http://dx.doi.org/10.5755/j01.eie ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 28, NO. 3, 2022

Airport Wildlife Hazard Management System - A Sensor Fusion Approach

Damian Dziak[1, *], Dawid Gradolewski[1], Szymon Witkowski[1], Damian Kaniecki[1], Adam Jaworski[1], Michal Skakuj[2], Wlodek J. Kulesza[3]
[1]*Bioseco S. A.,*
Budowlanych St. 68, 80-298 Gdansk, Poland
[2]*Ekoaviation,*
Piecewska St. 30B/16, 80-288 Gdansk, Poland
[3]*Institute of Mathematics and Nature Sciences, Blekinge Institute of Technology,*
371 79 Karlskrona, Sweden
damian.dziak@bioseco.com

***Abstract*—Aviation reports indicate that between 1988 and 2019 there were 292 human deaths and 327 injuries that had been reported from wildlife strikes with airplanes. To minimize these numbers, a new approach to airport Wildlife Hazard Management (WHM) is presented in the following article. The proposed solution is based on the data fusion of thermal and vision streams, which are used to improve the reliability and adaptability of the real-time WHM system. The system is designed to operate under all environmental conditions and provides advance information on the fauna presence on the airport runway.**

The proposed sensor fusion approach was designed and developed using user-driven design methodology. Moreover, the developed system has been validated in real-case scenarios and previously installed at an airport. Performed tests proved detection capabilities during day and night of dog-sized animals up to 300 meters. Moreover, by using machine learning algorithms during daylight, the system was able to classify person-sized objects with over 90 % efficiency up to 300 meters and dog-sized objects up to 200 meters. The general accuracy of the threat level based on the three safety zones was 94 %.

***Index Terms*—User-driven design; Image processing; Thermal sensors; Vision systems.**

I. INTRODUCTION

Wildlife Hazard Management (WHM) is a key component of the maintenance service of every airport [1] [2]. Monitoring bird activity in the vicinity of a runway, as well as detection of mammals' presence in the vast traffic area, are crucial for flight safety. Fauna-related accidents have caused not only damage but also deaths of both humans and animals. Even despite the decrease in flight traffic volume caused by the COVID-19 pandemic, more than 10,000 bird strikes were still observed just in the USA in the past year [3]. Incidents that involved mammals could even reach 10 % of all recorded events [4]. From 1988 to 2019, 292 human deaths and 327 injuries have been reported due to strikes by wildlife with airplanes, around the world [5].

However, fatalities are not the only consequences of interactions between wildlife and airplanes. Between 1988 and 2019, there were 271 civil aircraft destroyed or seriously damaged in total worldwide [5]. The last report shows that annual repair costs in the USA reached more than $200 million [6], and are predicted to reach more than $1.2 billion globally [7]. Therefore, in large and medium airports, Air Traffic Control (ATC) demands a systematic WHM [4].

The results of long-term observations from WHM systems allow identification of hot spots of wildlife activity, which can help to determine and control the effective deterrent and scaring methods. The most widely applied WHM techniques are ornithological observations and radar systems [8], as well as cost-effective vision-based solutions [9], [10]. The latter ones are affordable for small- and medium-sized airports; however, they may have some environmental limitations, e.g., daylight conditions.

One can state that there is a need for developing a more robust vision and AI-based real-time monitoring system for identification, classification, and localization of wildlife activities. Changing environmental and light conditions, a variety of species, and their distinctive movements make the development of such a WHM system a non-trivial task. A thermal imaging-based solution can overcome some of the environmental drawbacks by providing day and night monitoring.

In the proposed solution, thermal and vision camera data fusion is used to improve the reliability and adaptability of the real-time wildlife monitoring system. User-Driven Design (UDD) methodology has been applied to determine the core functionalities and constraints that the system needs to satisfy to provide the marked tailored solutions for each individual medium- and small-sized airport. The unit has been designed to handle the large monitoring area for robust

Manuscript received 12 November, 2021; accepted 16 April, 2022.
This research was supported by the National Centre for Research and Development of Poland under Grant "Carrying out research and development works necessary to develop a new autonomous AIRPORT FAUNA MONITORING SYSTEM (AFMS) reducing the number of collisions between aircraft and birds and mammals" No. POIR.01.01.01-00-0020/19.

operation in a radius of 300 m from the installation spot. The AI-based classification method is used to identify the threat level. System tests in real field installations have verified its capabilities in the detection, localization, and classification of birds and mammals.

II. BACKGROUND AND RELATED WORKS

To design an optimised solution of vision-based WHM, several issues needed to be considered in detail: the original problem, the most recent research in the field, related works, and, of course, the regulations.

A. *Regulations and Problem Origin*

There are civilian [11] and military [12] regulations that are dedicated directly to the WMH. There are also several international annual events organized to update the WHM guidelines [13]. Recent data shows that there were around 50,000 bird strikes annually around the world, but only 5 % of them damaged aircraft structures [14]. However, the problem of mammal strikes has also increased and could even reach 10 % of all strikes worldwide. Nevertheless, compared to bird strikes, terrestrial strikes are several times more damaging to aircraft [4].

There are a number of regulations concerning nature and wildlife protection that aim to minimise the negative impacts of anthropogenic changes. Currently, WHM is regulated by the European Union Aviation Safety Agency (EASA) [1] and the International Civil Aviation Organization (ICAO) [2]. Each country may have local agencies responsible for the implementation of the regulation, e.g., the Polish Civil Aviation Authority [15] or the Swedish Civil Aviation Administration (Luftfartsverket) [16].

The risk of wildlife strike in general could be minimized in two ways, by reducing the presence of wildlife in the airport vicinity or by the introduction of new technologies for the management and monitoring of hazard. Monitoring systems can be used to gather and process long-term observation in a systematic way. Particularly, larger species and species of concern like large and flocking birds (such as many species of gulls, raptors, or geese) and larger terrestrial mammals (such as roe deer or wild boar) must be recorded every time they approach the aerodrome. It is important to determine their location in the predetermined zone. The core monitoring activity is at an altitude of up to 500 ft AGL where most of the wildlife strikes occur.

B. *Methods and Technologies in Use*

There are different methods and technologies used to monitor and deter wildlife on aerodromes that are approved by international regulations [11]. The solutions include detection and classification methods.

1. *Detection methods*

The most popular wildlife monitoring methods are based on GPS and radio-based sensors. In [17], the authors propose the use of GPS and 433 MHz radio transmitters embedded in collars. Their solution is dedicated to monitoring wild lynxes and canines. For the detection of large birds, Kölzsch *et al.* [18] analyse the use of neckbands and backpack GPS. They found that both methods are safe for birds; however, the best location for the sensors depends on the behaviour of the bird. Moreover, they discovered that long-necked animals such as geese are easily able to destroy backpack tags. These methods share the common drawback that the animals must first be captured, which is likely to be stressful for them. Furthermore, they are limited only to animals that can be tagged.

The *non-invasive* radar- and vision-based solutions are used for comprehensive wildlife monitoring. The authors of [19] use the mm-wave frequency band to detect birds at a distance of 25 m from the wind turbine. The most sophisticated radars are capable of detecting birds at a distance of up to 10 km [20] in any weather and light conditions [21], [22]. They are able to estimate the position and velocity of the bird, and even movement [23] of each flying object [24].

To detect terrestrial animals, camera traps are widely used. Those solutions mainly rely on Passive Infrared Sensors (PIR), triggered when the difference in heat between an object and the background occurs [25]. However, with an ambient temperature above 31 $^{\circ}C$, the PIR camera trap is unreliable as the temperature difference between the animal and the background can be too small.

Despite the drawbacks of the PIR solution, Carswell, Rea, Searing, and Hesse [26] use it for long-term observations to estimate the risk of strike. The camera traps collected data between January 2012 and December 2018, which helped to estimate the seasons with the highest activity of coyotes at Prince George International Airport. Gradolewski *et al.* [9], [10] proposed the stereovision-based real-time bird detection system for wind farms and airports. The verification tests proved that the system could detect medium-sized flying birds with a wingspan of about 1.5 m up to a distance of 300 m from the system, with detection efficiency of at least 92 %.

More advanced but also more expensive solutions are thermal imaging-based sensors. Oishi, Oguma, Tamura, Nakamura, and Matsunaga [27] propose a system for automated detection of wild animals using a series of thermal images for detection of moving sika deers. They conclude that the accuracy of their method of approximately 77.3 % is many times greater than the human vision inspection and detection of 29.3 % accuracy.

2. *Identification and classification methods*

Identification of detected animals in the case of radio and GPS tags is straightforward. Each animal is equipped with a unique tag [17], whereas the classification of detected animals in a vision and radar-based solution is a more complex task. In [28], the authors propose an automated mammal classification based on visual images and SSD-Mobile Net based on AI. They achieved 98.7 % detection and classification accuracy.

In [29], a deep learning-based object detection is proposed with the aid of aerial photographs collected by an Unmanned Aerial Vehicle (UAV). Aerial photos of birds in various habitats like lakes or farmland were fed to Faster Region-based Convolutional Neural Network (R-CNN), Region-based Fully Convolutional Network (R-FCN), Single Shot MultiBox Detector (SSD), Retinanet, and You Only Look Once (YOLO) methods. Their performance in terms of computing speed and average precision was tested and the results show that the YOLO model is the fastest while Faster R-CNN is the most accurate.

In [9] and [10], the authors use the background subtraction algorithm to extract moving objects from the video frames and CNN to distinguish bird-like objects from other sky artifacts such as clouds, snow, and rain. The presented test results prove that the system classifies small objects (wingspan bellow 0.7 m) within a range of 100 m with an efficiency of 94 %, medium (wingspan in between 0.7 m and 1.5 m) up to a range of 250 m with an efficiency of 93 %, and large (wingspan above the 1.5 m) up to a 300 m range with detection efficiency of almost 93 %.

III. Problem Statement, Objectives, and Main Contributions

A survey of related works shows that the mutual coexistence of wildlife and technology is the cornerstone of sustainable development of modern air transport. However, the unwanted crossover between the two leads not only to accidents and damage, but also to fatalities for both sides. Therefore, there is an urgent need for the development of WHM systems that operate under all environmental conditions and provide advance information on the presence of fauna on the runway of the airport. The main technical challenges of the design are the demand for high reliability of object detection and identification, along with the wide monitoring area and changeable environmental conditions.

The main objective of this paper is to discover the optimal design of a comprehensive safety system for reliable and cost-effective real-time monitoring of the critical infrastructure in an airport. The system needs to ensure high reliability in detection, identification, and threat classification without compromising purchase, installation, and maintenance costs. The solution should comply with international and local safety and environmental regulations. The general aim of system development is to increase passenger safety and to preserve wildlife. The main desired functionalities are related to three issues: runway monitoring, threat and data management, and communication and interfacing.

The combination of thermal and vision cameras has been applied for the acquisition of target detection data. The sensor fusion approach is used to provide 24/7 monitoring capabilities. The motion detection and machine learning algorithm YOLO v3 are used for object identification and threat classification. The proposed scanning and tracking procedures allow for the ground monitoring of the airport runway within a radius of 300 m from the unit with a detection accuracy of 92 %.

The system has been designed based on User-Driven Design (UDD) methodology and implemented using the rapid prototyping tools of Raspberry PI and Jetson Nano. The system has been validated and tested in the field and verified by experts in environmental security.

IV. System Design

The Wildlife Hazard Management System at Airport (WHMSA) is designed based on the UDD methodology presented in [30] and [31]. According to this approach, at each stage of design and prototyping, airport stakeholders and authorities, such as ornithologists and aviation law experts, must be involved. Moreover, designers, as well as future users such as falconers, airport security and safety staff, pilots, maintenance service workers, and environmental workers, actively participate in the process.

Table I summarises expected functionalities and related constraints together with possible technologies and algorithms meeting the requirements.

TABLE I. DESIRED FUNCTIONALITIES AND RELATED CONSTRAINTS ALONG WITH APPLIED TECHNOLOGIES AND ALGORITHMS.

Functionalities		**Particular Constraints**	**Technologies and Algorithms Used**
General	**Itemized**		
Runway monitoring	Mammal and bird detection	Expected detection range 300 m	Vision, Thermovision, Motion detection, Machine learning, Distributed computing, Sensor fusion
		Detection reliability ≥ 90 %,	
		Real-time (latency ≤ 15 s),	
		Computation rate > 20 FPS,	
		False positive rate < 10 %,	
		Day and night operation	
		Minimal expected height/length/weight 0.3 m/0.5 m/8 kg	
		Humidity ≥ 90 %	
		Background temperature < -25 °C, +35 °C >	
	Daylight object classification (optional)	Small or Big category	
		Mammal/birds or other	
		Reliability ≥ 80 %	
Threat and data management	Threat level classification	On runway (High)/close to runway (Medium)/other part of airport (Low)	Machine learning, Audio, Distributed computing, Sensor fusion
	Information management	Automatic (system)	
		Semi-automatic (system confirmed by human)	
		Manual (Human)	
	Deterrent method	Siren (Frequencies, power)	
		Bang	
		Falcon	
		Suspension of reaction	
Communication and interfacing	Reporting	Automate and periodic reporting (monthly, quarterly, annually), compliant with the ICAO and the EASA	Edge/Chrome/Mozilla/Safari, MySQL, ReactJS, Ethernet, Wi-Fi, IoT
		Manual reporting of eyewitness observations	
	Archiving	Up to two years	
		Photo and video data	
		High level of security	
	Connection	Ping < 100 ms	
		Dropped signal rate < 2 per day	

The system should operate 24/7 in the temperature range between -20 ˚C and 35 ˚C, and with a humidity of up to 90 %.

As the goal of the designed system is to increase safety at airports, the requested detection reliability of all intrusions in a 300 m radius from the system is as high as 90 %. To ensure the time required for the action of the ground control, the warning information should be given in less than 15 seconds. The desired minimal sizes of detected animals are a height of 0.3 m, a width of 0.5 m, and a weight of 8 kg, which corresponds to the size of a medium-sized fox.

Optionally, classification of detected objects as “animals” or “others” is included. Moreover, the system should distinguish between two size categories of animals with a reliability of at least 80 %.

Furthermore, the designed system is expected to support threat level and data management. The system should assess whether the detected animal is on the runway, close to it, or heading away from the runway. This should correspond to the high, medium, and low threat levels, respectively. Based on the assessed threat level, the system must react automatically, e.g., using sirens to deter an animal from approaching the runway, semi-automatically, e.g., suggesting the use of a loud bang or a falcon to deter the animal, or to leave the decision to a human expert.

The system should periodically report the registered detections, along with the possibility of including eyewitness observations. All data including photos and videos would be stored for at least two years. The stored data should be easily available through a secure web application.

V. SYSTEM MODELLING

A block diagram showing the data flow of the decision-making process is presented in Fig. 1. Since the constraint of the desired system was to ensure the day and night operation of WHM, a thermal camera is used 24/7 as the main sensor of the system. However, during the day, the decision-making process is additionally supported by the vision camera providing reliable data for *Object classification*.

To ensure desired detection capabilities, a long-focus lens has been applied to adequately magnify objects in the image plane, which, however, compromises the Field of View (FoV) of the camera. The smaller FoV is compensated by using an increased number of units and by a *Positioning unit* which rotates the cameras towards a particular zone. This makes for a cost-effective solution.

The object detection algorithms applied to both vision and thermal images are congruous and are based on motion detection using *Background removal*. At each position, the cameras acquire N frames, which are averaged and considered as a background. Then, the $(N + 1)$ frame is compared with the background and used to detect moving or new objects in the framed zone. Objects larger than the given threshold are cropped from the image and considered as potential threats, and subjected to further analysis. The detection process is repeated within a given time T until the next camera position.

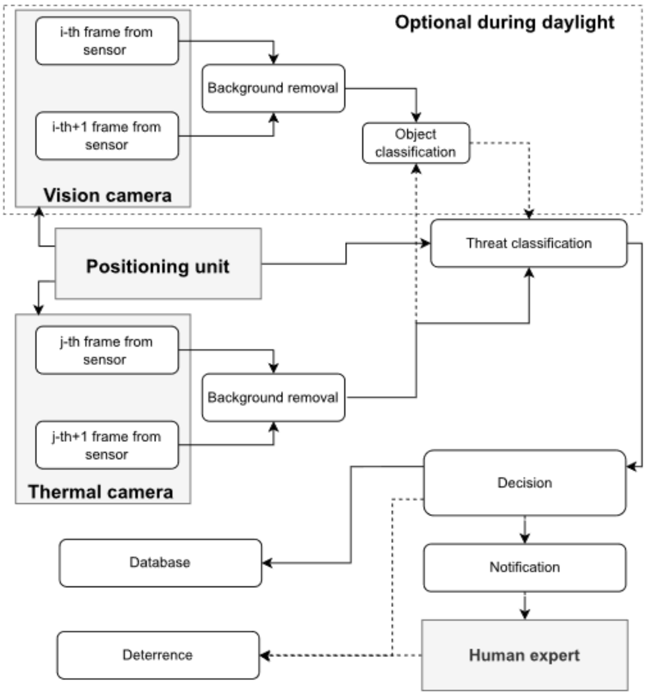


Fig. 1. Block diagram of the airport WHMS.

Based on the angular position of the *Positioning unit* and the position of the detected object in the images, the *Threat classification* algorithm assesses the threat level. There are three defined hazardous zones: on the runway, close to the runway, and other parts of the airport (see Fig. 2). These zones correspond to high, medium, and low threat levels, respectively.

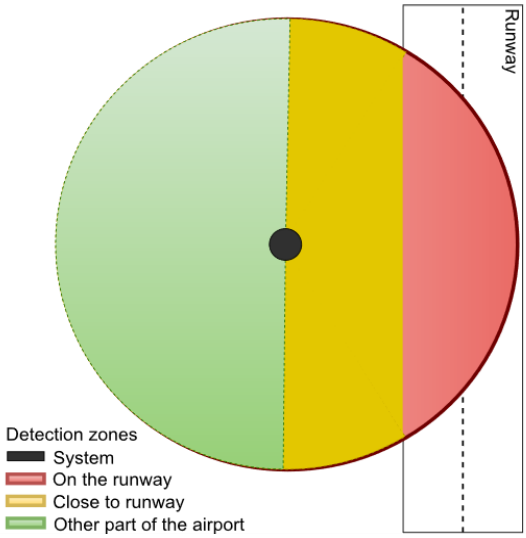


Fig. 2. Block diagram of the Airport WHMS.

During daylight, *Threat classification* is additionally supported by the vision system, which allows object classification. Information from *Threat classification* and optional *Object classification* is applied to the *Decision making* algorithm, which activates the deterrence system and/or sends the notification to the operator. In the case of a low threat level, when an object is detected at a further distance from the runway, the system works autonomously. While for medium threat level, when the object is located in close proximity to the runway, the system sends a notification about possible danger and waits for permission from the *Human expert* for autonomous reaction or inaction, since sometimes it is better to perform no action rather than scare the animals directly towards the plane engine. However, when the object is located directly on the runway, an alert notification is sent and the final decision is made by a human.

VI. PROTOTYPING

The prototype of the system presented in Fig. 3 was installed and tested in a controlled environment and then placed and optimised at an airport in Northern Poland. The modular parts of the system are interconnected using Ethernet supplied with safe voltage power (24 V DC). The two main components of the system, *Data acquisition* and *Data processing*, are described in the following subsections.

Fig. 3. Prototype of the system composed of thermal and vision sensors and positioning unit.

A. Data Acquisition

The selected vision camera is based on a Sony IMX477R sensor that provides the 12 Mpx image stream with a frequency of 30 Frames per Second (FPS).

The camera is equipped with a 12 mm focal length lens providing 29.4 ° × 22.2 ° FoV. The thermal camera applies an uncooled microbolometer sensor streaming images with a resolution of 384 px × 288 px at a frequency of 30 FPS. The camera is equipped with a 35 mm focal length lens providing 10.5 ° × 7.9 ° FoV. Both cameras are installed on the AXIS T99A11 Positioning Unit [32] enabling the desired coverage of 360 ° of the observation area around the installation spot with a speed of 0.67 rad/s and a ground-to-sky view of 0.75 rad/s with a speed of 0.33 rad/s.

During the scanning of the monitoring area, due to differences in FoV, the positioning unit rotates with an angle step 10.3 ° so that the frames of the neighbouring thermal camera overlap by 0.1 °. The system scans one spot for a T = 0.5 s and provides 15 images from each camera and then moves to the next spot. Therefore, to cover 360 ° of the monitoring area, 35 horizontal scans are required. To cover required 23 ° in the vertical direction, there are three vertical levels of ground-to-sky observation rows (see Fig. 4). Therefore, the system scans the entire runway area in a time of 52 s.

The data from the vision and thermal cameras are streamed using the safe Ethernet connection and processed by the on-the-board computational unit quipped with an ARM v8.2 processor with 8 GB RAM and 384 CUDA cores and 48 Tensor cores for the AI-based object classification. The SSD hard drive of 2 TB is used as a storage box for the database.

The panoramic views of both cameras, as well as an example of captured and cropped frames, are shown in Fig. 4. One can notice differences in the brightness of the rows but also between neighbour frames of vision and thermal images forming a panorama photo. For a vision camera, they are especially visible between the second and third rows, and they result from differences in the light intensity during recording.

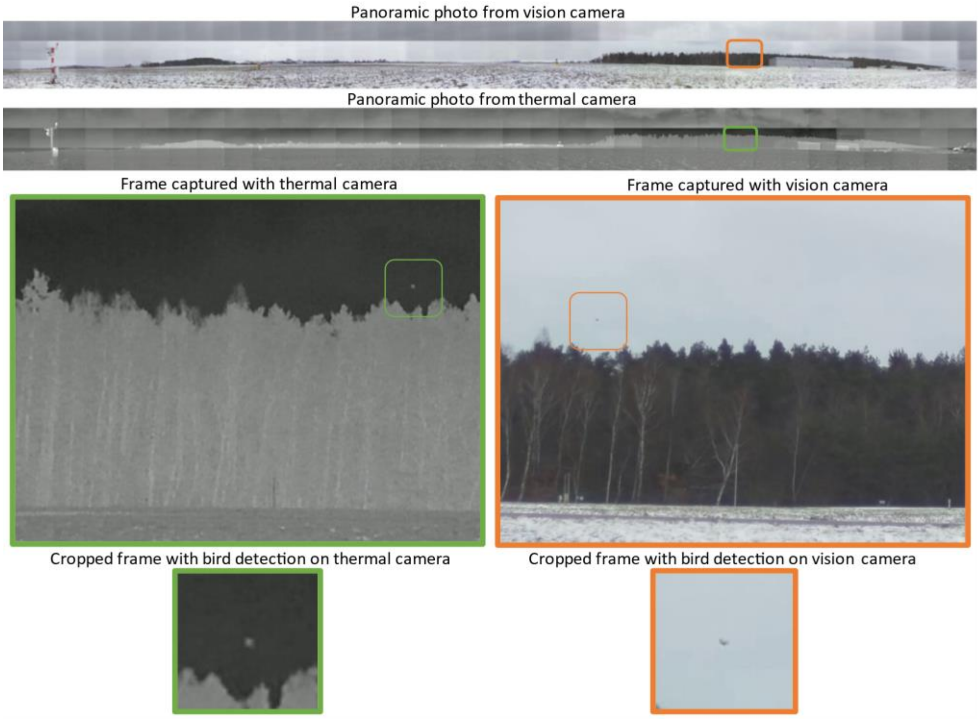


Fig. 4. Example of bird detection and scanning procedure in both vision and thermal images.

In the case of the thermal camera, differences in brightness are caused by the built-in camera automatic scaling to the average background temperature.

B. *Data Processing*

Since thermal and vision cameras are characterised by different FoVs and resolutions, it is necessary to fit the cropped images with detected objects. The vision camera, which is installed above the thermal camera, has higher resolution and wider FoV the initially cropped images must be downsampled. The fitting of the images is made manually once, using the *Transformation by handle* tool in the GIMP software, as illustrated in Fig. 5.

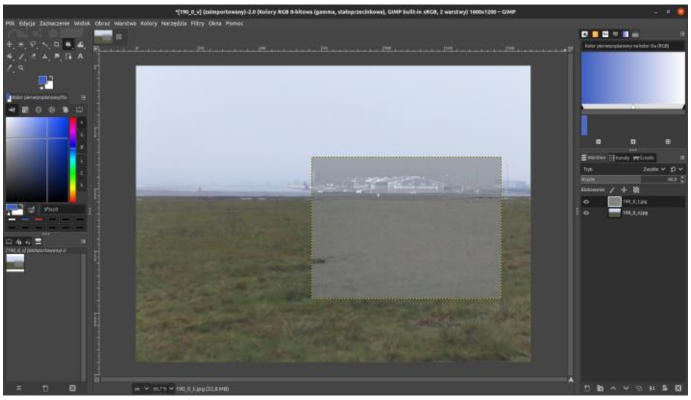


Fig. 5. An illustration of images from thermal and vision cameras from the same shot spot.

The resulting transformation matrix is later used for automatic fitting of both images. In Fig. 6, the fusion of the combined vision and thermal sensors is presented.

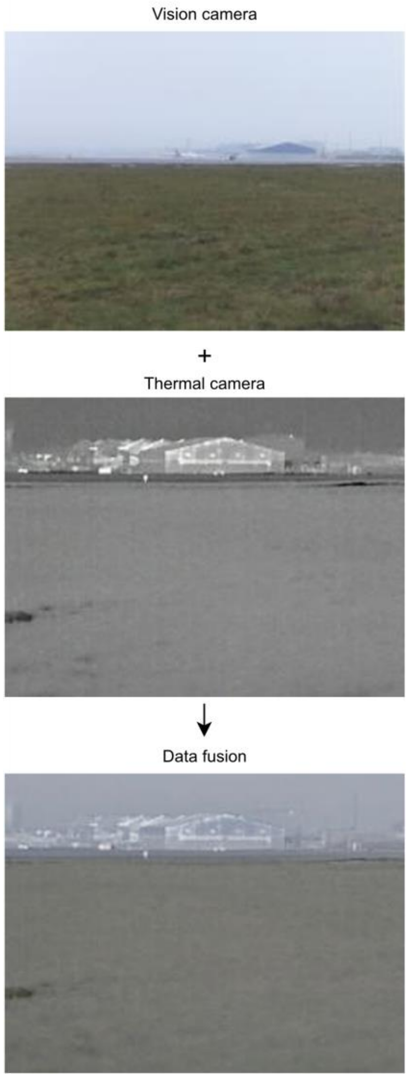


Fig. 6. An example of input and output images from fitting FoV process of both thermal and vision cameras.

Detailed processing flow applied to both thermal and vision images is illustrated in Fig. 7. The detection algorithms of both cameras are based on motion detection using a Gaussian Mixture-based Background/Foreground Segmentation Algorithm introduced in [33] and adopted to the security systems in [34]. Vision images are used here for object classification to minimize false actions during the day.

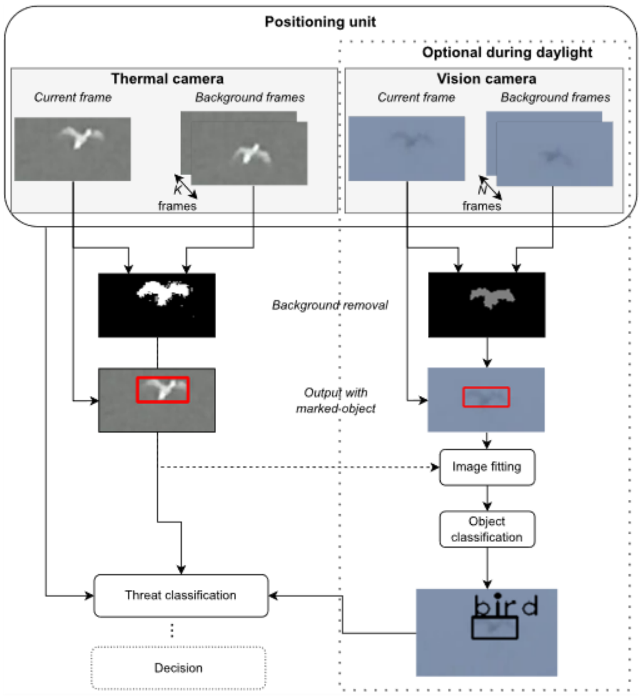


Fig. 7. Data processing flow of the system.

In the advance daylight scenario, the information as from the basic night scenario is supplemented by the data from the vision camera via the *Object classification* algorithm. There are three implemented and evaluated classifiers: Yolo-v3 [35], GoogLeNet [36], and Bioseco BPS for birds [9]. The classification of the detected objects makes the *Threat classification* more precise and reliable.

The *Threat classification* assesses the threat level with respect to zones defined by the airport authorities. If the *Object classification* identifies a mammal or bird in the monitoring area, then the threat level increases. Using the LTE connection, the notification about threat level is sent to the *Human expert*. At the same time, the event data composed of the raw images and video, as well as miniatures and object position, are stored in the database for possible scrutiny.

VII. VALIDATION AND VERIFICATION

Due to the airport safety policy, the validation of the proposed solution was performed in an environment that simulates the airport runway. The tests included three case scenarios.

In the first validation scenario, we determine the efficiency of the thermal system for detection of a human or small and medium-sized mammal in dark conditions. The man of 120 kg weight and 189 cm tall and a dog of 50 cm long and 30 cm tall with a weight of 8 kg were walking at given distances, starting from 25 m from the sensor up to 350 m with the 25 m gradient. The system detection efficiencies has been manually estimated based on the observed numbers of true and false notifications. The thermal vision system detection rate, calculated as a ratio of the number of frames with true detection to the total number of frames when the objects were in the observation area, is presented in Fig. 8.

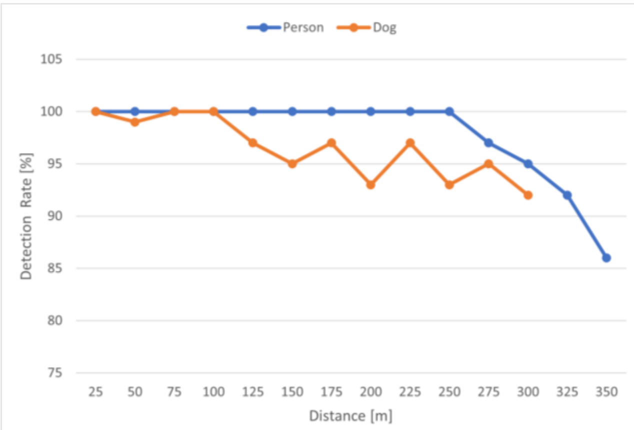


Fig. 8. Detection rate for person and dog of the thermal vision system with respect to distance.

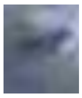
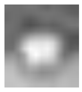
The results show that the system can detect small animals up to 300 m with a rate of 92 % and humans up to 325 m with a rate of 92 %, which meets the desired requirements (see Table I). There were also a small number of non-crucial singular false positive detections, which however did not exceed 7 % of all frames.

The *Threat classification* algorithm in dark conditions was verified for three safety zones: the first at a distance of 1 m and 100 m, the second at a distance of 101 m and 200 m, and the third at a distance of 201 m and 300 m from the reference point assigned to the installation spot. Based on the angular position of the *Positioning unit* and the location of the detected object in the images, the threat level is classified. The average accuracy of the *Threat classification* is 94 % and varied from 88 % in the most remote zone to 100 % in the closest zone.

The second scenario evaluated the system efficiency under good visibility conditions. Examples of cropped frames with detected objects at different distances from the system are presented in Table II. As one can see, the small dog could be recognized in the thermal and vision images even at 200 m. At 300 m, the images are blurred, and the number of pixels is too small to classify the object. However, the presence of an object could still be noticed. The human silhouette is well recognisable in both thermal and vision images up to 300 m.

The efficiency of *Object classification* applied for a human and a dog is presented in two columns of Table II. YOLO-v3 [35] correctly classifies the human with an efficiency of 90 % up to 200 m, but it totally fails in the recognition of the dog. The GoogLeNet [37] meets the desired requirements in recognition of the human within the whole monitoring area. However, the system is only capable of recognizing the dog with acceptable efficiency up to a distance of 100 m.

TABLE II. THE THERMAL AND VISION IMAGES OF THE RECORDED OBJECTS DETERMINED BY THE DETECTION ALGORITHM.

Distance [m]	Person		Dog	
	Vision	Thermo	Vision	Thermo
50				
100				
150				
200				
250				
300				

The third scenario verifies the performance of the system in situ. The system was placed near the airport runway, optimized, and tested for 39 days between December 2021 and January 2022. The bird detection efficiency of the proposed solution was verified using the Bioseco Bird Protection System (BPS) [9], [10] as a reference. During the test, there were no mammals observations reported by the system or by airport staff. However, in total, 61 bird observations were reported by the BPS system. Each observation was also detected by the tested system. The object classification efficiency of the three algorithms tested: YOLO-v3 [35], GoogLeNet [37] classifiers, and the

Bioseco BPS method [9] are presented in Table III.

TABLE III. THE OBJECT CLASSIFICATION ACCURACY OF THE SYSTEM CALCULATED FOR YOLO-v3 [35] AND GoogLeNet [37] CLASSIFIERS IN THE CASE OF MAMMALS AND BIOSECO BPS NEURAL NETWORK [9] IN A CASE OF BIRDS.

Distance [m]	**Classifier**	**Classification accuracy* [%]**		
		Person	**Dog**	**Bird**
50	YOLO-v3	100	0	70
	GoogLeNet	100	94	100
	Bioseco BPS	N.A.	N.A.	100
100	YOLO-v3	100	0	0
	GoogLeNet	100	83	92
	Bioseco BPS	N.A.	N.A.	100
150	YOLO-v3	98	0	0
	GoogLeNet	100	72	85
	Bioseco BPS	N.A.	N.A.	100
200	YOLO-v3	90	0	0
	GoogLeNet	100	55	68
	Bioseco BPS	N.A.	N.A.	100
250	YOLO-v3	46	0	0
	GoogLeNet	96	0	43
	Bioseco BPS	N.A.	N.A.	100
300	YOLO-v3	41	0	0
	Google Cloud	92	0	25
	Bioseco BPS	N.A.	N.A.	100

**Note: Human/animal related classes are considered as correct.*

Yolo-v3 fails to recognize birds, whereas GoogLeNet can detect birds with the desired efficiency in a range of up to 150 m. However, the Bioseco BPS classifier performed with a 100 % efficiency in a range of up to 300 m.

VIII. CONCLUSIONS

The tests confirm that the presented airport security solution performs the functionalities required by the Wildlife Hazard Management within the desired constraints. The applied User-Driven Design methodology provided a market-tailored solution affordable for medium and small size airports.

By combining thermal and vision images, the system ensures risk mitigation at airports during the day and at night.

The system has been designed, modelled, simulated, prototyped, and then validated. The prototype was installed and validated in an operational environment and verified at the medium-sized airport in Northern Poland.

The validation tests prove that the system attains a 92 % detection efficiency of small animals, like a dog at a distance of up to 300 m and a 92 % efficiency of large objects like humans at a distance of up to 325 m.

During daylight conditions and by applying state-of-the-art GoogLeNet cloud, the system classifies the detected large objects as human with an efficiency of 92 % at 300 m. Small objects like a dog are classified up to 200 m with an efficiency of at least 55 %. By means of the Bioseco BPS classifier, the system identifies birds at a distance of up to 300 m with 100 % accuracy.

The accuracy of threat level classification based on the three safety zones varies from 88 % in the furthest low threat zone up to 100 % in the closest dangerous zone.

The future development solution is to interconnect a network of sensors that covers the entire runway. Moreover, it is planned to test the latest machine learning classifiers such as YOLO-v4, YOLO-v5, and Haar cascade. The authors are going to adapt a Bioseco CNN classifier for thermal images allowing recognition of small and medium size mammals and birds.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] EASA, Certification Memorandum, European Union Aviation Safety Agency, Tech. Rep. 01, Mar. 2019. [Online]. Available: https://www.easa.europa.eu/downloads/128987/en

[2] ICAO provisions for wildlife strikes hazard reduction in aerodromes, Uniting Aviation, May 2019. [Online]. Available: https://unitingaviation.com/news/safety/icao-provisions-for-wildlife-strikes

[3] FAA Wildlife Strike Database. [Online]. Available: https://wildlife.faa.gov/home

[4] S. Ball, A. Caravaggi, and F. Butler, "Runway roadkill: A global review of mammal strikes with aircraft", *Mammal Review*, vol. 51, no. 3, pp. 420–435, 2021. DOI: 10.1111/mam.12241.

[5] Frequently Asked Questions and Answers, Federal Aviation Administration, Dec. 2021. [Online]. Available: https://www.faa.gov/faq

[6] N. S. Sodhi, "Perspectives in ornithology: Competition in the air: Birds versus aircraft", *The Auk*, vol. 119, no. 3, pp. 587–595, 2002. DOI: 10.1093/auk/119.3.587.

[7] J. R. Allan and A. P. Orosz, "The costs of birdstrikes to commercial aviation", 2001 Bird Strike Committee - USA/Canada, Third Joint Annual Meeting, Calgary, AB, Aug. 2001. [Online]. Available: https://digitalcommons.unl.edu/birdstrike2001/2

[8] P. Plonczkier and I. C. Simms, "Radar monitoring of migrating pink-footed geese: Behavioural responses to offshore wind farm development", *Journal of Applied Ecology*, vol. 49, no. 5, pp. 1187–1194, 2012. DOI: 10.1111/j.1365-2664.2012.02181.x.

[9] D. Gradolewski *et al.*, "Comprehensive bird preservation at wind farms", *Sensors*, vol. 21, no. 1, p. 267, 2021. DOI: 10.3390/s21010267.

[10] D. Gradolewski, D. Dziak, D. Kaniecki, A. Jaworski, M. Skakuj, and W. J. Kulesza, "A runway safety system based on vertically oriented stereovision", *Sensors*, vol. 21, no. 4, p. 1464, 2021. DOI: 10.3390/s21041464.

[11] *Airport Services Manual*, International Civil Aviation Organization (ICAO), 2020.

[12] "Wildlife strike prevention", NATO, 2013.

[13] Y. Wang, "Recent development of ICAO on wildlife strike hazard reduction", in *Proc. of the World Birdstrike Association Conference*, 2018, pp. 19–21.

[14] I. C. Metz, J. Ellerbroek, T. Mühlhausen, D. Kügler, and J. M. Hoekstra, "The bird strike challenge", *Aerospace*, vol. 7, no. 3, p. 26, 2020. DOI: 10.3390/aerospace7030026.

[15] Civil Aviation Authority. [Online]. Available: https://ulc.gov.pl/en

[16] "Air traffic control and associated services", LFV. [Online]. Available: https://lfv.se/en

[17] R. Zviedris, A. Elsts, G. Strazdins, A. Mednis, and L. Selavo, "Lynxnet: Wild animal monitoring using sensor networks", in *Real-World Wireless Sensor Networks. REALWSN 2010. Lecture Notes in Computer Science*, vol. 6511. Springer, Berlin, Heidelberg, 2010, pp. 170–173. DOI: 10.1007/978-3-642-17520-6_18.

[18] A. Kölzsch *et al.*, "Neckband or backpack? Differences in tag design and their effects on GPS/accelerometer tracking results in large waterbirds", *Animal Biotelemetry*, vol. 4, art. no. 13, 2016. DOI: 10.1186/s40317-016-0104-9.

[19] J. Moll *et al.*, "Radar-based detection of birds at wind turbine installations: Results from a fieldstudy", in *Proc. of 2020 23rd International Microwave and Radar Conference (MIKON)*, 2020, pp. 285–288. DOI: 10.23919/MIKON48703.2020.9253826.

[20] C. Nilsson *et al.*, "Field validation of radar systems for monitoring bird migration", *Journal of Applied Ecology*, vol. 55, no. 6, pp. 2552–2564, 2018. DOI: 10.1111/1365-2664.13174.

[21] Bird Radar Schiphol Airport, Robin Radar Technology Systems. [Online]. Available: https://www.robinradar.com/full-bird-radar-coverage-at-schiphol-airport

[22] Bird Control Radar Systems, DeTect. [Online]. Available: https://detect-inc.com/bird-control-radar-systems/

[23] H. van Gasteren *et al.*, "Aeroecology meets aviation safety: Early warning systems in Europe and the Middle East prevent collisions between birds and aircraft", *Ecography*, vol. 42, no. 5, pp. 899–911, 2019. DOI: 10.1111/ecog.04125.

[24] A. C. Phillips *et al.*, "Efficacy of avian radar systems for tracking birds on the airfield of a large international airport", *Wildlife Society Bulletin*, vol. 42, no. 3, pp. 467–477, 2018. DOI: 10.1002/wsb.910.

[25] F. Rovero, F. Zimmermann, D. Berzi, and P. Meek, ""Which camera trap type and how many do I need?" A review of camera features and study designs for a range of wildlife research applications", *Hystrix*, vol. 24, no. 2, pp. 148–156, 2013. DOI: 10.4404/hystrix-24.2-8789.

[26] B. M. Carswell, R. V. Rea, G. F. Searing, and G. Hesse, "Towards building a species specific risk model for mammal-aircraft strikes", *Journal of Airport Management*, vol. 15, no. 3, pp. 288–303, 2021.

[27] Y. Oishi, H. Oguma, A. Tamura, R. Nakamura, and T. Matsunaga, "Animal detection using thermal images and its required observation conditions", *Remote Sensing*, vol. 10, no. 7, p. 1050, 2018. DOI: 10.3390/rs10071050.

[28] E. M. T. A. Alsaadi and N. K. El. Abbadi, "An automated mammals detection based on SSD-mobile net", *Journal of Physics: Conference Series*, vol. 1879, no. 2, p. 022086, May 2021. DOI: 10.1088/1742-6596/1879/2/022086.

[29] S.-J. Hong, Y. Han, S.-Y. Kim, A.-Y. Lee, and G. Kim, "Application of deep-learning methods to bird detection using unmanned aerial vehicle imagery", *Sensors*, vol. 19, no. 7, p. 1651, 2019. DOI: 10.3390/s19071651.

[30] D. Dziak, B. Jachimczyk, and W. J. Kulesza, "IoT-based information system for healthcare application: Design methodology approach", *Applied Sciences*, vol. 7, no. 6, p. 596, 2017. DOI: 10.3390/app7060596.

[31] D. Dziak, "Detection and classification multi-sensor systems: Implementation of IoT and systematic design approaches", Ph.D. thesis, Blekinge Institute of Technology, Faculty of Engineering, Department of Mathematics and Natural Sciences, 2020.

[32] AXIS T99A11 Positioning Unit 24 V AC/DC, Documentation. [Online]. Available: https://www.axis.com/products/axis-t99a11-positioning-unit-24-v-acdc/support

[33] P. KaewTraKulPong and R. Bowden, "An improved adaptive background mixture model for real-time tracking with shadow detection", in *Video-Based Surveillance Systems*. Springer, Boston, MA, 2002, pp. 135–144. DOI: 10.1007/978-1-4615-0913-4_11.

[34] D. Gradolewski *et al.*, "A distributed computing real-time safety system of collaborative robot", *Elektronika ir Elektrotechnika*, vol. 26, no. 2, pp. 4–14, 2020. DOI: 10.5755/j01.eie.26.2.25757.

[35] A. Farhadi and J. Redmon, "Yolov3: An incremental improvement", 2018. arXiv: 1804.02767.

[36] R. Alake, "DeepLearning: GoogLeNet explained", *Towards Data Science*, Dec. 23, 2020. [Online]. Available: https://towardsdatascience.com/deep-learning-googlenet-explained-de8861c82765.

[37] E. Bisong, "Google autoML: Cloud vision", in *Building Machine Learning and Deep Learning Models on Google Cloud Platform*. Apress, Berkeley, CA, 2019, pp. 581–598. DOI: 10.1007/978-1-4842-4470-8_42.