Jakub SUDER, Tomasz MARCINIAK

Poznan University of Technology, Institute of Automatic Control and Robotics, Division of Signal Processing and Electronic Systems
ORCID: 1. 0000-0002-3156-0639; 2. 0000-0001-6035-7325

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Foreign Object Debris detection system using GoogLeNet

Abstract. *The article presents the concept of a vision system for Foreign Object Debris (FOD) detection in the airport environment, based on the GoogLeNet network. The authors present the motivation for the research carried out and the preliminary tests carried out at the Pozna-Ławica Airport and present the developed model of a convolutional neural network with an accuracy of 95.73%. The FOD-A dataset containing more than 19,000 images taken under various weather conditions was used to train the model to ensure the diversity of the dataset.*

Streszczenie*. Artykuł przedstawia koncepcję systemu wizyjnego do wykrywania ciał obcych Foreign Object Debris (FOD) w środowisku lotniskowym, opartego na sieci GoogLeNet. Autorzy przedstawiają motywację do podjętych badań i wstępne testy przeprowadzane w Porcie Lotniczym Poznań - Ławica oraz prezentują opracowany model konwolucyjnej sieci neuronowej o dokładności 95,73%. Do treningu modelu wykorzystano bazę FOD-A zawierającą ponad 19 000 obrazów, wykonanych w różnych warunkach atmosferycznych, aby zapewnić różnorodność bazy danych. (****System wykrywania ciał obcych przy użyciu GoogLeNet****).*

Keywords: Foreign Object Debris, embedded vision system, neural networks, GoogLeNet
Słowa kluczowe: ciała obce, wbudowane systemy wizyjne, sieci neuronowe, GoogLeNet

Introduction

Foreign Object Debris (FOD) is a major safety concern in the aviation industry and has the potential to cause significant damage to aircrafts and endanger the lives of passengers and crew members [1]. FOD refers to any object or debris that is present on airport runways, taxiways, or aprons, which can cause damage to aircraft components, such as engines, landing gears, or fuselages. The presence of FOD poses a significant safety risk to aircrafts and can cause delays and cancellations, as well as costly repairs and maintenance [2]**.** An exemplary FOD is shown in Fig.1.

Fig.1. An exemplary FOD that may be at the airport - a screw

The aviation industry is projected to suffer a financial loss of $4 billion annually, as reported in [3]. Additionally, there are immeasurable losses such as the tragedy that occurred in the year 2000 when Air France Flight 4590 crashed due to a tiny metal strip, resulting in an in-flight fire and loss of control. This metal strip was traced back to a Continental flight that had taken off from the same runway just moments earlier. Unfortunately, this incident led to 113 deaths [4].

Despite efforts by airport authorities and maintenance personnel to mitigate the risk of FOD, incidents continue to occur with alarming frequency. This highlights the need for new and innovative approaches to FOD detection and prevention, to ensure the safety of aircrafts and passengers. Airline agencies around the world establish a series of recommendations and regulations to minimise the risk of Foreign Object Debris (FOD) at airports and near aircrafts.

In previous publications, the authors analysed the use of individual components for the control of airport areas. They proposed a system to control in-pavement navigation lighting [5]–[8], analysed the possibilities of using cameras in vehicles moving around the airport [9], [10] as well as the potential use of embedded systems [11]–[13]. The proposed system is consistent with the area of interest of the authors and increases the possibilities of the already created systems, which are in the stage of final tests at cooperating airports.

This paper presents a new, cost-effective approach to FOD detection, based on the use of a visual system that can be deployed and used by airport personnel. The concept of the system includes an embedded system that can be installed in airport service vehicles that move in manoeuvring areas. The images captured by the cameras are then analysed in real-time using advanced image processing algorithms, which can accurately identify and locate foreign objects on the runway, taxiway or apron. By providing real-time information on the location and type of debris, the system can enable airport personnel to take immediate action to remove FOD, reducing the risk of safety incidents and minimising the impact on airport operations.

In this paper, authors present the design and implementation of the visual FOD detection system and evaluate its performance in a real-world airport environment. Authors will also compare the effectiveness and cost-effectiveness of the visual system with other FOD detection methods and discuss the potential impact of the system on airport safety and operations. Overall, the proposed visual FOD detection system offers a promising new approach to FOD detection and prevention, and has the potential to significantly improve the safety and efficiency of airport operations.

FOD detection

The International Civil Aviation Organization (ICAO) recommends applying various practices and procedures to prevent FOD [14]. ICAO recommends implementing appropriate procedures at airports to prevent foreign objects from reaching runways, taxiways, and aprons. They also recommend regular inspections of airport areas, especially critical areas such as runways, to ensure that there are no foreign objects.

The Federal Aviation Administration (FAA) in the United States also introduced many recommendations to reduce the risk of FOD [1]. The FAA recommends establishing regular inspections of airport surfaces, removing debris and garbage from runway, taxiways, and aprons, and inspecting vehicles and equipment operating in these areas to prevent FOD.

In addition, aviation agencies recommend training airport personnel and aircraft crews to detect and report FOD. The implementation of a comprehensive FOD prevention programme includes setting up a system to identify and remove FOD quickly and efficiently. Proper training and education can help reduce the incidence of FOD and minimise the potential for damage to aircraft and equipment.

To address this issue, a reliable, fast and effective solution for detecting foreign object debris (FOD) is essential. At present, in most airports, the detection of FOD is highly dependent on manual labour and human resources.

Various FOD detection systems have been developed and implemented in airports, such as the Tarsier Radar system from the UK, the FODetect system from Israel, the FODFinder system from the US, and the iFerret system from Singapore [15]. These systems utilise radar-based detection, optical camera-based detection, or multisensor fusion detection. Radar-based detection systems rely on radar returns to identify FOD, while optical-camera-based systems use images captured by cameras. However, the detection results of radar-based systems are better for objects larger than 5 cm × 5 cm and weaker for smaller objects such as nuts and rubbers. On the other hand, although optical images can be used to detect FOD, they are typically not utilised for this purpose. If the characteristics of FOD in optical images are used for detection, it can significantly reduce the damage caused by FOD and increase the use rate of runways at airports. Despite the use of optical images in the iFerret system, its detection results are still suboptimal for objects smaller than 5 cm × 5 cm.

In recent years, there has been a growing interest in the development of advanced FOD detection technologies, including the use of visual systems. These systems use high-resolution cameras and advanced image-processing algorithms to detect and identify foreign objects on airport surfaces. By providing real-time information on the location and type of debris, these systems can enable airport authorities and maintenance personnel to take immediate action to remove the FOD and prevent potential safety incidents.

FOD detection using vision systems

In the analysed solutions, the FOD detection based on image analysis and the Foreign Object Debris in Airports (FOD-A) dataset and other own datasets, which contain up to 2,000 photos and up to several classes, were used.

In paper [16] authors present a solution that uses video-based image processing techniques to detect foreign object debris (FOD) on airport runways. The authors use a background subtraction algorithm to detect moving objects and then apply image processing techniques to classify them as FOD or non-FOD. The system was tested using a dataset of runway video footage and achieved a detection rate of 96.67% and a false alarm rate of 5.26%.

Another solution is [17] which proposes a system that uses unmanned aerial vehicles (UAVs) and artificial intelligence (AI) to detect FOD on airport runways. The authors use an object detection algorithm based on the YOLOv3 model to detect FOD and a convolutional neural network (CNN) to classify FOD. The system was tested using UAV footage and achieved a detection accuracy of 94.5%.

The next system that uses the YOLOv3 model to detect FOD on airport runways is shown in another paper [18]. The authors used transfer learning to fine-tune the YOLOv3 model for FOD detection and achieve a detection accuracy of 94.5%. The system was tested using a runway image dataset and achieved a detection rate of 95.67%.

In the other case, the authors proposed a system that uses random forest classification to detect FOD in optical imaging sensor data [19]. The authors extract features from the image data and train a random forest classifier to classify FOD and non-FOD. The system was tested using a runway image dataset and achieved a detection rate of 93.1% and a false alarm rate of 5.5%.

The last one discusses the use of computer vision and unmanned aircraft technologies for the collection of foreign object debris (FOD) images in public inspection [20]. The authors propose a system that integrates computer vision and UAVs to detect and collect images of FOD in airfields. The article also describes the FOD-A dataset, which is a collection of more than 19,000 FOD images that were used to train and test the computer vision algorithm. The article concludes that the proposed system has the potential to improve the efficiency and accuracy of FOD detection in airfields and improve aviation safety. The system was tested using a FOD-A Dataset images and achieved a detection rate of 95.2%.

A comparison of the algorithms used is presented in the section "Proposed neural network model".

System concept

The concept of the system is based on a camera and an embedded device, located in the car of the airport services, moving on the critical parts of the manoeuvring planes. For this reason, the ability to use systems in multiple vehicles is necessary to increase the number of dangerous FODs.

Fig. 2 shows a block diagram of the FOD detection system. The system begins its work with video capture by a camera mounted on the hood of the car. Then the signal goes to the embedded system, where video preprocessing, FOD detection, and then classification of the detected object takes place. In the final phase, the user is informed that the object has been found and that it needs to be removed.

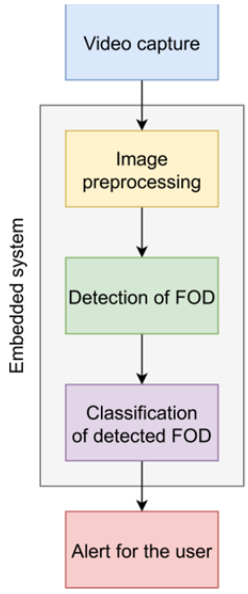

Fig.2. Block diagram of information processing in the proposed FOD detection system

Fig. 3 shows the concept implemented by the authors at the Poznań-Ławica Airport, where a camera was mounted on the front of the car. Ultimately, alerts about the detected object and the need to remove it will be displayed in the driver's cabin.

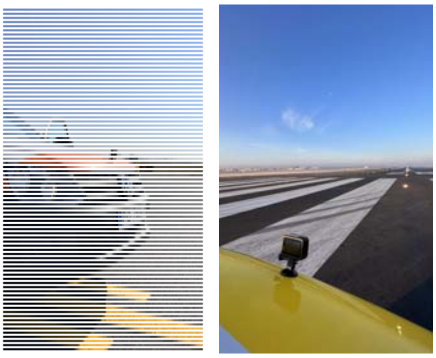

Fig.3. The concept of the FOD detection system (camera mounted on the front of a car moving along the runway at the Poznań-Ławica Airport)

FOD-A Dataset

The Foreign Object Debris in Airports (FOD-A) [21] dataset is a comprehensive dataset designed to aid in the development and evaluation of FOD detection systems (Fig. 4). It consists of over 30 000 high-resolution images captured at several different airports worldwide. The images were captured using various cameras, including RGB cameras and thermal cameras, and cover different weather conditions, lighting conditions, and types of debris.

The FOD-A dataset also contains annotations for each image, indicating the location and type of debris present in the image. The annotations were manually created by trained personnel, ensuring high accuracy and consistency across the dataset. In addition to the image and annotation data, the dataset also includes metadata for each image, such as location, date, and time of capture.

Fig.4. Examples of images from Dataset of the foreign object debris in airports (FOD-A) [21]

As part of the tests, the authors used 19,975 photos for training, validation and testing the system in 107 classes. The photos were selected in such a way as to represent different objects and were taken in different lighting conditions and with different backgrounds.

Proposed neural network model

The system was based on the GoogLeNet convolutional neural network with 144 values and 170 connections. The dataset consisted of 19,975 images, and 30% of them were used to validate the obtained results. Images with a resolution of 400 × 400 pixels have been scaled to 224 × 224 pixels, because this size is accepted by the neural network used. The implementation was performed using the MATLAB 2022a environment using the Deep Network Designer tool.

GoogLeNet is a deep convolutional neural network architecture that was developed by Google researchers in 2014. It is based on a neural network architecture called "Inception," which uses multiple layers of convolutions and pooling to extract features from images. GoogLeNet is notable for its depth and efficiency. The architecture also includes other innovations, such as the use of "1×1 convolutions" to reduce the number of channels in the intermediate representations and the use of global average pooling instead of fully connected layers at the end of the network. These design choices allow GoogLeNet to achieve high accuracy in image classification tasks while using fewer parameters and less computation than previous state-of-the-art architectures.

As part of the work, the augmentation of the data base by random rotation, rescaling, and reflection with respect to individual axes was also tested. During the tests, the selection of the database and individual network parameters was analysed, in the final validation the results of 95.73% correctness of the classification were achieved. Dataset training took 1422 minutes based on Intel Core i7-3770 3.40 GHz CPU. The training cycle lasted 30 epochs with 3270 iterations (109 iterations per epoch). Validation occurred after every 50 iterations. The learning process and loss are shown in Fig. 5.

The network takes an input image of size 224×224×3 (height, width, and RGB channels), which is the first layer of the network (*imageInputLayer*). Then, there is a convolutional layer with 64 filters of size 7×7 and a stride of 2 (*convolution2dLayer*).

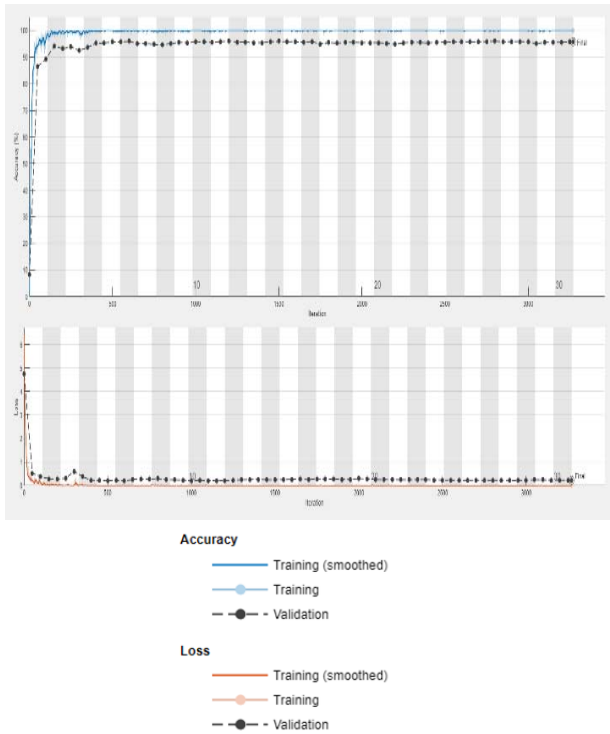

Fig.5. Course of training, validation and loss depending on the iteration.

The output of this layer is then passed through a rectified linear unit (ReLU) activation function (*reluLayer*). This is followed by a max pooling layer of size 3×3 with a stride of 2 (*maxPooling2dLayer*). After that a cross-channel normalization layer (*crossChannel-NormalizationLayer*) helps normalize the responses across feature maps. This layer is followed by another convolutional layer with 64 filters of size 1×1 (*convolution2dLayer*) and another ReLU activation layer. Next layer is a convolutional layer with 192 filters of size 3×3 (*convolution2dLayer*), followed by a ReLU activation layer and another cross-channel normalization layer. The next layers are repeated blocks of layers with different filter sizes and number of filters, followed by concatenation layers (*depthConcatenationLayer*) that merge the outputs of the layers into a single tensor. The final layer is a fully connected layer (*fullyConnectedLayer*) that outputs the classification probabilities for the input image. The network is trained using backpropagation to minimize the classification error between the predicted and actual labels.

The model has multiple branches that allow the network to learn different features at different scales, which can improve its accuracy.

Table 1. Comparison of FOD detection algorithms

Paper	Method	Dataset	Accuracy
[16]	Background subtraction	Own dataset (no information)	96.67%
[17]	YOLOv3	Own dataset (1700 images)	94.5%
[18]	YOLOv3	Own dataset (2000 images)	95.67%
[19]	Random forrest	Own dataset (1800 images)	93.1%
[20]	YOLOv3	FOD-A Dataset (over 14 000 images)	95.2%
Proposed	GoogLeNet	FOD-A Dataset (over 19 000 images)	95.73%

As can be seen in Table 1, the authors of most articles use their own datasets, which contain significantly fewer images. Additionally, these datasets are not publicly available. Only the authors of the datasets [20] tested the neural network on YOLOv3. They achieved an efficiency of 95.2% using 14,260 images from the FOD-A Dataset. More than 19,000 images from the same dataset were used for this article. Moreover, the result obtained is the best of the neural network models compared, which may lead to the conclusion about the correctness of the model selection and its learning. Thus, better results of the neural network model based on GoogLeNet were achieved than in the case of models based on YOLOv3.

Conclusions

The research and experiments conducted showed that it was right to raise the issue related to the threat associated with FOD, which is significant for the aviation industry. As part of the tests, it was possible to develop a neural network model based on the co-evolutionary neural network GoogLeNet. The validation results showed the correctness of object detection and classification in 95.73%. Importantly, the authors used a significantly expanded dataset of more than 19,000 images to properly train the network.

The next stage of the authors' activities will be the adaptation of the neural network model and its optimization for implementation in an embedded system, such as NVIDIA JETSON AGX ORIN, and conducting tests in a real environment, in cooperation with the Poznań-Ławica Airport.

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***Authors**: MSc. Jakub Suder, Poznan University of Technology, Institute of Automatic Control and Robotics, Division of Electronic Systems and Signal Processing, ul. Jana Pawła II 24, 60-965 Poznań, E-mail: jakub.suder@put.poznan.pl, PhD. Tomasz Marciniak, Poznan University of Technology, Institute of Automatic Control and Robotics, Division of Electronic Systems nd Signal Processing, ul. Jana Pawła II 24, 60-965 Poznań, E-mail: tomasz.marciniak@put.poznan.pl*

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