free and Shopping
	Catering and restaurants
	Car parking
	Car rental
	Other (Bank, Hotel, etc.)

Table 1: The three main categories of airport infrastructure from (Lahna et al., 2023).

Airport facilities are important economically and have exhibited exponential growth and profits" (Peneda et al., **2011).** This explains why researchers were performing many experiments to solve risk assessments around facilities (Attaccalite et al., 2012). Therefore, a group of researchers found that a 1%-point increase in airline traffic per capita implies an increase in GDP at a rate of 0.017% by using the two-stage least squares method (Baltaci et al., 2015). Tremendous runways are suffering from cracks. These cracks imply negative consequences for the airport traffic such as the interruption of the traffic and its economic impact. Therefore, it highlights the importance of treating cracks in runways before becoming critical. Thanks to the development of artificial intelligence, different researchers started having an interest in applying computer vision technology for roads generally to detect the origin.

2.2. Artificial Neural Network

Artificial Intelligence (AI) was initiated in 1943 and continues to progress exponentially starting from 2000 marking the beginning of the period called the "High-speed development period" (Zhang et al., 2019). In the Dartmouth Conference, as shown in Figure 1, it was stated that AI is the reaction of a machine similar to the intelligence of a person (Moor, 2006). However, Nils J. Nilsson thinks that AI is the subject of knowledge by expressing knowledge and acquiring it (Kuipers et al., 2017). In addition, AI includes many technologies such as computer vision, machine depth learning, virtual reality, and big data (Zhuang et al., 2017). The amount of data increased exponentially in many areas with a set of improved algorithms and more powerful computer hardware. That is why, it becomes necessary to maintain the development of new technologies of AI for organizations (Brynjolfsson and A.N.McAfee, 2017). Recently, artificial intelligence techniques such as machine learning and data science, are spreading in different fields (LeCun et al., 2015). These techniques are also used in structural engineering to detect damages and cracks.

TIMELINE DIAGRAM OF ARTIFICIAL INTELLIGENCE HISTORY

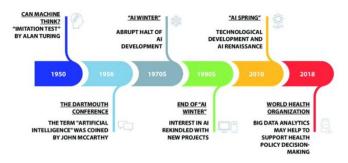


FIGURE 1: Timeline diagram showing the evolution of AI from (Bellini et al., 2022)

2.3. Convolutional Neural Network (CNN)

A convolutional Neural Network (CNN) is a specific case of the neural network. The design of a CNN was inspired by the discovery of a visual mechanism, the cat's brain's visual cortex. CNN is used in many fields such as image and pattern recognition, speech recognition, and natural language processing.

A CNN is composed of repeated convolutional and pooled layers, that are followed by one or more fully connected layers. The convolution layer slides multiple filters across the image to generate a matrix, and the pooling layer samples from the convolutional layer.

As shown in **Figure 2**, CNN is composed of two major parts:

- Feature Extraction: In this part, the neural network performs a series of convolution operations and pooling operations throughout which the features are detected.
- Classification: The fully connected layers function as a classifier on top of these extracted features. They will assign a likelihood for the object on the image to be what the algorithm predicts.

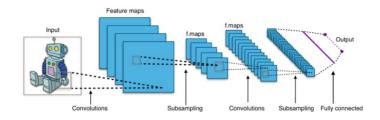


Figure 2: Structure of a convolutional neural network

As regards **Figure 3**, it shows an overview of a crack detection system. The detection system consists of two main modules, feature extraction, and classification.



Figure 3: an overview of a crack detection system

III. PROPOSED SYSTEM

This study aims to propose and describe a system to detect automatically pavement cracks in airport facilities

The proposed system illustrated in **Figure 4** is composed of three modules which are: (1) Image acquisition thanks to a drone and DSLR camera (2) Crack detection using CNN, and (3) Image-based 3D modeling. The output from the system is a 3D model and its associated images containing cracks.

Regarding the image acquisition, Unmanned Aerial Vehicles (UAVs) are ideal so that image processing algorithms are applied to inspect cracks across the runway area. Similarly, a team of researchers performed an image-based system to recognize automatically cracks in building facades using UAVs (Pereira et al.,2015).

For the crack detection part, CNN is proposed to distinguish between two classes: Crack and No crack. Finally, a 3D model based on point cloud is obtained thanks to the DSLR camera, which is a camera that operates with a fixed, digital sensor. This 3D model enables to build a 3D representation within the context of the digital twin and to participate to the progress of Building Information Modelling (BIM).

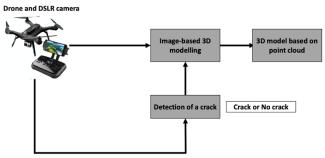


Figure 3: A proposed system to detect automatically pavement cracks in airport facilities

IV. CONCLUSION

The implementation of this system composed of a drone and DSLR camera will allow experts to easily identify cracks automatically in landing strips and anticipate the strengthening of certain cracks before they become critical. The introduction of CNN enables to detection of pavement cracks in airport facilities. As part of predictive maintenance, the implementation of this system will allow all participants to have a 3D point cloud model as part of BIM. Future work involves the implementation of automated classification algorithms (e.g., Convolutional neural networks) for the pavement cracks in airport facilities as part of predictive maintenance methods. Therefore, the proposed system detailed in this paper will guide researchers in investigating methods for automatically detecting the cracks as part of predictive maintenance methods.

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