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Development of a Detection System for People Drowning Through Aerial Images and Convolutional Neural Networks

Abstract. *This work develops a system capable of determining the presence of a person in the water by classifying a convolutional neural network (CNN). When a drowning is alerted, the drone camera takes aerial captures of the water area, the first trained CNN is in charge of determining if it is deep water or not, while the second CNN is in charge of identifying the presence of a person in that video frame; in case both detections are positive, the drone will drop the life ring it carries. The tests confirm that this system is capable of providing a means of survival to the person in an ideal time.*

Streszczenie. *Ta praca rozwija system zdolny do określania obecności osoby w wodzie poprzez klasyfikację konwolucyjnej sieci neuronowej (CNN). W przypadku ostrzeżenia o utonięciu kamera drona wykonuje zdjęcia z powietrza obszaru wodnego, pierwszy przeszkolony CNN jest odpowiedzialny za określenie, czy jest to głęboka woda, czy nie, podczas gdy drugi CNN jest odpowiedzialny za identyfikację obecności osoby w tym ramka wideo; w przypadku, gdy obie detekcje są pozytywne, dron upuści koło ratunkowe, które nosi. Testy potwierdzają, że system ten jest w stanie zapewnić człowiekowi środki na przeżycie w idealnym czasie.* ***(Opracowanie systemu wykrywania tonących osób na podstawie zdjęć lotniczych i konwolucyjnych sieci neuronowych)***

Keywords: People drowning; Convolutional neural network; Image processing.
Słowa kluczowe: sieci neuronowe, prztwarzanie obrazu

Introduction

According to the world report on drowning issued by the World Health Organization (WHO) [1], in 2019 about 372 thousand people lost their lives by drowning accidentally, making it a serious public health problem. In the chain of survival, in case of drowning it is stated that prevention and a float element are key to the survival of the person and a successful rescue [2]. In addition, it is known that a drowning person only has 10 minutes to be rescued, if it is prolonged for longer, it is very likely that their life will not be saved or they will suffer serious health problems in the future [3]. As the rescue time is so limited, it is necessary to propose and develop technologies that help to save human lives.

Nowadays, robotics research has focused on solving problems for the population, some examples are robots used in industrial manufacturing [4], robots used in space exploration [5], robots used in explosive deactivation tasks [6, 7], among others. Most of these applications share the feature of being challenging, dangerous or time-sensitive tasks. On the other hand, new designs of robots that perform tasks of assistance and support to rescuers have also been investigated [8, 9] and marine robots are no exception [10]. Some of the most well-known designs of aquatic robots are: autonomous underwater vehicles [11], fish-inspired robots [12], others inspired by octopuses [13] or amphibians [14]. Several sectors stand to benefit the most from this recent research, such as hydrographic mapping, marine exploration [15], marine archeology, and marine search and rescue [16]. Aquatic rescue robots are currently performing this type of tasks without the need for direct human intervention [17], in that context, the fast and timely intervention of robots to rescue a drowning person is crucial; likewise, the detection of people or objects by artificial vision becomes very important in rescue scenarios, which is why it is necessary to implement a technique that helps the detection of people in a dangerous environment.

It is for that reason that this work seeks to contribute to the development of aquatic rescue robots; we propose the development of a system that uses a drone to assist in the rescue of people in danger of drowning, which is equipped with a camera and will drop a ring lifebuoy for the person in danger when a human figure is detected in the video frame taken by the camera thanks to the convolutional neural network (CNN) based people detection technique. The rest of the paper is organized as follows: Related works are presented in Section II, the development of image classification is presented in Section III, the methodology proposed in this research is described in Section IV, the development of the proposed system can be found in Section V, the results and discussions are shown in Section VI of this paper, and finally, the conclusions of this research and the approach of future work are presented in Section VII.

Literature Review

Muhammad's paper [**?**] focuses on the comprehensive review of the mobility of aquatic robots based on the type of robot propulsion and the type of material they use. Aquatic fish propulsion is divided into two categories: body and/or caudal fins (BCF) and median and/or paired fins (MPF). On the other hand, in recent years many researchers have started to develop smart materials as impellers that can be grouped into four categories: shape memory alloy SMA, ionic polymer metal composite IPMC, lead zirconate titanate (PZT) and soft pneumatic actuator as pump or motor replacement. Despite the current efforts of scientists looking for solutions with smart materials, they are still slower than conventional motors, but with soft actuators a promising future is in sight. While, on the propulsion side, the hybrid design proposed in that research is a jellyfish-like robot that uses a hybrid method with rubber materials as the body to achieve propulsion forces by bending and contracting, this robot has good results. In the article, the development of a low-cost bio-inspired swimming robot (SRob) using IOT is presented. Tests determine that by using an accelerometer sensor, the position and state of the SRob can be effectively determined and its maximum speed is 20m/s.

The article [18] presents a review on the types, functions and hydrodynamic characteristics of typical multi-body marine robots. Such a system is generally characterized by underactuation, hyper-redundancy, power distribution, modularization, etc., its main advantages are: carrying more cargo and having more ways of movement. The multi-body marine robot with self-reconfigurable capabilities has advantages in transportation economy, simplification of deployment and recycling, environmental adaptability and work efficiency. The authors of this paper recommend that future multibody marine robot designs take into account the specialization of the overall structure, simplification of the unit structure, easy analysis of the coupled flow field, and simplification of the control because they can significantly improve the operational capability of the multibody marine robot. In [19], the authors present a review of current unmanned surface vehicle (USV) development. They first provide general definitions of USVs and the main approaches to USV guidance, navigation, and control.

In [2] the authors perform a simulation of a drowning person 100m from shore to determine which is the best rescue method: a drone flying to where the victim is carrying a life preserver or a surf swim to that same location. They conducted 30 tests and across the board the drone's success rate was 100 percent, concluding that using drones to deliver ring lifebuoys is safe and may be a faster method of providing first flotation devices for conscious drowning victims compared to rescue swimming.

The article [20] presents the design of an unmanned robotic lifesaver used to rescue people in the event of a disaster. This device can save conscious or unconscious people without causing any risk to their health. The literature reveals that all present solutions are based on air, surface or underwater systems that need a crew and can only save conscious people, so this invention fills that gap. The robot is electric and maneuverable from 400m, has a maximum speed of 5.15m/s and autonomy of 15 minutes. The results validate the costs and viability of the system. In this other paper [21], the design of a modified ring buoy controlled by a remote control to provide buoyancy is presented. The cost of the device is low, so it could be easily fabricated. The size of the ring buoy is SOLAS (Safety of Life at Sea) approved, which has been proven to work in extreme marine conditions. The article [22] applies convolutional neural networks in face recognition to determine if it is a real face, and compares Support Vector Machine (SVM) and LeNet-5 models with the proposed improved LeNet-5 model giving the best results. The article [23] applied convolutional neural networks for the recognition of the dorsal veins of the hand. Using CNN models with VGGNet which compared VGG16 with VGG19, the latter being 100% effective in the recognition of trained users. The article [24] proposes the use of this dataset for cancer classification based on histopathological images using EfficientNet-B0 in convolutional neural network (CNN). Their objective was to improve the performance of previous studies and to determine the effect of the augmentation and dropout layers on the proposed model obtaining as results that the EfficientNetB0 model improved the performance in previous studies with an accuracy of 98.90%. In [25] proposed a method based on 12 efficient layers, the five microclasses of heartbeat types from the MIT-BIH arrhythmia dataset and using the wavelet noise reduction technique for comprehensive analysis in the classification of electrocardiographic arrhythmias (ECG). They developed a proposed CNN network with Butterworth low-pass order denoising technique achieves outstanding results 99.99% overall classification accuracy.

Methodology

This paper presents the development of a support system for the rescue of people in danger of drowning in an aquatic environment. Figure 1 shows the block diagram of the proposed rescue system, which starts from the drowning survival chain, who is divided into three stages: prevention (green color), survival (yellow color), and drowning recovery (red color).

- Prevention: Lifeguard provides information and recommendations on the behavior of the waves to people and is attentive to any event or possible case of drowning.
- Survival: In this window, the drowning person has only 10 minutes to be rescued.
- Drowning Recovery: Lifeguard in this stage recover the drowning person out of the water to bring the required first aid.

This work focuses on the development of a system that is capable of supporting the person when it is in the survival stage (second stage). For this, a lifeguard is on the shore of the beach guarding the area as a preventive measure. When a distress alert occurs, the agent sends a drone equipped with a camera and a ring lifebuoy. This drone performs an autonomous flight to the area where the distress alert has occurred and sends real-time aerial images of the beach to the people detection algorithm. The developed algorithm consists of two CNN's trained to determine if the water is deep and to recognize people in the water, respectively. Once the first CNN determines that the water is deep, the second CNN is enabled to determine where the drowning person is located, and once the algorithm determines the person's position, the drone launches the ring lifebuoy into the water so that the person can grab hold and stay afloat.

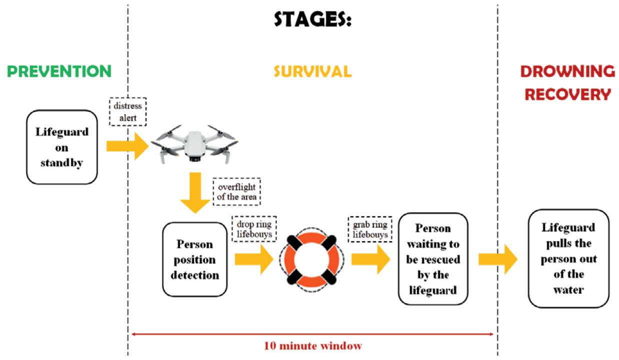

Fig. 1. Block diagram of the proposed system

Previous research estimates that the optimal survival time of a drowning person is 10 minutes, therefore, the proposed system will be evaluated in two aspects. The first aspect is the response time, for this, simulations of drowning people will be made to verify that the rescue time is adequate and will be compared with other methods seen in similar articles. The second aspect to be evaluated will be the performance of the CNN, for which we will make use of receiver operating characteristic (ROC) curves, which provide a graphical representation of the sensitivity of the classifier at the time of giving a successful detection of a human in danger of drowning.

Figure 2 shows the flowchart of the proposed sensing system architecture which is divided into three phases: Image adaptation, sea classification and drowning person classification.

0.1 Image Adaptation Phase

The algorithm starts with the adaptation phase, in this phase the image is first acquired from the drone camera and then the image is conditioned to a resolution suitable for input to the detection algorithm. This conditioned image then goes to the sea classification phase.

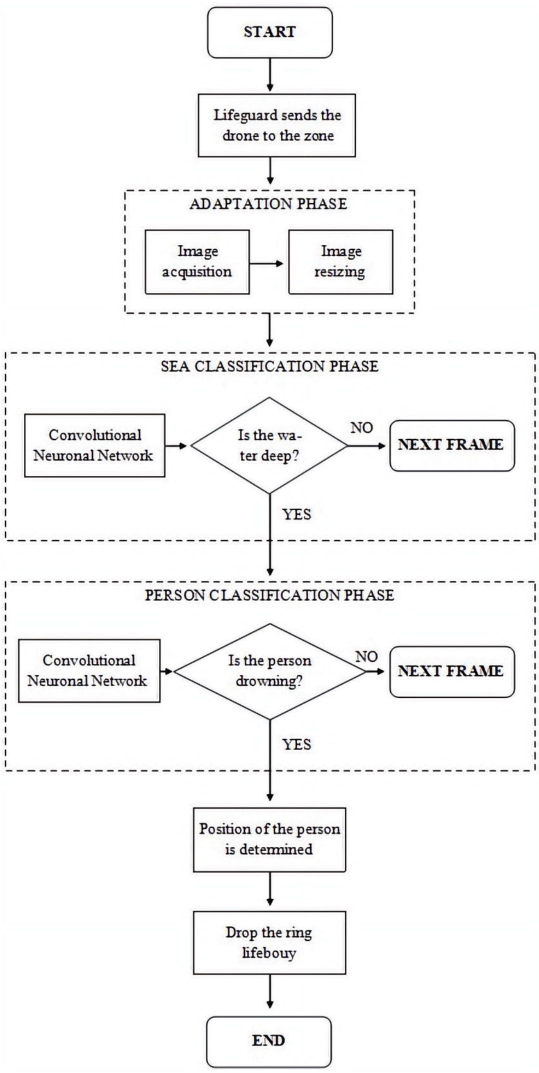

Fig. 2. The flow of proposed system architecture

0.2 Sea Classification Phase

In this stage the CNN is trained to detect if the sea is at a certain distance from the shore, this by means of color, if the color of the water is an intense blue it means that the depth is greater, it is in this area where the probability of drowning is higher. Figure 3 shows the difference in color of the water with respect to the distance from the shore, the farther away it is, the more intense the blue color, and therefore the deeper it is. If the image is classified as deep water, the algorithm continues with the third phase, otherwise it moves to the next frame of the video.

0.3 Drowning Person Classification Phase

In the third phase, the person classification phase, the CNN will determine if there is a person in the water, if this is correct the algorithm will determine the position of the person and will drop the ring lifebuoy, ending this detection system, otherwise it moves to the next image frame. In the aspect of the CNN and the development of the classification, a database taken by the development team of this article was used, which consists of 5000 images taken in a pool and the beach to objects and people, the images were taken by mounting a camera on a drone, in order to correctly perform the classification, the images were reduced to a dimension of 100 x 100 pixels. The CNN presented has the following distribution: an input layer, a convolution layer, a grouping layer, fully connected layers and an output layer where it will detect whether or not what is present in the image is a human in possible risk of drowning.

Fig. 3. Water depth classification

Proposed System Development

0.4 Image classification

In the convolution layer, a set of filters convolves the image to perform the extraction of image features, in this convolution, the filters move across the input matrix performing dot product between each element. In this extraction of features from an image, the first convolutional layers take basic features from the image while subsequent convolutional layers extract more specific features from the image [26]. The pooling layer has the function of combining each set of results obtained from the previous layer, thus greatly reducing the dimensions of the parameter map by making use of, generally one of two basic operations: max pooling or average pooling where max pooling is used much more frequently as it works better [27]. The images having a dimension of 100x100 and being in color, the 3 channels referred to RGB are considered, which are the synthesis of three matrices, so at the beginning there would be 100x100x3 input points for the network, that is why the convolution layers and the grouping layer are added, which allow reducing the dimension of the image by applying grouping filters. In this way it is possible to reduce the size to 6x6x64 with a total of 64 filters without losing the main features of the images.

0.5 Ring lifebuoy and drone

For the flight tests of this system, we used a DJI Phantom 3 Professional drone. Some of the most important features of this drone are the maximum flight time of 23 minutes, but with load we flew the drone for 15 minutes without problems, maximum speed of 15 m/s, and the weight of 1280 grams. The camera features 12.4 megapixels, 94° field of view and real-time video transmission with HD resolution (1280 x 720 pixels). A pilot performed the flights over the open sea, while the team ensured that the drone tests were carried out correctly. For the life-saving system, an electronic hook device was implemented in the lower part of the drone, which opens automatically when the CNN detects the person at sea. This device drops a QS lifebuoy (Quicksave AB, Falun, Sweden). In Figure 8 one can visualize the drone in the air and the buoy at the exact moment it was dropped. The total weight of the drone plus the implemented system is 1678 grams, in accordance with the maximum weight allowed by law. Figure 4 shows the drone dropping the ring lifebuoy during a flight.

Fig. 4. Image of the drone in the air and the buoy

0.6 Ethics and Approvals

Ethical approval does not apply to this study because no human trials are being conducted. The drone flights were in accordance with Peruvian law No. 30740 issued by the Ministerio de Transportes y Comunicaciones (MTC), which establishes some restrictions for Remotely Piloted Aircraft Systems (RPAS) [28]:

- Maximum height in open spaces not exceeding 106 meters.
- Drone weight less than 2 kg.
- Do not fly in restricted areas or within 4 kilometers of airports.
- It is forbidden to fly in public spaces without authorization from the competent authority.

During the flight, visual contact was maintained with the drone and clearance was obtained from the Coast Guard and the pool manager where the tests were conducted.

Result and Discussion

0.7 Detection of People at Sea

For the sample of results, see Figure 5, we made use of the ROC curves, which offers a graphical representation for a binary system evaluating its sensitivity versus specificity; 1000 images were used to be evaluated and, being a binary classification where there is only one class (Human or non-human), only one ROC curve will be shown. In addition, TensorFlow was chosen as the machine learning library to be used for the construction of the CNN.

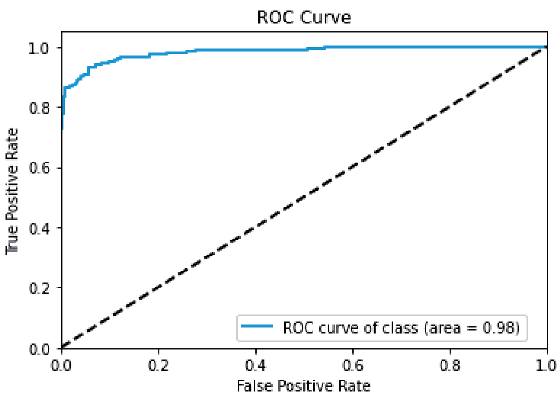

Fig. 5. ROC curve for the CNN model

Table 1 shows the results obtained from the tests performed on the previously trained CNN, the images collected were not part of its learning. For the calculation of Precision, Accuracy, Recall, F-Measure and the area under the curve (AUC), the equations of the article in "" [] were used; among all the parameters, Precision stands out, showing that the model was approximately 95 21% correct in determining whether it was a human or not what was visualized in the image, so the performance of this CNN is more than proven.

Table 1. CNN classifier performance measures.

Accuracy	AUC	Precision	Recall	F-Measure
95.21	94.97	93.64	95.83	94.72

Some of the images used in the tests with a dimension of 100 x 100 are shown in Figure 6.

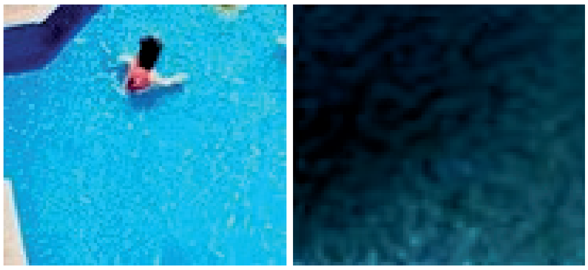

Fig. 6. An image of the dataset: Person drowing (left) No people in the sea (right)

0.8 Characteristics of Drone Rescue

A total of 70 drone flight tests were performed, distributed in 10 tests each day to evaluate the system in different conditions. The time measured was considered from the time the drone took off until the life preserver reached the drowning person, the average rescue time was 7 minutes, separated as follows: average time of the drone to reach the alert zone was TZA = 2 minutes, average time of detection of the person in the sea TPM = 4 minutes and the average time it took the drone to release the life preserver and the person to hold it was TSS = 25 seconds. The distance from the shore to where the person was located varied in the range of 250 to 300 meters. In all tests the hit rate of the drone leaving the life preserver was 100%, see Table 2. In comparison, the same tests were performed with equal conditions with rescuers who went to save people swimming, as they would normally do, giving an average time of 10 minutes.

Table 2. Average values of the drone tests.

Day	Drone		Rescue Swim	
	Time (s)	Success	Time (s)	Success
Monday	432	9	582	9
Tuesday	348	10	630	7
Wednesday	378	10	606	8
Thursday	354	10	672	9
Friday	402	10	576	10
Saturday	282	10	618	8
Sunday	414	9	678	7
Media	372.86	9.71	623.14	8.28

Conclusion

This work presents the development of a system to assist for the rescue of drowning persons. When the lifeguard observes a possible case of drowning, turns on the drone and starts his trajectory towards the drowning area; along the way the drone will capture and send images in real time, which will be processed by a convolutional neural network (CNN) to detect the exact location of the person. After detection, the drone drops a ring lifebuoy so that person in the water can hold on to it and save himself from drowning. Tests showed that the CNN is very good at classifying and detecting people in water (sea, pools, etc.), with a success rate of 95.21%. In addition, the drone leave the ring lifebuoy to the person in the exact place and without errors, in an average time of 6 minutes and 13 seconds, enough time for conscious people to be saved without suffering any subsequent consequences.

Further investigations will seek to replace the lifeguard by a group of drones that will be constantly patrolling the danger deep water areas, thus optimizing the rescue since it is in the possible drowning zone and possibly can pull the person out of the water.

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