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DEEP LEARNING APPROACH ON SHARK ATTACK RISK ASSESSMENT USING REAL-TIME AUTONOMOUS SURVEILLANCE SYSTEMS

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The paper outlines a prevention and control approach for coastline accidents, aiming to ensure a high level of safety through real-time autonomous surveillance. The risk analysis considerate a wide range of water sport activities in specific conditions: strong or undertow currents, crush against rocks, clash between surfers, jellyfish strings and shark attacks. Considering the autonomous surveillance is integrated into a wide system over an expanded area, it can provide a solid information database.

Unmanned Aircraft Systems design and hardware integration are taken into account for image acquisition and processing, so that the deep learning design includes detection robustness image enhancement.

Keywords: deep learning, structured predictive analysis, pattern recognition, risk assessment, surveillance system, convolutional neural networks.

1. Introduction

The paper presents research concerning the development of real-time autonomous surveillance system using unmanned aerial vehicles equipped with high-resolution specialized cameras able to capture images at increased distance.

The risk represented by the sharks on the shore proximity is analyzed by recent studies and a wide variety of possible solutions are investigated. Important data about the operating situations, potential impacts, testing status, environmental conditions, commercial readiness and costs of integration are presented in one comparative research for different detection and deterrent systems used to offer physical protection and/or shark detection [15]. The fixed wing and helicopter drones solution is presented as advantage for large areas and the most commonly used alternatives over long stretches of coastline. In autonomous surveillance systems that are using artificial intelligence methods for computer vision object

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recognition the most used algorithms are derived from the machine learning research fields and its subdomain deep learning [17][19]. Deep learning algorithms used in mobile, real-time applications, require small networks for integration. One network candidate tested for shark detection is the YOLO due to reduced size, reduced inference time and good level of accuracy [16]. A more robust automatic object detection and segmentation network, due to its auto-encoding structure, is the Unet network [11][13], with its the reduced size Mobile Unet [17] and deep-network Unet++ developed by Arizona State University.

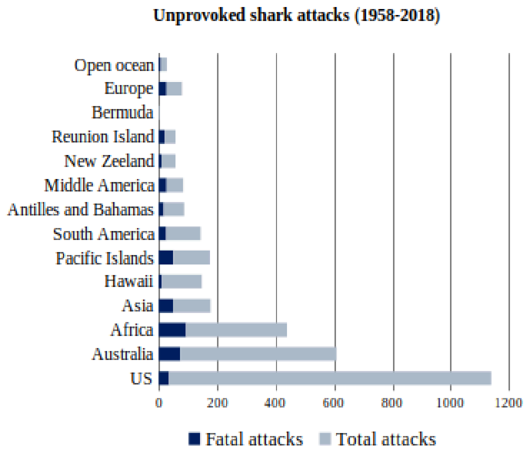
This research approach, based on a reduced size Unet, underlines an integrated approach for event analysis that considers monitoring sharks, swimmers and surfers in hazardous situations, and includes one additional layer of hazard detection based on relative distance between shark and surfers or swimmers. The compliance with regulatory framework aims to provide a safe operation of the drones used for coastal area monitoring.

2. Risk assessment

Human observers and motorized marine vessels were considered a valuable support for shark identification. However, the observers do not provide full area coverage, do not give images from deep seas and are not able to remove glare effects, etc.

Shark attack statistics show 130 accidents in 2018, from which 66 were unprovoked attacks [1]. The figures are lower than the last 5 year average, being reduced to almost half in Florida. Nevertheless, this mirrors a large reduction in safety margins. Water recreational activities have become a contributing factor for shark attacks; the rationales for attacks are in most cased either the curiosity to explore unusual circumstances or mistaking the swimmer to a prey [6].

The following table shows the number of unprovoked shark attacks for the 1958-2018 period.



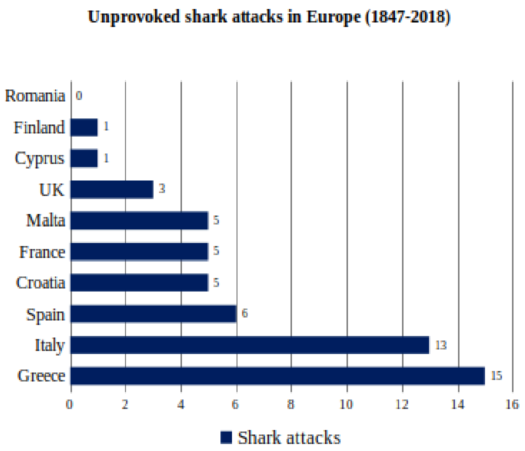


Fig. 1. Confirmed unprovoked shark attacks in world and Europe [5]

The Government of Western Australia [7], shows that incidents usually occur offshore, more than 30 NM from the coast and in waters deeper than 5 meters. In Europe, over a period of 171 years, 54 incidents have been recorded; most of them in Greece and Italy, but none in Romania (see fig. 1). The figure indicates low numbers of unprovoked shark attack, statistics that from the probabilistic risk assessment point of view are at an acceptable level; and usually just require safety mitigation.

The highest probability calculated for shark attack incidents are related to board sports activities (53% of the cases), which are attracting sharks due to splashing and paddling [1]. In this regard, in 90% of the cases, men are more likely to get attacked by sharks [2].

Table 1

Assessment of victim activity at time of shark attack [1]

Activity	**PROBABILITY**
Surfing	$5.3 \cdot 10^{-1}$
Swimming	$3 \cdot 10^{-1}$
Snorkeling	$6 \cdot 10^{-2}$
Scuba	$5 \cdot 10^{-2}$
Other shallow water activities	$3 \cdot 10^{-2}$

The following risk assessment for the analyzed events will be achieved considering the hazards described and their known consequence.

Table 2

Shark attack risk assessment

Risk	**SHARK ATTACK**
Probability	Frequent
Severity	Hazardous
Index	5B
Tolerability	Safety risk mitigation needed

Despite the fact that swimming is the the most widespread water activity, surfing is reckoned as the highest risk activity. Other risks will be analyzed further, considering the fact that the authors' proposal for a autonomous surveillance system takes into account a wide range of hazards. Currents in the shore area can be an aggravating factor for drowning.

Table 3

Currents in the shore area risk assessment

Risk	**CURRENTS IN THE SHORE AREA**
Probability	Remote
Severity	Major
Index	3C
Tolerability	Might require safety management decision

Surely, lifeguards are usually able to manage these kind of situations, but an autonomous monitoring system will provided optimized results regarding the hazard identification and providing a proactive method which warns if (for example), the swimmer has passed the buoy.

A major hazard to bathers is represented by rip currents which are the main cause of drowning on many areas around the world [8]. For that, the system proposed by the authors will use high resolution cameras, able to provide real time images useful for wave indicators, water and beach conditions analysis.

Short & Brander [8] show that risks of being crushed by rocks, coral reefs and other structures (grayness, seawalls) is in direct connection with the actual (or prevalent) wind intensity, speed and direction and the characteristics of the waves and tide (see tables 4, 5, 6).

Table 4

Swimmers crushed by the rocks risk assessment

Risk	SWIMMERS CRUSHED BY THE ROCKS
Probability	Remote
Severity	Major
Index	3C
Tolerability	Might require safety management decision

In the case of a clash between surfers, the use of emergency procedures is imperative. The deep learning architecture defining the author's study is developed detection of different hazards and is able to correlate the events and eliminate possible image overlap, this way minimizing the risk of erroneous decision making. Control measures should be taken for collision risk or equipment failure elimination while surfing. For providing a safe distance between the surfers, acoustic alerts provided by a monitoring system and are imperative as corrective and preventive actions.

Table 5

Swimmers crushed by the rocks risk assessment

Risk	CLASH BETWEEN SURFERS
Probability	Remote
Severity	Minor
Index	3D
Tolerability	Acceptable based on safety risk mitigation

Swimmers could come across different types of jellyfish, either poisonous or with long tentacles which could provoke different types of strings. Tingling or numbness are a usual effects of jellyfish strung, and although the probability for this risk is very low, the severity analysis shows results to be taken into account (major consequences can be reflected in the swimmers inability to continue performing in the water).

Table 6

Swimmers crushed by the rocks risk assessment

Risk	**JELLYFISH**
Probability	Improbable
Severity	Major
Index	2C
Tolerability	Acceptable

If the events considered are identified, then the sum of their probabilities is:

$$p_1 + \ldots + p_n = 1, \quad (1)$$

where p_i , $i = \overline{1, n}$ represents the probability of the event.

In the probabilistic hypothesis, for the events identified above, the cumulative probability for only some of the events can be calculated as follows:

$$p_i = p_i + \ldots + p_n \quad (2)$$

3. Development of a Logistic Surveillance System. Actual Challenges

The operation of Unmanned Aircraft Systems (UAS) in the coastal area implies compliance with national and international regulations. Nowadays, EASA's concerns are increasingly focused on establishing a single regulatory framework capable of providing solutions for the safe operation of these devices, as well as a solid basis for operational development. In accordance with regulation no. 216/2008, but also with the amendment proposals NPA 2017-05, EASA aims to reduce the risk of collision with other in-flight devices, but also with other persons or equipment on the ground.

The creation of an European level working group – JARUS, and the definition of common points of interest in the operation of UAS's, even in the form of NPA's, offer the possibility of operating them in more areas. The Class C3, subcategory A3 UAS's, according to JARUS-OPS/B, are best suited to the intended purpose, i.e. coast guard aerial surveillance.

In order to perform operations in the coastal area, it is necessary to comply with minimum requirements such as:

- Developing a Specific Operational Risk Assessment (SORA) [3].

- Establishment of a patrol coordination center on an extended distance, up to the UAS performance limit-for the category "certified" operating [4];

- Ensuring an adequate/acceptable level of safety through operating and maintenance conditions;

- Endowment with a command and control system (without automatic control module), with lost link management, (ADS-B) transponder, GPS, install geofencing and remote identification;
- Ensuring a safety risk management and a safety management system.

These means are needed to carry out specific surveillance activities in the coastal area, often populated with swimmers and surfers. Remote piloting also involves the help of observers, which can play the role of lifeguards in swimming areas. The existence of a high resolution camera, a sound alert system and/or a UAS positioning beacon allow for better management of the specific activity.

It is important that these UAS's are integrated into a wider system over an expanded area, providing an overview able to identify hazards in time, and also provide information capable of creating a solid database. Each of these elements plays a key role in surveillance. The high resolution cameras offer images for an extended surface, from a height of approx. 20 m, giving the possibility of a detailed analysis of the marine life that poses a potential hazard to the surrounding people. The air operator is assisted by a marine life detection system, based on "ground" footprint recognition. Image clarity is essential for accurate data evaluation. The factors determining the accuracy of the results are determined by:

- The height at which the flight is performed. In this respect, the recommendation to use an ADS-B to maintain the flight at a controlled height is essential. This way, the dependence of image clarity on the height and the angle the camera makes with the average sea level is determined with better accuracy.
- Water clarity is another factor, taking into account that fish and other aquatic animals do not always swim on the surface, but at different depths;
- The size and color of marine creatures in contrast with water is related to camera characteristics and the fly level;
- The height of the waves, the angle of lightning and the flight direction. In ridge waves a diminishing of the system's ability to properly distinguish the object is noticed [9];
- Marine fauna or rocky shores also make the data processing unclear;
- The number of targets per unit area [10];
- The image stabilizer and the number of frames per second. A catalyst factor in this respect is the wind (through its transversal component towards the flight direction and its intensity) and the nature of the raft;
- The architecture of the image processing system. In this regard, it is important that the database is as large as possible, well defined with regard to the sought-after items: shark, dolphin, jellyfish, surfer, swimmer, canoe and others;

A sound alert system should alert the swimmers, surfers or lifeguards of a potential danger so that they can take preventive actions.

4. UAS Design and Hardware Integration

The hardware requirements for UAS integration are based on a hexacopter drone with Gimbal stabilized camera. All the images are acquired by the UHD camera and processed by an embedded onboard Graphical Processing Unit (GPU) (fig. 2). At 30fps framerate and UHD frame resolution (3840x2160), the required bandwidth is about 6Gbps which is acceptable for a four lane MIPI interface yielding a maximum 10Gbps per link. For Jetson TX2 the processing performance is 1.33 Tera Floating Point Operations per second (TFLOPs) giving the demanded computing power for our application requirements (specified in the deep learning CNN developed architecture paragraph) with the real-time Jetson OS.

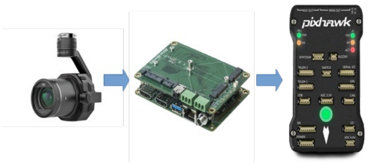


Fig. 2. Image acquisition, processing and signaling hardware equipment

The acquired image in order to be feed to the deep learning model has to be preprocessed manually for target selection and classification. The main target classes used for learning are sharks, surfers and swimmers. Each defined object is enclosed within a rectangle box and a number is attached to the image in order to be classified (fig. 3).

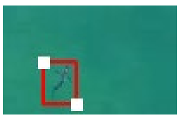


Fig. 3. Defined objects for analysis

Due to conditions regarding image clarity, exposure, camera angle, view and light intensity are important for the quality of detection. The next step of the deep learning design includes for detection robustness image enhancement, the illumination intensity variation and image translation [12] (fig. 4, 5)

Fig. 4. Detection robustness image enhancement

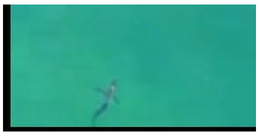


Fig. 5. Image translation enhancement

In the following picture one can see the available classes used to train the deep learning model (i.e. shark, swimmer and surfer) (fig. 6).

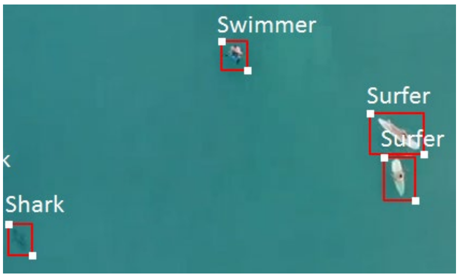


Fig. 6. Classes used for deep learning model

The processing software is developed under open source deep learning software with a Convolutional Neural Network (CNN) architecture. For the CNN architecture, the Unet type proved good performances [13]. The developed architecture can be seen in the figure 7.

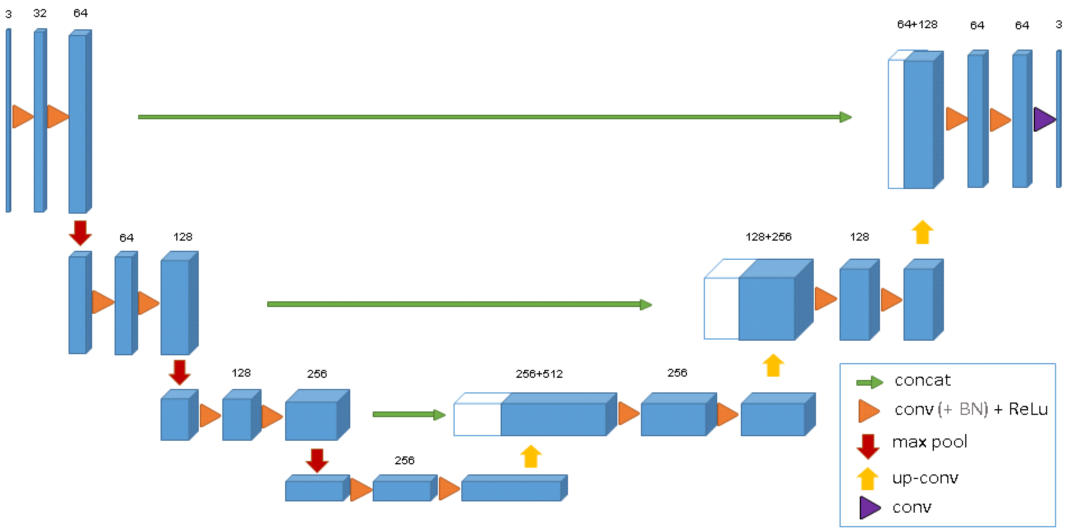


Fig. 7. CNN architecture [11]

The reduced size Small Unet architecture, designed to process UHD2 images, containing only 2M parameters , is under a half of 4.6M parameter of the Mobile Unet [18].

Table 7

Small UNET Network Compared with other Neworks [18]

	FCN	SegNet	U-net	PTIP	Mobile-Unet	**Small Unet**
Parameters (M)	18.6	29.4	31.1	7.15	4.6	2
FLOPs (M)	20.11	30.85	35.35	8.34	0.85	7.8

The deep learning CNN architecture developed for shark, surfer and swimmer detection has 23 2D convolutional layers (Table 8) for feature attributes (edges) detection, 5 Maxpooling layers to correlate the attributes with the targeted feature and 5 concatenate layer to spatially 2D localize the formed feature. The processing requirements for developed architecture is under 10 MFLOPs which gives real-time performance on Jetson TX2 and fully camera frame-rate response.

Table 8

Small UNET Network Architecture Convolutional Layers Details

Layers	**2xC1**	**2xC2**	**2xC3**	**2xC4**	**2xC5**	**2xC6**	**2xC7**	**2xC8**	**2xC9**	**2xC10**	**2xC11**	**1xC12**
No. of 3x3	2^3	2^4	2^5	2^6	2^7	2^8	2^7	2^6	2^5	2^4	2^3	0
No. of 1x1	0	0	0	0	0	0	0	0	0	0	0	2^0

After all the images from the database are manually processed for each target, the data structure is defined as frame number origin, box size coordinates, target class value/ name, and the information is used as output source for the training algorithm. The number of representative samples for each class is around 3000 (3K). In the following table (table 9), there is an example for the three target classes (swimmer, surfer, shark), frames, boxes coordinate from the used database:

Table 9

Defining Elements of Database

	Image_Path	Frame_nr	Label	x_min	x_max	y_min	y_max
69	images/frame152.png	frame152.png	Surfer	931	995	439	477
70	images/frame152.png	frame152.png	Surfer	719	788	692	726
71	images/frame152.png	frame152.png	Shark	993	1011	90	115

Table 10

Training Database Details

Class	**Training and Validation**	**Test**	**Color**
Surfer	2000 (1500 + 500)	1000	Red
Swimmer	2000 (1500 + 500)	1000	Green
Shark	2000 (1500 + 500)	1000	Blue

Frames from the dataset are divided, for each class, in equal samples for training, validation and testing (*Table 9)*. The algorithm used for training is Adamax with the loss function the loss function intersection over unity (IOU).

The intersection over union (IoU) for all frames as:

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{3}$$

where the Area of Overlap is the common area covered by the predicted and the ground truth bounding boxes, and the Area of Union is the union of the predicted and the ground truth bounding boxes [14]. The IoU value is computed at each frame. If it is higher than a threshold, the success rate is set to 1; otherwise, 0.

The CNN answer will consist in image segmentation and is weighted for feature classification and on the tested batches . It can dependent on the type of target, target size, illumination intensity and feature definition (resolution). The network detection based on image segmentation can be visualized on the figure 8.

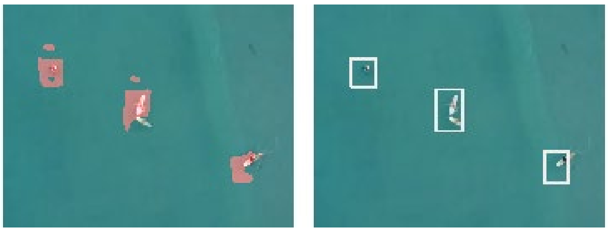


Fig. 8. Network detection

The risk assessment of detected targets is based on the relative distance between sharks and surfer/swimmer and the number of the detected sharks (fig. 9). The distance is obtained based on ground sampling distance, depending on the camera resolution and the altitude data from the on-board altimeter. For a 4|K camera oriented in vertical position, at altitude of 30 meters and 30º field of view, the ground sampling is about 7.6 millimeter per pixel. The threshold distance for issuing a risk hazard alert is within range of view (between 8-12 meters).

Fig. 9. Risk assessment of detected targets

As one can see, in table 11, performance obtained from the confusion matrix, for test samples of each class classification, gives comparable results with increased size YOLOv3 network [15] using low computation resources.

Table 11

The performance obtained from the confusion matrix for the test dataset classification

Class	**Method**	**Supervision**	**mask**	**Precision**	**Recall**	**F1-score**	**Samples**
Swimmer	BoxSup	Weakly(box)	3k	78.8	84.2	81.4	1000
Surfer	BoxSup	Weakly(box)	3k	84.6	85.1	84.9	1000
Shark	BoxSup	Weakly(box)	3k	89.2	83.4	86.2	1000

5. Conclusions

The proposed detection and identification method brings a considerable contribution to minimize the impact of potential risk occurrence, reducing the lifeguard human errors. The developed deep learning architecture is capable to detect and classify, with good accuracy, in high-resolutions images and real-time, sharks, surfers and swimmers, to spatially localize the events and to assess the risk through correlation of the detected feature attributes. Because the results are only conservative to the size, quality of images, illumination level and other objects that can partially obstruct the view, like waves or water, a research in this direction is anticipated in the near future.

The authors propose a coordination of processes between all states bordering on the respective seas, to gather data in case new situations arising regarding hazard detection. Thus, an alert system between states must be based on collaborative decision making.

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