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Person Detection in Maritime Search And Rescue Operations

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Abstract - *There is a growing necessity to arrange a search and rescue operation (SAR) to offer help and health care to the injured due to an increase in the number of persons who participate in various adrenaline activities or adventure tourism and stay in inaccessible regions. The goal of SAR is to search the broadest feasible area of the territory in the shortest amount of time in order to locate a lost or injured individual. Drones (also known as unmanned aerial vehicles or UAVs) are now widely used .Drones are increasingly being employed in search and rescue missions because they can quickly capture a vast, controlled area. However examining a huge amount of recorded data in detail remains a challenge. Even for an expert, it is not easy to find searched people who are relatively small considering the area where they are , often sheltered by vegetation or merged with the ground and in unusual positions due to falls, injuries, or exhaustion. As a result, automatic detection of people and objects in images/videos captured by drones during these activities is crucial. In SAR operations, the key object is the person, however, recorded from a bird's eye view, and such recordings are not contained in the large data sets on which these state-of the-art detectors are trained. To achieve the highest possible accuracy of the detection model, the data set on which the model is trained must have similar conditions to those that appear when testing the model, so it is necessary to train the model with a bird's eye view data. This study reviews various implementations as well as some predictions for the future of SAR operations.*

Key Words: object detector, person detection, search and rescue operations, UAV, image processing , machine learning

1. INTRODUCTION

In 2017, 3,116 migrants were killed in the Mediterranean Sea. Missing Migrants (Missing Migrants, 2018). When it comes to finding victims following shipwrecks, Unmanned Aerial Vehicles (UAVs) and Remotely Piloted Aircraft (RPAs) have a significant advantage over satellite surveillance since

they can explore specific locations utilising real-time route planning. Researchers recently investigated computer vision sensors, techniques, and strategies, with a focus on emergency scenarios that put people in danger (such as fire and flood) or are created by others (i.e. accidents). UAVs and RPAs are frequently used in search and rescue operations to classify scenes and identify commodities. When compared to prior techniques that relied on hand-crafted feature extraction, using both semi-supervised and supervised machine learning algorithms for aerial photo categorization and object recognition is a good strategy. Deep convolutional neural networks, such as Faster-RCNN , Cascade R-CNN , RetinaNet , SSD , and YOLOv3 , have been successful at recognising individuals in photographs of primarily urban scenes in recent years, and achieve even higher accuracy than humans. To achieve such high results, deep network models required to be trained on large data sets as MS COCO, Pascal VOC, and ImageNet. Then, in order to acquire good detection results or significant improvements in certain domains not included in big data sets, such as thermal images of the monitored region, some sports scenarios, and so on, it is required to train deep networks on the image set from the selected domain .The data set on which the model is trained must have similar conditions to those that emerge when testing the model, hence it is vital to train the model with a bird's eye view data to get the best possible accuracy of the detection model. One suitable dataset is the AFO dataset which contains images from fifty video clips of items floating on the lake surface that were acquired by the several drone-mounted cameras that were used to build AFO (resolutions ranging from 1280x720 to 3840x2160). We retrieved 3647 photos with 39991 items from these films and manually tagged them. The training set (67,4 percent of objects), the test set (19,12 percent of objects), and the validation set were then divided into three portions (13,48 percent of objects). The test set contains selected frames from nine videos that were not utilised in either the training or validation sets to prevent the model from overfitting to the available data.

2. MOTIVATION

For almost a century, search and rescue (SAR) operations have essentially been conducted in the same manner, utilising technology such as radar to get a general search area or human aided with the assistance of search dogs. Many additional uses of AI and machine learning across sectors, such as training algorithms to detect abnormalities that the human eye would overlook, might be quite useful in SAR operations. These technologies have the potential to be more efficient, cost-effective, and time-saving.

3. RECENT WORK

[1] This research looks at how automated search algorithms and network architecture may be coupled to increase the overall performance of the state-of-the-art Mobi leNetV3-Large and MobileNetV3-Small systems, which are designed for high and low resource use cases, respectively. These models are then tweaked and utilised for tasks like object detection. As explained in this article, the MobileNetV3 Large and Small models were created to offer the next generation of high-accuracy, efficient neural network models. Apps that use efficient neural networks are becoming increasingly widespread, enabling whole new on-device experiences. Higher accuracy and shorter latency are two benefits of improved neural network efficiency. To achieve this we introduce

(1) Complementary search strategies.

(2) New efficient network architecture.

[2] This work describes an aerial image-based identification and tracking algorithm for rescuing persons in catastrophe situations, which is supplemented by a semi-autonomous reactive control system. The following is a list of contributions: A colour and depth-based human detection stage, as well as the usage of a Human Shape Validation Filter A Convolutional Pose Machine provides the positions of human joints for this filter to examine the human skeleton form of the discovered detections in order to remove false positives. When the point of view is rotated in regard to the target objects, an automated Multi-Object Tracking method that is scale, translation, and rotation invariant. A revolutionary matching approach based on stance and look similarities that may re-identify persons who have vanished from the scene for an extended period of time. The unique body attitude and appearance-based association technique allows tracking and recognition tasks to be completed in exceedingly difficult aerial sequences. Furthermore, due to the filter's design based on the Convolutional Pose Machine, false positives have been reduced to zero (CPM).

[3] To aid in search and rescue, surveillance camera systems and unmanned aerial vehicles (UAVs) are deployed. Because a single human cannot monitor numerous surveillance screens at the same time for 24 hours, automatic object detection is critical. Furthermore, the object is frequently too small to be seen on the surveillance screen by the naked eye. To reduce detection time for small targets, we combined picture segmentation, enhancement, and convolutional neural networks. We compared the auto-detection system's performance to that of the human eye. Our technology spotted the target in 8 seconds, however it took the human eye 25 seconds to locate the object. For object recognition, we used an SSD module. Future research could use a variety of SSD networks, including concatenation and element-sum of each layer, to improve accuracy . Using numerous UAVs, we could boost search and rescue operations even further. Using video streams from several UAVs as one giant image, distributed deep learning can be implemented across multiple UAVs. Combining UAV sensor and image analysis processing can aid in the optimization of UAV flight parameters, such as UAV position, energy restrictions, environmental dangers, and data sharing constraints.

[4] In this article, we provide a unique technique for recognising persons in aerial photographs of nonurban territory obtained by an unmanned aerial vehicle (UAV). In both the region suggestion and classification stages, the technique leverages two separate convolutional neural networks. Contextual information is also employed to improve detection outcomes during the classification step. Experiment results on the HERIDAL dataset obtained 68.89 percent accuracy and 94.65 percent recall, which is superior to existing state-of-the-art approaches for human identification under comparable situations.

[5] The current research is focused on real-time human identification aboard a fully autonomous rescue UAV. The built embedded system was capable of recognising open water swimmers using deep learning techniques. As a consequence, the UAV was able to give precise support in an unsupervised way, boosting the operational capabilities of first responders. The proposed system is distinct in that it use a combination of GNSS technology and computer vision algorithms for both precise human detection and the release of rescue gear. While the suggested rescue system was designed to detect open water swimmers, with a few tweaks, it could also detect humans and provide emergency services to those participating in winter sports activities. Because of the high level of detection and classification accuracy achieved, the suggested approach has endless applications in SAR missions in a variety of terrains and situations.

[6] Unmanned Aerial Vehicles (UAVs) outfitted with multispectral cameras are used in this study to search for bodies during marine rescue missions. In the northwest of Spain, a number of flights in open water settings were conducted, utilising a qualified aquatic rescue dummy in dangerous areas and actual persons when weather conditions permitted. The multispectral pictures were aligned and utilised to train a body identification Convolutional Neural Network. A thorough analysis was conducted to determine the best combination of spectral channels for this purpose. Using 1) complete image, 2) sliding window, and 3) precise localization method, three approaches based on a MobileNet topology were tested. The first technique determines whether an input image contains a body, the second approach employs a sliding window to assign a class to each sub-image, and the third method use transposed convolutions to provide a binary output with the body pixels highlighted. To align the

multispectral camera channels, the MobileNet architecture was updated in all cases by adding custom layers and preprocessing the data. The precise localization strategy, we conclude, is the most suited method, achieving spatial localization close to 1m with equivalent accuracy to the sliding window. We plan to use this system in real-world cooperative missions with ground workers to search wider areas with an autonomous rotorcraft weighing 25 kilogrammes, carrying a payload of 10 kilogrammes, and flying for three hours. The data gathered from these real-world missions might potentially be utilised to retrain CNNs with additional photographs to increase their performance. Furthermore, our vision system will be enhanced in the future with additional cameras with varying spectral ranges and an integrated GPU mounted on the UAV.

[7] Because of their capacity to be deployed rapidly and often and fly at low altitudes, unmanned aerial vehicles (UAVs) have a lot of potential for use in natural resource monitoring methods. Texture measures are often used in pixel-based image analysis, but their application in an object-based context is less well documented. In this study, we employed subdecimeter UAV data to examine texture measures at various scales in object-based analysis with the goal of identifying broad functional categories of plants in arid rangelands. The decision tree was a helpful tool for cutting down viable texture measures for simplicity of computation, and the correlation analysis revealed important insights into the variations in correlation of texture measure pairs over many scales. The results show that unmanned aerial vehicles (UAVs) are viable platforms for rangeland monitoring and that the shortcomings of low-cost off-the-shelf digital cameras can be overcome by including texture measures and using object-based image analysis, which is well suited to very high resolution imagery. Our findings will be included into a procedure for monitoring rangeland with unmanned aircraft.

[8] Over hundreds of object categories and millions of pictures, the ImageNet Large Scale Visual Recognition Challenge establishes a standard for item category categorization and detection. From 2010 until the present, the challenge has been organised yearly, with over fifty colleges participating. This study outlines how this benchmark dataset was created as well as the advancements in item recognition that occurred. We explore the difficulty of accumulating large-scale ground truth annotation, highlight major developments in categorical object identification, present a thorough analysis of the current status of large-scale picture categorization and object detection, and compare computer vision accuracy to human accuracy. We conclude with lessons learned throughout the course of the five-year project, as well as recommendations for future routes and enhancements.

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[10] We look at the subject of automatically recognising persons in thermal records and photographs in this work. The thermal videos are filmed on a meadow with a little woodland, with up to three individuals in different postures and distances from the camera. The COCO picture dataset comprises RGB photos of a range of item categories, and YOLO is an object detector that has been pre-trained on it. In terms of human detection, the proposed structure uses the discriminant power of SC and LDA to surpass the rectangular feature-based method. Our next aim is to reduce computer costs.

[11] The challenge of automated human detection in thermal pictures utilising convolutional neural network-based models that were initially designed for detection in RGB images is studied in this research. On a dataset of thermal images collected from movies shot at night in clear weather, rain, and fog, at varying ranges and with different forms of movement - running, walking, and sneaking – the performance of the conventional YOLOv3 model is compared with that of a specially trained model. The tests show excellent results in terms of average precision for all scenarios investigated, as well as a significant increase in performance for human detection in thermal imaging with a small training set.

[12] Unmanned Aerial Vehicles (UAVs) are used to power a number of critical computer vision applications, providing more efficiency and convenience than traditional security cameras with fixed camera angles, sizes, and perspectives.As a result, moving further with related research necessitates the development of an unconstrained UAV benchmark. We build a new UAV benchmark in this study by concentrating on difficult circumstances with new level obstacles. Then, for each work, a thorough quantitative analysis is performed utilising the most recent state-of-the-art algorithms. Experimental results show that existing state-of-the-art algorithms perform considerably worse on our dataset

due to new hurdles that have evolved in UAV-based actual situations, such as high density, tiny objects, and camera motion. To our knowledge, this is the first time such challenges have been extensively explored in unrestrained scenarios.

[13] Existing counting methods frequently use regression-based methodologies and are unable to properly pinpoint the target objects, making further analysis difficult (e.g., high-level understanding and fine-grained classification). Furthermore, the majority of previous research has focused on counting objects in static situations using fixed cameras. We're interested in recognising and counting items in such dynamic situations because of the introduction of unmanned flying vehicles (i.e., drones). Unlike traditional region proposal approaches, we use spatial layout information (for example, cars generally park in a predictable pattern) to incorporate spatially regularised constraints into our network to increase localization accuracy. To put our counting approach to the test, we provide a new large-scale vehicle parking lot dataset (CARPK) encompassing around 90,000 autos collected from several parking lots. It is, to the best of our knowledge, the first and largest drone view collection that permits item counting and includes bounding box comments.

[14] We present a new aerial video dataset and benchmark for low altitude UAV target tracking in this research, a s well as a photo-realistic UAV simulator that may be used with tracking algorithms. On 123 fresh and completely annotated HD video sequences shot from a low altitude aerial perspective, our benchmark gives the first evaluation of numerous cutting-edge and popular trackers. We assess which of the compared trackers are best suited for UAV monitoring in terms of tracking accuracy and run-time. The simulator may be used to Test tracking algorithms in real-time settings before deploying them on a UAV "in the field," as well as to build synthetic but photo-realistic tracking datasets With automated ground truth annotations to simply augment existing real-world datasets. This lays the groundwork for future advances in accuracy and speed. Our suggested UAV simulator, in conjunction with unique assessment methodologies, allows tracker testing in real-world circumstances with live feedback before to deployment.

[15]The purpose of this study is to investigate the effect of convolutional network depth on large-scale picture recognition accuracy. Its primary contribution is a detailed analysis of increasing depth networks utilising an architecture with extremely tiny (3X3) convolution filters, demonstrating that raising the depth to 16–19 weight layers greatly improves performance over prior-art arrangements. The depth of ConvNet architecture design is another significant feature that we will address in this study. To accomplish so, we tweak different architecture variables and gradually increase the network's depth by adding additional convolutional layers, which is made feasible by the use of tiny (3 X 3) convolution filt ers at all levels. The goal of this research is to look at the influence of convolutional network depth on large-scale image recognition accuracy. Its main contribution is a thorough investigation of increasing depth networks using an architecture with extremely small (3X3) convolution filters, which demonstrates that extending the depth to 16–19 weight layers significantly increases performance over prior-art arrangements. Another important aspect of ConvNet architecture design that we shall investigate in this study is its depth. To accomplish so, we tweak different architecture variables and gradually increase the network's depth by adding additional convolutional layers, which is made feasible by the use of tiny (3 X 3) convolution filters at all levels.

[16] It's more harder to train deeper neural networks. For training networks that are far deeper than previously utilised networks, a residual learning technique is proposed. Rather than learning unreferenced functions, we explicitly reformulate the layers as learning residual functions with reference to the layer inputs. We show extensive empirical evidence proving that as network depth increases, residual networks become easier to optimise and achieve higher accuracy. Deep convolutional neural networks have been credited with several advances in image processing. clasification. End-to-end multilayer deep networks have low, mid, and high-level features and classifiers by default, with the number of stacked layers increasing the "levels" of features (depth).Recent evidence suggests that network depth is critical, and the top results on the difficult ImageNet dataset all use "extremely deep" models with depths of sixteen to thirty. Very deep models have also aided many other non trivial visual recognition problems.

[17] Feature pyramids are a common component of recognition systems for recognising objects at several sizes, however they are computationally and memory costly. For building high-level semantic feature maps of various sizes, a top-down architecture with lateral linkages is designed. This design is known as the Feature Pyramid Network (FPN). It's a significant improvement above regular feature pyramids. Recognizing things at widely different sizes is difficult in computer vision. The standard approach is based on feature pyramids built on picture pyramids. The scale change of an object is countered by moving its level in the pyramid, making these pyramids scale-invariant. This characteristic allows a model to recognise items at a variety of scales by scanning the model over both positions and pyramid levels. We've shown how to create feature pyramids in ConvNets using a clean and straightforward architecture. As a result, it provides a viable solution for feature pyramid research and applications without the requirement to compute image pyramids. Finally, our

findings imply that, despite deep ConvNets' tremendous representational power and implicit scale variation robustness, it is still necessary to actively handle multiscale challenges utilising pyramid representations.

[18] For emergency responders, coordinating many Unmanned Aerial Vehicles (UAVs) to conduct aerial surveys is a huge difficulty. UAVs, in particular, must fly at a kilometre scale. while attempting to find casualties as swiftly as possible It is necessary to assist in this process. it is desirable to take use of the rising availability of disaster data from sources such as manned reconnaissance, crowd reports, satellite remote sensing Such, in particular, Information can be a useful tool for guiding the planning of UAV flight paths over a given area. in order to locate those who are in risk However, there are difficulties with computational tractability. When planning over the resulting extremely large action spaces, keep this in mind. To address these issues, we define the survivor finding problem and offer the first example of a survivor discovery algorithm as our solution. The Monte Carlo tree search method is a coordinated Monte Carlo tree search approach with continuous factors. Our assessment in comparison to Benchmarks reveal that our approach, Co-CMCTS, is capable of localising more data. On simulations with real-world data, casualties were 7 percent or more faster than typical procedures. Unmanned Aerial Vehicles (UAVs) that are low-cost, reliable, and commercially available are becoming more common. (UAVs) has resulted in a concentrated attempt to use these platforms to assist first responders. obtaining sensory data without endangering human life.The concept of enabling coordinated UAVs to tour a catastrophe area in order to find the geographical location of victims is at the heart of this research. Given the huge region to cover and the continuous action-space represented by a UAV's axes of motion, this is a demanding assignment. Advances in data collection have facilitated this study by opening up new sources of information on disaster scenarios, resulting in a greater understanding of the situation on the ground during a disaster. Crowd-sourced data is becoming more readily available due to the speed with which it may be created and its capacity to immediately represent the experiences of those present. People who can often give a very accurate report on the hazards in their vicinity and the number of potential casualties.

[19] The process of seeking for and rescuing missing individuals or other objectives in marine territory is known as Maritime Search and Rescue (MSAR).The typical workflow of a search and rescue (SAR) operation, including MSAR. A SAR operation begins when the rescue organisation is notified of a distress alert from any authority. The location will be utilised to define the sort of SAR operation that will be done, such as wilderness, urban, combat, or marine, and then information on the search area will be acquired based on location, environment, and incident area size. The SAR team will choose the suitable search grid if the location of the subject(s) is unknown. Track line, parallel track, expanding square, sector search, creeping line search, and contour search are the six types of search patterns commonly utilised in marine SAR operations. As mentioned, the search here uses the parallel track search pattern (i.e. a Sweep Search/Parallel Pattern conducted on a square/rectangular/cell grid), the search being conducted with a few Rotary Wing UAVs flying in formation. This can be visualised, indicating also the camera line of sights of the UA Vs. The flight paths can be pre-programmed.

4. CONCLUSIONS

The ability to consequently perceive people on drone photos utilising PC vision advances is a gigantic guide in SAR tasks. In this exploration, we examined state of the art human recognition in drone photographs. On a few datasets, we explored the conduct of various CNN-based article locators, including MobileNetV3 and YOLOv4 and so on . As far as normal accuracy, YOLOv4 has achieved the best discovery results (AP). In SAR tasks, the model ought to have as not many bogus location (FPs) as practical to try not to squander assets. In any case, while searching for a missing individual, the most pivotal issue is that the locator finds that individual, and how exact the discovery is less huge. Just go for it outflanked any remaining APs as far as item size and location exactness.

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